



BOOK OF SHORT PAPERS



3rd ITALIAN CONFERENCE ON ECONOMIC STATISTICS

SUSTAINABILITY, INNOVATION AND DIGITALIZATION:
Statistical Measurement for Economic Analysis



UNIVERSITÀ DEGLI STUDI DI NAPOLI
PARTHENOPE



DIPARTIMENTO DI STUDI
AZIENDALI E QUANTITATIVI
DIPARTIMENTO DI ECCELLENZA



ENZO ALBANO
EDIZIONI

ICES 2025 - 3rd Italian Conference on Economic Statistics

BOOK OF SHORT PAPERS

Editors: Rosalia Castellano, Giovanni De Luca, Emma Bruno

Book of Short Papers
3rd Italian Conference on Economic Statistics (**ICES 2025**)
*Sustainability, Innovation and Digitalization:
Statistical Measurement for Economic Analysis*



UNIVERSITÀ DEGLI STUDI DI NAPOLI
PARTHENOPE



DIPARTIMENTO DI STUDI
AZIENDALI E QUANTITATIVI
DIPARTIMENTO DI ECCELLENZA



Organization

Scientific and Program Committee

Rosalia Castellano (Chair)	University of Naples Parthenope
Matilde Bini	European University of Rome
Vincenzo Candila	University of Salerno
Marcello Chiodi	University of Palermo
Andrea Ciccarelli	University of Teramo
Corrado Crocetta	University of Bari
Giovanni De Luca	University of Naples Parthenope
Elena Fabrizi	University of Teramo
Francesca Giambona	University of Florence
Chiara Gigliarano	Carlo Cattaneo University
Caterina Marini	University of Bari
Andrea Marletta	University of Milano-Bicocca
Vittorio Nicolardi	University of Bari
Paolo Mariani	University of Milano-Bicocca
Antonella Rocca	University of Naples Parthenope
Giuseppe Storti	University of Salerno
Giorgio Tassinari	University of Bologna
Roberto Zelli	Sapienza University of Rome

Local Organizing Committee

Giovanni De Luca (Chair)	University of Naples Parthenope
Rosalia Castellano	University of Naples Parthenope
Sergio Longobardi	University of Naples Parthenope
Paolo Mazzocchi	University of Naples Parthenope
Margherita Pagliuca	University of Naples Parthenope
Gennaro Punzo	University of Naples Parthenope
Andrea Regoli	University of Naples Parthenope
Giorgia Riveccio	University of Naples Parthenope
Antonella Rocca	University of Naples Parthenope
Giuseppe Scandurra	University of Naples Parthenope
Emma Bruno	University of Naples Parthenope
Anna Pia Di Iorio	University of Naples Parthenope
Michele Mario Ippolito	University of Naples Parthenope
Andrea Montanino	University of Naples Parthenope
Giuseppe Verdoliva	University of Naples Parthenope

Preface

This volume collects selected short papers presented at the 3rd *Italian Conference on Economic Statistics (ICES)*, held at the University of Naples Parthenope (Italy) on 13-14 February 2025.

The contributions offer an overview of recent developments and applications of statistical methodologies in the analysis of economic phenomena, with a particular focus on the themes of sustainability, innovation, and digitalization. These dimensions, central to contemporary social and policy agendas, call for the adoption of advanced methods and robust analytical tools to support informed, data-driven decision-making. In this context, the integration of new data sources and the use of cutting-edge techniques open new opportunities and improve the accuracy and timeliness of economic forecasts and policy assessments. The conference explored these challenges, focusing on the latest innovations in technological development and productivity while addressing the labour market, sustainability, and digitalization.

The papers included in this volume reflect the richness of the conference program, covering topics such as: innovation, technological development, and productivity; labour market, entrepreneurship, and digitalization; big data for economic, financial, and business decision-making; advances in spatial data analysis for economics; statistical models and deep learning methods for time-series in economics and finance; tourism and overtourism; advanced statistical models for policy impact assessment; data and indicators for sustainability analysis.

The *ICES* was first held in Milan in 2023 to promote dialogue and collaboration within the Italian community of economic statisticians. The conference has since become an annual event, taking place in Florence in 2024 and Naples in 2025.

Naples, Italy
February 2025

Rosalia Castellano
Giovanni De Luca
Emma Bruno

Contents

Forecasting tourist nights spent in Italy: a comparative analysis of statistical and neural network models	1
Fabrizio Antolini, Samuele Cesarini and Ivan Terraglia	
Tourism Satellite Accounts: preliminary estimation of production, value added, and internal tourism consumption for year 2022	5
Fabrizio Antolini and Ilaria Piscitelli	
The impact of digitalisation and sustainability on innovation propensity: firm-level evidence from European Union countries	9
David Aristei	
From Financial Stability to Climate Change: A BERTopic Analysis of ECB and National Central Bank Speeches	13
David Aristei, Mauro Bruno, Barbara Guardabascio and Francesco Ortame	
European Digital Skill Supply: A Latent Variable Perspective	17
Federico Bacchi, Pinuccia Pasqualina Calia and Maria Rosaria Ferrante	
Framing a field: Understanding collectible design through a Delphi study	21
Laura Benedan, Federica Codignola, Carlotta Galeone and Paolo Mariani	
Multidimensional Perspectives on Food Poverty in Italy: insights from POSet Analysis	25
Ilaria Benedetti and Chiara Grazini	
Spending diversity and quality indexes by SWB levels and urbanization degree	29
Cristina Bernini, Silvia Emili and Federica Galli	
From Choices to Change: Household Finance and Sustainability	33
Beatrice Bertelli, Marianna Brunetti, Costanza Torricelli, Arthur van Soest and Mariangela Zoli	

Municipal indicators for the analysis of the economy of Inner areas	37
Antonella Bianchino, Agata Maria Madia Carucci, Valeria Marzocca and Roberto Antonello Palumbo	
Estimating price pass-through from changes in VAT: a case study on the tampon tax in Italy	41
Beatrice Biondi, Silvia De Nicolò and Mario Mazzocchi	
A new composite bootstrap approach for estimating the long-memory parameter	45
Luisa Bisaglia, Margherita Gerolimetto and Margherita Palomba	
Intertemporal Mahalanobis Distance Matching for Heterogeneous-Treatment-Effect Evaluations of Air-Pollution-Abatement Policies	49
Daniele Bondonio and Paolo Chirico	
Exploring Globalization in the International Natural Gas Trade Market	53
Federico Brogi, Mauro Bruno, Erika Cerasti, Fabrizio De Fausti, Barbara Guardabascio and Giulio Massacci	
Assessing the Targeting of Austrian Social Assistance Schemes: who is left behind?	57
Alessia Broka, Silvia De Nicolò and Stefan Angel	
From micro to macro: Building up regional capabilities from individual firms and employees	61
Alessio Bumbea, Giuseppe Espa, Andrea Mazzitelli and Emanuele Pugliese	
Exploring Workplace Discrimination Through Digital Ethnography	65
Giovanni Busetta, Maria Gabriella Campolo, Antonia Cava and Debora Maria Pizzimenti	
A Systematic Review of Gender and Ethnic discrimination in Hiring	69
Giovanni Busetta, Maria Gabriella Campolo, Giovanni Maria Ficarra and Alessandra Trimarchi	
What are the complex interactions among the different Sustainable Development Goals (SDGs)? An analysis of European Island ecosystems	73
Simona Cafieri	
Analysis of the Wage Determination in Selected European Union Countries	77
Fabiano Campanelli and Mária Bohdalová	
Forecast reconciliation and Multivariate GARCH	81
Massimiliano Caporin, Daniele Girolimetto and Emanuele Lopetuso	
The Dual Impact of Energy Efficiency and Rebound Effects on Energy Poverty: An Italian Case Study	85
Alfonso Carfora, Francesco Maria Chelli and Giuseppe Scandurra	

The Impact of Technology Transfer in Italy: Some Preliminary Remarks	89
Andrea Ciccarelli, Audrey De Dominicis and Greta Torquati	
Impact of the National Recovery and Resilience Plan on the productivity in the Italian territories	93
Giuseppe Cinquegrana and Agata Maria Madia Carucci	
Assessing the spatial impact of the ‘display the average fuel prices’ obligation in Italy	97
Riccardo D’Alberto	
Environmental awareness and its determinants: a multilevel approach	101
Ida D’Attoma, Marco Ieva and Mariagiulia Matteucci	
Evaluating European Regional Policy using a Spatial Approach	105
Marusca De Castris and Guido Pellegrini	
The Effect of Covid-19 on Risk Aversion: Evidence from the SHARE Survey	109
Desiré De Luca and Giorgio Tassinari	
A non-parametric approach to employee performance in digital workplaces	113
Fabio Demaria, Maddalena Cavicchioli, Tommaso Fabbri, Ariadni Papan and Dagiasis and Anna Chiara Scapolan	
Italian Spatial Price Indices: using Web scraping in an experimental analysis for electricity	117
Cristina Dormi, Barbara Dramis and Agostina Zanolini	
Forecasting CO₂ emissions from electricity generation: comparison of methods	121
Pierdomenico Dutillo, Francesco Lisi and Marina Bertolini	
Modelling inefficiency in multi-output spatial stochastic frontiers for cultural and creative industries: a methodological proposal	125
Silvia Emili and Federica Galli	
Catastrophic Health Expenditure: heterogeneity among Regions and citizenship	129
Maria Rosaria Ferrante, Lorenzo Mori and Silvia Pacei	
A quantification of the costs and benefits of the “Green buildings” directive in two Italian regions	133
Lorenzo Forni, Filippo Fortuna, Elena Giarda, Francesco Giovanardi and Demetrio Panarello	
Integration of statistical and administrative data for companies in the non-energy mineral extraction sector	137
Flora Fullone, Mirella Morrone and Donatella Vignani	

Proposal of a Synthetic Measure of (E)Quality of Life Satisfaction: A Regional Perspective on Gender Disparities in Italy	141
Daniela Fusco, Paola Giordano, Maria A. Liguori and Margherita Maria Pagliuca	
A decision-oriented approach to assess tourism sustainability in Italian regions	145
Elisa Fusco and Alessandro Magrini	
Spatial Dependence in the Dynamics of the 2020 Presidential Election Polls Trackers	149
Giampiero M. Gallo, Demetrio Lacava and Edoardo Otranto	
Cultural Capital and Economic Growth	153
Giorgio Garau, Andrea Karim El Meligi, Giuliana Altea, Antonella Camarda and Luca Poddighe	
Italian Social Security System Sustainability: a statistical study based on INPS Data Bank	157
Massimiliano Giacalone, Maria Longobardi, Stefano Marra and Gianfranco Piscopo	
The effect of energy efficiency upgrades on residential property prices: evidence from Italy	161
Elena Giarda and Demetrio Panarello	
Inner Areas in Lombardy: An Analysis of Vulnerability	165
Chiara Gigliarano, Annamaria Bianchi, Sara Maiorino and Rashad Mammadli	
Forecasting Italian daily electricity generation disaggregated by geographical zones and energy sources using coherent forecast combination	169
Daniele Girolimetto and Tommaso Di Fonzo	
Economic complexity, technological innovation, and co-location of activities	173
Annamaria Giuffrida, Alessio Bumbea, Giuseppe Espa and Andrea Mazzitelli	
Leveraging Data Integration for Effective Revenue Management	177
Andrea Guizzardi, Ercolino Ranieri and Federico Zardo	
Examining the Impact of Geopolitical Risk, Climate Policy Uncertainty, Waste Management, and Financial Efficiency on Renewable Energy Investment in the USA: A Novel Dynamic Simulated ARDL Approach ..	181
Aamir Javed and Agnese Rapposelli	
Digital skills of citizens, enterprises and local PA	185
Valeriana Leporanico and Cira Acampora	

Exploring Occupational Mismatch in European Labor Markets: Measures, Determinants, and Implications	189
Sergio Longobardi and Margherita Maria Pagliuca	
Cointegrated Matrix Auto-Regressive Model	193
Emanuele Lopetuso and Massimiliano Caporin	
A study on the impact of “Reddito di Cittadinanza” using a multivariate linear mixed model	197
Paolo Maranzano, Laura Marcis, Gianluca Monturano, Maria Chiara Pagliarella and Renato Salvatore	
Forecasting short social time series with Theta method: an application to worldwide human development	201
Raffaele Mattera, Germana Scepi and Parmjit Kaur	
Towards the balancing of Italian quarterly national accounts	205
Filippo Moauro	
Forecasting VaR and ES from high-frequency quantiles and consistent loss functions	209
Antonio Naimoli, Ostap Okhrin and Giuseppe Storti	
Tourism and Energy Decoupling in Mountain Areas. Towards an Integrated Framework for Analysis and Forecasting	213
Consuelo Rubina Nava and Stefano Tedeschi	
Cluster-based Weighting Approach for Composite Indicators with an Application to Measuring Well-being in European Regions	217
Viet Duong Nguyen and Chiara Gigliarano	
Sustainable Development Goals in Italian Regions: Temporal dynamics and spatial patterns	221
Giuseppe Notarstefano and Giuseppe Terzo	
Common Features in Volatilities: a New Multiplicative Error Model	225
Edoardo Otranto and Luca Scaffidi Domianello	
Corporate Sustainability: a Technical Rehearsal for the Construction of a Composite Index	229
Luca Patelli and Daniele Toninelli	
Unveiling Underemployment Through a Fuzzy Approach: A Comparison of Fuzzy and Official Employment Rates in Italy (2021–2023)	233
Andrea Regoli, Bruno Cheli and Alessandra Coli	
Beyond the Multidimensional Poverty Index (MPI): a fuzzy approach based on proximity measures to investigate household deprivation in three Italian regions	237
Andrea Regoli and Giuseppe Verdoliva	

Testing the convergence hypothesis on per capita GDP across European provinces from 1997 to 2023	241
Giulia Sacchetti, Bruno Paolo Bosco and Paolo Maranzano	
Corruption and sustainable development	245
Fabrizio Sbicca	
Spatial Spillovers and Tourism: The Impact of Sustainable Initiatives in Italian Provinces	249
Riccardo Gianluigi Serio, Diego Giuliani, Giuseppe Espa and Maria Michela Dickson	
Caveat about non-normality in relative importance estimation from tourism surveys	253
Annalisa Stacchini and Andrea Guizzardi	
Green Tourism Competitiveness in Italian Provinces	257
Furio Urso, Martina Aronica, Salvatore Costantino, Davide Piacentino and Maria Francesca Cracolici	
Firm Resilience to Exogenous Shocks: The Impact of Gender Diversity in Leadership	261
Furio Urso, Cristina Leone, Pasquale Massimo Picone and Maria Francesca Cracolici	
Reconstructing climate change awareness survey data using socio-economics and geographical information	265
Gianpaolo Zammarchi	
Updating the estimate of transport costs in Europe: a focus on insularity	269
Gianpaolo Zammarchi and Paolo Mattana	

Forecasting tourist nights spent in Italy: a comparative analysis of statistical and neural network models

Fabrizio Antolini, Samuele Cesarini and Ivan Terraglia

Abstract Tourism in Italy, as in other countries, has become an increasingly significant sector, making the need for short- and medium-term forecasts of tourist nights spent essential. Forecasting tools must be accurate, easy to apply, and straightforward to interpret. The statistical models predominantly used in other countries are ETS and SARIMA. However, in recent years, neural network algorithms (CNN, LSTM) have also been applied to time series of tourist nights spent, which, while not volatile, exhibit recognizable temporal patterns. The comparison between results obtained from statistical approaches and deep learning algorithms is conducted by evaluating not only the MAPE but also the balance between the costs and benefits of each methodology.

Key words: Tourism, Forecasting, Seasonality

1 Introduction

Tourism is a growing sector in many countries. In 2023, Italy ranks as the second country in Europe for inbound tourism, with 234.1 million nights of stays, preceded only by Spain with 301.8 million. This metric, often used alongside the average length of stay, is a key indicator for measuring a country's attractiveness. For this reason,

Fabrizio Antolini
University of Teramo, e-mail: fantolini@unite.it
Samuele Cesarini
University of Teramo, e-mail: scesarini@unite.it
Ivan Terraglia
University of Teramo. e-mail: iterraglia@unite.it

many countries have developed forecasting models for tourist nights spent to evaluate tourist expenditure, which is closely correlated with these [1]. Additionally, having forecasts with different temporal lags (annual, monthly) supports the planning of tourism-related services, considering that during peak seasons, the present population often far exceeds the resident population, traditionally used to define service levels. When choosing a forecasting model, the trade-off between model accuracy and the ease of interpreting the predicted results must be considered. This evaluation involves comparing the results of traditional models - ETS (Error Trend and Seasonality) and (S)ARIMA (Seasonal Autoregressive Integrated Moving Average) - with those of Artificial Intelligence (AI), which leverage neural network algorithms (LSTM and CNN).

2 Forecasting models: the trade-off between accuracy, interpretability, and accessibility

The most recent literature on the application of neural network models for forecasting tourist nights spent has focused on the national level, encompassing inbound, domestic, and total components. This differentiation is of particular interest for Italy, as the trend has exclusively characterized inbound flows (3% annual growth), surpassing domestic nights of stays since 2016. This aspect is especially relevant for ETS models, which rely on unobserved components like trend and seasonality as key inputs for predictions [2]. Conversely, (S)ARIMA models are based on the autocorrelation function, both total and partial, to work with stationary time series (I), linking variable information at different time points (AR) and incorporating random impulses or errors (MA) that occur over time.

AI-based approaches using neural networks, such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) [3], offer significant advantages over the previously described methods in handling complex and non-linear data. These models offer improved forecast accuracy compared to traditional methods but require significant data for calibration [4]. Moreover, unlike conventional models, neural networks iteratively process and weight data, enabling adaptive handling of anomalous periods such as the COVID years without relying on dummy variables.

3 Monthly tourist nights of stays in Italy: a comparison between traditional models and neural network algorithms

This study analyzed monthly time series of Italian tourist nights spent from January 2015 to December 2023. Data was split into a training set (2015–2022) for model training and a test set (2023) for validation. ETS and SARIMA parameters were determined automatically, aiming to minimize the Bayesian Information Criterion

(BIC) for each time series analyzed. LSTM and CNN were configured and trained over 500 epochs. The batch size was set to 8, and the optimization algorithm used was Adam. The time window was set to 12 observations, enabling the models to learn significant sequential and local relationships within the data. Specifically, LSTMs, as recurrent neural networks, are designed to model sequential dependencies in data by utilizing memory cells and gating mechanisms, enabling the retention of long-term information and avoiding distorted forecasts caused by misinterpreted autocorrelations. Conversely, CNNs identify local patterns in data through convolutions, excluding spatial dependencies. By applying dilated convolutions, CNNs analyze temporal relationships in 1D signals using filters (kernel) that extract local features and detect anomalies. Despite the complexity of their configuration, their ability to learn without prior knowledge makes them well-suited for time series analysis.

However, the parameters used were defined without conducting an in-depth hyperparameter grid search that would have allowed a systematic exploration of different configuration combinations, such as the number of hidden units, learning rate, and layer structure, potentially improving model performance. This choice was driven by time and computational constraints but represents a limitation of the approach adopted, as an optimized configuration could enhance predictive accuracy. For the sake of brevity, only the MAPE (Mean Absolute Percentage Error) is reported. The following tables (1 and 2) show the MAPE and predictions calculated on the test data for each model, both including and excluding the pandemic years (2020 and 2021), for national, domestic, and foreign nights of stays.

Table 1 MAPE and Predictions with/without 2020-2021: Foreign nights spent

WITH 2020 AND 2021													
DATE	OBSERVED	ETS	DIFF	MAPE	SARIMA	DIFF	MAPE	LSTM	DIFF	MAPE	CNN	DIFF	MAPE
2023-01-01	7.566.036	7.062.680	6,65%		7.172.774	5,20%		9.266.495	22,47%		6.987.030	7,65%	
2023-02-01	9.487.659	8.831.574	6,92%		8.144.967	14,15%		10.447.372	10,12%		9.727.368	2,53%	
2023-03-01	10.433.155	8.949.516	14,22%		7.265.205	30,36%		11.892.455	13,99%		8.215.048	21,26%	
2023-04-01	16.894.983	11.393.950	32,56%		9.099.843	46,14%		12.085.724	28,47%		13.699.114	18,92%	
2023-05-01	22.454.283	16.010.559	28,70%		12.592.374	43,92%		20.529.856	8,57%		19.926.108	11,26%	
2023-06-01	29.204.324	21.887.260	25,05%	16,47%	18.431.009	36,89%	27,59%	28.128.236	3,68%	10,76%	29.388.076	0,63%	12,38%
2023-07-01	37.989.324	32.128.457	15,43%		28.550.900	24,84%		37.705.400	0,75%		37.508.264	1,27%	
2023-08-01	36.247.678	32.020.723	11,66%		29.513.042	18,58%		34.549.256	4,69%		35.176.028	2,96%	
2023-09-01	29.981.365	25.195.721	15,96%		23.158.615	22,76%		27.408.502	8,58%		27.127.948	9,52%	
2023-10-01	19.152.955	15.179.695	20,74%		13.495.321	29,54%		17.606.842	8,07%		19.544.268	2,04%	
2023-11-01	7.277.583	6.678.306	8,23%		5.232.031	28,11%		7.977.330	9,62%		10.584.623	45,44%	
2023-12-01	7.492.910	6.629.247	11,53%		5.197.557	30,63%		8.254.285	10,16%		5.614.000	25,08%	
WITHOUT 2020 AND 2021													
DATE	OBSERVED	ETS	DIFF	MAPE	SARIMA	DIFF	MAPE	LSTM	DIFF	MAPE	CNN	DIFF	MAPE
2023-01-01	7.566.036	6.903.051	8,76%		6.041.175	20,15%		6.966.622	7,92%		4.586.106	39,39%	
2023-02-01	9.487.659	8.554.167	9,84%		7.619.015	19,70%		8.528.659	10,11%		7.355.326	22,47%	
2023-03-01	10.433.155	10.303.564	1,24%		9.149.708	12,30%		10.784.442	3,37%		10.275.805	1,51%	
2023-04-01	16.894.983	13.914.657	17,64%		14.301.858	15,35%		14.292.066	15,41%		14.023.015	17,00%	
2023-05-01	22.454.283	19.566.566	12,86%		18.118.908	19,31%		19.736.962	12,10%		19.373.398	13,72%	
2023-06-01	29.204.324	26.469.139	9,37%	10,05%	28.575.051	2,15%	11,50%	27.669.250	5,26%	10,53%	28.274.358	3,18%	12,58%
2023-07-01	37.989.324	36.155.279	4,83%		36.400.834	4,18%		36.017.476	5,19%		36.848.016	3,00%	
2023-08-01	36.247.678	34.419.341	5,04%		34.288.330	5,41%		34.165.588	5,74%		34.674.996	4,34%	
2023-09-01	29.981.365	26.774.723	10,70%		27.402.825	8,60%		26.469.616	11,71%		27.209.692	9,24%	
2023-10-01	19.152.955	16.078.869	16,05%		17.055.669	10,95%		16.330.020	14,74%		17.585.432	8,18%	
2023-11-01	7.277.583	6.508.790	10,56%		6.510.668	10,54%		6.281.207	13,69%		6.890.215	5,32%	
2023-12-01	7.492.910	6.463.173	13,74%		6.790.154	9,38%		5.906.261	21,18%		5.723.520	23,61%	

Table 2 MAPE and Predictions with/without 2020-2021: Domestic nights spent

WITH 2020 AND 2021													
DATE	OBSERVED	ETS	DIFF	MAPE	SARIMA	DIFF	MAPE	LSTM	DIFF	MAPE	CNN	DIFF	MAPE
2023-01-01	10.844.945	9.982.991	7,95%	6,33%	9.998.077	7,81%	18,52%	9.388.328	13,43%	8,23%	9.367.447	13,62%	6,64%
2023-02-01	9.113.918	9.587.311	5,19%		8.846.301	2,94%		9.191.967	0,86%		8.723.117	4,29%	
2023-03-01	9.985.077	9.719.871	2,66%		6.835.133	31,55%		8.877.022	11,10%		8.731.383	12,56%	
2023-04-01	13.109.684	10.914.839	16,74%		7.884.887	39,85%		9.525.935	27,34%		10.719.113	18,24%	
2023-05-01	11.599.827	11.571.306	0,25%		8.306.465	28,39%		11.916.679	2,73%		11.784.002	1,59%	
2023-06-01	24.981.389	23.666.398	5,26%		19.197.254	23,15%		23.420.672	6,25%		23.718.226	5,06%	
2023-07-01	37.275.842	38.264.157	2,65%		34.347.947	7,85%		37.785.348	1,37%		36.151.136	3,02%	
2023-08-01	46.360.628	51.752.594	11,63%		48.433.151	4,47%		47.188.972	1,79%		47.066.296	1,52%	
2023-09-01	19.900.161	20.506.972	3,05%		18.820.429	5,43%		17.654.954	11,28%		19.075.866	4,14%	
2023-10-01	9.898.896	10.953.143	10,65%		9.188.862	7,17%		9.917.375	0,19%		9.532.055	3,71%	
2023-11-01	8.460.707	8.881.607	4,97%		5.959.036	29,57%		8.609.820	1,76%		8.245.362	2,55%	
2023-12-01	11.456.720	10.889.012	4,96%		7.561.755	34,00%		9.089.509	20,66%		10.384.459	9,36%	
WITHOUT 2020 AND 2021													
DATE	OBSERVED	ETS	DIFF	MAPE	SARIMA	DIFF	MAPE	LSTM	DIFF	MAPE	CNN	DIFF	MAPE
2023-01-01	10.844.945	9.940.216	8,34%	4,56%	8.207.466	24,32%	8,56%	8.554.286	21,12%	10,73%	8.490.209	21,71%	7,18%
2023-02-01	9.113.918	9.307.561	2,12%		7.666.444	15,88%		8.964.320	1,64%		8.098.157	11,15%	
2023-03-01	9.985.077	10.742.128	7,58%		8.804.335	11,83%		9.533.033	4,53%		9.342.860	6,43%	
2023-04-01	13.109.684	12.741.580	2,81%		11.693.020	10,81%		11.146.300	14,98%		11.422.007	12,87%	
2023-05-01	11.599.827	12.430.463	7,16%		12.361.830	6,57%		13.864.847	19,53%		13.617.315	17,39%	
2023-06-01	24.981.389	25.442.783	1,85%		25.825.012	3,38%		22.346.322	10,55%		25.296.362	1,26%	
2023-07-01	37.275.842	38.301.603	2,75%		38.232.025	2,57%		35.428.892	4,95%		37.551.180	0,74%	
2023-08-01	46.360.628	50.640.715	9,23%		48.509.279	4,63%		44.430.376	4,16%		47.363.272	2,16%	
2023-09-01	19.900.161	19.429.512	2,37%		19.696.449	1,02%		17.885.482	10,12%		20.228.150	1,65%	
2023-10-01	9.898.896	10.388.336	4,94%		11.096.327	12,10%		10.826.807	9,37%		10.377.409	4,83%	
2023-11-01	8.460.707	8.834.664	4,42%		8.064.757	4,68%		8.595.994	1,60%		8.745.410	3,74%	
2023-12-01	11.456.720	11.325.825	1,14%		10.889.013	4,96%		8.458.998	26,17%		11.159.250	2,60%	

Including or excluding the pandemic years, it is observed that neural network-based models effectively weight the information, avoiding excessively distorted forecasts. In contrast, parametric models, which are heavily influenced by the temporal structure of the data, are significantly impacted by the discontinuity caused by the pandemic, showing a marked increase in forecasting errors. This highlights the greater adaptive capacity of AI models in volatile situations.

References

1. Antolini, F., Cesarini, S., & Simonetti, B.: Factors determining Italian tourists' expenses: a machine learning approach. Qual. Quant. 1, 1–19 (2024).
2. Hyndman, R., Koehler, A. B., Ord, J. K., & Snyder, R. D.: Forecasting with exponential smoothing: the state space approach. Springer, Heidelberg (2008).
3. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I.: Attention is all you need. Adv. Neural Inf. Process. Syst. 30, (2017).
4. Amir, W., Md Soom, A. B., Mat Jasin, A., Ismail, J., Asmat, A., & An, R.: Sales forecasting using convolution neural network. J. Adv. Res. Appl. Sci. Eng. Technol. 30, 290–301 (2023).

Tourism Satellite Accounts: preliminary estimation of production, value added, and internal tourism consumption for year 2022

Fabrizio Antolini and Ilaria Piscitelli

Abstract Tourism is playing an increasingly central role in the economies of many countries. In 2019, the contribution of tourism to generated income in Europe averaged 4.5 percent, though significant differences exist among countries, with Italy reporting a share of 6.2 percent. The COVID-19 pandemic led to a contraction of the tourism sector across all nations. This paper presents preliminary estimates of production and employment for tourism industries, as well as key macroeconomic aggregates for the tourism sector, for the year 2022. The aim is to provide an initial comparison with pre-COVID data.

Key words: Tourism Satellite Account (TSA), national accounts, tourism expenditure, tourism

1 Tourism Satellite Accounts: between past and future – a missed opportunity?

Satellite accounting was introduced with the System of National Accounts [1] and was almost entirely incorporated into subsequent versions of the System of European and Regional Accounts [2]. The Satellite Accounts framework is closely linked to, yet distinct from, the central System of National Accounts. Its primary objective is to provide flexibility while accommodating numerous elements that remain invisible in the central accounts. There are two types of satellite accounts:

Fabrizio Antolini
University of Teramo, e-mail: fantolini@unite.it
Ilaria Piscitelli
ISTAT, e-mail: piscitelli@istat.it

the first involves a rearrangement of central classifications, allowing for the inclusion of complementary elements; the second employs alternative concepts compared to those in the SNA, such as different boundaries for production, consumption, or investment. The first type of satellite account can be considered an extension of the main sectoral accounts, whereas the second type serves as a supplement to the aggregates in the central accounts. Tourism Satellite Accounts (TSA) fall into the first category, offering detailed insights—for instance, on tourism consumption, expenditure, and value added—that are methodologically consistent with National Accounts but remain invisible within the central account system [3]. This distinction between the two groups is critical for understanding the appropriate scope of application of tourism satellite accounting. Its main purpose is to quantify the tourism sector's contribution to the overall economic generation of wealth and employment.

This consideration leads to two additional reflections, not always adequately emphasized in the scientific debate. The first and most significant point is that the contribution of the tourism sector is already included in the central national accounts. Tourism, although not formally defined as an economic sector, predominantly operates within the services sector. It is also important to note that in industrialized countries, economic growth in recent years has been primarily driven by services, which have contributed, on average, 70 percent to the generation of national income. Within the broader services sector, specific services consumed by visitors are included. These encompass accommodation and food services, passenger transport, travel agencies, sports, recreational, cultural and other services. The role of visitor—distinguished between tourists and same-day visitors—is crucial for defining the tourism sector within the framework of satellite accounts, relying on the fundamental concept of the usual environment. This key definition for tourism statistics is based on an official concept of the usual environment adopted by all countries, finding different applications in practice [4]. Additionally, the increasing digitalization within the tourism sector, the use of big data, particularly data derived from mobile phone usage or toll payment systems, can enhance estimates of tourist arrivals and overnight stays. As marked by Eurostat [5], "the arrival of big data is also changing the working environment for statisticians. Many sources of big data measure flows or transactions. Tourism statistics try to capture physical flows of people — as well as the accompanying monetary flows; big data provides promising new sources of data and previously unavailable indicators to measure these flows (and stocks)."

In the framework just described, Tourism Satellite Accounts (TSA) is a tool to makes visible what is already measured within the national accounts. However, as tourism does not find a specific classification within the economic frameworks used by national accounts—such as consumption (COICOP), economic sectors (NACE), products (CPC), and public expenditure (COFOG)—its measurement process is complex. The second consideration concerns the discrepancy between the provisions of the EU regulation on tourism statistics (692/2011) and the statistics produced. The regulation recognizes tourism as playing a significant role within economic systems: "Tourism plays an important role in the EU because of its economic and

Tourism Satellite Account: preliminary estimation of production, value added, and ... employment potential, as well as its social and environmental implications. Tourism statistics are not only used to monitor the EU's tourism policies but also its regional and sustainable development policies" [6]. The importance of the tourism industry, concentrated in services utilized by visitors, is further emphasized in the context of enhancing small and medium-sized enterprises (SMEs). For many EU countries, SMEs represent the predominant economic structure capable of generating significant employment and job opportunities. Despite these recommendations, the Tourism Satellite Accounts (TSA) and the economic indicators and aggregates defined by the methodological framework [7,8] are not yet regulated.

2 The estimation of consumption and value added for the year 2022

The approach used for estimating tourism value added is expenditure-based. This method requires distinguishing between tourism expenditure and tourism consumption. "The concept of tourism consumption will be used in the TSA in tables 4 and 6, and will be the basis for the compilation of tourism direct gross value added (TDGVA) and tourism direct gross domestic product (TDGDP)" [7]. The Tourism Satellite Account, compiled for the first time by Istat for the year 2010, estimates two different aggregates of value added: Tourism Value Added (TVA) and Value Added of Tourism Industries (VATI). The former includes contributions from both tourism and other industries, directly driven by internal tourism consumption. The latter refers to the value added generated solely by tourism industries, regardless of whether it satisfies tourism demand (visitor demand) or non-tourism demand (consumer demand).

The difference between tourism expenditure and tourism consumption is mainly attributable to the value of housing services from second homes, expenses incurred by businesses for employee business trips, and, to a lesser extent, social transfers in kind (not necessarily monetary). Tourism expenditure, by contrast, is exclusively monetary and consists of the expenses made by visitors during and in preparation for their trips [7].

In compiling the TSA for Italy, official statistical sources are used, specifically Istat data—primarily from national accounts but also from tourism surveys—and data from the Bank of Italy. The transition to ESA95, with the adoption of Supply and Use Tables within the Italian accounting framework, has already enabled interaction between products and industries. In constructing the TSA, a top-down approach was followed for the Table of Internal Tourism Consumption (T4), while a bottom-up approach was applied to the Table of Production of Tourism and Other Industries (T5) and the Table of Employment in Tourism Industries (T7) [9,10].

The latest TSA for Italy estimated by Istat refers to 2019. With reference to the year 2020, only a preliminary estimate was published on Istat website in order to provide timely information on the impacts of the ongoing pandemic on tourism sector. For the present work, instead, partial and aggregate-level elaborations were

conducted to simulate the scenario of tourism sector in its main aggregates allowing an initial analysis in a pre- and post-pandemic perspective. To this end, the data in the table below are presented. In 2022, tourism sector seems to have almost returned to the pre-pandemic levels in terms of the key economic aggregates of a TSA, such as production, value added, tourism consumption and employment and their share on total economy. It should be noted, however, that the aggregates estimate is at current prices, and the inflation rate in 2022 is around 8.5%. The estimated shares of the tourism sector relative to the total economy highlight the significant contribution of the overall tourism industry.

Table 1 Economic aggregates of tourism industries, tourism sector and total economy. Year 2022 vs 2019 (data in millions of euros at current prices and percentage shares)

Aggregates	2019*	2022**
	mln - %	
Production of T.I.	363,651	387,851
Share of T.I. Production in Total Italy	10.7%	9.4%
Share of T.I. Value Added in Italy's Total VA	13.8%	12.7%
TVA (Tourism Value Added)	99,903	102,177
Share of TVA in Total Italy	6.2%	5.7%
Internal Tourism Consumption	164,012	170,295
Share of T.I. FTEs in Total Italy	14.0%	13.1%

Source: *Istat, National Accounts, TSA for Italy 2019 - ** Istat, National Accounts, elaborations

T.I.= tourism industries

References

1. United Nations *System of National Accounts (SNA)*, Washington 1993, 2008.
2. Eurostat, European System of Economic and Regional Accounts, Luxembourg 1995, 2010.
3. Antolini F., Giusti A., Petrei F., Tourism and territorial economy: beyond satellite accounting (2023) in Data Driven Decision Making ASA 2022.
4. Antolini F, Grassini L. Issue in Tourism Statistics: a critical review, In Social Indicators research, 2020.
5. Eurostat, Tourism Statistics; Early adopters of big data? Statistical working Paper, Lux. 2017.
6. Eurostat, Tourism Statistics, Statistics Explained March 2021.
7. United Nation, UNWTO, Eurostat, OECD, Department of Economic and Social Affairs, Statistics Division. 2010. *Tourism Satellite Account: Recommended Methodological Framework 2008*. Studies in Methods, Luxembourg, Madrid, New York, Paris.
8. United Nation, UNWTO. Department of Economic and Social Affairs, Statistics Division. 2010. *International Recommendations for Tourism Statistics 2008*. Studies in Methods, New York.
9. Maresca S., Piscitelli I., *Il Conto Satellite del Turismo nell'ambito dei Conti Nazionali*, work presented within the seminar *Il primo conto Satellite del turismo per l'Italia*, Rome, 2012.
10. Maresca S., Piscitelli I., *Il CST per l'Italia: aggiornamenti, approfondimenti e studi di fattibilità per il CST regionale*, Final Report, 2014.

The impact of digitalisation and sustainability on innovation propensity: firm-level evidence from European Union countries

David Aristei

Abstract This paper investigates how digitalisation and sustainability efforts influence the innovation propensity of European firms. We tackle potential endogeneity issues and demonstrate that companies utilising digital technologies and engaging in sustainability initiatives significantly enhance their likelihood of introducing product, environmental, and social innovations. Furthermore, we uncover a significant complementarity between digitalisation and sustainability in enhancing firms' propensity to innovate, especially concerning sustainable innovations.

Key words: Digital technologies, Sustainability orientation, Innovation propensity

1 Introduction

Firms' digitalisation and sustainability initiatives are garnering increased attention as they offer significant opportunities to enhance organisational efficiency, productivity, and innovation performance (Ferreira et al., 2019; Cattani et al., 2023). Despite the challenges posed by the digital and green twin transitions, their interaction may generate synergistic effects that provide an additional source of competitive advantage (Ardito et al., 2021; Böttcher et al., 2024). In this regard, the combined impact of digital and sustainable strategies on firms' innovation outcomes has not yet been fully explored (Ardito, 2023; Lan and Zhou, 2024).

This study contributes to the literature by assessing the direct causal effects of adopting Industry 4.0 technologies and implementing sustainability practices on innovation propensity, whilst also examining potential complementary effects.

David Aristei
University of Perugia, e-mail: david.aristei@unipg.it

2 Data and methods

We use data from the Flash Eurobarometer 486 survey for about 12,000 firms across the 27 European Union member states in 2020.

We focus on various types of innovation activities and define dummies indicating whether the firm introduced a new or significantly improved product or service (*Product innovation*), an innovation with an environmental benefit (*Eco-innovation*), or an innovation that aims to improve society (*Social innovation*) during the past year.

Our main explanatory variables relate to firms' digital and sustainable strategies. We define two indexes (normalised between 0 and 10) as the first factor scores from factor analyses on the tetrachoric correlation matrices of dummies indicating the adoption of Industry 4.0 technologies (*Digitalisation*) and the implementation of environmental and social sustainability actions (*Sustainability*), respectively.

To account for the potential endogeneity of digitalisation and sustainability on innovation propensity, we consider a probit model with two endogenous regressors:

$$\begin{aligned} Innov_i &= 1(\beta_1 Digit_i + \beta_2 Sust_i + \beta_3 Digit_i \times Sust_i + \mathbf{x}_i' \boldsymbol{\beta}_4 + \varepsilon_i > 0) \\ Digit_i &= \mathbf{x}_i' \boldsymbol{\alpha}_1 + \mathbf{z}_{1i}' \boldsymbol{\alpha}_2 + u_i \\ Sust_i &= \mathbf{x}_i' \boldsymbol{\gamma}_1 + \mathbf{z}_{2i}' \boldsymbol{\gamma}_2 + v_i \end{aligned} \quad (1)$$

where $\mathbf{x}_i$ is a set of exogenous firm-level controls, while $\mathbf{z}_{2i}$ and $\mathbf{z}_{3i}$ include additional instruments assumed to affect only firm digitalisation and sustainability directly. The errors ε_i , u_i and v_i follow a trivariate normal distribution with zero means, variances equal to 1, σ_u^2 , and σ_v^2 , and correlations $\rho_{\varepsilon u}$, $\rho_{\varepsilon v}$ and ρ_{uv} . Endogeneity arises from error correlation: when $\rho_{\varepsilon u} \neq 0$ and/or $\rho_{\varepsilon v} \neq 0$, a standard probit for $Innov_i$ will lead to inconsistent results.

3 Results

Table 1 reports our main empirical findings. First, the results of the overidentification and weak instrument tests support the validity of our identification strategy. Additionally, the exogeneity of digitalisation and sustainability scores is not rejected, indicating that the endogenous probit in (1) should be preferred over a standard probit to consistently estimate their causal effect on firms' innovation propensity.

Column 1 of Table 1 shows that adopting digital technologies and implementing sustainability actions significantly enhance the likelihood of introducing product innovations. The estimated average marginal effects of digitalisation and sustainability scores are significant at the 1% level, suggesting that a one-unit increase in each score raises product innovation probability by 13.9 and 4.7 percentage points, respectively. Additionally, the estimated interaction effect is equal to 1.0 percentage points and is statistically significant, providing evidence of a strong complementarity between digitalisation and sustainability in fostering product innovation.

From columns 2 and 3 of Table 1, we notice that digitalisation and sustainability positively and significantly affect the probability of ecological and social innovations.

Table 1 The determinants of innovation propensity

	(1) Product innovation	(2) Eco-innovation	(3) Social innovation
Digitalisation	0.1388*** (0.0139)	0.0724*** (0.0114)	0.0881*** (0.0111)
Sustainability	0.0473*** (0.0118)	0.1201*** (0.0122)	0.0711*** (0.0103)
Interaction effect <i>Digit</i> × <i>Sust</i>	0.0100*** (0.0028)	0.0182*** (0.0031)	0.0203*** (0.0037)
Additional control variables	Yes	Yes	Yes
Amemiya-Lee-Newey overid. test	[0.7189]	[0.9766]	[0.4840]
Weak instruments <i>F</i> test:			
<i>Digitalisation</i>	[0.0000]	[0.0000]	[0.0000]
<i>Sustainability</i>	[0.0000]	[0.0000]	[0.0000]
Exogeneity test:			
<i>Digitalisation</i>	[0.0000]	[0.0000]	[0.0000]
<i>Sustainability</i>	[0.0000]	[0.0000]	[0.0000]
N	12,318	12,318	12,318

Notes: The Table reports estimated average marginal effects on innovation probability, estimated from the endogenous probit model in (1). Robust standard errors are reported in parentheses below the estimates. All models include additional control variables related to firm age and size, ownership structure, international activities, market structure, area of location, and sector and country fixed effects. The p-values of the Amemiya-Lee-Newey overidentification test, the *F* tests for weak instruments, and the exogeneity tests are reported in square brackets. The additional instruments for *Digitalisation* are a binary variable equal to 1 if the firm has no interest in digitalisation and a dummy indicating that the firm has no strategy or action plan to digitalise. The instruments for *Sustainability* are a binary variable equal to 1 if the firm lacks the willingness to implement sustainable activities and a dummy indicating that the firm does not have a strategy or action plan to become sustainable. Complete estimation results are available upon request.

***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Sustainability actions promote sustainable innovations more effectively than product innovations. A one-unit increase in the sustainability score enhances the likelihood of ecological and social innovations by 12 and 7.1 percentage points, respectively.

The interaction effects for the probability of ecological and social innovations (1.8 and 2.0 percentage points, respectively) are significant at the 1% level and larger than that estimated for product innovation. This confirms the mutually reinforcing effects of digitalisation and sustainability in enhancing firms' innovation propensity.

Figure 1 displays three-dimensional surface plots and contour plots of predicted innovation probabilities, providing further insights into the impact of digitalisation and sustainability. From panel A, we observe that product innovation probability significantly increases as both scores rise, even though digitalisation has the largest impact. Similarly, digitalisation and sustainability scores enhance firms' sustainable innovation activities. Nevertheless, implementing sustainability actions emerges as the primary driver of eco-innovations (panel B), whereas the likelihood of introducing social innovations rises more uniformly with the two scores (panel C).

4 Conclusions

This study demonstrates that firms adopting digital technologies and pursuing sustainability initiatives significantly increase their likelihood to introduce product innovations, as well as innovations with environmental and social benefits.

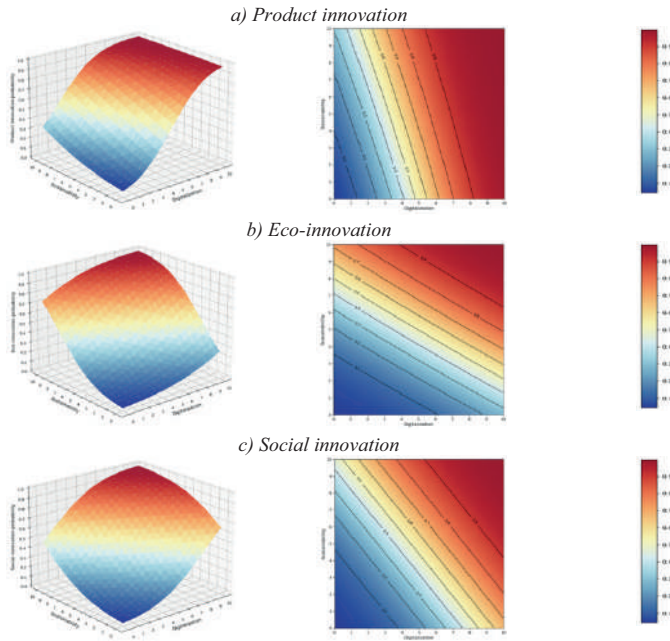


Fig. 1 Predicted innovation probabilities by level of digitalisation and sustainability

Furthermore, we provide evidence indicating a significant complementarity between digitalisation and sustainability in boosting firms' innovation propensity.

From a policy perspective, our findings emphasize the importance of initiatives that foster corporate digitalisation and sustainability, as they both play a pivotal role in enhancing firms' capacity to innovate.

References

1. Ardito, L.: The influence of firm digitalization on sustainable innovation performance and the moderating role of corporate sustainability practices: An empirical investigation. *Bus. Strategy Environ.* 1-21 (2023).
2. Ardito, L., Raby, S., Albino, V., Bertoldi, B.: The duality of digital and environmental orientations in the context of SMEs: Implications for innovation performance. *J. Bus. Res.* 123, 44-56 (2021).
3. Böttcher, T., Empelmann, S., Weking, J., Hein, A., Kremer, H.: Digital sustainable business models: using digital technology to integrate ecological sustainability into the core of business models. *Inf. Syst. J.* 34(3), 736-761 (2024).
4. Cattani, L., Montesor, S., Vezzani, A.: Firms' eco-innovation and Industry 4.0 technologies in urban and rural areas. *Reg. Stud.*, 1-13 (2023) DOI: 10.1080/00343404.2023.2243984
5. Ferreira, J.J.M., Fernandes, C.I., Ferreira, F.A.F.: To be or not to be digital, that is the question: Firm innovation and performance. *J. Bus. Res.* 101, 583-590 (2019).
6. Lan, L., Zhou, Z.: Complementary or substitutive effects? The duality of digitalization and ESG on firm's innovation. *Technol. Soc.* 77, 102567 (2024).

From Financial Stability to Climate Change: A BERTopic Analysis of ECB and National Central Bank Speeches

David Aristei, Mauro Bruno, Barbara Guardabascio and Francesco Ortame

Abstract This study examines the evolution of central bank communication by analysing speeches from the European Central Bank (ECB) and major Eurozone central banks using advanced natural language processing (NLP) techniques, particularly BERTopic modeling. The research identifies key thematic trends and variations across central banks in the Eurozone, with particular attention to climate change. The comparative analysis shows thematic alignment and divergence between the ECB and national central banks, reflecting differing regional priorities. Results show an upward trend toward the inclusion of sustainability-related topics.

Key words: ECB Speeches, Climate Change, Text Analysis, BERTopic Modeling

1 Introduction

The European Central Bank (ECB) has transformed the focus of its communication over time to reflect changing economic and societal contexts. Initially emphasizing traditional monetary policy themes like inflation and financial stability, the ECB expanded to include unconventional policies, like quantitative easing, following the 2008 Global Financial Crisis and the Eurozone debt crisis. Several approaches,

David Aristei
University of Perugia, e-mail: david.aristei@unipg.it

Mauro Bruno
ISTAT, e-mail: mbruno@istat.it

Barbara Guardabascio
University of Perugia, e-mail: barbara.guardabascio@unipg.it

Francesco Ortame
ISTAT, e-mail: francesco.ortame@istat.it

including dynamic topic modeling, have shown how these shifts aligned communication strategies with evolving policies and market expectations [1], [2]. Advances in natural language processing (NLP) have improved insights into ECB communication. For example, [3] used sentiment analysis to track tone shifts during the global financial crisis, while [4] developed Central Bank Sentiment Indices (CBSIs) to assess emotional tones in speeches and their market impacts. In 2015, the ECB began integrating climate change into its communication, following the Paris Agreement. [5] identified a surge in climate-related discussion using keyword-assisted topic modeling, and [6] showed how these communications positively influenced green portfolios and increased investor focus on sustainability assets.

Our research examines the thematic evolution of central bank communication, comparing the ECB with national central banks. While the ECB’s broadening from traditional monetary policy is well-documented, less is known about its alignment with Eurozone central banks, which often prioritize domestic concerns. Using BERTopic modeling, we analyse thematic variations to show how global mandates are balanced with localized economic priorities and how these evolve across institutions over time.

2 Data and Methodology

We sourced the data from the Bank of International Settlements (BIS) “Central Bankers’ Speeches” dataset [7] and filtered documents to include speeches from the top five institutions by number of observations in the dataset, obtaining a total of 4,910 speeches from 1996 to 2024. Table 1 shows data distribution.

Table 1 Total number of speeches by institution

Institution	ECB	France	Germany	Ireland	Italy	Spain
N	2553	392	863	324	419	359

In addition to standard text cleaning for PDF-crawled files, we implemented sentence extraction – splitting full texts into shorter segments to avoid input cut-off and/or suboptimal performance, obtaining approximately 100 sentences per speech. We linked each processed sentence to its original speech to ensure that topics could be traced back to speeches, letting us define a distribution of topics over speeches.

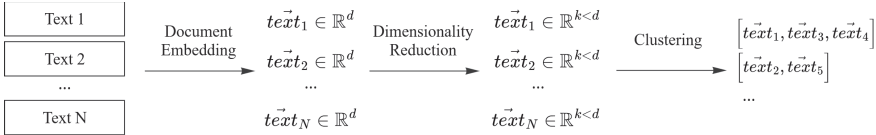


Fig. 1 Main steps of the BERTopic algorithm.

We implemented BERTopic modelling [8] to cluster texts in sequential steps. A standard BERTopic pipeline (Figure 1) consists of (1) *Document Embedding*, each

sentence is transformed into a dense, 384-dimensional vector using the *all-MiniLM-L12-v2* model from Sentence-BERT [9]. This allows similar texts (vectors) to be close in the embedding space. (2) *Dimensionality Reduction*, the dimensionality of the embedding vectors is reduced using Uniform Manifold Approximation and Projection (UMAP) to reduce noise and computational requirements; (3) *Clustering*, the reduced embedding vectors are clustered using Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN); (4) *Topic Representation*, for each cluster, the most representative words and sentences are extracted based on their statistical importance.

BERTopic assigns one topic to each text, which works best when the number of topics to extract is not predetermined. Therefore, we manually reviewed and further grouped the extracted topics, assigning names based on their content.

3 Results

Out of the 81 topics extracted by the algorithm, we manually identified 17 clusters. Figure 2 shows a slight uptick in mentions for the Climate Change cluster (consisting of several related individual topics), around 2015 for France, consistent with the Paris Climate Agreement (COP21).

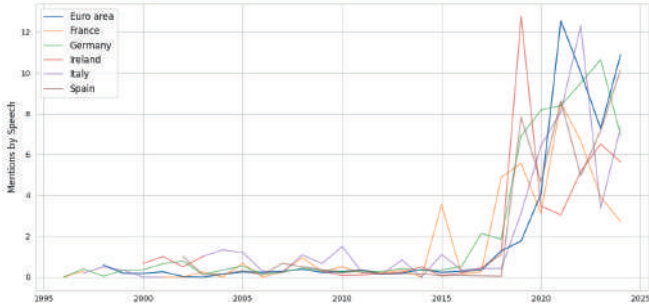


Fig. 2 Climate Change-related topic mentions per speech across countries over time.

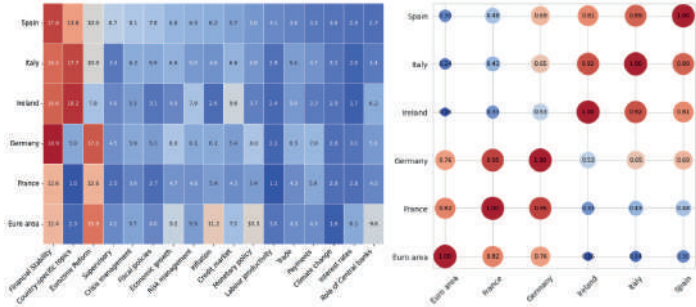


Fig. 3 Time-independent topic distributions across countries and correlation matrix.

A general upward trend starts around 2018, coinciding with growing public awareness driven by global climate strikes. The Network for Greening the Financial System (NGFS), a group of 114 central banks and supervisory authorities, was established in December 2017. Another significant spike occurs around 2021, aligning with the European Green Deal and the COP26 summit. From 2022 to 2024, mentions remain high but fluctuate, likely reflecting the impact of global energy crises and conflicts.

Figure 3 illustrates the topic-country distribution (average mentions by speech) and the related correlation matrix, regardless of time. France and Germany exhibit the highest correlation with the ECB (0.82 and 0.76). This correlation is significantly lower for Spain (0.30) and Italy (0.24) and reaches its lowest value with Ireland (0.16). The correlation matrix shows two distinct high-correlation clusters: (1) ECB, Germany, and France, and (2) Ireland, Italy, and Spain.

4 Conclusion

We analyse the evolving nature of central bank communication, focusing on the European Central Bank (ECB) and its transition from conventional monetary policy discussions to more expansive themes like climate change. By implementing BERTopic modeling, we identify significant variations and similarities in thematic priorities across several central banks. These results point to an increasing commitment to global sustainability objectives by the ECB and other Eurozone central banks of interest.

References

1. Hansson, M. "Evolution of topics in central bank speech communication", arXiv preprint arXiv:2109.10058, (2021).
2. Jurkšas, L., Kaminskas, R. "ECB monetary policy communication: does it move euro area yields?", No. 29. Bank of Lithuania, 2023.
3. Warin, T., Sanger, W. "The speeches of the European Central bank's presidents: an NLP study." *Global Economy Journal*, 20.02 (2020): 2050009.
4. Priola, M.P., Molino, A., Tizzanini, G. "The informative value of central banks talks: a topic model application to sentiment analysis." (2021)
5. Feldkircher, M., Teliha V. "Speeches in the green: The political discourse of green central banking." *Energy Economics*, (2024): 107646.
6. Ebeling, A. "ECB's Climate Speeches and Market Reactions." (2024).
7. Bank for International Settlements (2024). Central bank speeches, 1996-2024, <https://www.bis.org/cbspeeches/download.htm>.
8. Grootendorst, Maarten. "BERTopic: Neural topic modeling with a class-based TF-IDF procedure." arXiv preprint arXiv:2203.05794 (2022).
9. Reimers, N. "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks." arXiv preprint arXiv:1908.10084 (2019).

European Digital Skill Supply: A Latent Variable Perspective

Federico Bacchi, Pinuccia Pasqualina Calia and Maria Rosaria Ferrante

Abstract The European labour market is characterized by persistent shortages of ICT specialists. In this context, a key role is played by individual digital skill levels, which are currently measured by Eurostat according to the “Digital Competence framework for citizens” (DigComp). A Multidimensional Item Response Theory analysis on the data used by Eurostat revealed that a different latent structure might be more suitable than DigComp. Then, this data driven latent structure was used to further investigate the phenomenon via application of multilevel latent variable analysis. As a result, with the help of some individual and contextual covariates, five distinct attitudes of European citizens towards ICTs and four different levels of digital skill distribution across European regions were identified.

Key words: Digital skills, Labour supply, Latent variable analysis, Multilevel models

1 Background

The importance of having basic knowledge about Information and Communications Technologies (ICTs) has become crucial in the last few years. International organizations, such as European Union (EU), Organisation for Economic Co-operation and Development (OECD) and UNESCO, have put a great emphasis on the importance for individuals of being able to deal with these devices. Most frequently, their primary concern was on the implications on economic growth and competitiveness.

Federico Bacchi
University of Bologna, e-mail: federico.bacchi3@unibo.it

Pinuccia Pasqualina Calia
University of Bologna, e-mail: pinuccia.calia@unibo.it

Maria Rosaria Ferrante
University of Bologna, e-mail: maria.ferrante@unibo.it

In general, individual digital skills play a key role in labour market dynamics in a European context characterized by the persistent lack of ICT specialists [1]. Roughly speaking, individuals in working age constitute the labour market supply in a given geographic area. Thus, their digital skills might be seen as the digital skill supply in that area.

The objective of the present work was twofold: on one hand, a major concern was on how to measure individuals' digital skill levels, with particular attention on assessing the adequacy of the existing framework adopted by Eurostat; on the other hand, a great attention was paid to the geographical distribution of these skills. These aims were addressed by performing a two-stage latent variable analysis, which additionally enabled to study the determinants of the phenomenon.

2 Data

The empirical analysis was based on micro-data from 2021 edition of "ICT Usage in Households and by Individuals" annual survey, whose target population consisted of citizens from 29 European countries (EU27, Iceland and Norway) aged 16 – 74.

This data source is currently used by Eurostat to compute its Digital Skills Indicators (DSI 2.0 [5]). DSI 2.0 are conceptually based on the "Digital Competence framework for citizens" (DigComp [4]), which postulates the existence of five digital competence areas encompassing a total of twenty-one unobservable sub-competences. To compute an indicator of proficiency in each of these competence areas, Eurostat selects a set of binary items from the survey, representing specific digital activities, and assigns a digital skill level to individuals based on the number of activities they declared to have performed in the three months before the survey.

3 Digital skills measurement: a latent variable approach

The present work started from the analysis of the same set of binary variables ($p = 29$) used by Eurostat to compute the competence area indicators. The total number of respondents was $N = 197,950$, divided into 77 sub-national areas coinciding with the first level of the Nomenclature of Territorial Units for Statistics (NUTS-1).

The sub-sample of individuals who declared to have used Internet in the three months preceding the survey was preliminarily analyzed in a Multidimensional Item Response Theory (MIRT) perspective. An exploratory MIRT analysis on the resulting $169,721 \times 29$ data matrix was performed with the aim of identifying the underlying latent structure and to see if it coincided with the theory driven one, which might be derived from DigComp. The resulting data driven latent structure was five-dimensional but presented some differences with the one postulated by adopting DigComp: only one latent factor from the data driven scheme coincided with a competence area from DigComp. A confirmatory MIRT analysis aimed to

compare the two structures revealed that the former was better suited to the data set than the latter. For this reason, the following Multilevel Latent Class Analysis (MLCA) was based on it.

MLCA encompasses all models that aim at classifying statistical units, in the context of data with some hierarchical structure, by postulating the existence of latent constructs at every level of the structure. In the present case, individuals (level-1 units) were nested within geographic areas (level-2 units). More specifically, the latter were $N_2 = 228$ sub-domains obtained by crossing the information on the NUTS-1 region and on the degree of urbanization of residence, while the former were $N_1 = 178,100$ respondents¹.

By adopting MLCA, the digital skill level of individuals was modeled as a discrete latent construct y derived from a set of $K = 5$ manifest count variables, which represented the number of digital skills possessed by individuals in each of the dimensions arising from the exploratory MIRT analysis. The other discrete latent variable w represented the level-2 group classes. The most general probability structure for a MLCA Model might be written as ([2]):

$$P(\mathbf{x}_j | \mathbf{z}_{ij}, \mathbf{z}_j^g) = \sum_{m=1}^M \left\{ P(w_j = m | \mathbf{z}_j^g) \times \left[\prod_{i=1}^{n_j} \sum_{t=1}^T P(y_{ij} = t | w_j = m, \mathbf{z}_{ij}) \times \right. \right. \\ \left. \left. \times \prod_{k=1}^K P(x_{ijk} | y_{ij} = t, w_j = m) \right] \right\},$$

where $t = 1, \dots, T$ are the values of the discrete latent variable y , $m = 1, \dots, M$ are the values of the discrete latent variable w , x_{ijk} is the value of the k^{th} count indicator for individual i ($i = 1, \dots, n_j$) in group j , $\mathbf{z}_{ij}$ is the vector of covariates for the individual i in group j and $\mathbf{z}_j^g$ is the vector of contextual covariates for the group j . The individual covariates included in the model were age class, gender, educational attainment, quintile to which household income belongs in the national distribution and the main occupational status, while the contextual explanatory variables were share of households with access to Internet, median equivalized income (in thousand euros) at national level and by degree of urbanization, and activity rate.

Following [3], the proper number of discrete values for each latent variables was identified by, first, estimating single-level LC models and by looking at the BIC values of the estimated models. After identifying the optimal $T = 5$, a series of MLC models were estimated and an analogous criterion was applied to determine the appropriate number of group classes ($M = 4$). Lastly, individual and contextual covariates were added to the MLC model with $T = 5$ and $M = 4$ and their significance was tested. This final model was the one showing the lowest BIC and all the considered covariates were found to be significant according to the Wald test.

The final model enabled to clearly distinguish five individual clusters on the basis of individual attitudes towards ICTs. The largest cluster (46%) was made up of skilled ICT users, characterized by the highest mean values of each indicator. On the other hand, individuals who declared to have not used internet (12%) were all

¹ German respondents were excluded because of the lack of information on their NUTS-1 region.

grouped in the same cluster. The remaining clusters were composed, respectively, by individuals with low digital skill level (15%), medium digital skill level but low creativity (18%) and medium digital skill level but low risk awareness (9%). The occurrence of having higher levels of digital competence was associated with higher educational attainment levels, higher income, lower age and an occupational status of employed or student.

On the basis of the distribution of the clusters in the geographic areas, it was possible to distinguish four levels of diffusion of digital skills. Almost all the digitally disadvantaged regions were located in Eastern Europe and were more likely rural. On the other hand, the regions where the diffusion was found to be good were almost equally divided between North, West and South. Higher median income levels, higher share of households having access to Internet and higher activity rates were associated with higher diffusion of digital skills.

4 Final Remarks

A two-stage latent variable analysis was performed on micro-data from 2021 edition of “ICT Usage in Households and by Individuals” annual survey. The first preliminary stage consisted of the estimation of MIRT models aimed at finding the underlying latent structure of the data set. The obtained data driven scheme was slightly different from the one currently used by Eurostat to measure individuals’ digital skill levels. Then, adopting this new factor structure, a MLCA aimed at classifying European citizens and geographical areas on the basis of individual digital skill levels was performed. As a result, common traits among European citizens and regions on which policy actions for the digital upskilling might focus were identified.

Acknowledgements F. Bacchi is supported by funds FSE REACT-EU - A.A. 2023/2024.

References

1. European Commission: Employment and Social Developments in Europe. Publications Office of the European Union, Luxembourg (2023)
2. Vermunt, J. K.: Multilevel latent class models. *Sociological methodology* **33** 213–239 (2003)
3. Mäkikangas, A. and Tolvanen, A. and Aunola, K. and Feldt, T. and Mauno, S. and Kinnunen, U.: Multilevel latent profile analysis with covariates: Identifying job characteristics profiles in hierarchical data as an example. *Organizational Research Methods* **21** 931–954 (2018)
4. Vuorikari, R. and Punie, Y. and Gomez, S. C. and Van Den Brande, G. et al.: DigComp 2.0: The digital competence framework for citizens. Update phase 1: The conceptual reference model. Joint Research Centre, Sevilla (2016) doi: 10.2791/11517
5. Vuorikari, R. and Jerzak, N. and Karpinski, Z. and Pokropek, A. and Tudek, J.: Measuring Digital Skills across the EU: Digital Skills Indicator 2.0. Publications Office of the European Union, Luxembourg (2022) doi: 10.2760/897803

Framing a field: Understanding collectible design through a Delphi study

Laura Benedan, Federica Codignola, Carlotta Galeone and Paolo Mariani

Abstract This study investigates collectible design, a growing market category that blends functionality with symbolic value. The Delphi method was used to explore characteristics and market dynamics. Following a review of the literature and analysis of qualitative interviews, valuable insights emerged. These insights led to the development of a questionnaire, which was subsequently administered to a panel of experts. The findings highlight the hybrid nature of this category, which spans historical and contemporary rare items. The results also reveal tensions between economic and symbolic drivers as well as pragmatic and figurative approaches. This study provides a foundational framework for understanding collectible design and offers actionable insights for stakeholders.

Key words: collectible design, art market, Delphi study

1 Introduction

The creative and cultural industries encompass businesses that produce and distribute goods that hold symbolic rather than material value, often characterised by artistic innovation and limited reproducibility (Caves, 2000; Hirsch, 1972). Among

Laura Benedan

University of Milano-Bicocca, e-mail: laura.benedan@unimib.it

Federica Codignola

University of Milano-Bicocca, e-mail: federica.codignola@unimib.it

Carlotta Galeone

University of Milano-Bicocca, e-mail: carlotta.galeone@unimib.it

Paolo Mariani

University of Milano-Bicocca, email: paolo.mariani@unimib.it

these, collectible design has emerged as a notable trend, combining elements of artistic creativity with functional attributes.

Design objects, when fulfilling specific criteria of collectability - such as uniqueness, rarity, and authenticity - become part of a hybrid market which performs exceptionally well through the art market whilst also functioning independently. These items, traded across platforms ranging from auction houses to resale e-commerce sites, occupy a unique space within the art and design markets.

Although no specific indexes currently track collectible design, existing art market indexes reveal a rise in the auction process of these items over the past decade. This growth reflects increasing demand and a proliferation of institutions and actors specialising in this domain, including galleries, fairs, and museums. Furthermore, rising cultural attention underscores the expanding interest in collectible design, evidenced by its frequent appearance in traditional and digital media.

Given its growing relevance and the scarcity of dedicated research, this study aims to further explore the category of collectible design, using a structured methodology to deepen understanding.

2 Conceptualising collectible design

The concept of 'collectible design' blends artistic and functional aspects. For example, Wu (2013) defined 20th-century design as encompassing functional yet collectible objects with potential financial returns. Similarly, Bertacchini and Friel (2014) highlighted collectible furniture as a segment evolving from functional goods to art-like objects integrated into curated collections and exhibitions.

This dual nature places collectible design at the intersection of the design and art markets, creating a hybrid field. It spans specific sectors (e.g., furniture, glassware, ceramics, etc.) and movements (e.g., Scandinavian design, Art Deco, etc.), including both historical and contemporary limited-edition or unique pieces. This excludes antiques which typically form a separate category.

The motivations driving the acquisition of collectible design extend beyond functionality. Collectors often value these items for their emotional, symbolic, and aesthetic appeal, contributing to self-image and social identity. As a hybrid realm, collectible design exemplifies a space where symbolic value significantly influences market performance and economic valuation (Codignola & Mariani, 2022; Throsby, 2008).

3 Methodological approach

This study explored the dimensions of collectible design, using the Delphi method, a structured approach for gathering expert insights (Dalkey & Helmer, 1963). A panel of international experts provided iterative feedback through multiple questionnaire rounds, refining their responses toward consensus. Since the preliminary stages of the project, all pertinent requirements for a high-quality Delphi study have been considered, namely anonymity, iteration, controlled feedback and the statistical stability of consensus (Nasa et al., 2021).

The initial step was to analyse existing literature on the topic. Subsequently, three in-depth interviews were conducted with collectible design experts from Italy and France.

The interviews yielded preliminary insights into the field, identifying key themes and uncertainties within the ground of enquiry. The findings from this initial phase enabled the identification of key concepts, which constituted the foundation for the subsequent development of the first questionnaire. The survey comprised 45 questions and covered various topics, including demographic detail, the conceptual understanding of 'collectible design', personal experiences with collectible objects, and expert perceptions elicited through visual stimuli. Furthermore, experts were invited to contribute their critical perspectives on the practice of design collecting.

The questionnaire was distributed online to a panel of carefully selected experts (50 individuals) with diverse backgrounds, comprising designers, collectors, art and design professionals, and academics. Their responses were subjected to analysis to identify areas of agreement and disagreement.

Subsequently, a shorter questionnaire was distributed to gain further insight into areas lacking consensus from the initial round.

4 Empirical findings

Before data collection, the research team established that achieving a consensus among experts would be defined as attaining a convergence of 67% in responses. Accordingly, a substantial consensus emerged regarding the definition of 'collectible design', with an overwhelming majority (91%) of experts agreeing that it denotes a tangible, physical entity. This shared understanding emphasises the fact that collectible design is a materiality-based concept, which sets it apart from purely digital or conceptual forms of design.

Furthermore, to gain a deeper insight into the defining characteristics of collectible design, a series of five images, each representing one of five objects within the collectible design category, was presented to the panel of experts. The participants provided key terms for each item, which were subsequently analysed to identify any recurring themes. The findings indicated that collectible design is most frequently associated with the quality of being 'distinctive', characterised by

attributes such as originality, rarity, and uniqueness. These features align with the notion that collectible design items are not only aesthetically or culturally appealing but also possesses inherent value as exclusive objects.

In addition to the aforementioned criteria of ‘distinctiveness’, experts identified two further attributes of critical importance: ‘functionality’ and ‘craftmanship’. The functionality of collectible design was identified as a salient factor, with the observation that many such items possess both practical utility and artistic or collectible appeal. Conversely, ‘craftmanship’ was regarded as an indicator of quality, reflecting the meticulous attention to detail and expertise required in the production process.

Collectible design can thus be seen to occupy a unique position at the intersection of utility, artistry, and exclusivity.

5 Conclusion

This study analyses collectible design, integrating theoretical frameworks with insights from experienced industry stakeholders. The results contribute to our understanding of collectible design, offering a more nuanced and precise definition of this market and product category that has yet to be fully identified. The Delphi method, employed to achieve a structured consensus, facilitated a robust exploration of current practices, expert opinions, and anticipated future directions. The findings highlight the hybrid nature of collectible design, combining artistic and functional values within a distinct market space which performs at the intersection of art, design, and commerce.

These findings will benefit various stakeholders, from designers to collectors, from art market practitioners to academics, by offering valuable perspectives into the evolving dynamics of this market and product category.

References

1. Bertacchini, E., Friel, M.: Determining the value of modern and contemporary furniture design: An exploratory investigation. University of Turin working paper series (2014)
2. Caves, R.E.: *Creative Industries: Contracts between Art and Commerce*. Harvard University Press (2000)
3. Codignola, F., Mariani, P.: Investigating preferences in art collecting: The case of the François Pinault Collection. *Ital. J. Mark.*, 107-133 (2022) doi: 10.1007/s43039-021-00040-x
4. Dalkey, N., Helmer, O.: An experimental application of the Delphi method to the use of experts. *Management Science*, 9(3), 458-467 (1963) doi: 10.1287/mnsc.9.3.458
5. Nasa P., Jain R., Juneya, D.: Delphi methodology in healthcare research: How to decide its appropriateness. *World J. Methodol.*, 20; 11(4), 116-129 (2021) doi: 10.5662/wjm.v11.i4.116
6. Throsby, D.: *The Economics of Cultural Policy*. Cambridge University Press (2008)
7. Wu, L.T.J.: *Financial Returns and Price Determinants in the 20th Century Design Market*. Sotheby’s Institute of Art (2013)

Multidimensional Perspectives on Food Poverty in Italy: insights from POSet Analysis

Ilaria Benedetti and Chiara Grazini

Abstract Food poverty, a key dimension of economic deprivation, refers to the inability to afford a nutritionally adequate diet, adversely impacting health and well-being. This study uses data from the 2022 Household Budget Survey (HBS) carried out by ISTAT and applies the Partially Ordered Set (POSet) methodology to analyse food poverty in Italy. Unlike traditional unidimensional approaches, POSet evaluates multidimensional deprivation, considering economic and social dimensions. Findings highlight complex deprivation patterns, informing targeted, multidimensional policy interventions.

Keywords: Food poverty, Multidimensional Deprivation, POSet Methodology

1 Introduction and aim of the paper

Food poverty, defined as the inability to acquire or consume sufficient food in socially acceptable ways, or the uncertainty of doing so, represents a critical dimension of economic deprivation.

Within the European Union (EU), food poverty is strongly linked to economic inequality. In 2023, food accounted for 13% of household consumption expenditure in the EU, the second-largest expenditure share, ranging from 8.6% in Ireland to 20.6% in Latvia. The At-Risk-of-Poverty or Social Exclusion (AROPE) indicator highlights economic barriers to food access, with 9.5% of the EU population unable to afford a meal with meat, fish, or vegetarian equivalent every second day - a 1.2% increase from 2022.

Ilaria Benedetti
University of Tuscia, e-mail: i.benedetti@unitus.it
Chiara Grazini
University of Tuscia, e-mail: c.grazini@unitus.it

Current methodologies for assessing food poverty rely on two primary approaches. The Food Insecurity Experience Scale (FIES) measures food access using eight binary indicators, analysed via the Rasch model to classify insecurity as moderate or severe. The consumption-based approach evaluates economic access to food through indicators, such as the At-Risk-of-Food-Poverty (AROP), based on Household Budget Survey (HBS) data to estimate traditional and fuzzy measures (Marchetti & Secondi, 2021; Benedetti et al., 2024), and the Food Insecure Households (FIH) indicator, linking food expenditure to insecurity using IPC's classification: no insecurity (<40%), mild (40–50%), moderate (50–70%), and severe ($\geq 70\%$). These methods address physical access and economic vulnerability but often fail to capture the multidimensional nature of food poverty.

To address this limitation, this study uses data from the 2022 HBS conducted by ISTAT to examine food poverty in Italy through the Partially Ordered Set (POSet) methodology. This innovative approach is ideal for analysing ordinal data and evaluating deprivation profiles by considering interrelations among multiple deprivation dimensions. Unlike traditional methods, which assess dimensions in isolation, POSet captures the complexity of multidimensional deprivation by analysing relationships between achievement profiles, acknowledging that individuals face overlapping disadvantages.

Using the POSet methodology, this study constructs achievement profiles by integrating several key variables. The first is the AROFP indicator, which represents the traditional food poverty measure based on the relative poverty line, set at 60% of the median income. The second variable is the FIH indicator, reflecting the budget share allocated to food expenditures. Finally, as a proxy of the FIES indicator, we considered whether households experienced a reduction in the quality and/or quantity of food consumed during the past year. By analysing these variables collectively, the study uncovers distinct patterns of deprivation that are often overlooked by conventional unidimensional approaches.

By employing the POSet methodology, this study provides a robust framework for understanding and measuring food poverty from a multidimensional perspective, offering valuable insights for more comprehensive policy interventions.

2 The HBS data and the POSet method

The HBS offers insights into household consumption expenditure behaviours, and it is used to produce official statistics on poverty in Italy. In order to categorise profiles into completely deprived, partially deprived, or non-deprived, providing a nuanced analysis of deprivation intensity and extent, the POSet approach has been used (Fattore, 2016; Fattore and Arcagni, 2018).

The POSet approach analyses deprivation profiles, representing individuals' achievements across k ordinal attributes, each with an ordinal scale of $m_1, m_2, \dots, m_k$. These profiles form an achievement space where comparisons are made to identify higher or lower deprivation levels. A partial order relation $q \preceq p$ is defined as:

$$q_i \leq p_i \quad \forall i = 1, 2, \dots, k \quad (1)$$

Here, q is as deprived or more than p if all scores of q are not better than p . Profiles are either comparable (one dominates the other) or incomparable (conflicting scores). Deprivation thresholds (τ) are identified through the antichain of the achievement POSet, including only incomparable and fully deprived profiles (Fattore, 2016). Profiles below this threshold are deemed fully deprived, while others may be partially deprived or not deprived. An identification function assigns each profile p a deprivation score $idn(p) \in [0,1]$, based on the fraction of linear extensions $\mathcal{L} \in \Omega(\Pi)$ classifying p as deprived: $idn(p) = \frac{1}{|\Omega(\Pi)|} \sum_{\ell \in \Omega(\Pi)} idn_{\ell}(p)$. The severity of deprivation is computed using a severity function $svr(p)$, which measures the profile's distance from non-deprivation (Fattore and Arcagni, 2018):

$$svr(p) = \frac{1}{|\Omega(\Pi)|} \sum_{\ell \in \Omega(\Pi)} svr_{\ell}(p)$$

3 Results and discussion

The analysis using the POSet approach yielded insightful findings on the incidence and intensity of deprivation. The Hasse diagram (Figure 1) illustrates the partial ordering of deprivation profiles, showing the hierarchical relationships within the multidimensional achievement space for the three variables scored on a $1 < 2 < 3$ scale. It consists of 16 elements, arranged in 5 levels, each comprising profiles with the same score “sum”. It has 232 (individual not deprived in all the dimensions) and 111 (individual deprived in all the dimensions) as top and bottom. The threshold profile (131) represents the cut-off point distinguishing deprived from non-deprived individuals. This profile corresponds to individuals experiencing deprivation in both food quality and quantity dimensions but not in monetary terms. As the most deprived profile among those not classified as non-poor, it serves as a reference for identifying food poverty, meaning that any individual with an equal or worse deprivation status (i.e., dominated by this profile in the partial order) is considered deprived. The identification function (Figure 2) provides a distribution of deprivation scores, effectively categorizing profiles into completely deprived, partially deprived, and non-deprived groups. This representation showcases the nuanced capacity of the POSet methodology to differentiate among varying levels of deprivation based on fractional scoring. On average, the incidence of poverty was estimated at 7.465%, indicating that a relatively small proportion of the population is fully deprived based on the established multidimensional threshold. The poverty gap, reflecting the average distance of deprived profiles from the deprivation threshold, was calculated as 0.1003. This value highlights that the severity of deprivation among those classified as deprived is relatively modest, pointing to a population where most individuals fall close to the threshold.

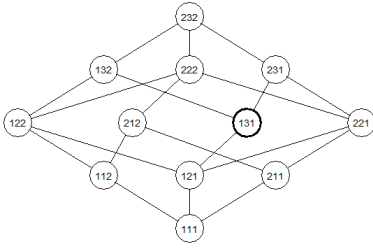


Fig. 1 Hasse diagram

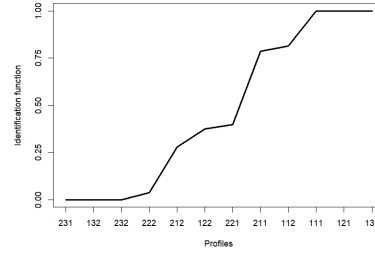


Fig. 2 Identification function

Finally, the rank distribution (Figure 3) presents the positioning of profiles in terms of deprivation severity. The bar plot provides the rank distribution of each profile (X-axis). The heights of the blocks represent the frequency, while the grey scale colours represent the spread of deprivation intensity of food poverty (white for non-deprived profiles and black for fully deprived profiles), drawing attention to the most and least deprived profiles and offering a comprehensive view of the underlying distribution of deprivation.

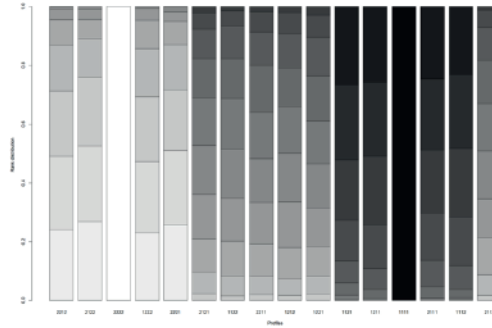


Fig. 3 Rank distribution

Together, these results confirm the utility of the POSet approach in addressing the complexity of multidimensional deprivation by capturing both the incidence and severity of food poverty, while accounting for the inherent incomparability of profiles.

References

1. Benedetti, I., Crescenzi, F., Laureti, T., & Secondi, L. (2024). Adopting the fuzzy approach to analyze food poverty in Italy: A study on vulnerable households using Household Budget Survey data. *Socio-Economic Planning Sciences*, 95, 102006.
2. Fattore, M.: Partially ordered sets and the measurement of multidimensional ordinal deprivation. *Social Indicators Research*, 128(2), 835–858 (2016)
3. Fattore, M., Arcagni, A.: A reduced posetic approach to the measurement of multidimensional ordinal deprivation. *Social Indicators Research*, 136(3), 1053–1070 (2018)
4. Marchetti, S., & Secondi, L. (2022). The economic perspective of food poverty and (in) security: An analytical approach to measuring and estimation in Italy. *Social indicators research*, 162(3), 995-1020.

Spending diversity and quality indexes by SWB levels and urbanization degree

Cristina Bernini, Silvia Emili and Federica Galli

Abstract: This study examines how individual spending patterns modify for different levels of subjective well-being (SWB) and urbanization degree, specifically focusing on spending diversity and quality indexes. Estimates are obtained using Italian data in 2016, with Engel curves estimated using threshold regression models with endogenous threshold.

Key words: Engel curves, Expenditure elasticity, Spending diversity and quality

1 Introduction

Analyzing household expenditure patterns is an essential tool for policymakers to make informed decisions that support economic stability, enhance social welfare, and foster sustainable development within society. Despite extensive research into the factors affecting household expenditure decisions, studies on individual spending habits based on both subjective well-being (SWB) and degree of urbanization are rare and controversial in findings. Individuals' consumption habits are influenced by the urban environment in which they live [4] and by the emotional character of people: *“there is mounting evidence that emotions, including happiness, exert considerable influence on decision-making”* [6, p.62].

Cristina Bernini
University of Bologna, e-mail: cristina.bernini@unibo.it

Silvia Emili
University of Bologna, e-mail: silvia.emili2@unibo.it

Federica Galli
University of Bologna, e-mail: federica.galli14@unibo.it

To address this gap, this study aims to analyze how varying levels of SWB, alongside diverse urbanization levels, identify distinct consumption profiles, in terms of spending diversity and quality [2], henceforth DI and QI respectively. To this end, we use 2016 Italian data on individual SWB, expenditure, and urbanization degree and we estimate Engel curves (ECs) using threshold regression models.

2 Data

In order to obtain joint information on expenditure, urbanization and SWB for Italian residents, we created a comprehensive dataset by taking advantage of statistical matching techniques. In particular, we matched data from two ISTAT surveys, "Aspects of Daily Life" (ADL) and "Household Budget Survey" (HBS) for 2016, employing a constrained distance hot deck procedure [5].

We defined urbanization using the ISTAT classification from the HBS dataset, where urbanization degree is categorized into three levels: metropolitan areas, which include Italy's 12 largest cities; urban areas, referring to cities with population over 50,000; and rural areas, representing areas with population under 50,000.

According with [8] and the multiple nature of life satisfaction, we do not use overall life SWB scores provided by ADL, but we estimate a synthetic measure of satisfaction with different life domains as the predicted value of a linear regression for ADL's satisfaction (on a 0-10 scale) on different life domain scores (satisfaction with family, friends, leisure time, economic conditions, environment, and health, on a 0-4 scale).

For analyzing individual spending habits, we selected expenditure categories based on ISTAT's classification: Food (covering food and beverage expenses); Work-related (meals away from home, clothing, personal care, communication, education, and transport costs); Health (expenses for hospital stays, medical visits, etc.); Durables (durable transports, home appliances, furniture, and recreational items); Housing (rent, utilities, repairs, etc.); and Leisure (spending on sports, cultural events, and travel). Finally, individual expenditure has been adjusted for the household composition and possible scale economy mechanisms by means of Carbonaro equivalence scale.

3 Methodology

The proposed model is affected by two sources of endogeneity: SWB and total expenditure as proxy of income in ECs' specification.

The first source is handled by means of the non-parametric integrated difference kernel estimator (IDKE) by [9]. Without using instruments in the identification and estimation of the threshold value, the estimator compute the SWB level at which a jump in the distribution of spending behaviour is detected. Then, the proposed

procedure consists in the estimation of ECs and expenditure elasticities for the set of spending aggregates by means of a quadratic log-log specification [1] with the SWB threshold obtained at the previous step. The endogeneity concerning total expenditure is handled by instrumental variable approach, with instruments proposed by [7]. Finally, starting from the expenditure elasticities we compute the spending diversity and quality indexes following [3]. These indexes are calculated by urbanization degree and SWB region. The model and the associated indexes are estimated separately for individuals living in metropolitan, urban and rural areas of Italy (treating individuals as a unique population or separated for urbanization levels has been tested appropriately in a preliminary step of the analysis).

4 Results

The estimation results indicate that one unique threshold level of satisfaction (7.52) exists for all spending aggregates. Therefore, we can identify people with a SWB level greater than 7.52 as Happy and individuals with SWB lower or equal to 7.52 as Unhappy. Once ECs and expenditure elasticities are obtained for Happy and Unhappy in the three urbanization-based samples, DI and QI have been calculated. The results by SWB level and urbanization degree are displayed in Figure 1.

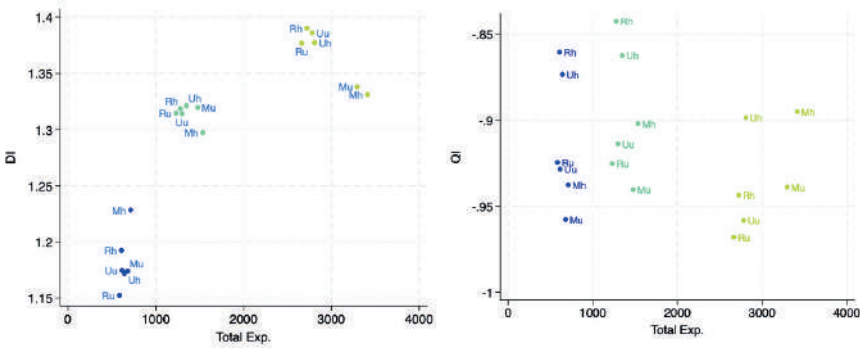


Fig. 1 Quality (QI) and diversity index (DI) by urbanization degree (R=rural; U=urban; M=metropolis) and SWB (U=unhappy; H=happy). Blue dots: lower 20% of the expenditure distribution; Light blue: from 21% to 79%; Green: upper 20%.

The Figure shows that, in general, while DI increases as total expenditure raises, a less pronounced pattern can be observed for the QI index. Focusing on SWB levels, while for spending diversity small differences can be observed between Happy and Unhappy individuals, notable differences can be detected in terms of spending quality. Focusing on DI, Happy people tend to consume higher quality goods compared to Unhappy. Comparing the indexes across urbanization categories, we

find that among low-income consumers, happy people living in metropolises are those with the highest level of spending diversity. However, they tend to show a lower spending diversity than urban and rural dwellers for high-income consumers. For QI, among low-income consumers, happy rural and urban dwellers are those consuming better-quality products while in metropolises people show the lowest quality levels, even if the index tend to raise as total expenditure increases, reaching the highest level for the high-income group.

5 Conclusions

This work investigates how individuals' spending quality and diversity vary across different SWB and urbanization levels, integrating emotional and cultural factors in the analysis of consumer spending patterns. Based on this work, an R-Shiny app will be developed to support the data production objectives of the GRINS project (PNRR). The app will allow computing DI and QI indexes as well as expenditure elasticities across Italian regions differentiating by expenditure level and urbanization degree.

Acknowledgements This study was funded by the European Union -NextGenerationEU, Mission 4, Component 2, in the framework of the GRINS -Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 – CUP E63C22002120006). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

References

1. Banks, J., Blundell, R., Lewbel, A.: Quadratic Engel curves and consumer demand. *Rev. Econ. Stat.* 79(4), 527–539 (1997)
2. Chai, A., Moneta, A.: Back to Engel? Some evidence for the hierarchy of needs. *J. Evol. Econ.*, 22, 1–28 (2012)
3. Chai, A., Stepanova, E., Moneta, A.: Quantifying expenditure hierarchies and the expansion of global consumption diversity. *J. Econ. Bus. Organ.*, 214, 860–886 (2023)
4. Currid-Halkett, E., Lee, H., Painter, G. D.: Veblen goods and urban distinction: The economic geography of conspicuous consumption. *J. Reg. Sci.*, 59, 83–117 (2017)
5. D'Orazio, M., Di Zio, M., Scanu, M.: *Statistical Matching, Theory and Practice*. Wiley, New York (2006)
6. Lane, T.: How does happiness relate to economic behaviour? A review of the literature. *J. Behav. Exp. Econ.*, 68, 62–78 (2017)
7. Lewbel, A.: Using heteroskedasticity to identify and estimate mismeasured and endogenous regressor models. *J. Bus. Econ. Stat.*, 30(1), 67–80 (2012)
8. Van Praag, B. M. S., Frijters, P., Ferrer-i-Carbonell, A.: The anatomy of subjective well-being. *J. Econ. Behav. Organ.*, 51, 29–49 (2003)
9. Yu, P., Phillips, P.C.B.: Threshold regression with endogeneity. *J. Econom.*, 203, 50–68 (2018)

From Choices to Change: Household Finance and Sustainability

Beatrice Bertelli, Marianna Brunetti, Costanza Torricelli, Arthur van Soest and Mariangela Zoli

Abstract The growing awareness of the need for an energy transition has led to the development of new financial products aimed at promoting sustainability, with a focus on Socially Responsible Investments (SRI). Research on household savings and their allocation into SRI has increased since the 2000s, exploring motivations, return comparisons, and socio-demographic profiles. The rise of ESG (Environmental, Social, Governance) investing, particularly after the 2015 Paris Agreement, has expanded asset options, including Green Bonds and Sustainable Bonds. Households are increasingly aware of sustainability, but preferences vary between direct (stocks, bonds) and indirect (funds) investments. The study uses survey and experimental data to examine household preferences, willingness to pay for sustainability, and the effectiveness of nudges in promoting green investments. Results show growing ownership of ESG assets and a preference for environmental over social or governance aspects, with mutual funds being more attractive than individual assets. Households are willing to accept slightly lower returns for investments focusing on environmental or ESG issues.

Key words: household finance, ESG (Environmental, Social, Governance) assets, willingness to pay, nudges

Beatrice Bertelli
University of Modena and Reggio Emilia, e-mail: beatrice.bertelli@unimore.it

Marianna Brunetti
University Rome Tor Vergata, e-mail: marianna.brunetti@uniroma2.it

Costanza Torricelli
University of Modena and Reggio Emilia, e-mail: costanza.torricelli@unimore.it

Arthur Van Soest
Tilburg University, e-mail: A.H.O.vanSoest@tilburguniversity.edu

Mariangela Zoli
University of Rome Tor Vergata, e-mail: zoli@uniroma2.it

1 Introduction and Literature Overview

Increased awareness of the need for the energy transition and the necessary investments has pushed the markets to offer new products. Most attention has been devoted to the role that firms and institutional investors can play in the transition to a greener economy, also fostered by new regulations in that direction in the financial market industry. However, households also play a crucial role in this picture.

Research on the role of household savings and their allocation into Socially Responsible Investments (SRI) dates back to the early 2000s, with focus on: i) households' motivations and underlying theoretical framework (e.g. Beal et al. 2005, Bollen, 2007, Aryeli et al., 2009); ii) comparison of SRI vs conventional assets' returns and the existence of a premium, with contrasting empirical results (e.g. Renneboog et al., 2008, Hong and Kacperczyk, 2009, Bertelli et al., 2021); iii) the SRI profiling in terms of socio-demographic and economic features (e.g. Bauer & Smets, 2015, Rossi et al., 2019).

The role of households in financing the energy transition needs further investigation because of the relevant changes occurred recently both in the sustainable asset universe (supply side), and in the households' attitudes towards these assets (demand side).

On the supply side, different types of assets are now available, focusing on one or more of the three dimensions of sustainability, Environmental, Social or Governance (ESG). Debt products now range from the most widespread Green Bonds considering the Environmental issue only and Social Bonds focused on social objectives to Sustainable bonds having a combination of ESG objectives and the so-called second-generation Sustainability linked bonds, whose return is linked to such objectives. The Covid-19 pandemic has fostered the issuance of Social Bonds, simple fixed-income securities whose proceeds are allocated to social initiatives (e.g. Torricelli and Pellati, 2023). As for capital products, they can be in form of stocks or equity funds with E(SG) rating up to the most recent Net zero funds. Several important open issues from the supply side remain, including: a) the need of a refinement in the taxonomy, which is mainly there in the form of guidelines (e.g. for bonds see International Capital Market Association, ICMA), yet not regulation, and b) the risk of green/social/sustainability washing due to the problems in ESG rating assignment and possible divergence in ratings (Berg et al., 2022). Furthermore, the new MiFID II requirement, amended through two delegated regulations, 2021/1253 and 2021/1269, as part of a broad Sustainable Finance Action Plan (SFAP) developed by the European Commission (EC) and come into effect in August 2022, obliges advisers to ask their clients about their sustainability preferences as part of the existing suitability assessment.

As for the demand side, it is important to assess the awareness of households about the importance of financing a sustainable economy with attention to all the dimensions; the preferences for direct investments (e.g., stocks with ESG rating, Green Bonds, Social bonds etc) versus indirect investments (cf. funds with ESG rating or specific carbon profile); the role of socio-demographic characteristics, also

in light of changes (cf. population ageing), affecting cognitive abilities and financial skills.

This study provides answers to some of these research questions: Do households care only for the low carbon feature or are they aware that sustainability means ESG? Do they prefer direct or indirect investments? Do they think they can “do well while doing good” or that they have to sacrifice return? If so, what is their “willingness to pay” (WTP)? Can they be nudged to support sustainability?

2 Dataset and methodology

The empirical analysis is based on two sets of data. First, we use survey data taken an online survey administered to a sample of 2414 people representative of the Dutch adult population, conducted in February 2024 by Centerdata at Tilburg University. The response rate is pretty high (around 70%) and the data provide detailed information on individual characteristics, employment, pensions, living conditions, household financial and housing wealth, mortgages and loans, income, health, and psychological concepts. Next, we use data resulting from a lab-in-the-field experiment run between November and December 2024 in 2 different branches of a large Italian bank in two different Italian cities (Modena and Rome). The data provide information about the knowledge of ESG products, the propensity to invest on these products, either directly or indirectly through mutual funds, as well as the WTP for such financial products. In running the experiment, each participant was assigned to a random group between three: the first received a card picturing a wonderful landscape, aimed at evoking positive sensations related to green environment, the second a card picturing a natural disaster, thus aimed at evoking negative sensation, and the third group received nothing, thus acting as control group. It can thus be used to evaluate the potential impact of different nudges on financial investors’ choice and their WTP (Thaler and Sunstein, 2009; Hansen, 2016; Giaccherini et al, 2021, D’Amato et al, 2023).

Empirical methods include linear and non-linear models, where the dependent variable is – in turn – the knowledge, the probability to invest and the WTP for sustainable products, while controls include age, gender, education, and preferences.

3 Main results

Ownership of ESG assets in the Netherlands has risen from 8.5% to 14.7% between 2016 and 2024, while knowledge has remained substantially unchanged. Data for Italy show that about 43.8% of the interviewed know the ESG assets.

In both countries, assets targeting the mix of the three dimensions (ESG) are the most preferred, while among individual factors the Environmental one is the most popular and Governance the less attractive. Moreover, indirect investments through mutual funds are preferred with respect to individually chosen assets (54% of the versus 30% based on the Italian data, similar picture for the Netherlands).

Finally, in both countries we find evidence of a positive willingness to pay for sustainable assets, that correlates both with the factor of interest (E, S, G or mix) and with socio economic variables. Quite interestingly, data from the lab-in-the-field experiment show that the willingness to pay can be nudged with visuals evoking negative emotions.

References

1. Bauer R, Smeets P (2015) Social identification and investment decisions. *Journal of Economic Behavior and Organization*, 117: 121–134.
2. Beal DJ, Goyen M, Philips P (2005) Why do we invest ethically? *Journal of Investing*, 14(3): 66–78.
3. Berg F., J. Kölbel, R. Rigobon (2022) Aggregate Confusion: The Divergence of ESG Ratings, *Review of Finance*, Volume 26, Issue 6, November 2022, Pages 1315–1344.
4. Bertelli B., Boero G., Torricelli C. (2021). The market price of greenness: a factor pricing approach for Green Bonds, Working Paper Cefin N.83, June.
5. Bertelli, B., Torricelli, C. (2024). The trade-off between ESG screening and portfolio diversification in the short and in the long run. *Journal of Economics and Finance*, 48(2), 298–322.
6. Bertelli, B., Torricelli, C. (2025), Sustainable optimal portfolios: what relationship between sustainability and performance? *European Journal of Operational Research*, 323(1), 323–340.
7. Bollen NPB (2007) Mutual fund attributes and investor behavior. *Journal of Financial and Quantitative Analysis*, 42(3): 683–708.
8. Brunetti M., C. Torricelli, 2017, “Second homes in Italy: every household’s dream or (un)profitable investments?”, *Housing Studies*, 32 (2), 168–185.
9. Brunetti M., Giarda E., Torricelli C., 2016, Is financial fragility a matter of illiquidity? An appraisal for Italian households, *Review of Income and Wealth*, 62 (4), 628–649
10. D’Amato, T. Goeschl, L. Lorè and Zoli, M. (2023) True to type? EU-style date marking and the valuation of perishable food, *Food Policy*, 114, 102381.
11. Giaccherini, M. Gilli M., Zoli, M (2021) Nudging food waste decisions at restaurants, *European Economic Review*, 103722.
12. Hansen, P. G. (2016) The definition of nudge and libertarian paternalism: Does the hand fit the glove? *European Journal of Risk Regulation*, 7(1), 155–174.
13. Hong H, Kacperczyk M (2009) The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, 93(1): 15–36.
14. Renneboog L, Ter Horst J, Zhang C (2008) Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of Banking and Finance*, 32(9): 1723–1742.
15. Rossi M.C., Sansone D., A. van Soest, C. Torricelli, 2019, Household preferences for Socially Responsible Investments, *Journal of Banking and Finance*, 105, 107–120.
16. Thaler, R. H. and Sunstein, C. R. (2009) *Nudge. Improving decisions about health, wealth, and happiness*. Penguin.
17. Torricelli C., Pellati E., 2023, Social Bonds and the “Social Premium”, *Journal of Economics and Finance*, Accepted February 2023

Municipal indicators for the analysis of the economy of Inner areas

Antonella Bianchino, Agata Maria Madia Carucci, Valeria Marzocca and Roberto Antonello Palumbo

Abstract “A misura di comune” represents an important Istat information system that provides public decision makers with socio-economic and demographic indicators on a municipal basis. The development of the information system is made possible by the joint use of data provided by official statistics and open data. In this work, we want to describe the economic well-being and the production system of the municipalities classified by degree of territorial marginality. This aspect is traced back to the use of the SNAI classification according to which municipalities are defined as Centers when they simultaneously present essential services (health, education and transport) and Inner Areas based on the distance from the Centers.

Key words: A misura di comune, SNAI, Economic well-being, Production system, Municipal indicators

1 Introduction

The development of official statistics over the last decade has led to a real paradigm shift for territorial analyses. On the one hand, the integration between statistical and administrative data has constituted a push towards the creation of statistical registers and on the other, open data and big data have completely revolutionized and enriched the information assets underlying territorial statistics.

Antonella Bianchino
ISTAT, e-mail: bianchin@istat.it

Agata Maria Madia Carucci
ISTAT, e-mail: carucci@istat.it

Valeria Marzocca
ISTAT, e-mail: valeria.marzocca@istat.it

Roberto Antonello Palumbo
ISTAT, e-mail: palumbo@istat.it

This innovation has led to the implementation of analyses and indicators on a municipal and inter-municipal territorial basis. This analysis is even more indispensable in a country like Italy, characterized by great territorial variability both in geopolitical terms, in orographic terms and in the marginality of the territories. With the experimental statistics "A misura di comune" [1], Istat provides data and indicators at municipal level. The information system, whose last update of which is being published, is structured by thematic areas and involves socio-demographic and economic themes. The sources that feed the information system are both official (Istat surveys, statistical registers...) and experimental (open data).

In particular, the economic aspect is described by the indicators of economic well-being and those of the production system. In this work, starting from a selection of municipal indicators for the two thematic areas, the different territorial behaviours by degree of marginality are analysed. In particular, the marginality of the territories is described by the widely used classification of municipalities according to the National Strategy for Inner Areas (SNAI) [2], [3]. The SNAI is the most important territorial cohesion strategy of the last decade and aims to classify territories based on access to essential services: hospitals, schools and the railway network that meets certain requirements. The municipalities that simultaneously provide the three essential services are classified as Pole municipalities and depending on the distance from the Pole municipalities, they are defined as Belt municipalities, Intermediate, Peripheral and Ultraperipheral municipalities.

2 Analysis of economic well-being indicators for Inner Areas

The "A misura di comune" information system presents four indicators for the thematic area "Economic well-being": Average income per taxpayer, Incidence of taxpayers with an income less than 10 thousand euros per year, Single-income families with children under 6 years of age, Low work intensity of registered families. To analyse the well-being of the population living in areas with different degrees of marginality, two indicators were selected in this work: Average income per taxpayer, Incidence of taxpayers with an income less than 10 thousand euros per year. On average, a taxpayer who lives in a Central area (Pole, Intermunicipal Pole and Belt) receives just under 24,000 euros, 4,500 euros more than those who live in an Inner Area. The greater the distance from essential services, the lower the income per taxpayer. In the ultraperipheral municipalities, the income per taxpayer is less than 18,000, 8,000 euros less than those who live in the pole municipalities (Fig. 1).

Approximately 25% of taxpayers in the Centers have an income of less than 10,000 euros, a value that reaches 31% in the municipalities of the Inner Areas and 34% in the Ultraperipheral municipalities (Fig. 2)

SNAI Classification	Average income per taxpayer
Pole	26,010
Intermunicipal Pole	22,146
Belt	22,112
Intermediate	19,802
Peripheral	18,405
Ultrapерipheral	17,991

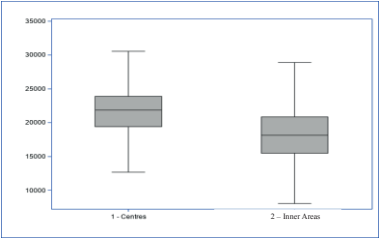


Fig. 1 Average income per taxpayer by SNAI. Source: “*A misura di comune*” - ISTAT

SNAI Classification	Incidence of taxpayers with less than 10 thousand euros per year
Pole	24.9
Intermunicipal Pole	27.2
Belt	24.7
Intermediate	29.7
Peripheral	33.1
Ultrapерipheral	34.3

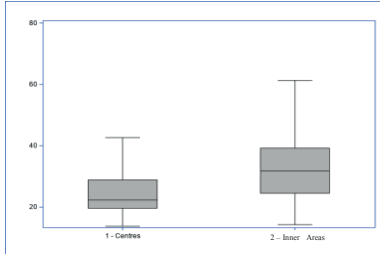


Fig. 2 Incidence of taxpayers with less than 10 thousand euros per year by SNAI. Source: “*A misura di comune*” - ISTAT

3 Analysis of indicators of production system by Inner Areas

The lower incomes of the population living in Inner Areas are strictly connected to the type of income received. The Inner Areas are notoriously territories characterized by significant depopulation and demographic aging; therefore, the greater burden of pension income could lead to a reduction in individual well-being indicators. It is therefore considered appropriate to also analyse the structure of the production system of the Inner Areas to comprehensively describe the economy of territories "far away" from essential services. The “*A misura di comune*” information system presents six indicators in the production system thematic area: Entrepreneurship rate, Density of local units, Localization quotients by economic activity, Number of non-profit institutions per 100,000 inhabitants, Local units by economic activity, Employees by economic activity. In this work three were selected: Entrepreneurship rate, Local units by economic activity, Employees by economic activity.

The first indicator does not show the classic decreasing trend when moving towards municipalities in Inner Areas and the distance between the indicator calculated on the municipalities of Centers and Inner Areas is not very significant (Fig. 3). There are 81 enterprises per 1000 inhabitants in the Centers and 68 in the Inner Areas. Nonetheless, the indicator of the ultra-peripheral municipalities is in line with that of the inter-municipal hub municipalities (75 enterprises per 1000 inhabitants). This trend in the municipalities furthest from essential services can be explained by the need to do business to satisfy the needs of the population.

SNAI Classification	Entrepreneurship rate
Pole	96.2
Intermunicipal Pole	75.4
Belt	68.5
Intermediate	66.8
Peripheral	68.3
Ultrapерipheral	76.1

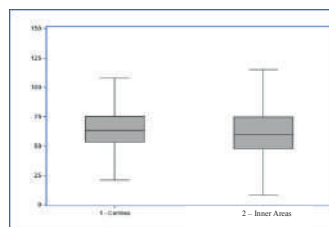


Fig. 3 Entrepreneurship rate by SNAI Source: “A misura di comune” – ISTAT

It is therefore useful to understand what the predominant activities are both in terms of local units and employees in the two areas. In the Inner Areas there is a greater weight of employees in enterprises in the manufacturing sector than in the Centres (Fig. 4).



Fig. 4 Local units and employees by economic activity and SNAI. Source: “A misura di comune” - ISTAT

4 Conclusions

The experimental statistics "A misura di comune" aims to provide data and indicators at municipal level, to give public decision-makers tools to know, intervene and monitor the effectiveness of active policies in the territory.

The analysis of municipal indicators, if on the one hand responds perfectly to the needs of the territory, on the other hand cannot be limited to the description of a single indicator but must be supported by a multidimensional analysis and summary indicators. In particular, the information system is well suited to economic, social and demographic analyses for the municipalities of the Inner Areas. The economic aspect is analysed both in terms of individual well-being and the production system.

References

1. Bianchino A., Carucci A.M.M., Vannella G. 2018. Il nuovo sistema statistico “a misura di comune”: un’applicazione sul territorio lucano, Metodi e analisi statistiche, Università degli studi di Bari Aldo Moro, pp. 83-108.
2. Dipartimento per le politiche di coesione. 2022. Aggiornamento 2020 della mappa delle aree interne. NUVAP Technical Note
3. Dipartimento per le politiche di Sviluppo (2013). Strategia nazionale per le Aree interne: definizione, obiettivi, strumenti e governance – Technical document attached to the draft Partnership Agreement submitted to the EU

Estimating price pass-through from changes in VAT: a case study on the tampon tax in Italy

Beatrice Biondi, Silvia De Nicolò and Mario Mazzocchi

Abstract In Italy, menstrual hygiene products were classified as non-essential until 2020 and subjected to the full tax rate. Subsequent VAT reforms gradually reduced taxation, but the latest change increased VAT from 5% to 10%, citing the inefficacy of the previous cut. This study examines the impact of these tax changes on prices using a difference-in-difference approach, analyzing four years of consumer panel data on purchases. Control units include periods with standard VAT rates and similar products with unchanged taxation. Findings and policy implications are discussed.

Key words: Gender equality, Hygiene products, Tampon tax, VAT pass-through.

1 Introduction

Tax policies play a crucial role in shaping consumer behavior and market dynamics, particularly in sectors where price sensitivity is high. One notable case is the taxation of menstrual products, which has been the subject of policy debates across various countries. In Italy, the Value Added Tax (VAT) on tampons and other menstrual products was reduced from 22% to 10% in 2022 and further lowered to 5% in 2023, only to be raised again to 10% in 2024. These fluctuations provide a unique opportunity to analyze the extent to which tax changes are transmitted to consumer prices and how they influence demand and consumption patterns.

Beatrice Biondi
University of Bologna, e-mail: b.biondi@unibo.it

Silvia De Nicolò
University of Bologna, e-mail: silvia.denicolo@unibo.it

Mario Mazzocchi
University of Bologna, e-mail: m.mazzocchi@unibo.it

This paper examines the price transmission mechanism following the VAT adjustments, investigating whether the reductions and subsequent increases were fully passed on to consumers or absorbed by retailers and producers. Understanding price transmission is essential for evaluating the effectiveness of tax policies in making essential goods more affordable.

Broad literature investigating the effects of VAT changes on consumer prices exists; however, few contributions focus on the tampon tax. For instance, [3] assess the New Jersey 2005 VAT reform, also evaluating its impact on consumers across different income ranges, while [1] estimate the pass-through of the VAT reforms in Germany in 2020. All of them find evidence of a 100% pass-through—that is, the tax break is fully shifted to consumers.

By leveraging household consumer panel data and quasi-experimental estimation techniques, this study contributes to the broader discussion on taxation, price elasticity, and consumer welfare. The findings are relevant for policymakers assessing the impact of fiscal measures on gender-equitable pricing and consumer well-being.

2 Data and Methodology

The data used come from the Yougov Consumer Panel¹. This dataset includes household-scanner recorded purchases of all fast moving consumer goods made by a representative sample of households in Italy during over a period of more than five years. Each household in the panel records all grocery purchases they make at the product level and with additional information, such as price and promotional status.

The raw data contains individual daily purchases for all female hygiene products (tampons, menstrual pads and panty liners), we take intimate detergents and intimate wipes as control products. Each row contains information about amount (in number of items or litres), expenditure in Euros, number of packs purchased, purchase channel (e.g. hypermarket, supermarket, local store), and whether the purchased product was on promotion. We filtered the dataset to include only products purchased at least four times per year, ensuring the selection of representative products and excluding those that were reformulated or at the end of their lifecycle. The resulting sample includes 897 unique products, including both treatment and control groups. Specifically the treated products include 369 products as external pads, 29 as tampons and 141 as panty liners. The control group includes 288 items as intimate detergents, and 70 as intimate wipes. We considered the time period 2021-2024.

We estimate two difference-in-difference (DD) fixed effects models on the logarithm of consumer unit prices recorded for each product p in store s at time t . The first model considers the three VAT adjustments as three sequential treatments:

$$\ln Y_{pst} = \alpha_p + \alpha_t + X_s^T \beta_s + Z_{pst}^T \beta_{pst} + \gamma \text{target}_p + \delta_1 \times 2022 \times \text{target}_p + \delta_2 \times 2023 \times \text{target}_p + \delta_3 \times 2024 \times \text{target}_p + \varepsilon_{it} \quad (1)$$

¹ Obtained from YouGov CP Italy S.r.l.

where *target* is a dummy variable indicating whether the purchased product is subject to the reduced VAT rate, and *year* is a dummy variable indicating whether the purchase was recorded in the respective year. The vector X_s includes control variables related to store characteristics, such as store type, location, and urbanization level. The vector Z_{pst} includes control variables related to purchase details, such as promotion status. Lastly, time-specific intercepts α_t include both month-specific and year-specific terms. Standard errors are clustered by product type.

A second approach considers a single treatment with varying treatment intensities, represented by the current VAT rate, as outlined in [4]. The model is as follows:

$$\ln Y_{pst} = \alpha_p + \alpha_t + X_s^T \beta_s + Z_{pst}^T \beta_{pst} + \gamma \text{target}_p + \delta_1 \times 2022 \times \ln(\tau_{pt} + 1) + \delta_2 \times 2023 \times \ln(\tau_{pt} + 1) + \delta_3 \times 2024 \times \ln(\tau_{pt} + 1) + \varepsilon_{it} \quad (2)$$

Here, τ_{pt} denotes the VAT rate applied to product p at time t . The pass-through rate, δ_t , which is estimated for each year, is given by $\delta = (\Delta Y / Y) / (\Delta \tau / (1 + \tau))$.

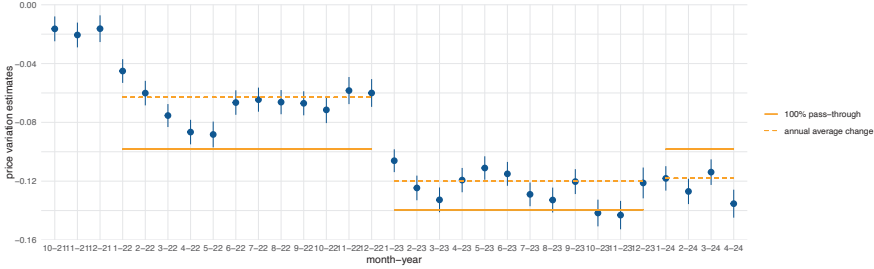


Fig. 1 An event-study specification of model (1), where the y-axis represents the estimates of month-specific intercepts and the x-axis shows the temporal reference. The dashed lines indicate the annual average rate, while the solid line represents the expected rate under the assumption of 100% pass-through.

3 Preliminary Results

Table 1 presents the results of price adjustments over three periods, with reference to 2021 as the baseline (pre-treatment year). The data show that the price decline following the introduction of the reduced VAT is significant, with further decreases occurring in the subsequent adjustment periods. Additionally, Table 1 reports the outcomes of the model specified in Equation (2), which estimates the pass-through rates for the three consecutive reductions (-12%, -17%, and -12%). Notably, the price adjustment in 2023 exceeds the 5% VAT reduction by achieving an estimated pass-through of almost the 80%. Figure 1 reports the price change rate estimates for

Table 1 Estimates of DD models in equations (1) and (2).

Models	(2)	(1)
2022 × log_vat	0.610*** (0.023)	- -
2023 × log_vat	0.797*** (0.017)	- -
2024 × log_vat	1.143*** (0.032)	- -
target × 2022	- -	-0.063*** (0.002)
target × 2023	- -	-0.120*** (0.003)
target × 2024	- -	-0.118*** (0.003)
Num.Obs.	152994	152994
AIC	166305.7	166305.7

each month, estimated via an event-study specification of model in equation (1). The findings indicate that prices display limited reactivity to VAT adjustments—both during the gradual decrease and subsequent increase—thereby contradicting the asymmetric response commonly reported in the literature. To assess potential differential trends, we tested for variations in the pre-treatment period (2019) and found no significant evidence. However, conducting similar tests for 2020 and 2021 presents challenges due to the specific market dynamics induced by the COVID-19 pandemic. Further robustness checks are necessary, particularly through the use of alternative control groups.

4 Concluding Remarks

The analysis provides evidence of a partial pass-through at different stages of VAT adjustments. Overall, the results indicate a low price reactivity. Further investigation is needed to explore the potential contributing factors, extending the analysis in two key directions. First, incorporating a proxy for media coverage over different time periods may help assess the role of public pressure on firms to adequate the price. Second, distinguishing between product labels could allow for a more precise evaluation of price adjustments, particularly by isolating effects among the most competitive products (e.g., main brands vs. private labels). Additionally, refining the methodological framework by accounting for the autocorrelation of observed prices would strengthen the robustness of the findings.

References

1. Frey, A., Haucap, J.: VAT pass-through: the case of a large and permanent reduction in the market for menstrual hygiene products. *Int. Tax Public Finance* **31**(1), 160–202 (2024)
2. Buettner, T., Hechtner, F., Madzharova, B.: Taxes and gender equality: The incidence of the ‘tampon tax’. *CESifo Working Paper* (2023)
3. Cotropia, C., Rozema, K.: Who benefits from repealing tampon taxes? Empirical evidence from New Jersey. *J. Empir. Legal Stud.* **15**(3), 620–647 (2018)
4. Hindriks, J., Serse, V.: The incidence of VAT reforms in electricity markets: Evidence from Belgium. *Int. J. Ind. Organ.* **80**, 102809 (2022)

A new composite bootstrap approach for estimating the long-memory parameter

Luisa Bisaglia, Margherita Gerolimetto and Margherita Palomba

Abstract This study investigates whether combining different bootstrap methods can enhance performance, focusing on long-memory time series. Specifically, we examine a preliminary Monte Carlo experiment integrating various established parametric and non-parametric bootstrap approaches. By linearly combining the outputs of these methods, we aim to develop a novel combined bootstrap technique called composite bootstrap. First results show improved accuracy and reliability, opening the door to methodological advancements.

Key words: bootstrap, long memory, combinations

1 Introduction

Bootstrap is a computationally intensive resampling method that provides solutions to various statistical inference problems without making strict structural assumptions about the data-generating process. Originally developed for independent observations, bootstrap has been adapted to handle time dependence in time series. In this context, long memory time series represent quite a complex setting since the strong dependence characterizing those data often requires specific techniques to form a valid resampling strategy.

Traditional bootstrap strategies for time series fall into two categories. The first includes methods that resample the residuals of a parametric estimated model (assuming they are *iid*) and the validity of these methods is based on the correct specification of the model and on the consistency of the estimation methods (e.g [1]). The

Luisa Bisaglia

University of Padua, e-mail: luisa.bisaglia@unipd.it

Margherita Gerolimetto

Ca' Foscari University of Venice, e-mail: margherita.gerolimetto@unive.it

Margherita Palomba

University of Padua, e-mail: margherita.palomba@studenti.unipd.it

second category gathers bootstrap techniques that do not strongly rely on parametric restrictions, the most popular in case of long memory time series are the Sieve Bootstrap ([2]), that is considered semiparametric, and the Block Bootstrap ([3]), that is considered nonparametric. Both categories aim to sample approximately independent quantities (either residuals or blocks). This assumption is often satisfied in short-memory series but rarely in long-memory series where dependence remains significant even between distant observations, as emphasized by [4] in a review that presents also an extensive Monte Carlo experiment together with a possible guide for practitioners. An alternative approach involves applying a preliminary filter to the time series observations to obtain approximately independent residuals or blocks for subsequent sampling ([5]).

In literature, "hybrid bootstrap" refers to a resampling technique that integrates multiple bootstrap approaches into a single procedure. This methodology has been developed to improve the accuracy of statistical estimates or to address specific issues related to data sampling. In general, the idea behind hybrid bootstrap is to leverage the characteristics of different bootstrap methods to obtain better results than those that would be obtained using a single resampling method (see [7]). The composite bootstrap approach proposed in this work, however, represents a significant innovation compared to what is present in literature. Unlike existing approaches, which integrate bootstrap methods at the algorithm level, our work introduces a new concept based on the direct combination of bootstrap samples generated from different methods. This methodology, to our knowledge, has no precedent in existing literature and offers a new perspective for improving estimator performance. This work focuses on the study of stationary long-memory time series, for which we want to estimate the long-memory parameter d .

The structure of the paper is as follows. In the second section we present our methodological framework. In the third section we describe the Monte Carlo experiment and some results.

2 Composite bootstrap

Long memory time series, y_t , are characterized by a significant dependence between distant observation such that, asymptotically, the autocovariance function satisfies: $\Gamma_y(k) = \text{Cov}(y_t, y_{t-k}) \sim Gk^{2d-1}$, where G is a finite constant and d is the memory parameter that governs the strong persistence of y_t . When $|d| < 1/2$ the series is stationary, but it shows long memory. The ARFIMA(p, d, q) is undoubtedly the most used long-memory model. It is defined as $\Phi_p(B)(1-B)^d y_t = \Theta_q(B)\varepsilon_t$, where $\Phi_p(B)$ and $\Theta_q(B)$ are polynomials of order p and q respectively, with all roots outside the unit circle and no roots in common. As for the estimation of the long memory parameter d , the literature is rich of proposals, we will focus here on the most traditional ones. They are the Log-periodogram estimator (GPH), the Local Wittle estimator (LWE), and the Maximum Likelihood Estimator (MLE) (see [6] for details). Due to lack of space, we refer to the original literature for the technical details of the estimators.

The key idea is to combine bootstrap samples from various methods into a composite sample y_t^{**} , which is then used to estimate the long-memory parameter d . In particular, bootstrap samples obtained from: parametric bootstrap (PB), wild bootstrap (WB), sieve bootstrap (SB), moving block bootstrap (MBB), circular block bootstrap (CBB), pre-filtered sieve bootstrap (PFSB) and pre-filtered moving block bootstrap (PFMBB) will be combined.

Combination strategies include simple means (mean), linear regression (reglin), and weights based on mean squared error (rMSE) and mean absolute error (MAE) of bootstrap series.

The statistic $\hat{d}$ is evaluated on the composite bootstrap sample. The algorithm for $b = 1, \dots, B$ bootstrap samples is the following:

1. Starting from the original series y_t , the bootstrap series y_t^{*boot} are generated using the bootstrap methods described earlier, specifically $boot \in \text{PB, WB, SB, MBB, CBB, PFSB, PFMBB}$.
2. (a) Quantities of interest are computed to determine the weights for combining the bootstrap samples; (b) the weight for each bootstrap sample, w^{boot} , is calculated; (c) the bootstrap samples are combined using a linear combination scheme based on the calculated weights to obtain the composite bootstrap sample y_t^{**} ; (d) d^* is calculated as a function of y_t^{**} , using the same procedure that would be employed to compute the statistic of interest d from the original sample y_t .
3. Repeat Steps 1 and 2 B times to generate B composite bootstrap samples $y_{t,b}^{**}$, $b = 1, \dots, B$, and compute B values of the desired statistic d_b^* , $b = 1, \dots, B$. Approximate the distribution of the statistic $\hat{d}$ using the bootstrap distribution:

$$\hat{d}^*(s) = \frac{1}{B} \sum_{b=1}^B I(d_b^* \leq s), \quad (1)$$

where I is the indicator function.

Obviously, the composite bootstrap series y_t^{**} obtained in step 2 depends on the chosen combination scheme.

3 Monte Carlo experiment

A Monte Carlo experiment in [4] compares the composite bootstrap with single methods using 1000 simulations from an ARFIMA(0,d,0) model, for sample sizes $T=250, 500$ and $d=0.2, 0.4$. The study examines LWE, GPH, and MLE estimators of the long memory parameter, using R software ([8]). Performance is measured by two metrics ([4]). The first is Root Mean Square Deviance (RMSD) of the bootstrap probability density function to the true probability function:

$$RMSD(boot) = \sqrt{\frac{1}{S} \sum_{j=1}^S (p_{boot}(\hat{d}_j - d_0) - p_{mc}(\hat{d}_j - d_0))^2} \quad (2)$$

where *boot* is one of the bootstrap methods, d_0 is the true value, $p_{mc}(\hat{d}_j - d_0)$ are kernel densities based on Monte Carlo and bootstrap estimates, respectively. Lower RMSD indicates better performance. The second is the coverage frequency of confidence intervals: $CI_{1-\alpha}^*(\hat{d}_a) = (\hat{d}_{a,\alpha/2}; \hat{d}_{a,1-\alpha/2})$ where $\hat{d}_{a,\alpha}$ is the $B\alpha$ ordered value of the bootstrap estimate of d for $a = \text{LWE, GPH and MLE}$. Coverage frequency closer to $1 - \alpha$ (95% in this case), indicates better performance.

Table (1) summarizes some of the results of the preliminary experiment. We propose the results for $d = 0.4$ and $T = 500$, since the others are analogous.

Table 1 RMDS and Coverage Frequency and amplitude of bootstrap distributions for LWE, GPH and MLE estimators, when $D = 0.4$ and $T = 500$.

	LWE			GPH			MLE		
Metodo	RMSD	Cov Freq	Ampl	RMSD	Cov Freq	Ampl	RMSD	Cov Freq	Ampl
Mean	0.897	0.907	0.301	1.883	0.985	0.229	2.582	0.906	0.132
Reglin	1.147	0.920	0.297	2.097	0.973	0.227	1.771	0.882	0.132
Corr	0.982	0.975	0.325	1.815	0.994	0.234	2.659	0.918	0.134
rMSE	0.853	0.870	0.301	1.979	0.983	0.229	2.406	0.900	0.133
rMAE	0.861	0.883	0.301	1.926	0.982	0.229	2.497	0.902	0.133
PB	1.545	0.992	0.303	2.119	0.995	0.231	0.919	0.872	0.135
WB	3.830	0.956	0.226	5.697	0.967	0.164	17.627	0.629	0.073
SB	1.585	0.700	0.313	1.966	0.954	0.228	5.133	0.925	0.131
MBB	1.131	0.715	0.299	2.462	0.947	0.223	3.544	0.860	0.132
CBB	1.134	0.727	0.299	2.445	0.949	0.223	3.616	0.872	0.133
PFSB	1.570	0.990	0.303	2.173	0.990	0.230	2.900	0.881	0.132
PFMBB	1.120	0.940	0.297	1.957	0.986	0.225	2.430	0.869	0.128

This preliminary results show that the composite bootstrap proposed in this work matches the PB in coverage and outperforms it in RMSD, making it a strong and valide alternative. The intuition we get from these set of preliminary results is that the composite bootstrap, could significantly represent a valid alternative to existing bootstrap strategy.

References

1. Andrews, D.W.K., Lieberman, O., Marmer, V.: Higher-order improvements of the parametric bootstrap for long-memory Gaussian processes. *Journal of Econometrics*. **133**: 673-702. (2024)
2. Buhlmann, P: Sieve bootstrap for time series. *Bernoulli*. **3**: 123 - 148. (1997)
3. Carlstein, E.: The Use of Subseries Values for Estimating the Variance of a General Statistic from a Stationary Sequence. *Annals of Statistics*. **14**: 1171-1179. (1986)
4. Artech, J.: Bootstrapping long memory time series: Application in low frequency estimators. *Econometrics and Statistics*. **29**: 1-15. (2024)
5. Poskitt, D. S., Grose, S. D., and Martin, G. M.: Bias correction of semiparametric long memory parameter estimators via the prefiltered sieve bootstrap. *Journal of Econometrics*. **188**: 94-110. (2015)
6. Palma, W.: *Long-Memory Time Series*. Wiley, New Jersey (2007)
7. Kreiss, J.-P., Paparoditis, E.: The Hybrid Wild Bootstrap for Time Series. *Journal of the American Statistical Association*. **107**: 1073-1084. (2012)
8. R Core Team: *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. (2023)

Intertemporal Mahalanobis Distance Matching for Heterogeneous-Treatment-Effect Evaluations of Air-Pollution-Abatement Policies

Daniele Bondonio and Paolo Chirico

Abstract This paper develops a novel Intertemporal Mahalanobis-Distance Matching (IMDM) model for evaluating air-pollution-abatement interventions, such as limited-traffic and congestion-charge zones, bans of fossil-fuel traffic and switches to low-emission public transportation. These policies have a strong potential for heterogeneous impacts based on prevailing daily meteorological conditions, determining different average baseline pollution levels, and they pose quite unique causal impact identification conditions. Under these conditions, our IMDM model offers a number of relevant advantages with respect to the existing alternatives. An empirical analysis on data from the covid-19-lockdown traffic abatement in Northwestern Italy illustrates the applicability of the model and shows the policy-relevance of the heterogeneous impacts.

Key words: Policy impact evaluations, Intertemporal Mahalanobis-Distance Matching, heterogeneous impacts, air -pollution abatement policies

1. Introduction

Long-lasting air quality improvements have long-term benefits and make citizens more sensitive to the presence of chronic air pollution, especially in highly congested urban areas, thus increasing political pressure for effective environmental reforms [6, 3, 5]. For this reason, impact evaluations of air-pollution-abatement policies (such as urban limited-traffic and congestion-charge zones, bans of fossil fuel vehicular traffic and switches to low-emission public transportation) will increasingly gain importance. In this regard, as discussed in [2], it is important to notice that the causal impact identification conditions posed by these policies are quite unique for a number of reasons. First, the data are in terms of multiple multivariate time-series, one for each air-pollution measurement station, with units of observations represented by the calendar days in

Daniele Bondonio
University of Eastern Piedmont, e-mail: daniele.bondonio@uniupo.it
Paolo Chirico
University of Eastern Piedmont, e-mail: paolo.chirico@uniupo.it

which air pollution and control variables are measured. Within each of these multivariate time-series, the abrupt change in the secular air-pollution trend brought by the policy under investigation is the treatment of interest which determines a set of treated and non-treated calendar days.

All the major confounding factors, typically in terms of weather characteristics, are observable in the data and exogenous to the treatment status and they can be safely assumed of not being subject to unobserved secular trend (within the short pre- and post-treatment periods of times considered in the analysis). In addition, in order to enlarge the external validity and policy relevance of the findings, it is also often crucial to empirically estimate how the causal impact of the policy under investigation varies based on the different prevailing degrees of favorable/unfavorable meteorological conditions (at the locations in which the air-pollution outcome is measured) which determine different average baseline pollution levels. For this reason, building on the intertemporal statistical matching approach for estimating average treatment effects on the treated (ATT) illustrated in [2], this paper develops a novel heterogeneous-treatment-effect intertemporal Mahalanobis-Distance matching (IMDM) model for evaluating the differential impacts of air-pollution-abatement policies at different levels of baseline pollution. Under the specific causal impact identification conditions posed by air-pollution multivariate time series data, our IMDM model offers a number of advantages with respect to the existing empirical approaches used in the literature.

Compared to MR models [4, 11], IMDM shares the same well-known advantages [9, 10] of the standard (cross-sectional) statistical matching (SM) models in reducing the sensibility of the estimated impacts to the functional forms of the control variables. Compared to RRD-in-time, our intertemporal matching approach is more efficient (granting larger external validity) and better suited to handle the potential of chance bias arising from accidental unbalances in the distribution of the control variables between the treated and the control-group days. This is because, holding constant the same seasonal period, the main daily confounding factors (i.e. meteorological covariates) erratically distribute at random on the specific single dates around the cut-off, without any monotonic increasing of the unbalance of such confounders for the calendar days that are more distant from the cut-off. Under this circumstance, while any RDD-in-time model would obviously pass the standard no-treatment manipulation test at the threshold, it would be still vulnerable to chance bias caused by small sample sizes [7, 8, 1], requiring to control for the absence of chance unbalancing between the treatment and the control days. In this scenario, our IMDM model offers a more straightforward and transparent balancing of the main confounders for all of the treated days, even away from the cutoff date, without risking to unnecessarily restrict the estimation sample to the dates within narrower bandwidths across the cut-off date.

2. Intertemporal Mahalanobis-Distance Matching (IMDM) for Estimating Heterogeneous-Treatment Effects

Let $\{Y_{i,t}\}$ be a stochastic process in terms of the daily air pollution values (Y) recorded in a given measuring station (i) on which a policy intervention produces heterogeneous causal effects on different categories of treated days (t^1) belonging to a treatment period P_1 . The causal effect of the policy for each treated day $t^1 \in P_1$ recorded in a measuring station i is then definable as:

$$\tau_{i,t^1} = [Y_{i,t^1}^{(1)} - Y_{i,t^1}^{(0)}] \quad (1)$$

where $Y_{i,t^1}^{(1)}$ is the observable air pollution outcome recorded in i at day t^1 if day t were treated by the policy intervention, and $Y_{i,t^1}^{(0)}$ if not treated. Because $Y_{i,t^1}^{(0)}$ is not observable, the causal effect τ_{i,t^1} can be estimated under a standard *conditional mean stationery* assumption:

$$E[Y_{i,t^1}^{(0)} | X_{i,t^1} = x] = E[Y_{i,t^0}^{(0)} | X_{i,t^0} = x] \quad \forall (t^1 \in P_1; t^0 \in P_0) \quad (2)$$

where, $\{X_t\}$ is a multivariate process of observable weather controls, and t^0 are untreated days belonging to the non-treatment period P_0 recorded in the same measuring station i .

Consistent with assumption (2), the estimate of $Y_{i,t^1}^{(0)}$, given the information set $I = \{(y_{i,t}, x_{i,t}) : t \in (P_1 \cup P_0)\}$, is the average of the y -observations of the untreated days $t^0 \in P_0$ matched to the treated day $t^1 \in P_1$ using the matching criterion $x_{i,t^0} = x_{i,t^1}$, i.e.:

$$\hat{Y}_{i,t^1}^{(0)} = \bar{Y}(S_{i,t^1}^0) \quad (3)$$

where:

$$S_{i,t^1}^0 = \{t^0 \in P_0 : x_{i,t^0} = x_{i,t^1}\} \quad (4)$$

is the set of the untreated days of P_0 matched to the treated day t recorded in the same measuring station i . Consequently, the local causal effect τ_{i,t^1} can be estimated as:

$$\hat{\tau}_{i,t^1} = Y_{i,t^1}^{(1)} - \hat{Y}_{i,t^1}^{(0)} \quad (5)$$

Because the exact matching criterion (4) poses a strong limitation to the analysis the greater is the number of covariates X_t and the smaller is the number of days in P_0 , the estimation of τ_{i,t^1} , is best implemented by means of a Mahalanobis Distance (MD) matching approach in which the set S_{i,t^1}^0 is composed of the untreated days of P_0 closest to t^1 based on the Mahalanobis distance.

The estimated local causal effects of the policy ($\hat{\tau}_{i,t^1}$) are then aggregated into policy-relevant categorical treatment effects $\hat{\tau}_i(C)$ based on clusters of the treated days t^1 determined by their weather characteristics which lead to different intervals of baseline air pollution (as estimated by $\hat{Y}_{i,t^1}^{(0)}$):

$$\hat{\tau}_i(C) = \frac{1}{n_i(C)} \sum_{\forall t^1 \in C} \hat{\tau}_{i,t^1} \quad (6)$$

where $n(C)$ is the number of treated days t^1 recorded in the measuring station i that satisfy the requirements of category C . In the case of data from multiple measuring stations i , the categorical treatment effects $\hat{\tau}_i(C)$ are further aggregated across the multiple units i to yield the following categorical average treatment effects:

$$\hat{\tau}(C) = \sum_i \hat{\tau}_i(C) n_i(C) / \sum_i n_i(C) \quad (7)$$

3. Empirical Application

Our IMDM model for heterogeneous impacts is applied to a set of multivariate time-series data on daily nitrogen dioxide (NO_2) and meteorological characteristics recorded by the air-pollution measuring stations of the Regional Agencies for Environmental

Protection (ARPA) located in urban areas of Northwestern Italy (Piedmont and Lombardy regions). In order to proxy the implementation of fossil-fuel-traffic abatement policies, the observation period covers the entire Italian covid-19 lockdown (i.e. treated days t^1) in addition to a suitable pre-lockdown period (i.e. untreated days t^0).

The categories C for which the impact heterogeneity is estimated are based on discrete-intervals of baseline pollution levels that are optimized to both cover in detail the entire distribution, and to ensure strong policy relevance of the results. The estimated NO_2 impacts of the lockdown-induced traffic abatement (i.e. the policy treatment of interest) are summarized in Table 1.

Table 1 IMDM heterogeneous impact estimates based on baseline NO_2

Category C of baseline NO_2 ($\mu\text{g}/\text{m}^3$)	N. treated days (t^1)	$\hat{\tau}(C)$	SE	$CI(95\%)$	
0 - 20	527	-2.8	0.2	-3.2	-2.4
20 - 40	660	-13.4	0.4	-14.2	-12.7
40 - 60	306	-23.4	0.7	-24.7	-22.0
> 60	126	-40.1	1.5	-43.0	-37.3

These IMDM results are robust to wide array of sensitivity analysis and placebo tests and illustrate the replicability of the analysis to a wide typology of air-pollution abatement interventions. Our findings also show a high policy relevance of the heterogeneous-impact estimates, because of significant variations of the policy-induced air-quality benefits depending on the prevailing meteorological conditions of the treated locations which induce different degrees of baseline NO_2 accumulation.

References

1. Bondonio D.: Does the Running Variable Matter? A Second Look at Discontinuity Designs for Evaluating Regional Economic Development and Business Incentive Policies, *Eval. Rev.*, 46 (5): 598-625, (2022).
2. Bondonio, D., Chirico, P.: Intertemporal Statistical Matching for Causal Inference in the Context of Multivariate Time-Series Data. In: Bini, M., Balzanella, A., Masserini, L., Verde, R. (eds) *Adv. Meth. in Stat., Data Scien. and Related Appl.* Springer, (2024). https://doi.org/10.1007/978-3-031-65699-6_3
3. Currie J., Walker, R.: Traffic Congestion and Infant Health: Evidence from E-ZPass. *American Economic Journal: Applied Economics*, 3(1), 65-90, (2011).
4. Dang, H.A.H., Trinh, T.A.: Does the COVID-19 lockdown improve global air quality? New cross-national evidence on its unintended consequences. *Journal of Environmental Economics and Management*, 105, 102401, (2021).
5. Faustini, A., Rapp, R., Forastiere, F.: Nitrogen dioxide and mortality: review and meta-analysis of long-term studies. *European Respiratory Journal*, 44(3), 744-753, (2014).
6. Lagravinese, R., Moscone, F., Tosetti, E., Lee, H.: The impact of air pollution on hospital admissions: evidence from Italy. *Regional Science and Urban Economics*, 49, 278-285, (2014).
7. Lee, D. S., and Card, D.: Regression discontinuity inference with specification error. *Journal of Econometrics*, 142(2), 655-674, (2008).
8. Lee, D.S., and Lemieux, T.: Regression discontinuity designs in economics. *Journal of economic literature*, 48(2), 281-355, (2010).
9. Rosenbaum, P. R., Rubin, D. B.: The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41-55, (1983).
10. Stuart, E. A.: Matching methods for causal inference: A review and a look forward. *Statistical Science: A Review Journal of the Institute of Mathematical Statistics*, 25(1), . (2010).
11. Wang, J., Xu, X., Wang, S., He, S., He, P.: Heterogeneous effects of Covid-19 lockdown measures on air quality in northern china. *Applied Energy* 282:116-179, (2021).

Exploring Globalization in the International Natural Gas Trade Market

Federico Brogi, Mauro Bruno, Erika Cerasti, Fabrizio De Fausti, Barbara Guardabascio and Giulio Massacci

Abstract The European natural gas market has undergone significant transformations due to recent geopolitical events, including COVID pandemic and the Russia-Ukraine war. These crises disrupted global energy markets, causing record-high gas and exposing Europe's heavy dependency on external suppliers. This study analyses natural gas trade flows in Europe from September 2018 to March 2024, using data from Eurostat and graphical methods to explore dynamics before and after the conflict. Key findings include a huge drop in Russian gas exports and a sharp rise in imports from the USA and Netherlands. Network analysis highlights a shift from Russian centrality to diversified links, particularly with the USA and intra-European exchanges. These insights offer valuable guidance for policymakers to adapt to evolving market dynamics.

Keywords: International Trade, Global Value Chain, Time Series Analysis, Network Analysis, Big Data

Federico Brogi
ISTAT, e-mail: federico.brogi@istat.it

Mauro Bruno
ISTAT, e-mail: mauro.bruno@istat.it

Erika Cerasti
ISTAT, e-mail: erika.cerasti@istat.it

Fabrizio De Fausti
ISTAT, e-mail: fabrizio.defausti@istat.it

Barbara Guardabascio
University of Perugia, e-mail: barbara.guardabascio@unipg.it

Giulio Massacci
ISTAT, e-mail: giulio.massacci@istat.it

1 Introduction

Natural gas is a complex resource due to its uneven distribution, storage, and transport challenges. As of 2020, the global market was divided into North America, Europe, and Asia. The EU market was less competitive [1],[2], relying on three main suppliers: Russia (43% of imports), Norway (21%), and Algeria (8%), with the UK and the Netherlands covering 28%. The EU's import dependency was 58%, with the import dependency rate ranges from over 90% in Malta, Cyprus, and Luxembourg to 10% in Estonia [3].

Two major shocks—the COVID-19 pandemic and the Russia-Ukraine war—triggered a global energy crisis. Gas leaks in the Nord Stream pipelines further exacerbated supply issues, causing record-high gas and electricity prices, with oil reaching 2008 levels. Europe, heavily dependent on Russian gas, which provides more than 40% [4]. Unlike past crises, this one involves multiple factors, necessitating energy diversification and system-wide transformation [5].

This paper analyzes the European gas market, assessing its trade network and potential alternatives to ensure supply security. It also examines disruptive events' impact on trade policies and offers strategic insights for policymakers.

2 On the European Energy Market Data

International trade in goods data is provided by official EU statistics compiled by the European Member States using harmonized methods in line with EU statistical regulations. This information is available in Eurostat's COMEXT database [6] and includes detailed records of trade transactions. We will focus on the "Natural gas, liquefied or in gaseous state" product, classified as 062 under the 3-digit of the Classification of Products by Activity (CPA) [7]. The data covers monetary values (Euros), physical quantities (Kilograms), product characteristics, partner countries, modes of transport, and types of transactions, with high granularity and monthly frequency. These records are divided into two trade flows (import/export). COMEXT data gives a general overview of Europe but does not fully represent global trade, as it relies solely on declarations from European countries. Additionally, there can be discrepancies in the values reported in import and export declarations. For instance, country A may declare that it receives a certain value from country B, while country B may report a different value for its exports to country A. As a result, the average value is used.

3 Case Study: natural gas trade during the COVID pandemic and the Russia-Ukraine war

Over five years, we analyzed the EU natural gas trade using time series and network analysis, focusing on trade volumes from September 2018 to March 2024. We assessed shifts before and after two major events: COVID-19 and the Russia-Ukraine conflict. Figure 1 and Figure 2 show the distributions of imports and exports, respectively, covering 80% of the shared natural gas. Then, we compared the average value of trades in quantity before and after the conflict.

COVID-19 had minimal impact on imports but significantly reduced exports. Norway's exports fell 65% (3.42B to 1.17B Kilos), Qatar's dropped 41% (1.37B to 0.80B Kilos), and Algeria saw a 32% decrease (1.73B to 1.17B Kilos).

The Russia-Ukraine conflict had a stronger effect, particularly on imports. Italy's imports declined by 9% (4.18B to 3.82B Kilos), and Hungary's by 34% (0.89B to 0.59B Kilos). In contrast, Germany's imports surged 893% (0.14B to 1.39B Kilos). Russia remained Europe's top exporter but saw exports fall by 45% (3.68B to 1.99B Kilos). Meanwhile, the U.S. increased exports by 236% (0.69B to 2.32B Kilos), and the UK by 123% (0.61B to 1.36B Kilos).

The Netherlands' imports rose 202% (0.77B to 2.33B Kilos), while its exports dropped 27% (0.52B to 0.38B Kilos). Belgium increased both imports and exports by 51% (from 1.88B to 2.84B Kilos). The analysis highlights the conflict's major role in reshaping European natural gas trade flows.

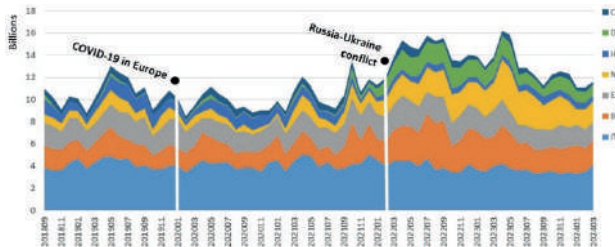


Fig. 1 Natural gas import of the major countries (80% shared)

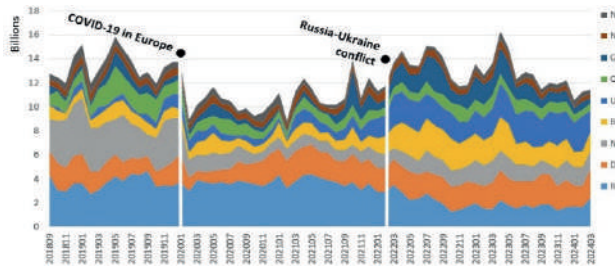


Fig. 2 Natural gas export of the major countries (80% shared)

The time series analysis reveals significant insights despite excluding trade relations. To address this, Figure 3 presents trade networks covering 80% of gas

exchanges, averaged six months before and after key geopolitical events. These visualizations highlight structural trade shifts, using color for export levels, node size for import levels, and edge thickness for transfer share. The pandemic caused minimal changes, except for increased UK imports from Russia and the withdrawal of Nigeria and the Czech Republic. However, the Russia-Ukraine war triggered major shifts: the US strengthened ties with Spain and the Netherlands, Russia lost Greece, Belgium expanded exports to Germany and the Netherlands, and Algeria deepened its relationship with Italy.

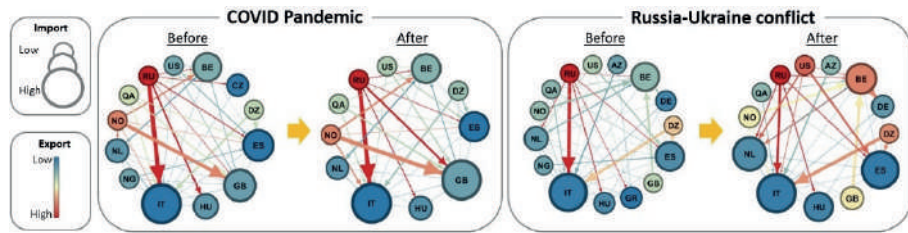


Fig. 3 Network comparison before and after the COVID pandemic

4 Conclusions

This paper examines the impact of recent events, such as the COVID pandemic and the Russia-Ukraine conflict, on the natural gas market. By applying time series and network analysis to COMEXT data, we demonstrate how European natural gas supply dynamics have shifted since 2020.

Specifically, we observe a transition from a market predominantly controlled by Russia to a more diversified one. This change is marked by the increasing role of U.S. liquefied natural gas (LNG) exports, along with a growing share of natural gas trade from Algeria and Great Britain.

References

1. D. Zhang and Q. Ji, 'Further evidence on the debate of oil-gas price decoupling: A long memory approach', *Energy Policy*, vol. 113, pp. 68–75, Feb. 2018, doi: 10.1016/j.enpol.2017.10.046.
2. P. Erdos, 'Have oil and gas prices got separated?', *Energy Policy*, vol. 49, pp. 707–718, Oct. 2012, doi: 10.1016/j.enpol.2012.07.022.
3. I. - International Energy Agency, 'A 10-Point Plan to Reduce the European Union's Reliance on Russian Natural Gas', 2022. [Online]. Available: www.iea.org/t&c/
4. C. McGlade, J. Speirs, and S. Sorrell, 'Unconventional gas - A review of regional and global resource estimates', *Energy*, vol. 55, pp. 571–584, Jun. 2013, doi: 10.1016/j.energy.2013.01.048.
5. 'World Energy Outlook 2022'. [Online]. Available: www.iea.org/t&c/
6. <https://ec.europa.eu/eurostat/comext/newxtweb/>
7. [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Statistical_classification_of_products_by_activity_\(CPA\)](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Statistical_classification_of_products_by_activity_(CPA))

Assessing the Targeting of Austrian Social Assistance Schemes: who is left behind?

Alessia Broka, Silvia De Nicolò and Stefan Angel

Abstract Minimum Income Schemes (MIS) are fundamental policies for reducing poverty and social exclusion in the European Union. However, their effectiveness varies widely across countries and, in some cases, even within regions. This is the case for Austria, where MIS are implemented regionally. Our goal is to evaluate the targeting efficiency of these schemes in Austria at the local level, considering different household typologies, recognizing that aggregated analyses may obscure disparities between poor households. To do so, we apply small area estimation methods to estimate the coverage rates, relying on survey and register data. We contribute to the literature by providing model-based estimates of the at-risk-of-poverty rate and offering a new insight into poverty targeting in Austria.

Key words: minimum income, social assistance, small area estimation, coverage, take-up, poverty

1 Introduction

In Europe, social protection against poverty and social exclusion relies mainly on Minimum Income Schemes (MIS) and other means-tested transfers, designed to provide a baseline level of economic security for individuals when other income sources fall short. However, despite these policies' intent to guarantee a minimum monthly income for all households, evidence reveals persistent poverty and the inability of many households to escape this condition. It is therefore important to un-

Alessia Broka
University of Bologna, e-mail: alessia.broka@unibo.it

Silvia De Nicolò
University of Bologna, e-mail: silvia.denicolo@unibo.it

Stefan Angel
Austrian Economic Research Institute (WIFO), e-mail: stefan.angel@wifo.ac.at

derstand to which extent these policies can effectively target those in need, if there are some households that are systematically left behind, and why. In Austria, minimum income programs have historically been fragmented across regions, resulting in variations in eligibility criteria, benefit levels, and organizational structures. The most recent attempt to harmonize the system was the 2019 Basic Social Assistance Act; however, it faced significant controversy and was ultimately unsuccessful. As of January 2024, only six out of nine regions had enacted implementation laws, potentially exacerbating regional disparities. Furthermore, specific household types in Austria have been debated to be inadequately addressed by policy frameworks, facing implicit penalties due solely to their family structure. To address these issues, our analysis incorporates regions and household typologies as levels of disaggregation. This approach allows us to capture differences that aggregate analyses are not able to detect [3]. We evaluate the targeting efficiency across 45 domains, defined by the interaction between Austria's 9 federal regions and 5 household typologies: individuals living alone, couples without children, couples with children, single parents with children, and others. Targeting efficiency is evaluated using the coverage rate [4]. To do so, we integrate income data from the Austrian-SILC 2022 survey with cash transfer beneficiary counts published by Statistik Austria. However, the poverty rates required for these calculations are unreliable at the disaggregated level due to small sample sizes, as our domains are not planned within the EU-SILC sampling design. To address this limitation, we employ Small Area Estimation (SAE) methods, which combine direct survey estimates with domain-level covariates through statistical modeling to improve estimate precision, in line with Tonutti et al. [3]. The main contribution of this study is providing new insights into the characteristics of social assistance and minimum income schemes in Austria, highlighting regional and household-type differences in targeting.

2 Data and Methodology

It is well known that estimation of socioeconomic indicators at the local level is difficult due to the limited representativeness of socio-demographic and economic surveys. In fact, our research and methodology are closely linked to the availability of data. We utilize Austrian EU-SILC 2022 data, whose income reference period is 2021, to derive direct estimates of the At-Risk-Of-Poverty (AROP) rate for our domains of interest. Recognizing that EU-SILC is not representative at this granular level, we enhance the dataset with domain-specific covariates, including 2021 census data on subpopulation characteristics: citizenship, education level, migration status, and unemployment rates from the Labour Force Survey. Additionally, beneficiary counts from Statistik Austria are included, enabling the calculation of coverage rates. The coverage rate is calculated following Ravallion (2009) [4]:

$$CR_{dAROP} = \frac{\sum_{j=1}^{N_d} T_{dj} \cdot \mathbf{1}(R_{dj} \leq z)}{\sum_{j=1}^{N_d} \mathbf{I}(R_{dj} \leq z)} \quad (1)$$

Where N_d is the number of households belonging to domain d , T_{dj} is an indicator variable that takes value 1 if household j of domain d is beneficiary of minimum income cash transfer. R_{dj} is the household income measure and z is the poverty threshold (set at 60% of the national median income under EU guidelines). For this analysis, we assume, based on existing literature [1], that all social assistance beneficiaries in Austria are poor.

2.1 Model

We employ an area-level Beta regression model to produce predictions of poverty rates for each domain with an acceptable level of uncertainty. The methodology employed is specified in the Bayesian inferential framework and estimated via MCMC methods. We implemented the model through the “tipsae” R package from De Nicolò et al. [2], let $\hat{Y}_d$ be the unreliable poverty rate estimate and μ_d the true poverty rate for subpopulation d , and let $\mathbf{x}_d$ be the vector of our area-specific predictors:

$$\hat{Y}_d \mid \mu_d, \phi_d \stackrel{\text{ind}}{\sim} \text{Beta}(\mu_d \phi_d, (1 - \mu_d) \phi_d) \quad (2)$$

$$\text{logit}(\mu_d) = \mathbf{x}_d^\top \boldsymbol{\beta} + e_d, \quad d = 1, \dots, D \quad (3)$$

$$e_d \mid \sigma_u \stackrel{\text{ind}}{\sim} \mathcal{N}(0, \sigma_u^2), \quad \sigma_u \sim \text{Half-}\mathcal{N}(0, h_u^2), \quad \boldsymbol{\beta}_j \sim \mathcal{N}(0, h_c^2) \quad (4)$$

Where ϕ_d is the area-specific dispersion parameter, which is fixed and estimated from the data, and e_d are random effects for the linear prediction with a zero-mean normal prior. Priors for intercept and the regression coefficients $\boldsymbol{\beta}_j$ are zero-mean normal priors and we assume a half-normal prior for σ_u .

3 Results

This section presents an analysis of the obtained results. Figure 1 illustrates notable disparities in coverage across household types, alongside significant regional variations. The estimated mean coverage rate for Austria in 2021 is 14.5%, which aligns with findings in the existing literature [1], indicating that a considerable proportion of individuals in need remain excluded from social assistance. A more detailed examination reveals that Vienna demonstrates the highest performance, whereas Upper Austria exhibits the lowest coverage. Substantial differences are also observed among household types: couples without children and individuals living alone represent the least covered groups, whereas single-parent households benefit from the highest coverage rates. Identifying these disparities is crucial for evaluating the limitations of current policies, addressing coverage gaps among vulnerable household categories, and mitigating regional inequalities.

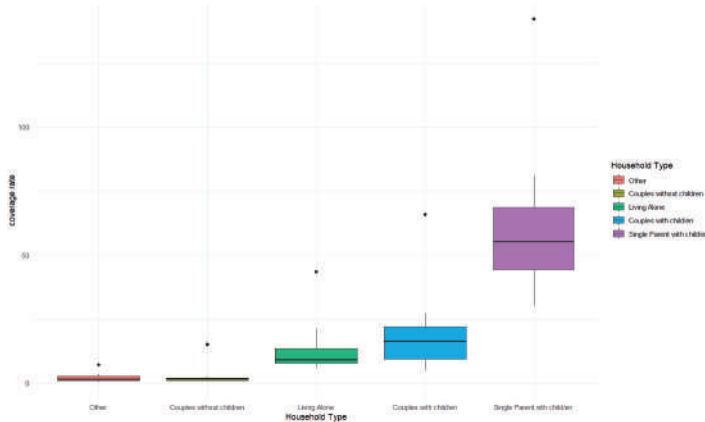


Fig. 1 Coverage rates by household typology

4 Conclusions and Future Directions

We analyzed the targeting effectiveness of social assistance in Austria by examining coverage rates at the local level. This disaggregated approach revealed significant heterogeneities across regions and household types. Using small area estimation methods, we highlighted the fragility of social assistance in one of Europe’s wealthiest countries. Further research is needed to determine whether under-coverage results from inadequate targeting due to restrictive eligibility criteria or from non-take-up driven by complex procedures, asymmetric information, or stigma.

References

1. Almeida, V., Poli, S. De, Hernández, A.: The effectiveness of Minimum Income schemes in the EU. JRC Working Papers on Taxation and Structural Reforms, No. 09/2022.
2. Nicolò, S. De, Gardini, A.: The R package tipsae: Tools for Mapping Proportions and Indicators on the Unit Interval. *Journal of Statistical Software*, 1–36 (2023).
3. Tonutti, G., Bertarelli, G., Giusti, C., Pratesi, M.: Disaggregation of poverty indicators by small area methods for assessing the targeting of the “Reddito di Cittadinanza” national policy in Italy. *Socio-Economic Planning Sciences* **82** (2022).
4. Ravallion, M.: How Relevant Is Targeting to the Success of an Antipoverty Program? *The World Bank Research Observer* **24**(2), 205–231 (2009).

From micro to macro: Building up regional capabilities from individual firms and employees

Alessio Bumbea, Giuseppe Espa, Andrea Mazzitelli and Emanuele Pugliese

Abstract The study aims at leveraging the economic complexity framework to examine how individual firms' capabilities contribute to broader regional economic development. We used hexagonal H3 grids to segment spatial data from single firm level to macro regions, moving through many gradual increases of scale. For each scale of analysis, we capture the diversity of local capabilities using the education level of employees that fall within a certain hexagon. The distribution of the education levels is not spatially homogeneous across the Italian territory, and it shows non trivial dynamics that should be addressed and discussed when analyzing official statistical data.

Key words: Capabilities, Economic complexity, H3, Education diversification

1 Introduction

Firms' capabilities have a central role in explaining firms trajectories [1]. Not only what a firm is able to do is a key determinant of its growth potential [2], but it determines its future trajectory in terms of diversification [3, 4]. Firms grow organically like plants, adding functions and new structures that are required to sustain their size along the growth process [5]. This same process is true for the development

Alessio Bumbea
Universitas Mercatorum, e-mail: alessio.bumbea@studenti.unimercatorum.it

Giuseppe Espa
University of Trento, e-mail: giuseppe.espa@unitn.it

Andrea Mazzitelli
Universitas Mercatorum, e-mail: a.mazzitelli@unimercatorum.it

Emanuele Pugliese
UNU-Merit, e-mail: pugliese@merit.unu.edu

of regions and countries [6, 7, 8]: advanced capabilities at the country level like diffused skills and infrastructure coevolve with the firms, shaped by incentives and bottlenecks [9].

In this work we will look at this process by proxying firms function and complexity by looking at the diversity of the education paths of their work force for the universe of almost 4.5 million Italian firms. We proceed by looking at how this need for different structures and functions evolves with the aggregation of spatially contiguous firms in a territory. We will observe how this relates to spatial dynamics when changing the scale of observation, from single firms to regional areas. The unique feature of our analysis is a smooth transition from single firms to a fine partitioning of the territory. Looking at the relation between economic scale and the requirement of capabilities for growth will help shed light on the coevolution between firms and regional economic growth.

2 Data and methods

The dataset that we used in our analysis was created by the Italian National Statistical Institute, by looking at data collected for tax purposes and official registries for the firms and at customs for the export data. The data gathered has been used to create the ASIA[10] database¹ that contain information about the structural characteristics of each business including the economical performances of the firms and characteristics of the employees. These statistical registries have been georeferenced by the Italian Chambers of Commerce study center Guglielmo Tagliacarne and the data have been used to study the workforce's general level of academic qualifications, as shown in Figure 1. The fraction of the workforce in the dataset that has a tertiary-level education is very small compared to the rest. This summary statistic fails to take into account the spatial characteristics and inhomogeneities that arise when the geographical position of firms is considered; better results can be obtained with the use of tools like the H3 spatial index[11], which is a geospatial indexing system designed to efficiently handle spatial data across various scales by using a hexagonal grid system. This hexagonal grid divides the earth's surface into finer resolution levels, allowing flexible scaling from large regions to fine details. Generally, the H3 index provides a spatial subdivision as an effective alternative to traditional local and regional administrative boundaries. Administrative areas are often irregularly shaped and vary greatly in size, making it challenging to compare data accurately. Using hexagons to divide a territory offers a practical solution for visualizing variables. This approach provides balanced and uniform geometry, allowing for more accurate regional comparisons and improved spatial coverage. There are 16 resolution levels in total ranging from 0, the largest one, with an average edge size length of 1281.3 km down to 15 where the average edge size is 0.6 m.

¹ Notably, the datasets used do not contain information about the agricultural enterprises.

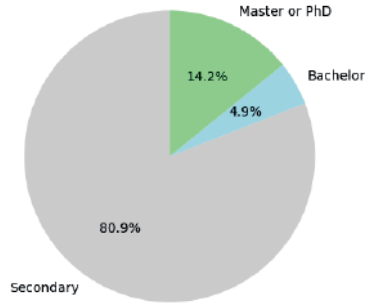


Fig. 1 Academic qualifications of employees in georeferenced Italian firms in the year 2019, the Secondary fraction includes also people with less than Secondary level degree of education.

3 Results and Conclusions

Given that the firms have been georeferenced, it is possible to associate each firm's latitude and longitude with the corresponding hexagon for any given level of resolution and cumulate the variable associated with the same hexagon. For instance, the number of employees in a hexagon is computed as the sum of the number of employees of each firm within the hexagon. The tertiary education level of the hexagons, a key finding of our research, has been computed as the number of employees with a tertiary education level within a hexagon divided by the total number of employees in the same territory. The results, which provide valuable insights into the spatial distribution of education levels, are presented in Figure 2. The distribution of the tertiary education level is highly spatially nonhomogeneous and is more concentrated in bigger cities. The higher education level in the south than in the north might be due to another effect. For instance, in cities in the south where the informal sector makes up an essential part of the economy[12] and informal networks play a significant role in the hiring process[13], having a tertiary education becomes a necessary condition to access the formal market. The H3 index effectively reduces bias and standardizes the spatial analysis by offering uniform grids. However, to fully address spatial inhomogeneity, it may need to be supplemented with other spatial and non-spatial methods considering the underlying variability of geographic or socio-economic factors in order to offer decision-makers valuable tools to make changes in education and economic development.

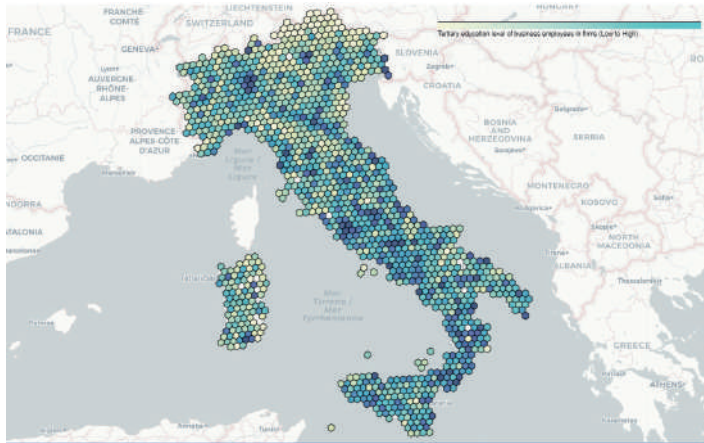


Fig. 2 Tertiary education fraction of the workforce for Hexagons computed at resolution level 5 for the year 2019

References

1. Penrose, E.T.: *The Theory of the Growth of the Firm*. Oxford University Press, Oxford (2009)
2. Teece, D.J., Pisano, G., Shuen, A.: Dynamic capabilities and strategic management. *Strateg. Manag. J.* **18**(7), 509–533 (1997)
3. Teece, D.J., Rumelt, R., Dosi, G., Winter, S.: Understanding corporate coherence: Theory and evidence. *J. Econ. Behav. Organ.* **23**(1), 1–30 (1994)
4. Dosi, G., Mathew, N., Pugliese, E.: What a firm produces matters: Processes of diversification, coherence and performances of Indian manufacturing firms. *Res. Policy* **51**(8), 104152 (2022)
5. Coad, A., Mathew, N., Pugliese, E.: *Positioning Firms Along the Capabilities Ladder*. Maastricht Economic and Social Research Institute on Innovation and Technology, Maastricht (2021)
6. Cirera, X., Maloney, W.F.: *The Innovation Paradox: Developing-Country Capabilities and the Unrealized Promise of Technological Catch-up*. World Bank Publications, Washington, D.C. (2017)
7. Hausmann, R., Rodrik, D.: Economic development as self-discovery. *J. Dev. Econ.* **72**(2), 603–633 (2003)
8. Cimoli, M., Dosi, G., Stiglitz, J.: The political economy of capabilities accumulation: The past and future of policy for industrial development. In: Cimoli, M., Dosi, G., Stiglitz, J. (eds.) *Industrial Policy and Development: The Political Economy of Capabilities Accumulation*, pp. 1–18. Oxford University Press, Oxford (2009)
9. Diodato, D., Hausmann, R., Schetter, U.: A simple theory of economic development at the extensive industry margin. HKS Working Paper No. RWP22-016 (2022)
10. Statistical registry of active businesses by the Italian national statistical institute <https://www.istat.it/scheda-qualita/registro-statistico-delle-imprese-attive-asia-imprese-2/> Cited 11 Dic 2024
11. H3: A Hexagonal Hierarchical Geospatial Indexing System <https://h3geo.org/>. Cited 11 Dic 2024
12. Harney, N.: Rumour, migrants, and the informal economies of Naples, Italy. *International journal of sociology and social policy* **26** (9-10), 374-384 (2006)
13. Pistaferrì, L.: Informal networks in the Italian labor market. *Giornale degli Economisti e Annali di economia* **58**(3-4), 355-375 (1999)

Exploring Workplace Discrimination Through Digital Ethnography

Giovanni Busetta, Maria G. Campolo, Antonia Cava and Debora M. Pizzimenti

Abstract Workplace discrimination remains a pressing issue that traditional research methods often struggle to fully capture. Digital ethnography offers a fresh perspective by tapping into authentic and unfiltered narratives shared in online spaces. By analyzing user-generated content on platforms like Reddit, this methodology reveals unique insights into the dynamics of bias and inequality. This paper examines the potential of digital ethnography as a methodological tool for economic statistics, highlighting its strengths, challenges, and role in advancing our understanding of workplace discrimination.

Key words: digital ethnography, workplace discrimination, online platforms, economic statistics, methodological innovation

1 Introduction

Traditional methods of studying workplace discrimination, including surveys and interviews, often fall short in capturing real-time, unfiltered experiences. Digital ethnography bridges this gap by systematically analyzing online communities and digital platforms where individuals share their experiences openly. This approach provides a richer understanding of workplace discrimination while shedding light on its broader implications for economic research and policy. Digital ethnography

Giovanni Busetta

University of Messina, e-mail: gbusetta@unime.it

Maria Gabriella Campolo

University of Messina, e-mail: mgcampolo@unime.it

Antonia Cava

University of Messina, e-mail: acava@unime.it

Debora Maria Pizzimenti

University of Messina, e-mail: deboramaria.pizzimenti@unime.it

draws on data from forums, social media, and other online spaces, offering several distinct advantages. The anonymity of these platforms often encourages candid and honest discussions, reducing the influence of social desirability bias. Moreover, they attract diverse voices, including those who might be overlooked in traditional studies, and provide real-time insights into evolving trends and narratives in workplace dynamics. Unlike traditional ethnography, which typically involves in-person immersion, digital ethnography allows researchers to observe and analyze virtual interactions. This expands its scope, making it particularly effective for examining complex social phenomena like workplace discrimination. Hine (2015) emphasizes that digital ethnography captures the fluid and interconnected nature of digital life, making it well-suited to studying the interplay of individual and systemic factors in discriminatory practices. Building on this foundation, Jensen et al. (2022) highlight its capacity to generate rich, context-sensitive knowledge that integrates socio-cultural and political dimensions. This makes digital ethnography an innovative alternative to purely quantitative or usability-focused methods, as it centers narratives and insider perspectives. Furthermore, Hammersley (2018) underscores its ability to adapt traditional ethnographic principles to online environments, effectively capturing the complexity of virtual interactions.

This methodology is especially relevant to the Italian context, where labor market inequalities—shaped by gender, age, and life choices—persist as pressing challenges. By analyzing user-generated content on platforms frequented by Italian audiences, digital ethnography offers unique opportunities to explore and monitor these issues, providing valuable insights for targeted policy development and fostering a deeper understanding of workplace dynamics.

2 Data Collection and Findings

Data collection involved identifying relevant discussions, applying thematic coding, and analyzing discourse to uncover patterns of discrimination. Workplace-related forums and other digital platforms proved rich in content that revealed how individuals navigate and confront workplace biases. Through this analysis, three primary dimensions of discrimination emerged: i) Biased expectations often manifest in assumptions about employees' availability or workload capacity, with those perceived as "less burdened," such as childfree individuals, frequently assigned disproportionate responsibilities; ii) Structural inequities arise from workplace policies that prioritize traditional family structures, inadvertently excluding or disadvantaging others; iii) Cultural stigma further compounds these challenges, as non-traditional life choices are often associated with a perceived lack of commitment or responsibility, perpetuating biases in professional settings.

Digital platforms also serve as spaces for resistance and advocacy, where users share strategies to combat prejudice, build solidarity, and promote organizational change. This multi-platform approach highlights the nuanced ways discrimination is experienced and challenged, providing critical insights into organizational practices and broader societal norms.

The insights derived from digital ethnography resonate strongly with the themes of sustainability, innovation, and digitalization. By leveraging advanced technologies like Natural Language Processing (NLP) and machine learning for data analysis, this methodology exemplifies the integration of innovation and digitalization in understanding economic phenomena. Furthermore, addressing workplace discrimination contributes to the broader goals of sustainable economic development by promoting inclusivity and equity in labor markets, aligning with Sustainable Development Goals (SDGs).

Digital ethnography also enables the study of workforce dynamics in real-time, providing a robust framework for monitoring changes in labor market inequalities across regions and industries. In the context of the Italian labor market, this approach offers a unique opportunity to analyze the interplay between systemic discrimination and local socio-economic factors, paving the way for more targeted policy interventions.

3 Methodological Insights and Analytical Approaches

Digital ethnography offers several methodological strengths. One of its primary advantages lies in its access to rich, real-world narratives that provide deep and nuanced insights into social dynamics. This approach enables researchers to reach diverse and often hard-to-access populations, ensuring inclusivity in capturing varied experiences. Furthermore, its temporal capacity allows for the tracking of evolving trends and narratives over time, offering dynamic perspectives on workplace discrimination. Despite these strengths, digital ethnography is not without its challenges. Ethical considerations are paramount, as researchers must navigate issues of privacy and consent when utilizing publicly available data. The findings may also be influenced by platform bias, as the culture and demographics of specific digital spaces can shape the data. Additionally, managing and analyzing large volumes of unstructured data requires significant resources and expertise.

To address these challenges, researchers can employ a range of statistical and computational techniques to enhance their analysis. Descriptive analysis provides an initial understanding of the data distribution and thematic prevalence. Social Network Analysis (SNA) can be used to map interactions and identify influential contributors within online communities. Sentiment analysis, powered by NLP, quantifies the emotional tone of discussions, while regression models help identify predictors of specific discrimination-related outcomes. Advanced methods like topic modeling (e.g., Latent Dirichlet Allocation) can uncover hidden themes in large datasets, and temporal analysis tracks changes in narratives over time. These techniques, when combined, offer a comprehensive toolkit to analyze the rich, unstructured data typical of digital ethnography. Integrating digital ethnography with traditional economic statistics marks a significant advancement in analyzing labor market inequalities. For example, combining regression models with sentiment analysis on digital data can provide more granular insights into the factors contributing to workplace discrimination. This integration enhances the design of

equitable policies and strengthens the capacity to address systemic inequities (Pink et al., 2016).

4 Implications for Economic Statistics and Conclusions

Digital ethnography complements traditional economic statistics by adding qualitative depth to quantitative findings. Its application in workplace studies uncovers overlooked dimensions of inequality, providing actionable insights for policy and organizational change. Integrating ethnographic insights with survey data offers several opportunities to enhance our understanding and approach to workplace equity. It can refine the design of workplace equity programs by providing a deeper, more nuanced perspective on the lived experiences of employees. Additionally, these insights can inform the development of inclusive policies and benefits that address the diverse needs of the workforce. By amplifying the voices and experiences of those directly affected by discrimination, this integration also strengthens advocacy efforts, ensuring that proposed solutions are grounded in the realities of those they aim to support. As Marres (2017) argues, the integration of digital methods into traditional research frameworks not only broadens the scope of inquiry but also enhances the interpretive capacity of data analysis, making it particularly valuable in addressing contemporary societal challenges.

In conclusion, digital ethnography represents a transformative approach to studying workplace discrimination in a digital society. By capturing the voices of marginalized groups and analyzing their narratives, it bridges critical gaps left by traditional methods. This study underscores its potential to advance economic statistics and offers a robust framework for addressing contemporary issues of bias and inequality. Future research should integrate digital ethnography with mixed-method designs to fully leverage its strengths in informing policy and practice.

Acknowledgments This work was supported by the funding from PNRR – Miss. 4, Comp. 2, Investment 1.1 -Prin 2022 Call for Proposals PNRR - Directorial Decree No. 1409 of 09/14/2022, project title Ethnic And Gender Labor Experimental Studies (EAGLES) over discrimination, CUP code J53D23016930001, project identification code P2022HKP7L.

References

1. Hine, C.: Ethnography for the Internet: Embedded, Embodied and Everyday. Bloomsbury Academic, London (2015)
2. Marres, N.: Digital Sociology: The Reinvention of Social Research. Polity Press, Cambridge (2017)
3. Pink, S., Horst, H., Postill, J., Hjorth, L., Lewis, T., Tacchi, J.: Digital Ethnography: Principles and Practice. SAGE Publications, London (2016)
4. Jensen, L.X., Bearman, M., Boud, D., Konradsen, F.: Digital ethnography in higher education teaching and learning—A methodological review. *Higher Education* extbf{84}, 1143--1162 (2022)
5. Hochschild, A.R.: The Time Bind: When Work Becomes Home and Home Becomes Work. Metropolitan Books, New York (1997)

A Systematic Review of Gender and Ethnic discrimination in Hiring

Giovanni Busetta, Maria G. Campolo, Giovanni M. Ficarra and Alessandra Trimarchi

Abstract European economies face growing labor shortages at both ends of the skill spectrum, increasing the need to address hiring discrimination based on gender and ethnicity. Rising labor demand highlights the underutilization of groups such as women and ethnic minorities. This study reviews factorial survey experiments on hiring bias. Focusing on the combined effects of gender and ethnic biases, we use a modified Population, Intervention, Comparison, Outcome framework to assess studies from 2010 to 2024. Findings reveal consistent discriminatory hiring practices, with amplified impacts for individuals facing both biases. This review emphasizes the need for targeted hiring interventions and suggests expanding Factorial Survey Experiments to better capture the interplay of multiple discrimination factors, supporting a more equitable EU labor market.

Key words: Systematic literature review, vignette, hiring, gender, ethnicity, discrimination

1 Introduction

In the modern western labor market, the demand for workers continues to grow steadily. All major European economies are currently facing labor shortages at both ends of the skills spectrum [3]. At the same time, the aging of the European population is leading to workforce reductions and increased strain on public finances to support the growing number of retirees. This is also affecting firm productivity

Giovanni Busetta
University of Messina, e-mail: gbusetta@unime.it
Maria Gabriella Campolo
University of Messina, e-mail: mgcampolo@unime.it
Giovanni Maria Ficarra
University of Messina, MAECI, e-mail: gioficarra@unime.it
Alessandra Trimarchi
University of Messina, e-mail: alessandra.trimarchi@unime.it

[1]. In this deteriorating environment, a renewed effort to better integrate previously untapped labor resources is becoming increasingly urgent. This challenge is evident in the need to integrate women into the labor force, as well as to improve the inclusion of ethnic minorities within these countries, including both first- and second-generation individuals [7]. Nevertheless, women and ethnic minorities continue to face discrimination when attempting to enter the labor market.

In this context, understanding the drivers of hiring discrimination, and deriving the necessary tools to tackle this issue, is pivotal to the European economy.

Several systematic reviews have analysed hiring discrimination using Field experiments, focusing on biases related to age, disability, employment status, and ethnicity. However, these reviews predominantly rely on correspondence tests, which, while effective at identifying discriminatory patterns, offer limited scope for understanding complex interactions between multiple bias factors.

Building on these foundations, our systematic review seeks to advance the field in two significant ways: a focus on the vignette methodology and a narrower evaluation of the roles of gender and ethnicity in the hiring bias. The first one is aimed at coalescing knowledge derived by the adoption of Factorial Survey experiments (from now on FSEs), especially during the second part of the 2010s.

The second contribution consists in analysing the combined dimensions of gender and ethnicity in hiring discrimination. While these factors are often considered in several studies, they are typically used as moderator variables rather than as interconnected drivers of discrimination.

Our aim is, therefore, to examine how FSEs have been employed and conducted over the last 14 years in contexts where gender and ethnic discrimination are addressed jointly. By advancing these methodological and thematic approaches, our review aims to enhance the understanding of hiring discrimination and provide a fresh perspective on addressing complex biases in labor markets.

2 Methodology

Our systematic review employed a modified version of the Population, Intervention, Comparison, Outcome (PICO) framework to refine the research question and establish clear inclusion and exclusion criteria, adhering to PRISMA [9] guidelines for rigor and transparency. Building on prior studies, we excluded "Intervention" and added study type, context, and timing to better align with our objectives. The population comprised fictitious individuals (vignettes), including women, ethnic minorities, and their majority counterparts. Comparisons focused on hiring discrimination based on gender and ethnicity, evaluating differences within and between groups during the hiring phase. Our analysis centered on vignette experiments published between 2010 and 2024. To ensure relevance, we included only works in English, within economics, statistics, political economy, and sociology of labor, and limited to peer-reviewed articles, books, and chapters. Literature searches on Web of Science, Scopus, EBSCO, and Google Scholar ensured a comprehensive review of hiring discrimination patterns.

3 Research strategy

Before developing our systematic review, we performed a backward and forward citation study on 7 relevant works. From these, we derived 119 backwards citations and 229 forward citations. We then performed a frequency study on titles, abstracts and keywords, to identify suitable keywords for our systematic review. Lastly, we implemented three sets of keywords. They were adapted to the specificities of each dataset. The research boxes were connected using the logical connector “AND” while, the keywords were connected using either the “|” connector or the “OR” connector, depending on the peculiarities of the database. Moreover, we allowed the research strings to be adapted to linguistic discrepancies.

After collecting the results using Publish or Perish and the in-database tools for the other databases, they were catalogued using Zotero and subsequently transferred to Excel. A preliminary screening excluded 192 documents. At this stage, two authors independently performed the initial screening by reviewing titles and abstracts, working separately and without knowledge of each other’s actions. After completing the independent screenings, the two authors resolved any disagreements through discussion. The remaining papers (92) were then downloaded, and the two authors independently conducted a second blind evaluation of the documents. Following the second screening, disputes were resolved, and 18 papers were selected for inclusion in the review.

After completing the main review, a citation and reference analysis of the 18 selected papers was conducted. Using a similar approach to that described earlier, a total of 1073 papers were evaluated. After a thorough evaluation, three additional studies were identified and included. Except for the records excluded prior to screening, all phases were performed independently by two authors in a blinded manner with conflicting decisions resolved through post-screening discussion.

4 Results and Conclusions

The 21 studies included in the review are all FSEs. Despite the broad variety of topics covered in the studies, our analysis focused on six main characteristics: the type of respondents, the number of respondents and vignettes, ethnicity, the research question and primary focus of each study. The respondents can be broadly divided in two categories, i.e., job market professionals (Employers and HR) and non-professionals (University students, Citizens, Civil servants, general public) [2,6]. In terms of number of respondents, we see ample variation. On average, each study surveyed roughly 500 respondents which analysed a median number of six vignettes.

The concept of ethnicity is more complex. Most studies reflect the typical ethnic composition of primary minorities within the borders of the nation where the study was conducted. Another central aspect of this systematic review is the main research question. The most common used variable across articles is the likelihood of hiring, although this is often replaced or supplemented by the likelihood of being invited to

an interview. Nonetheless, two studies employ the expected wage as a proxy for hiring discrimination. This measure provides an additional benchmark, as employers often use expected wages as a proxy of expected productivity [4].

In terms of experiment focus the results are mixed. While our research criteria required all selected papers to address both gender and ethnicity, not all studies examined their joint effects, often focusing more on one factor than the other. A common finding across studies is the negative impact of belonging to an ethnic minority or being a woman on hiring probabilities. However, studies that analyse the combined effect consistently demonstrate stronger negative impacts.

In conclusion, our analysis highlights key trends and opportunities for improvement. First, despite the diversity in the selection of ethnic groups, the studies consistently find that individuals from ethnic minorities face lower hiring chances. This holds true, to varying degrees, in all cases where a domestic ethnic group is compared with a foreign ethnic group, even among EU member states with close geographic and cultural ties [5,8]. Furthermore, while all studies confirm that the hiring chances of women and ethnic minorities are significantly smaller than majority-groups, the joint effects of gender and ethnicity demonstrates that these forms of discrimination compound.

Acknowledgments This work was supported by the funding from PNRR – Miss. 4, Comp. 2, Investment 1.1 -Prin 2022 Call for Proposals PNRR - Directorial Decree No. 1409 of 09/14/2022, project title Ethnic And Gender Labor Experimental Studies (EAGLES) over discrimination, CUP code J53D23016930001, project identification code P2022HKP7L.

Disclaimer The views and opinions expressed in this paper are solely those of the authors and do not necessarily reflect the official policy or position of the Italian Ministry of Foreign Affairs. The authors bear full responsibility for the content of this paper.

References

1. Aiyar, S.Ebeke, C., Shao, X.: The Impact of Workforce Aging on European Productivity. (2017).
2. Baert, S., De Pauw, A.: Is ethnic discrimination due to distaste or statistics? *Economic Letters*, pp. 270-273 (2014).
3. Eures, Labour shortages and surpluses in Europe 2023. Luxembourg: P.O. of the EU, (2024).
4. Fossati, F., Liechti, F., Auer, D.: Can signaling assimilation mitigate hiring discrimination? Evidence from a survey experiment. *Research in Social Stratification and Mobility* (2020).
5. Gutfleisch, T.: Hiring discrimination against foreigners in multi-ethnic labour markets: Does recruiter nationality matter? Evidence from a factorial survey experiment in Luxembourg. *Research In Social Stratification and Mobility* (2022).
6. Jankowski, M., Prokop, C., Tepe, M.: Representative Bureaucracy and Public Hiring Preferences: Evidence from a Conjoint Experiment among German Municipal Civil Servants and Private Sector Employees. *Journal of Public Administration Research and Theory*, pp. 596-618 (2020).
7. Kanistar, G.: The same social elevator? Intergenerational class mobility of second-generation immigrants across Europe, *European Sociological Review*, (2024).
8. Lippens, L., Vermeiren, S., Baert, S.: The State of Hiring Discrimination: A Meta-Analysis of (Almost) All Recent Correspondence Experiments. *SSRN Electronic Journal* (2023).
9. Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D.: The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. (2021).

What are the complex interactions among the different Sustainable Development Goals (SDGs)? An analysis of European Island ecosystems

Simona Cafieri

Abstract. Recent crises, including the pandemic and wars, have disrupted the global economy. Climate change and digital transformation add uncertainty, demanding innovative governance for Sustainable Development Goals (SDGs) achievement, especially in vulnerable economies such as Islands. This paper emphasizes data-driven analysis to understand the complex interactions among different SDGs, focusing on the European Island ecosystems. It examines how policies and ecological dynamics influence their achievement, highlighting synergies and trade-offs. The analysis employs both quantitative and qualitative approaches and cover the main dimensions of sustainable development: environmental, economic, and social. Recognizing SDG interconnections supports the development of effective policies to enhance community resilience.

Key words: SDGs Goals, Insularity, Sustainable development index

1 Introduction

Island territories, with their rich cultural and biological diversity, serve as experimental laboratories for sustainability and evolution, as demonstrated by Darwin [2] and Wallace [7]. Due to their unique geography, limited resources, and vulnerability to climate change, Islands face significant challenges in achieving sustainable development, often reflecting broader global issues [1]. While the UN SDGs [6] provide a universal framework, Islands require tailored strategies, prioritizing specific goals and carefully addressing interlinkages to avoid unintended consequences. The aim of this work is to evaluate progress toward SDGs in Island

Simona Cafieri
ISTAT, e-mail: cafieri@istat.it

contexts, uncovering trade-offs and synergies among goals. The findings offer valuable insights for designing targeted policies to enhance sustainability and well-being in these fragile ecosystems.

2. Data and methodology

This study focuses on European Islands for which comprehensive data¹ at the NUTS2 level are available for all variables required to assess progress toward the Sustainable Development Goals (SDGs) outlined in the UN 2030 Agenda. The Islands analyzed are:

- Balearic Islands (Spain)
- Canary Islands (Spain)
- South Aegean Islands (Greece)
- Crete (Greece)
- Azores (Portugal)
- Sardinia (Italy)
- Sicily (Italy)

The analysis is based on data from Eurostat databases and considers indicators related to the following SDGs:

SDG 1: No poverty

SDG 3: Good health and well-being

SDG 4: Quality education

SDG 7: Affordable and clean energy

SDG 8: Decent work and economic growth

For each Island, the indicators were calculated using the Mazziotta-Pareto Index, then a Principal Component Analysis (PCA) was conducted to identify the key factors influencing overall sustainability performance. The results provide a valuable knowledge base for guiding sustainable development efforts on European Islands. Each index consists of 3 to 5 sub-dimensions, some of which have a positive impact and others a negative impact on the sustainable development of each Island. These dimensions were then aggregated into a final score using the Mazziotta-Pareto model. This model, based on a linear aggregation process, introduces penalties for geographical regions with unbalanced indicators, i.e. those with an uneven distribution of dimensions.

The process was carried out in two main steps:

- Standardization of indicators to ensure comparability.
- Aggregation of standardized indicators to obtain the final index.

The outcome of this phase consists of tables for each Goal, presenting the Mazziotta-Pareto Index for years 2018-2022 for each Island (as shown in the table below).

¹ years 2018-2022

What are the complex interactions among the different Sustainable Development Goals (SDGs)?

Table 1 MPI INDEX value

Islands	Goal 1	Goal 3	Goal 4	Goal 7	Goal 8
Notio Algaio	55,24	100,64	100,34	46,03	141,89
Kriti	56,65	101,73	97,26	49,92	147,1
Illes Balear	63,81	101,67	113,6	51,55	159,82
Canarias	54,02	101,74	111,44	51,57	153,07
Sicilia	54,99	101,61	110,7	72,45	115,95
Sardegna	56,72	101,79	107,28	61,21	131,73

The key questions we aim to answer are: Which components determine an island’s sustainability? And which of the indices we have calculated plays the most significant role in achieving the Goals of the 2030 Agenda?

To address these questions, we apply Principal Component Analysis (PCA) to identify a limited number of particularly significant dimensions. The significance of these dimensions is measured by the extent of variation in observations across them.

Once the principal components are computed, we can visualize them in relation to each other, creating low-dimensional data representations. The Mazziotta-Pareto indices calculated in the previous phase serve as input for the Principal Component Analysis, providing a foundation for identifying the most influential factors driving sustainability performance.

3. A deeper analysis and results

To determine which dimensions are most relevant in assessing an island’s level of sustainable development, we analyze the percentage of variance explained (PVE) by each component and the cumulative PVE. These metrics help identify the most significant components contributing to data variability.

Based on this information, we build a scree plot to detect an inflection point, beyond which additional dimensions contribute only marginally to explaining variance. The variables with the highest loading factors on the two main components are prioritized, allowing us to identify which factors have the greatest influence on each island’s sustainable development. This analysis is crucial in determining the

optimal number of dimensions to retain, ensuring effective data representation while minimizing dimensionality and preserving as much information as possible.

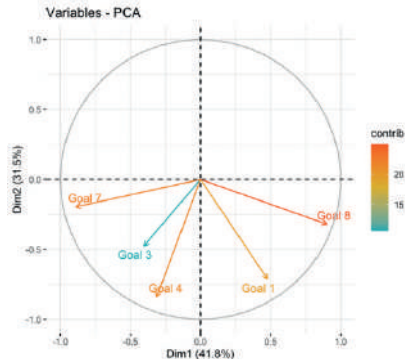


Fig.1 Relationship between goals

In this analysis, the first three principal dimensions account for approximately 90% of the total variance, indicating that the fourth and fifth dimensions are not critical to sustainability performance. The results show that Goals 4, 7 and 8 play a significant role in shaping the first two principal dimensions. Additionally, a strong negative correlation is observed between Goal 8 and Goals 3 and 7, suggesting that higher economic activity often coincides with weaker performance in public health and sustainable energy supply.

This analysis provides a comprehensive framework for assessing sustainable development on islands by identifying key dimensions and their interrelationships. Such an approach is particularly valuable in small territories like islands, which can serve as experimental models for sustainability strategies applicable on a larger scale. The insights gained can support policy formulation and decision-making aimed at improving sustainability in these regions. As strategic contexts become increasingly uncertain, data-driven insights like these are crucial for informed decision-making and planning.

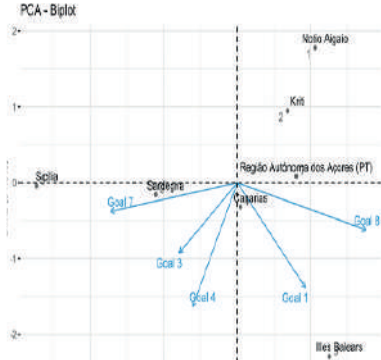


Fig.2 Sustainable development of Islands

References

1. Baldacchino G, Kelman, Critiquing the pursuit of island sustainability. *Shima* 8(2):1–21,(2014)
2. Darwin C., On the origin of species by means of natural selection, or the preservation of favoured races in the struggle for life. London: Oxford Univ. Press (1856)
3. Eurostat, Regional statistics by Nuts Classification (2024)
4. Haase, D & Maier, A, Islands of the European Union: State of play and future challenges, European Parliament, Policy Department for Structural and Cohesion Policies, Brussels, (2021)
5. Mazziotta M., Pareto A., On a Generalized Non-Compensatory. Composite Index for Measuring Socio-economic Phenomena, *Social Indicator Research*, Vol. 127, No. 3, pp. 983-1003 (2016)
6. United Nations, Transforming our World: The 2030 Agenda for Sustainable Development, (2015)
7. Wallace A.R., The Malay Archipelago, The Malay Archipelago; the land of the orang-utan and the bird of paradise; a narrative of travel with studies of man and nature, 2 voll. Macmillan & Co., London & New York(1869)

Analysis of the Wage Determination in Selected European Union Countries

Fabiano Campanelli and Mária Bohdalová

Abstract The paper analyses wage growth in the labour market in selected eurozone countries. We used a panel linear regression model to identify differences in wage determination in selected eurozone countries. Our results show that unemployment in the analysed sample of selected European Union countries significantly reduces wages, confirming economic theories. If we do not consider the impact of inflation, we have revealed two groups of countries in which macroeconomic factors affect wages comparably. The inflation growth in individual countries has caused only Ireland to react differently than the other analysed countries. In conclusion, we can state that the selected macroeconomic determinants statistically significantly affect wages in individual European Union countries.

Key words: wage, unemployment rate, gender, labour market

1 Introduction

Labour market analysis focusing on wages in European countries remains a research subject. The main question is whether the homogeneity of the wages of the European countries to understand how different reasons influence inequality between wages in countries.

The main objective of our contribution is to measure the growth rate of real wages in eleven EU countries and to find out how it changes depending on the country's productivity growth, unemployment growth, inflation growth and real effective rate. Countries that have joined the monetary union do not use independent

Fabiano Campanelli
University of Teramo, e-mail: fcampanelli@unite.it

Mária Bohdalová
Comenius University Bratislava, e-mail: maria.bohdalova@fm.uniba.sk

monetary and exchange rate policies. Sufficient flexibility of real wages is desirable in the countries of the monetary union. Therefore, we decided to examine the main factors that influence wage growth in eleven EU countries and to verify whether a single model for wage growth is valid within EU countries that use common currency. We decided to use a panel framework, including countries as specific factors.

We want to find the determining factors for wage growth because of the labour market reforms introduced by the European Commission, the ECB and other authorities in recent years. The conditions imposed by the Maastricht Treaty of 1992 defined the nominal convergence in variables such as interest rates, inflation, exchange rates and government deficits. As Buti and Turrini [1] wrote, implementing the single currency was supposed to create an incentive for member states to implement structural reforms that would encourage convergence between countries to equilibrate labour markets among many European States. Dosi *et al.* [3] discovered that wage and productivity converge. Based on household data, the view on wage and price inflation solved Jain *et al.* [4]. We can find the actual state of the labour market and wages in the EU annual review [5].

The paper is organised as follows. The next chapter defines the data and methodology with two wage growth models. Section Results presents obtained statistical models. The last chapter concludes our findings.

2 Data and Methodology

We analyse wage growth homogeneity across EU countries using a common currency: Belgium, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, Austria, Portugal, and Finland. Analysed data period included annual data from 1996 to 2023. Average full-time adjusted salary per employee (AFTA), productivity (GDP), real exchange effective rate (REER), unemployment and inflation (CPI) were obtained from the Eurostat database with annual frequency and World Bank. Our empirical research is based on two growth models inspired by the article by Camarero *et al.* [2]. In Model 1, the average full-time adjusted salary per employee growth is the dependent variable, while productivity growth and unemployment are the independent variables.

$$Wage_t^c = \beta_1 GDP_t^c + \beta_2 Unemployment_t^c + country_t + \varepsilon_t \quad (1)$$

We assume that growth of productivity growth caused increasing in wage growth ($\beta_1 > 0$), while increasing unemployment decreases wage growth ($\beta_2 < 0$).

In Model 2, we considered the independent variables – inflation and REER growth in Model 1. In both models, we consider the country factor.

$$Wage_t^c = \beta_1 GDP_t^c + \beta_2 Unemployment_t^c + \beta_3 REER_t^c + \beta_4 CPI_t^c + country_t + \varepsilon_t \quad (2)$$

We assume $\beta_1 > 0$, $\beta_2 < 0$, β_3 is real number and $\beta_4 < 0$.

The growth values are calculated as year-on-year differences divided by the previous value to avoid the nonstationarity of the data. Our estimation method is panel regression. The sample size for each country includes 28 measurements.

3 Results

From our sample, it is evident (see Table 1) that during the analysed period, the largest decrease in wage growth was recorded in Greece (8%). We found that Greece also had the lowest average wage growth of 2.1%, with the highest variability. Conversely, employees in Finland experienced the lowest wage growth of 0.7% and the highest growth of 5.1%, with the lowest variability among the analysed countries.

Table 1 Average full-time adjusted salary per employee growth rate per country

Country	Minimum	Maximum	Mean	Std. Deviation
Austria	-0.022	0.074	0.026	0.017
Belgium	-0.021	0.086	0.027	0.024
Finland	0.007	0.051	0.027	0.012
France	-0.039	0.056	0.023	0.017
Germany	-0.022	0.068	0.022	0.017
Greece	-0.080	0.121	0.021	0.049
Ireland	-0.011	0.165	0.044	0.036
Italy	-0.046	0.143	0.026	0.032
Luxembourg	0.005	0.075	0.032	0.019
Portugal	-0.025	0.085	0.031	0.025
Spain	-0.012	0.072	0.025	0.023

Table 2 Estimated models based on Eurostat data

AFTA Growth	Model 1	P> z	Model 2	P> z
GDP Growth	0.198	0.000	0.199	0.000
Unemployment Total	-0.183	0.000	-0.096	0.000
REER Growth			0.133	0.000
CPI Growth			0.455	0.000
Country				
Belgium	0.009	0.147	0.005	0.379
Finland	0.015	0.017	0.011	0.054
France	0.013	0.044	0.009	0.119
Germany	0.002	0.777	0.002	0.760
Greece	0.032	0.000	0.014	0.049
Ireland	0.021	0.001	0.019	0.001
Italy	0.019	0.003	0.009	0.147
Luxembourg	0.003	0.580	0.004	0.473
Portugal	0.016	0.009	0.011	0.060
Spain	0.040	0.000	0.019	0.010
Cons	0.043	0.000	0.024	0.000

Table 2 reports panel regression results. The coefficient of productivity growth implies around 19.8% of growth in GDP passed into wages. The coefficient of unemployment growth implies an 18.3% decrease in the wage. Both coefficients are statistically significant for a significance level of 0.01. Model 2 implies a 19.9% increase in wage growth to an increase in GDP growth, and a 1% growth of unemployment caused a 9.6% wage decrease. The highest increase in the wage is due to increased inflation growth. We can divide analysed countries into two groups based on the coefficients of country factors. Belgium, Finland, France, Germany, Luxembourg, and Austria show zero impact on wages at a significance level of 0.01. Based on Model 1, the estimated coefficient for countries Ireland, Italy, Portugal, Greece and Spain show a small positive statistically significant impact on wage growth. Only Ireland's coefficient is passed into wages when inflation and REER growth are included in the model (Model 2).

4 Conclusions

This paper examined the macroeconomic factors important in determining wage growth in the euro area. Like Camarero et al. [1], we identified two groups of countries. The first group comprises Germany, Austria, Belgium, Luxembourg, Finland, and France. The second group comprises Italy, Ireland, Spain, Portugal, and Greece. In our research, France already belongs to the first group of countries.

Based on the descriptive analysis, we found that wages in Greece have the most significant variability and are among the lowest in the EU of the analysed countries. Our findings benefit economic policy in designing further structural reforms in the euro area.

References

1. Buti, M., Turrini, A. Three waves of convergence. Can Eurozone countries start growing together again? <http://voxeu.org/article/types-ez-convergence-nominal-real-and-structural>. (2015)
2. Camarero, M., D'Adamo, G., & Tamarit, C. The role of institutions in explaining wage determination in the Eurozone: A panel cointegration approach. *International Labor Review*, 155(1), 25–53. (2016)
3. Dosi, G., Virgillito, M., E., Yu, X. The wage-productivity nexus in the world factory economy. *World Development*, Vol. 129, 104875, <https://doi.org/10.1016/j.worlddev.2020.104875>. (2020)
4. Jain, M., Kostyshyna, O., Zhang, X. How do people view wage and price inflation? *Journal of Monetary Economics*, Vol. 145, 103552, <https://doi.org/10.1016/j.jmoneco.2024.01.005>, (2024)
5. European Commission., Darnaut, N.: Labour market and wage developments in Europe. Annual review 2024. Available at: <https://op.europa.eu/en/publication-detail/-/publication/057f23e9-bdc5-11ef-91ed-01aa75ed71a1/language-en>. (2024)

Forecast reconciliation and Multivariate GARCH

Massimiliano Caporin, Daniele Girolimetto and Emanuele Lopetuso

Abstract By resorting to simulations we assess the advantage of combining univariate and multivariate portfolio risk forecast with the aid of forecast reconciliation techniques. Our results suggest relevant advantages when multivariate models are misspecified.

Key words: Multivariate GARCH, Forecast reconciliation, Portfolio Risk

1 Introduction

Multivariate Generalized Auto Regressive Conditional Heteroskedasticity (MGARCH) models represent a classical tool for the prediction of a conditional covariance matrix. Since the seminal contributions of [1] and [2] the literature has sensibly expanded, going beyond the survey of [3]. This model class is commonly used as a tool for providing the needed inputs for portfolio allocation programs or for market risk management applications. Irrespective of their practical use, MGARCH models still present a relevant challenge, the so-called curse of dimensionality, due to the large number of parameters they include, easily making the models unfeasible even for moderate cross-sectional dimensions. Several solutions have been proposed, from the use of restricted parametrizations, to factor structures, up to the introduction of model designs allowing for simpler estimation schemes, or characterized by strong assumptions on the underlying dynamic. The intricate relationship across financial asset returns is, however, only partially accounted for in feasible

Massimiliano Caporin

University of Padua, e-mail: massimiliano.caporin@unipd.it

Daniele Girolimetto

University of Padua, e-mail: daniele.girolimetto@unipd.it

Emanuele Lopetuso

University of Padua, e-mail: emanuele.lopetuso@unipd.it

MGARCH models which, in general, allow for limited (or null) interdependence across conditional variances, covariances and/or correlation dynamics. The consequence is that MGARCH models are, generally, misspecified.

In this work we take a different perspective. We start from the availability of n assets whose returns $\mathbf{r}_t$, are available for a given time span, $t = 1, 2, \dots, T$. Moreover, we assume the knowledge of a vector of portfolio weights $\boldsymbol{\omega}$. Given the weights, it is possible to reconstruct the portfolio returns $r_{p,t} = \boldsymbol{\omega}'\mathbf{r}_t$, that would be obtained from $t = 1$ to $t = T$. We thus take the point of view of a market risk manager whose purpose is to forecast the portfolio variance for $T + 1$. In this framework, with known weights, it is possible to predict the portfolio risk both by forecasting the covariance of $\mathbf{r}_T$, that is $\boldsymbol{\Sigma}_T$, and then obtaining $\sigma_{p,T}^2 = \boldsymbol{\omega}'\boldsymbol{\Sigma}_T\boldsymbol{\omega}$, or to predict directly $\sigma_{p,T}^2$ by fitting a univariate model on $r_{p,t}$. This is coherent with the need of predicting the risk of the current portfolio whose returns can be backward reconstructed given, i) the availability of the asset returns over the entire sample, and ii) the knowledge of the weights. Note that these returns are not the past realized returns of the portfolio, but represent the returns that the current portfolio $\boldsymbol{\omega}$ would have realized in the past.

In this situation, given the availability of two possible forecasts, one from a MGARCH model, and one from a univariate GARCH model, forecast reconciliation methods [8] can be used to efficiently combine the available information.

In the following Section we discuss the forecast reconciliation approach for MGARCH models and in Section 3 we provide some information about a simulation we plan to use for assessing the role of forecast reconciliation.

2 Portfolio Variance Reconciliation

For simplicity, we remove the time index t from the equations in this section. Let $\boldsymbol{\Sigma}$ be an $(n \times n)$ covariance matrix such that

$$\sigma_p^2 = \boldsymbol{\omega}'\boldsymbol{\Sigma}\boldsymbol{\omega} \quad (1)$$

where $\boldsymbol{\omega}$ is a $(n \times 1)$ vector of known weights. According to the forecast reconciliation notation for the cross-sectional case, see [4], we can express (1) as

$$\sigma_p^2 = \boldsymbol{\omega}'\boldsymbol{\Sigma}\boldsymbol{\omega} = (\boldsymbol{\omega}' \otimes \boldsymbol{\omega}')\mathbf{D}_n \text{vech}(\boldsymbol{\Sigma}) = \mathbf{A}\boldsymbol{\sigma} \quad (2)$$

where $\mathbf{A} = (\boldsymbol{\omega}' \otimes \boldsymbol{\omega}')\mathbf{D}_n$ is the $(1 \times m)$ linear combination (also known as the aggregation) matrix with $m = \frac{n(n+1)}{2}$, $\otimes$ indicates the Kronecker product [5], $\boldsymbol{\sigma} = \text{vech}(\boldsymbol{\Sigma})$ is a $(m \times 1)$ vector, vech is the half-vectorization operator such that

$$\text{vec}(\boldsymbol{\Sigma}) = \mathbf{D}_n \text{vech}(\boldsymbol{\Sigma})$$

and $\mathbf{D}_n$ is an $(n^2 \times m)$ duplication matrix [5].

Let $\widehat{\sigma}_p^2$ and $\widehat{\sigma}$, respectively, the forecasts for σ_p^2 and σ , obtained from a univariate and a multivariate GARCH model, respectively. These forecasts do not necessarily satisfy the aggregation constraint in (2). The bottom-up (*bu*) reconciled forecast for σ_p is

$$\widetilde{\sigma}_{p,bu} = \mathbf{A}\widehat{\sigma}. \quad (3)$$

This forecast is obtained from just MGARCH predictions and represents the standard approach in the MGARCH literature. However, such an approach is neglecting the possibility of predicting the portfolio variance directly from the backward reconstructed portfolio returns. Denote $\mathbf{C} = [\mathbf{I}_{n_y} \quad -\mathbf{A}]$ and $\mathbf{\Omega}$ a p.d. matrix – e.g. $\mathbf{\Omega} = \mathbf{I}_m$ (*ols*) or a diagonal (*wls*), shrunk (*shr*), or full (*sam*) “covariance” matrix obtain from some in-sample residuals of the base forecasts’ models [6, 7] – then

$$\begin{bmatrix} \widetilde{\sigma}_p \\ \widetilde{\sigma} \end{bmatrix} = [\mathbf{I}_m - \mathbf{\Omega}\mathbf{C}'(\mathbf{C}\mathbf{\Omega}\mathbf{C}')^{-1}\mathbf{C}] \begin{bmatrix} \widehat{\sigma}_p \\ \widehat{\sigma} \end{bmatrix}.$$

The reconciled forecasts are provided for both the portfolio variance as well as for the entire covariance matrix. According to the forecast reconciliation literature, the reconciliation provides an improvement of the forecast accuracy; see [8, 9].

Starting from these observations, we assess if the introduction of forecast reconciliation improves the prediction of the portfolio variance forecast. In this respect, we evaluate the impact of the use of either a correctly specified or of a miss-specified MGARCH model.

3 Simulation Design

To evaluate the benefits of forecast reconciliation we plan to simulate time series of fixed length (ideally $T = 1250$) reserving the first 1000 observations as estimation sample and the following 250 for forecasting. The data will be generated from different MGARCH models, namely, the DCC-GARCH of [10], the Scalar, Diagonal, and Full BEKK of [2], and the OGARCH of [11]. The models will be designed in such a way they will include spillovers between variances (Full BEKK), or are capturing only contemporaneous interdependence (DCC, Scalar and Diagonal BEKK, OGARCH). On the simulated data, correctly specified and miss-specified MGARCH models will be estimated, as well as, univariate GARCH on the reconstructed portfolio returns. As portfolio weights we will use both the $1/N$ portfolio as well as a randomly generated portfolio with only long positions. For what concerns the cross-sectional size, we will explore different dimensions, starting from $N = 5$ up to $N = 50$.

Models will be compared using standard tools. First of all, taking advantage of the knowledge of the true (simulated) conditional covariances, we will evaluate the Mean Squared Error, Mean Absolute Error, and QLIKE loss functions. The models, will also be compared by means of the Model Confidence Set approach [12].

Our results will allow shedding light on the impact of forecast reconciliation and on the role played by model misspecification when the purpose of the researched is the prediction of portfolio risk (as summarized by the variance).

Acknowledgements The authors acknowledge financial support from project PRIN 2022: PRICE – “A New Paradigm for High-Frequency Finance”– 2022C799SX.

References

1. Bollerslev, T.: Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized Arch Model. *J. Bus. Eco. Stat.* **72(3)**, 498–505 (1990).
2. Engle, R.F., and Kroner, K.K.: Multivariate simultaneous generalized arch, *Econometric Theory*, **11**, 122–150 (1995).
3. Bauwens, L., and Laurent, S., and Rombouts, J.V.K.: Multivariate GARCH models: a survey, *J. Appl. Econometrics* **21(1)**, 79–109 (2005).
4. Hyndman, R. J., Ahmed, R. A., Athanasopoulos, G., and Shang, H. L.: Optimal combination forecasts for hierarchical time series. *CSDA*, **55(9)**, 2579–2589 (2011).
5. Magnus, J. R., and Neudecker, H.: *Matrix differential calculus with applications in statistics and econometrics*. Hoboken, NJ: Wiley, third edition (2019).
6. Wickramasuriya, S. L., Athanasopoulos, G., and Hyndman, R. J.: Optimal Forecast Reconciliation for Hierarchical and Grouped Time Series Through Trace Minimization. *JASA*, **114(526)**, 804–819 (2019).
7. Girolimetto, D., and Di Fonzo, T.: Point and probabilistic forecast reconciliation for general linearly constrained multiple time series. *Stat. Methods Appl.*, **33**, 581–607 (2024).
8. Athanasopoulos, G., Hyndman, R. J., Kourentzes, N., and Panagiotelis, A.: Forecast reconciliation: A review. *Int. J. Forecast.*, **40(2)**, 430–456 (2024).
9. Caporin, M., Di Fonzo, T., and Girolimetto, D.: Exploiting Intraday Decompositions in Realized Volatility Forecasting: A Forecast Reconciliation Approach. *Journal of Financial Econometrics*, **22(5)**, 1759–1784 (2024).
10. Engle, R.F.: Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *J. Bus. Econ. Stat.*, **20(3)**, 339–350 (2002).
11. Alexander, C.: Principal Component Models for Generating Large GARCH Covariance Matrices, *Econ. Notes*. **31(2)**, 337–359 (2002).
12. Hansen, P.R., Lunde, A., and Nason, J.M.: The Model Confidence Set. *Econometrica*, **79(2)**, 453–497 (2011).

The Dual Impact of Energy Efficiency and Rebound Effects on Energy Poverty: An Italian Case Study

Alfonso Carfora, Francesco Maria Chelli and Giuseppe Scandurra

Abstract This paper investigates the impact of energy efficiency on energy poverty and examines the mitigating effect of the rebound effect within the Italian residential energy sector. Using a stochastic frontier analysis (SFA) model, the study overcomes limitations in existing models that assume a zero-rebound effect. The analysis aims to provide policymakers with improved insights into how energy efficiency influences energy poverty.

Keywords: Energy efficiency; Energy poverty; Rebound effect; Italian Household Budget Survey

1 Introduction

Reducing energy consumption and lowering emissions are critical policy goals for governments worldwide. Promoting energy efficiency measures is a key step toward achieving these objectives. However, realizing actual energy savings involves two main challenges. First, policymakers need precise tools to assess and compare energy efficiency across different regions and time periods. Second, actual reductions in energy consumption may fall short of expectations due to the rebound effect. This effect occurs when improved efficiency reduces the cost per unit of energy service,

Alfonso Carfora
University of Macerata, e-mail: alfonso.carfora@unimc.it

Francesco Maria Chelli
Marche Polytechnic University, e-mail: f.chelli@staff.univpm.it

Giuseppe Scandurra
University of Naples Parthenope, e-mail: giuseppe.scandurra@uniparthenope.it

potentially leading to increased consumption that partially offsets the predicted savings. Understanding and measuring the rebound effect is essential for evaluating energy efficiency policies' effectiveness. Numerous studies attempt to measure the rebound effect using econometric models, yet methodological discrepancies result in varied estimates. The authors develop an SFA model that integrates energy demand frontier analysis with the rebound effect to address these gaps, offering a more comprehensive approach. This paper highlights the importance of accurately measuring rebound effects to analyze their influence on energy poverty, focusing on the Italian residential energy sector. By overcoming existing models that assume a zero-rebound effect, the study introduces an SFA model to more accurately measure rebound effects, thereby equipping policymakers with better tools to assess the impact of energy efficiency on energy poverty.

2 Data and Empirical approach

This study examines energy poverty using the latest available data from the 2022 Household Budget Survey (HBS) conducted by the Italian National Statistical Institute (ISTAT). The survey collects data on Italian households' consumption behaviors and socio-demographic characteristics, providing insights into their economic conditions and guiding policy and commercial decisions. The survey sample comprises 28,416 households, representing the heterogeneity of the Italian population. The results and microdata are publicly accessible through ISTAT's website.

Consistent with the HBS dataset, the analysis calculates the expenditure-based energy poverty indicator proposed by Betto et al. (2020) as the target variable. Other HBS variables are used to develop an SFA model, whose estimates of efficiency and rebound serve as regressors in a probabilistic model analyzing the determinants of energy poverty. The selected variables are *i)* the monthly average household's residential energy consumption, (q); *ii)* the monthly average household's total consumption (Y), as proxy of disposable income; *iii)* real energy prices index (P) *iv)* other control variables (X) like household sizes and characteristics; the share of detached houses and two policy variables indicating whether the household has been a beneficiary of policies supporting energy efficiency and/or energy expenditures. The empirical approach employs a SFA model to measure energy inefficiency in which the dependent variable (q) is represented by the monthly average household's residential energy consumption, and the explicative variable is those listed in the previous section:

$$\ln q = \ln f(Y; P; X; \beta) + v + u \quad (1)$$

where $u = -\ln e \geq 0$. The error term in Eq. (1) thereby comprises two independent parts. The first part, v , is the classical symmetric random noise, often assumed to be

normally distributed. The second part, u , is a one-sided error term capturing the level of underlying energy inefficiency. Therefore, the rebound effect issue can be introduced in an energy demand application of the SFA approach as a correction factor $(1 - R)$ that interacts with the energy inefficiency term (u). It can be estimated by introducing a function captures variations in the rebound effect based on a set of variables ($\gamma'z$) related to: income, energy prices, and household size that is:

$$\ln(q) = \ln f(Y; P; X; \beta) + v + [1 - R(\gamma'z)]u \quad (3)$$

The maximum likelihood estimation (MLE) of Orea et al. (2015) suggested a functional form where the energy efficiency and rebound effect can be simultaneously obtained by estimating the stochastic energy demand frontier model:

$$e = \exp(-\hat{u}) \quad \text{and} \quad R(\gamma'z) = \frac{e^{\gamma'z}}{1 + e^{\gamma'z}} \quad (4)$$

The probabilistic method used to estimate the impact of energy efficiency on energy poverty, is shown in Eq. (5)

$$ep_i = \beta_0 + \beta_1 e_i + \beta_2 re_i + \beta_3 X_i + \sigma_i \quad (5)$$

where ep is a dummy variable indicating whether in energy poverty or not, e is the energy efficiency obtained from Eq. (3), X is a series of control variables listed in the previous section and re is the rebound effect obtained from Eq. (3). We mainly focus on β_1 and β_2 to denote the regulation of the efficiency and rebound effects.

3 Results

The Results of the probabilistic logit model are reported in Table 1, while those of the estimation of the SFA model, from which the efficiency and rebound estimates were derived will be made available by the authors on request.

The findings demonstrate that improved energy efficiency significantly reduces the likelihood of energy poverty. However, the rebound effect partially offsets these benefits, as evidenced by the positive rebound coefficient nearly matching the magnitude of the efficiency coefficient. While energy efficiency reduces energy poverty by lowering demand and costs, larger household sizes exacerbate it, despite potential economies of scale. Higher cooling needs also intensify energy poverty. Policies such as energy bonuses effectively mitigate energy poverty, while more generic renovation incentives fail to target low-income households adequately.

Table 1 Logit model estimates

Variable	Description	Estimate	p-value
<i>(Intercept)</i>		20,090	0.000***
<i>efficiency</i>	efficiency of the SFA model	-9,829	0.000***
<i>rebound</i>	rebound of the SFA model	6,078	0.000***
<i>exp_equiv</i>	total household equivalent consumptions	-0,017	0.000***
<i>members</i>	household's member	0,170	0,003**
<i>heating</i>	number of heating days	-0,001	0,729
<i>cooling</i>	number of cooling days	0,025	0,0150*
<i>HCR</i>	household's concentration index	-0,020	0.000***
<i>house_occup_2</i>	house tenant	-0,561	0.000***
<i>house_occup_3</i>	house loan of use	-0,427	0,199
<i>house_occup_4</i>	other	0,814	0.000***
<i>ren_bonus</i>	taken energy bonuses	-1,555	0.000***
<i>ene_bonus</i>	taken renovation tax incentives	0,412	0,297

4 Conclusions and policy implications

Income, energy costs, and home efficiency are key determinants of energy poverty. While long-term solutions prioritize energy efficiency improvements, short-term affordability measures dominate current funding. The rebound effect hinders poverty reduction efforts, with maximum achievable reductions limited to 10.23% under high-efficiency scenarios. Targeted policies and equitable incentives distribution are essential to effectively addressing energy poverty. The EU's emphasis on energy poverty highlights its significance within the green transition, requiring accurate metrics and fair resource allocation. The findings of this work offer valuable insights for other European countries as well preparing to implement the EU Energy Performance of Buildings Directive, because they highlight as the efforts to resolve tensions between environmental objectives and financial constraints require for balanced, inclusive strategies.

References

1. Betto, F., Garengo, P., Lorenzoni, A.: A new measure of Italian hidden energy poverty. *Energy policy*, 138, 111237 (2020).
2. Orea, L., Llorca, M., Filippini, M.: A new approach to measuring the rebound effect associated to energy efficiency improvements: An application to the US residential energy demand. *Energy Economics* (2015).
3. ISTAT The household budget survey (HBS) for consumption expenditure behaviors of households residing in Italy.: <https://www.istat.it/en/microdata/household-budget-survey/> (2022).

The Impact of Technology Transfer in Italy: Some Preliminary Remarks

Andrea Ciccarelli, Audrey De Dominicis and Greta Torquati

Abstract Many scholars have examined the evolution of economic growth theories, focusing on the shift from neoclassical to endogenous models, which highlight knowledge, ideas, and human capital as productivity drivers. Many among them agree that innovation has a key role in economic development, with R&D investments crucial for national competitiveness; in this contest, university R&D generally provides long-term benefits, while corporate R&D yields quicker returns. This study explores the impact of patents and R&D expenditures by universities and firms on national and regional economic growth in Italy. Panel data analysis shows a positive correlation between value added per worker and R&D expenditures, with university R&D having a greater impact than firm R&D. Patents affect growth with a five-year lag, while gross fixed investments show an immediate, lower impact.

Key words: R&D, economic growth, knowledge, university, firm, patent, spin-off

1 Introduction

In recent years, universities have gained prominence as intermediaries in transferring academic research and innovation to the market. Technology transfer, a key aspect of the Third Mission of Universities, includes academic entrepreneurship (e.g., spin-offs, start-ups), intellectual property valorization (e.g., patents), and collaborations between universities and enterprises (Rambe and Khaola, 2023; Padilla Bejarano et al., 2023). This process bridges the gap between research and application, enabling

Andrea Ciccarelli

University of Teramo, e-mail: aciccarelli@unite.it

Audrey De Dominicis

University of Teramo, e-mail: adedominicis@unite.it

Greta Torquati

University of Teramo, e-mail: gtorquati@unite.it

businesses to access advanced technologies while minimizing R&D costs and risks, thereby boosting innovation and global competitiveness (Secundo et al., 2017). Innovation, increasingly the result of structured R&D investments rather than chance, is crucial for economic growth and territorial competitiveness (Ciccarelli, 2008). This study examines the impact of R&D investments and patents on GDP growth, focusing on national dynamics. The findings aim to inform targeted technology transfer policies. The paper is structured as follows: Section 2 reviews the literature; Section 3 outlines data and methodology; Section 4 concludes.

2 Literature review

Economic growth theories have evolved to reflect a deeper understanding of growth drivers. The concept of endogenous growth emerged in the 1980s to address limitations in the neoclassical Solow-Swan model, which treated technological progress as external. Economists like Paul Romer emphasized the role of knowledge, ideas, and human capital as non-rival goods, enabling sustainable growth through increasing returns to scale. Lucas (1988) highlighted education's role in enhancing productivity, while Jones (1995) critiqued R&D-based models for weak links between engineers/scientists and productivity in major economies.

Aghion et al. (1998, 2009) refined these models by addressing scale effects and showing how technological change can lead to balanced growth. Empirical studies, such as Mankiw et al. (1992), linked human capital accumulation to growth rate differences, and Coe and Helpman (1995) highlighted R&D's domestic and international productivity spillovers. Further research by Frantzen (2000) and Griffith et al. (2004) supported the R&D-productivity relationship globally. Despite criticism for empirical challenges and policy complexity, endogenous growth models offer valuable insights for innovation and long-term prosperity.

This paper examines R&D expenditures' impact, focusing on university and corporate R&D. While university R&D benefits emerge slower, studies (e.g., Siegel et al., 2003) show technology transfer offices can accelerate its economic impact.

3 Data Description and methodology

In order to investigate the impact of innovation on value added per worker, we gathered national and regional data spanning from 1995 to 2021 available on Istat and on Ministry of Enterprises and Made in Italy websites. The dataset includes R&D expenditures faced by universities and firms, the number of patents, and the employment figures in the technological sector. Building our model from the Romer's work (1990), we assume that: i) technological changes drive the economic growth; ii) people's intentional actions lead to technological changes; iii) production designs are not rival goods. Starting from the Romer's model we have:

$$Y_t = A_t K_t^\alpha L_t^{1-\alpha}$$

where A_t is the technological efficiency of the economic system, K_t and L_t respectively the capital and the labour at time t . This relationship leads to the following equation:

$$Y_t = \alpha h_t + \gamma i_t + (1 - \alpha - \gamma)X_t + \varepsilon_t$$

which represents a simplified formulation of how various factors (h_t is the human capital computed as number of employed in the tech sector, i_t the gross fixed investment normalized to the population, X_t is compounded by the firms and universities R&D expenditures and the patent stock, ε_t as the stochastic error) concur to the value added per worker y_t .

Considering a fixed effects panel regression (confirmed by the Hausman test; Greene, 2011), we used proxy variables for innovation including university and firm R&D expenditures and patent stock. Following Ulku (2004)'s work, we incorporated in the model the number of employees in the tech sector and gross fixed capital investments per capita. To understand the impact over time of the dependent variables that characterize innovation, we introduced time lags of 1, 3, and 5 years.

The following table shows some results at national level:

Table 1 Panel regression analysis of value added (per worker) after 1, 3, 5 years - Italy.

Variable	Coefficient	Standard error	P> t
<i>Constant</i>	54833.56	1093.655	0.000
Lag 1	53921.81	1089.737	0.000
Lag 3	55079.86	1165.165	0.000
Lag 5	57643.87	1303.15	0.000
<i>Employees in tech sector (%)</i>	115.4537	48.40561	0.018
Lag 1	49.57321	48.2322	0.305
Lag 3	-15.6204	51.57071	0.762
Lag 5	-40.15708	55.91478	0.473
<i>Gross fixed investment per capita</i>	.2939677	.131462	0.026
Lag 1	.5101986	.1309911	0.000
Lag 3	.3658761	.1400579	0.009
Lag 5	.115176	.1517277	0.448
<i>Universities R&D expenditure</i>	19.28649	5.390106	0.000
Lag 1	24.46961	5.370796	0.000
Lag 3	23.52585	5.742549	0.000
Lag 5	9.949198	6.436143	0.123
<i>Firms R&D expenditure</i>	7.236004	1.8276	0.000
Lag 1	7.909385	1.821053	0.000
Lag 3	5.142473	1.947101	0.009
Lag 5	4.327868	2.176393	0.191
<i>Patents stock per capita</i>	-.5544672	.9190907	0.547
Lag 1	-.9968152	.9157981	0.277
Lag 3	.4633372	.9791872	0.636
Lag 5	1.388024	1.05958	0.191

Source: Our estimates on Istat Data.

4 Some concluding remarks

The analysis reveals that investments and R&D have a positive impact on value added per worker, though their effects vary. University R&D expenditure has a broader and stronger influence, benefiting numerous enterprises and the broader economy, while company R&D shows more localized effects. Gross fixed investments have early but weaker impacts, often failing to reshape production models. These findings suggest optimizing public policies by increasing university R&D investments and fostering business-university partnerships, especially in regions with smaller companies that struggle to independently invest in innovation.

Acknowledgements This research was funded by the European Union – Next Generation EU. Project Code: ECS00000041; Project CUP: C43C22000380007; Project Title: Innovation, digitalization and sustainability for the diffused economy in Central Italy – VITALITY.

References

1. Aghion P., Boustan L., Hoxby C., Vandenbussche J.: The Causal Impact of Education on Economic Growth: Evidence from US, Brookings papers on economic activity, Vol. 1 No., pp. 1-73 (2009)
2. Aghion P., Howitt P., Brant-Collett M., García-Peñalosa C.: Endogenous Growth Theory. Cambridge: MIT press (1998)
3. Ciccarelli A.: Competitività del sistema Italia e deficit di innovazione, Roma: Aracne ed. (2008)
4. Coe, D. T., & Helpman, E.: International R&D Spillovers, European economic review, Vol. 39, No. 5, pp. 859-887 (1995)
5. Frantzen D.: R&D, Human Capital and International Technology Spillovers: a Cross-Country Analysis, Scandinavian Journal of Economics, Vol. 102, No. 1, pp. 57-75 (2000)
6. Greene W.H.: Econometric Analysis, 7th ed., Upper Saddle River: Prentice Hall (2011)
7. Griffith R., Redding S., Van Reenen J.: Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries, The Review of Economics and Statistics, Vol. 86, No. 4, pp. 883–895 (2004)
8. Jones C.I.: R & D-based Models of Economic Growth, Journal of political Economy, Vol. 103, No. 4, pp. 759-784 (1995)
9. Lucas R.E Jr.: On the Mechanics of Economic Development, Journal of monetary economics, Vol. 22, No. 1, pp. 3-42 (1988)
10. Mankiw NG, Romer D, Weil D.: A Contribution to the Empirics of Economic Growth, Quarterly Journal of Economics, No. 107, pp. 407-437, (1992)
11. Padilla Bejarano J.B., Zartha Sossa, J.W., Ocampo-López C., Ramírez-Carmona M.: University Technology Transfer from a Knowledge-Flow Approach—Systematic Literature Review, Sustainability, Vol. 15, No. 8, pp. 1-21 (2023)
12. Rambe P., Khaola P.: Enhancing Competitiveness through Technology Transfer and Product Quality: the Mediation and Moderation Effects of Location and Asset Value, Journal of Innovation and Entrepreneurship, Vol. 12 No. 1, pp. 1-23 (2023)
13. Romer P.M.: Endogenous Technical Change, Journal of Political Economy, Vol. 98, pp. 71-102 (1990)
14. Secundo G., De Beer C., Schutte C.S.L., Passiante G.: Mobilising Intellectual Capital to Improve European Universities' Competitiveness: The Technology Transfer Offices' Role, Journal of Intellectual Capital, Vol. 18, No. 3, pp. 607-624 (2017)
15. Siegel D.S., Waldman D., Link A.: Assessing the Impact of Organizational Practices on the Relative Productivity of University Technology Transfer Offices: an Exploratory Study, Research policy, Vol. 32, No. 1, pp. 27- 48 (2003)
16. Ulku H.: R&D, Innovation, and Economic Growth: An Empirical Analysis, IMF Working Paper 185, International Monetary Fund (2004)

Impact of the National Recovery and Resilience Plan on the productivity in the Italian territories

Giuseppe Cinquegrana and Agata Maria Madia Carucci

Abstract This paper briefly describes the effect of the potential impact of NRRP on labour productivity in the Italian territories. The aim is to verify whether the use of the NRRP can reduce the development differential between different areas of the country, particularly by improving the efficiency and competitiveness of southern enterprises. We also investigated whether the NRRP is able to stimulate the digitisation of public administration and productive realities by reducing the digital gap between the Center-North and the South. We identified the value added per employee as a proxy for labour productivity since the purpose of this work is precisely to verify the theoretical impact of the use of NRRP funding on the territorial productive context.

Key words: NRRP, impact, estimate, territories, digitalisation

1 Introduction

The effect of the National Recovery and Resilience Plan (NRRP) on the Italian economy has been widely debated in recent years. Padoan P. C. [1] reports that an impact estimate around 3.0 percent on Italian Gross Domestic Product is plausible with the international scenario. Institutional estimates of the impact of the NRRP on economic growth show an impact of between 3.6 and 2.8 per cent in the period 2021-2026 (see [2, 3, 4, 5]). The main macroeconomic models considered are

Giuseppe Cinquegrana
ISTAT, e-mail: gicinque@istat.it

Agata Maria Madia Carucci
ISTAT, e-mail: carucci@istat.it

QUEST model [6] implemented by European Union and Italian Ministry of Finance (MoF), and REF model [5] developed by *Confindustria* (the main association representing manufacturing and service companies in Italy). On the other hand, from a micro-economic point of view, the study of the effects of the NRRP on enterprises and households has to be thoroughly analysed yet as it has been with the macroeconomic impact. This is due to the lower timeliness of economic data at territorial level (especially at the municipal one), the choice of indicators for monitoring the NRRP and the need to carry out ad hoc surveys on firms and households.

This paper briefly describes the potential impact of the Plan on labour productivity in Italian territories. The purpose is to investigate whether the use of the NRRP can reduce the development differential between areas of the country, particularly by improving the efficiency and competitiveness of southern enterprises. The study also investigated whether the NRRP is able to stimulate the digitalisation of public administration and productive realities by reducing the digital gap between the North-Center and the South of Italy. We analysed NRRP data extracted from the government platform *Italia domani* and labour productivity data at the municipal level from ISTAT sources. Using municipal data, we estimated the coefficients of impact of NRRP funds on the value added per employee of the Italian macro areas (Northwest, Northeast, Center and South). We elaborated additional detailed estimates to verify the effects of the NRRP's Mission 1 – (Digitalisation, Innovation, Competitiveness and Culture) on the Italian macro areas.

2 Data on the NRRP and the impact estimates

The Italian government's "Italia Domani" platform provides open data on the NRRP by reporting the details of the funds financed by mission, sub-measure and territory. A Unique Project Code, CUP, links each project to NRRP at national level, while different Local Project Codes, CLP, identify the place (municipality) of implementation of the NRRP-funded works. The platform presents information extracted from the NRRP's Single Management System, REGIS (source: MoF). From this data, it was possible to define a database on NRRP funding expected in the 2021-2026 period for each Italian municipality and by mission/submission.

We integrated the NRRP data by municipality with data on value added per employee for each Italian municipality (year 2021) available from Local SBS FRAME, the statistical register on local business units, from ISTAT. This framework is part of Istat's larger integrated system of registers on enterprises and local units. In fact, the information framework is the result of the integration of the basic register of local units of industry and services (Asia UL), the extended register on economic variables at the enterprise level (Frame SBS), and structural and economic information by local unit derived from data of the Survey of Local Units of Large Enterprises (IULGI).

We identified the value added per employee as a proxy for labour productivity since the purpose of this work is to verify the theoretical impact of the use of NRRP funding on the territorial productive context, particularly for the Italian macro areas (Northwest, Northeast, Center and South). Further, we investigated the impact of Mission 1 (Digitalisation, Innovation, Competitiveness and Culture), considered a “flywheel” of the digital transition in Italy.

Figure 1 shows the municipal distribution of the ratio of NRRP funds to Value Added and we can see that in southern areas this incidence is higher than in other areas of the country, particularly in Basilicata, Calabria and Campania. In the same regions, the weight of Mission 1 on business value added is higher.

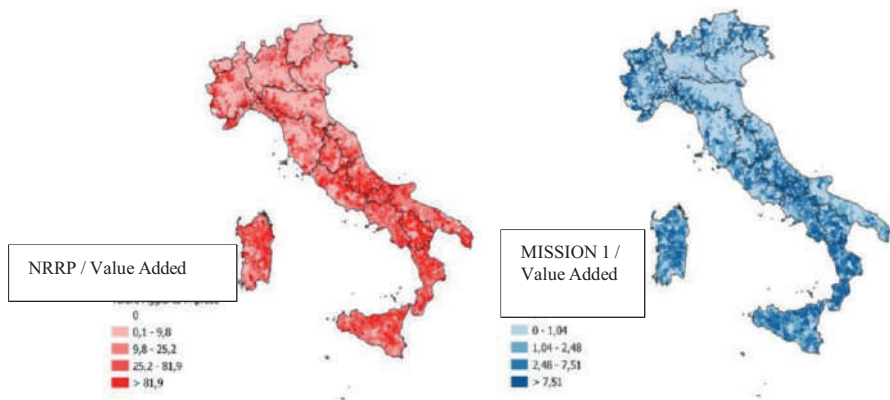


Fig. 1: Municipal distribution of *NRRP /VA* and *Mission 1/VA*. Source: Our Elaborations on ISTAT and *Italia domani* data

3 NRRP’s impact estimates by Italian Macro Areas

In order to evaluate the impact of NRRP funds on the economic context in the Italian macro areas we considered a cross-sectional model where we estimated the potential impact of NRRP funds per municipality on the labor productivity of enterprises.

The analysed model is:

$$VA_i = \alpha + \beta NRRP_i + \varepsilon_i \quad (1)$$

VA_i : value added per employee of the i -th municipality for the year 2021;

$NRRP_i$: NRRP funds for the i -th municipality for the period 2021-2026.

The estimate of coefficient β provides the potential impact of the NRRP on the value added per employee in the Italian territories.

In order to assess the impact of Mission 1 funds (Digitalisation, innovation, competitiveness and culture on productivity) we replace NRRPi with Mission M1i in the model (1):

$$VA_i = \alpha + \gamma M1_i + \varepsilon_i \quad (2)$$

M1i: NRRP mission M1 funds for the i-th municipality for the period 2021-2026;

The estimated coefficient γ provides the potential impact of the use of the NRRP funds of Mission 1 on the value added per employee in the territories.

We estimated the coefficients in the models (1) and (2) using municipalities' data in order to obtain the estimates of coefficients β and γ in the Northwest, Northeast, Center, and Southern macro areas (Table 1).

Table 1 Impact estimates of NRRP-MISSION M1 on labour productivity

FUNDS	IMPACT COEFFICIENTS per ITALIAN MACRO AREA				
	ITALY	NORTH- WEST	NORTH- EAST	CENTER	SOUTH
NRRP	19%	12%	9%	8%	22%
M 1	20%	27%	11%	25%	20%

Source: Our Elaborations on ISTAT and *Italia domani* data

The impact on the productive context for each geographical macro area is positive, but significant differences there are by both territory and mission M1. Compared to the Northeast, the Center and Italy as a whole, in the South the use of NRRP funds seems to stimulate moreover the growth of THE of enterprises' labor productivity. On the other hand, the investments in digitalisation in Mission M1 seem to have a significant impact in the North-West where the stock of human capital is historically higher. Expertise and digital skills are more persistent [7] in such local systems acting as a "driver" for further investments in Mission 1 of the NRRP.

References

1. Padoan, P.C., The priorities for the country: investments, reforms, starting with the PNRR, and support for participation in the labor market, *Economia Italiana*, 2024, vol. n. 2.
2. Country Report 2020 – Italy, European Commission, SWD (2020) 511 final, 26 February 2020.
3. Il Piano Nazionale di Ripresa e Resilienza, *Italia Domani*, 2021.
4. Documento di Economia e Finanza, DEF, MoF, 2022; 2023, 2024.
5. L'economia italiana torna alla bassa crescita?, *Rapporto di Previsione - Centro Studi Confindustria*, 2023.
6. D'Auria F., Pagano A., Ratto M., Varga J. (2009), "A comparison of structural reform scenarios across the EU member states: Simulation-based analysis using the QUEST model with endogenous growth", *European Economy, Economic Papers* No. 392, ECFIN.
7. Digital Economic and Society Index 2022 Osservatorio Digitale del Politecnico di Milano. <https://www.osservatori.net/agenda-digitale/report-posizionamento-regioni-province-autonome-desi-regiona-le-2022/>

Assessing the spatial impact of the ‘display the average fuel prices’ obligation in Italy

Riccardo D’Alberto

Abstract This study explores the impact of the mandatory display of average fuel prices at gas stations in Italy, implemented on August 1st, 2023. Using daily price data at municipal level, the analysis examines the effects on fuel prices transparency and volatility by employing a panel event study design. Results show no statistically significant changes in fuel prices, except for Liquefied Petroleum Gas.

Key words: fuels, price transparency, Italian municipalities, event study

1 Introduction

Fuel prices in Italy are affected by a complex interplay of global and local factors (e.g., global market conditions, geopolitical instability, national policies) leading to a significant volatility. Recently, the latter has been exacerbated by several causes. First, the impact of the COVID-19 pandemic. Its global effects and the lockdown led to a significant drop in global energy consumption. Particularly, in March-May 2020, mobility restrictions led to a decrease in fuel consumption [1], followed by a gradual recovery characterized by subsequent shocks in fuel prices [5]. Second, in late 2021, inflation and the energy crisis triggered the fuel prices (also, they increased due to the imported energy costs). Third, the geopolitical tensions generated by the war in Ukraine and the subsequent economic sanctions and restrictions on, e.g., Russian gas imports intensified the energy crisis. These shocks affected all the European countries (although to different extents), but Italy is especially vulnerable to energy crises, having peculiar energy market dynamics. For example, a heavy reliance on imported fossil fuels (particularly, Russian gas): in 2021, 93.7% of gas consumed in Italy was imported, with 38% of imports coming from Russia [7]. Finally, we must consider the price structure and governments intervention: fuel prices

Riccardo D’Alberto
University of Verona, e-mail: riccardo.dalberto@univr.it

to the consumer are comprised of *i*) the cost of the raw material, *ii*) taxes, *iii*) system charges, plus *iv*) refining and distribution costs.

The Italian debate on fuel ‘costs’ is vivid and the governments have often pursued different solutions to mitigate them. For example, in 2007, the Italian Parliament imposed the display of fuel prices on electronic signs along highways, aiming to increase transparency and promote competition among gas stations. This measure led to an average reduction of 1 cent of Euro per liter in gasoline prices, which represented approximately 20% of gas station margins [8]. Effects were long-lasting (around 16 months after the policy implementation) with little on price dispersion [8]. In 2022, in response to rising fuel prices, the Italian Government implemented several measures, including tax reductions on fuel and VAT, as well as bonuses for low-income families and tax credits for businesses. However, these interventions have mostly been short-term compensatory measures, without addressing the structural causes of Italy’s energy dependency [7].

In March 2023 the Italian Government adopted by Decree (abbreviate legislative procedure) the obligation to display the average fuel prices (per Region – NUTS2¹) at the gas stations alongside their own prices. The Decree was published in the Official Gazette of the Italian Republic in May 22nd and became effective in August 1st (i.e. mandatory communication to the Ministry of Enterprises and Made in Italy – MIMIT of the daily fuel prices adopted at the gas station, mandatory display of the average regional price, controls at random and ad hoc fines). The obligation was intended by the Government to mitigate price speculation and promote price transparency. A dedicated online platform for communicating the price of gasoline, diesel, Liquefied Petroleum Gas (LPG) and methane gas (CNG, LNG, GNL) was set up by the MIMIT as well as the mandate for controls and specific fines. Using daily price data retrieved and assembled from MIMIT plus additional statistics from the Italian National Institute of Statistics (ISTAT), the present study aims to estimate the impact of the ‘display the average fuel prices’ obligation at the municipal level in years 2023-2024.

2 Data and methods

2.1 Data

Daily prices data from gas stations, along with Italian gas stations registry data (including gas station owner, brand, address, etc.), were retrieved from [6], considering only the ‘road’ gas stations (i.e. excluding from the analysis the highway gas stations). The variables of interest are *date* (every day from January 1st, 2023 to September 30th, 2024); (daily) *price* for different types of fuels (gasoline, diesel, LPG and methane gas); *self*, indicating if the fuel service is automatic (1) or served

¹ Cf. the Nomenclature of territorial units for statistics (NUTS) at <https://ec.europa.eu/eurostat/web/nuts> [accessed December 14th, 2024]

(0); *municipality*. Additional covariates (*nuts2*, *municipality_population*, *municipality_area* in km², *altitude* above sea level) as well as shape files data on municipal and regional borders were retrieved from [3, 4].

Considering both the analysis purposes and the practical issues imposed by data dimensionality, data were subsetting by the 4 types of fuel and each fuel type data set was then split between automatic and served gas stations. Data were also wrangled to build up balanced panels at the municipality level (daily gas station prices were averaged per municipality). Panel data count observations for 638 days and vary according to the coverage of gas stations at the Italian national level as well as due to data completeness, coherence and correctness. Namely, (out of the 7,896 Italian municipalities) we observe $n = 4,604$ municipalities related to served gasoline stations ($n = 5,292$ for automatic ones); $n = 4,592$ municipalities related to served diesel stations ($n = 5,289$ for automatic ones); $n = 2,179$ municipalities covered by LPG gas stations and $n = 979$ related to methane gas stations.

2.2 Method

Each panel covers the municipality m at the time period t . The ultimate goal is to estimate the impact of the occurring event e_{mt} (i.e. the obligation to display the average fuel prices) the 1st of August 2023 (denoted as ‘treatment’). The outcome variable of interest $price_{mt}$ is the average municipal price for the municipality m at time period t . The panel event study specification (cf. [2]) is then

$$price_{mt} = \alpha + \sum_{j=2}^J \beta_j (\text{Lag } j)_{mt} + \sum_{k=1}^K \gamma_k (\text{Lead } k)_{mt} + \mu_m + \lambda_t + X'_m \Gamma + \varepsilon_{mt},$$

with μ_m , λ_t municipality and time fixed effects, X_m time-invariant covariates to control for, ε_{mt} unobserved error term. The lags and leads of interest with respect to the event (the subscript t of e is dropped due to the fact that all the municipalities become treated after the treatment period of the event) are defined as

$$\begin{aligned} (\text{Lag } J)_{mt} &= \mathbb{1}[t \leq e_m - J], \\ (\text{Lag } j)_{mt} &= \mathbb{1}[t = e_m - j], \text{ for } j \in \{1, \dots, J-1\}, \\ (\text{Lead } k)_{mt} &= \mathbb{1}[t = e_m + k], \text{ for } k \in \{1, \dots, K-1\}, \\ (\text{Lead } K)_{mt} &= \mathbb{1}[t \geq e_m + K]. \end{aligned}$$

Lags and leads indicate the exposure of the municipality to a number of time periods away from the event of interest (*before* and *after* the event occurred).

3 Results and discussion

We consider $j = 72$ lags and $k = 30$ leads, assuming, from one hand, the hypothesis of an ‘anticipation’ effect corresponding to the time of Decree publication on the Official Gazette and, from the other hand, one month of duration of the potential effects of the policy.

Results show, for all the four types of fuel (as well as for the two typologies ‘automatic’ and ‘served’ of gasoline and diesel), non-statistically significant anticipation effects (joint tests for anticipation effects show non statistically significant p-values at 10% level) up to the 7 days before the 1st of August 2023 (the day of the Decree effectiveness). However, no statistically significant effects related to the potential reduction (or mitigation) of the fuel prices are found, except for LPG which, during the second week of Decree effectiveness, shows a mean reduction equal to -0.0121 euro (p-value < 0.05). These results hint at the fact that the ‘display the average fuel prices’ policy generated no tangible effects. However, two main issues must be further explored methodologically: the seasonality characteristics of fuel prices as well as the heterogeneity of prices within the Italian regions (and provinces). Additional research should be dedicated to exploring **i)** the suitability of the analysis on different statistical units (municipality vs individual gas stations); **ii)** the robustness of the estimates; **iii)** the treatment effect(s) on the potential outcome (mean price vs price volatility or deviation from the regional mean price); **iv)** the spatial effect of the treatment, given that volatility of prices can be influenced by regional differences in fuel prices and gas stations sensitiveness to location at borders.

References

1. Alfano, V., Capasso, S.: Fuelling the pandemic: The impact of fuel prices on COVID-19. *Case Studies on Transport Policy* **18**, 101314 (2024)
2. Freyaldenhoven, S., Hansen, C., Shapiro, J.M.: Pre-event trends in the panel event-study design. *Am. Econ. Rev.* **109**, 3307–3338 (2016)
3. Italian National Institute of Statistics: Confini delle unità amministrative a fini statistici. <https://www.istat.it/notizia/confini-delle-unita-amministrative-a-fini-statistici-al-1-gennaio-2018-2/>. [accessed October 20th, 2024]
4. Italian National Institute of Statistics: iStat – Banca Dati ISTAT. <http://dati.istat.it>. [accessed October 08th, 2024]
5. Kuik, F., Adolfsen, J.F., Lis, E.M., Meyler, A.: Energy Price Developments In and Out of the COVID-19 Pandemic – From Commodity Prices to Consumer. *Economic Bulletin. ECB, The European Central Bank* **4** (2022)
6. Ministry of Enterprises and Made in Italy: Carburanti – Prezzi praticati e anagrafica degli impianti. <https://www.mimit.gov.it/it/open-data/elenco-dataset/carburanti-prezzi-praticati-e-anagrafica-degli-impianti>. [accessed October 10th, 2024]
7. Nascia, L., Simone, G., Pianta, M.: Aligning Social and Climate Objectives: The Effects of the Fossil Fuel Price Crisis – The Case of Italy. In: Galgóczi, B. et al. (eds.) *Response measures to the energy crisis: Policy targeting and climate trade-offs*, pp. 1–24. ETUI, The European Trade Union Institute (2023)
8. Rossi, F., Chintagunta, P.K.: Price Transparency and Retail Prices: Evidence from Fuel Price Signs in the Italian Highway System. *J. Marketing Res.* **53**, 407–423 (2016)

Environmental awareness and its determinants: a multilevel approach

Ida D'Attoma, Marco Ieva and Mariagiulia Matteucci

Abstract The present paper develops a measure of Environmental Awareness based on item response theory to score respondents in terms of their environmental awareness. In addition, this work employs a multilevel regression model to investigate the individual and country determinants of environmental awareness, considering both individual and contextual factors.

Key words: Environmental Awareness, Multilevel model, Item Response Theory

1 Introduction

The European Commission's 2030 Climate Action Plan aims to significantly reduce greenhouse gas emissions by 2030 (EU, 2021). However, the effectiveness of the above commitment requires significant changes in consumer behaviours. Consumer pro-environmental behavior depends largely on consumers' Environmental Awareness (EA) (Golob and Kronegger, 2019). Over the past two decades, academic research has sought to define and measure EA, leading to the development of numerous metrics. However, two main gaps emerge in previous academic studies. First, few studies have measured EA by adopting an international perspective, particularly within Europe (e.g. Bassi et al., 2023): the available measures of EA are mostly country-specific and developed in the United States (Diamantopoulos et al.,

Ida D'Attoma
University of Bologna, e-mail: ida.dattoma2@unibo.it

Marco Ieva
University of Parma, e-mail: marco.ieva@unipr.it

Mariagiulia Matteucci
University of Bologna, e-mail: m.matteucci@unibo.it

2003). Second, few studies have focussed on the determinants of EA both at the country and individual level. Previous studies were not able to also consider the country contextual factors that can influence the development of EA in each country. To address the above gaps, the present paper develops a measure of EA based on item response theory to score the respondents in terms of their EA by means of a latent variable. In addition, this work employs a multilevel regression model to investigate the individual and country determinants of EA, considering the hierarchical data structure (respondents are nested in countries).

2 EA: measures and determinants

EA can be defined as the understanding of multiple environmental issues and related indicators that need to be measured to leverage good practices with the final goal to protect the environment (Dabbous et al., 2023). EA is a general construct that involves opinions, concerns, and different perspectives related to environmental issues (Dabbous et al., 2023). Due to its complexity, multiple measures of EA have been developed in previous studies. Moreover, given the importance of EA in guiding pro-environmental behavior, research has focused on its key determinants. Previous studies have shown that multiple variables can influence EA, namely demographic characteristics at both individual and household levels (e.g., gender, age), social factors (e.g., culture belief), psychological factors, economic factors and contextual factors (e.g., Peisker, 2023). Most studies in this stream of literature only consider a few contextual variables in isolation without controlling for effects driven by determinants at the individual or household level (Peisker, 2023). For instance, with reference to the contextual factors, EA is reported to be positively driven by income level, by a more equal distribution of income and a less greenhouse gas-intensive industrial sector (Peisker, 2023). In light of the aforementioned gaps, the present work aims to develop a new measure of EA and to focus on its determinants considering both the individual and the contextual level. Specifically, we develop our framework by relying on contextual theory with a multilevel approach (Hox and Roberts, 2010), that provides a theoretical rationale supporting the role of both contextual and individual factors in shaping the development of attitudes and behaviours. Therefore, we consider the country as the context of reference, and we include as determinants of EA several country level variables together with individual characteristics.

3 Data

The study utilizes Eurobarometer 92.4 (EB 92.4) data, which surveys European citizens' attitudes toward the environment. The EB 92.4 survey includes responses from 27,498 individuals across 28 EU Member States, allowing for a robust analysis

of environmental attitudes and behaviors in Europe. The analysis focuses first on assessing environmental awareness through items categorized under four dimensions: Affective, Cognitive, Active, and Dispositional. These items explore various aspects of individuals' perceptions, behaviors, and attitudes toward environmental issues using Likert-type scales. Then, the individual-level factors include: age, occupation, marital status, gender, education, type of community, difficulty paying bills, internet use, social class, life satisfaction. The country-level covariates are the followings: GDP per Capita Based on Purchasing Power Parity, The Index of Economic Freedom, Per Capita CO2 Emissions and Carbon Intensity per Unit of GDP.

4 Methodology

The study employs a two-step approach to analyze environmental awareness. In the first step, the graded response model (GRM; Samejima, 1969), based on item response theory (IRT), is used to estimate item properties (e.g., discriminatory power) and respondents' scores on the environmental awareness (latent variable). The probability of endorsing a response category $P(Y_i = k|\theta)$ is calculated as:

$$P(Y_i = k|\theta) = P_{ik}^*(\theta) - P_{i(k+1)}^*(\theta), \quad (1)$$

where:

$$P_{ik}^*(\theta) = P(Y_i \geq k|\theta) = \frac{\exp[a_i(\theta - b_{ik})]}{1 + \exp[a_i(\theta - b_{ik})]} \quad (2)$$

is the operating characteristic curve. Here:

- a_i : Discrimination parameter, which indicates the item ability to distinguish between individuals with different latent trait levels.
- b_{ik} : Threshold parameters, which represent the ability level needed for a 0.5 probability of endorsing category k or higher.

In the second step, multilevel models are used to explore the relationship between environmental awareness (dependent variable) and covariates, accounting for the hierarchical structure (respondents nested within countries).

The empty model is expressed as:

$$Y_{ij} = \mu + u_j + \varepsilon_{ij}, \quad (3)$$

where Y_{ij} is the dependent variable (score) for the first-level unit i belonging to the second-level unit j , with $i=1, \dots, n_j$ and $j=1, \dots, J$ clusters, μ is the overall mean, u_j is the between-clusters (or second-level) error, and ε_{ij} is the within-clusters (or residual) error.

The random-intercept model integrates individual-level covariates ($x_1, \dots, x_p$) and country-level covariates ($w_1, \dots, w_r$) and is written as:

$$\begin{cases} Y_{ij} = \beta_{0j} + \beta_1 x_{ij1} + \dots + \beta_p x_{ijp} + \varepsilon_{ij} \\ \beta_{0j} = \gamma_{00} + \gamma_{01} w_{j1} + \dots + \gamma_{0r} w_{jr} + u_{0j} \end{cases} \quad (4)$$

This two-step approach combines the GRM to analyze ordinal data with multilevel models to investigate individual and country-level determinants of environmental awareness.

5 Preliminary results

The study utilized the GRM to estimate item parameters, including discrimination (a) and threshold (b) parameters, to measure EA. The model was estimated using Marginal Maximum Likelihood and the EM algorithm via the mirt R package. The respondents' scores for EA were derived using the Expected A-Posteriori method. The discrimination parameter (a) indicates how well each item differentiates between individuals with varying levels of EA. Higher values of a suggest that an item has a stronger ability to distinguish between subjects with different levels of EA. For instance, certain items had relatively high discrimination parameters (around 2.5-3.1), indicating that they are more sensitive in capturing differences in EA. The threshold parameters (b_1 , b_2 , b_3) reflect the level of EA required for individuals to move from one response category to another. Items with lower threshold values indicate that it is easier to select higher categories for these items, suggesting these items might address less challenging aspects of environmental awareness. The findings show that certain items in the environmental awareness questionnaire are more effective at distinguishing between individuals' levels of awareness, with specific thresholds indicating the difficulty of moving between response categories. The multilevel analysis demonstrated that most of the variance in environmental awareness is due to individual-level factors, though country-level effects are still significant. Variables related to economic and environmental factors, such as GDP and CO2 emissions, were found to influence EA, highlighting the role of socio-economic and environmental contexts in shaping environmental consciousness.

References

1. EU (2021). Stepping up Europe's 2030 climate ambition Investing in a climate-neutral future for the benefit of our people, <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0562>
2. Diamantopoulos, A., Schlegelmilch, B. B., Sinkovics, R. R., & Bohlen, G. M. (2003). „Can socio-demographics still play a role in profiling green consumers? A review of the evidence and an empirical investigation.” *Journal of Business Research*, 56(6), 465-480.
3. Golob, U. and Kronegger, L. (2019). “Environmental consciousness of European consumers: A segmentation-based study”, *Journal of Cleaner Production*, 221: 1-9”.
4. Bassi, F. (2023). “European consumers' attitudes towards the environment and sustainable behavior in the market.” *Sustainability*, 15(2), 1666.
5. Dabbous, A., Horn, M., & Croutzet, A. (2023). “Measuring environmental awareness: An analysis using google search data”. *Journal of Environmental Management*, 346, 118984.
6. Peisker, J. (2023). “Context matters: The drivers of environmental concern in European regions”. *Global environmental change*, 79, 102636.
7. Hox, J. J., & Roberts, J. K. (2011). “Multilevel analysis: Where we were and where we are.” In *Handbook of advanced multilevel analysis* (pp. 3-11). Routledge.
8. Samejima, F. (1969). “Estimation of latent ability using a response pattern of graded scores”, *Psychometrika Monograph Supplement*, 34, 100–114.

Evaluating European Regional Policy using a Spatial Approach

Marusca De Castris and Guido Pellegrini

Abstract In this study, we evaluate the impact of Structural and Cohesion Funds (SF) on regional economic growth, considering spatial interactions among regions and variations in policy intensity. We propose a novel methodology for estimating the unbiased “net” effect of SF, based on a new “spatial GPS” technique that compares treated and untreated regions experiencing similar spillover effects from SF impact. The results show that the net effect of SF on regional growth, when considering spatial interactions with neighboring regions, is lower than the gross effect. This is because such interactions generally amplify the impact of European Regional Funds.

Key words: Generalized Propensity Score, spatial dependence, European Regional Policy

1 Introduction

Policy evaluation literature often overlooks spatial externalities, despite regional policies aiming to boost growth, employment, and investment while generating spillovers across firms, industries, and territories. Accounting for neighbouring regions is essential when assessing these policies, particularly in the European context. This paper evaluates European regional policy within a counterfactual framework, considering both direct and indirect spatial effects. EU transfer intensity

Marusca De Castris
Roma Tre University, e-mail: marusca.decastris@uniroma3.it

Guido Pellegrini
Sapienza University of Rome, e-mail: guido.pellegrini@uniroma1.it

varies widely, from less than 1% to over 10% of regional GDP (Pieńkowski & Berkowitz, 2015).

Since the Rubin Causal Model (Rubin, 1974) assumes no interference between treated and untreated units, it is unsuitable for policies with spatial interactions. This study develops an alternative approach that incorporates spatial effects.

The analysis builds on the generalized propensity score (GPS) method (Becker, 2012), which enables the estimation of a Dose-Response Function (Hirano & Imbens, 2004; Imai & Van Dyk, 2004; Flores et al., 2012; Bia & Mattei, 2012; Cerulli, 2012; Kluve et al., 2012; Wu et al., 2024), capturing variations in marginal treatment effects across different treatment levels.

1.1 The method and empirical strategy

This framework for continuous treatment follows Hong and Raudenbush (2013). The potential outcome (Rosenbaum and Rubin, 1983) for region i depends on both its own treatment intensity (T_i) and that of other regions (T_{-i}):

$$Y_i(T) = Y_i(T_i, w_i Y_{-i}(T_{-i})) \quad (1)$$

where Y_i is the outcome, T_i is a continuous treatment (ranging from 0 to $T_{\max}$, w_i is a spatial weight. If $T_i > T_j$, the “net” effect of increasing T from T_i to T_j is given by:

$$E[Y_i(T_i, w_i Y_{-i}(T_{-i})) - Y_i(T_j, w_i Y_{-i}(T_{-i})) | T] \quad (2)$$

Estimating this effect is complex. Without spatial interference, the Generalized Propensity Score (GPS) (Hirano & Imbens, 2004) is commonly used:

$$Y_i = Y_i(T_i) \quad (3)$$

where the conditional density of treatment given pre-treatment covariates X is:

$$r(T; X) = f_{T|X}(T|X) \quad (4)$$

The GPS, defined by $r(T, X)$ adjusts for differences between treatment levels. However, spatial interference requires incorporating spillovers, meaning units are matched based on neighboring covariate levels. We define the Spatial GPS (S-GPS) as:

$$R_i = r(T_i; X_i; w_i X_{-i}) \quad (5)$$

where the unconfoundedness assumption ensures independence between potential outcomes and treatment:

$$Y_i(T_i) \perp T_i | X_i, w_i X_{-i} \text{ for all } t \in T \quad (6)$$

This adjustment ensures that within strata of $r(T, X)$, the probability of T is independent of both individual and neighboring covariates.

We estimate the conditional expectation of the outcome:

$$E[Y | T=t, R=r] = E[Y(t) | r(t, X)=r] = \beta(t, r) \quad (7)$$

as a function of treatment level (T) and GPS (R). The probability of an observed treatment being assigned is independent of X_i once conditioned on R . Averaging over the marginal distribution of $r(T, X)$ gives the dose-response function:

$$\mu(t) = E[E[Y(t) | r(t, X)]] \quad (8)$$

This allows causal inference by comparing $\mu(T)$ for different values of T . Our model uses a cubic approximation:

$$E[Y | T; R] = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 T_i^3 + \alpha_4 R + \alpha_5 R^2 + \alpha_6 R^3 + \alpha_7 T^*R \quad (9)$$

Our dataset includes 200 regions from EU15 countries, excluding overseas territories but including Eastern Germany. Covariates include GDP (PPP), employment, population, investment (NUTS-2), education levels, and structural indicators. The treatment variable is the percentage of Structural Funds (2000–2006) relative to regional population.

To account for spatial dependence, we estimate an S-GPS using a binary spatial weights matrix W . Regions are contiguous if their centroids are within 350 km. This matrix, symmetric with zero diagonals, captures spatial spillovers by incorporating the spatial lag of treatment and covariates (investment, employment, education in 2000).

2 Results

We estimate the dose-response functions following Bia and Mattei (2008). The non-spatial GPS includes multiple covariates, all displaying expected signs and statistical significance. In the spatial GPS, we additionally incorporate the spatial lag of yearly public funds, the service sector, the share of highly educated individuals, and fixed capital.

Using the generalized propensity score, we derive the dose-response functions (Figures 1 and 2) and compute the marginal treatment effects for both non-spatial and spatial cases (Table 1).

Table 1 Marginal effects of the European Regional Policy treatment

<i>Treatment Percentile</i>	<i>Treatment Intensity</i>	Marginal effects without interference		Marginal effects with interference	
		<i>dy/dT</i>	<i>Std error</i>	<i>dy/dT</i>	<i>Std error</i>
1 st	9.5	-.000220	.000574	-.000240	.0005479
5 th	12.8	-.000181	.000543	-.000197	.0005194
10 th	14.7	-.000159	.000526	-.000172	.0005033
25 th	22.4	-.000075	.000458	-.000077	.0004415
50 th	32.1	.000023	.000381	.000033	.0003695
75 th	85.1	.000411	.000155	.000470	.0001346
90 th	208.4	.000336	.000249	.000440	.0002318
95 th	253.7	-.000035	.000240	.000047	.0002550

The policy impact is heterogeneous across different levels of treatment intensity. The results suggest that spatial interference amplifies treatment effects at higher

intensities while having minimal influence at lower levels. Extremely low and high levels of treatment intensity may not generate significant benefits, possibly due to diminishing returns or confounding interference.

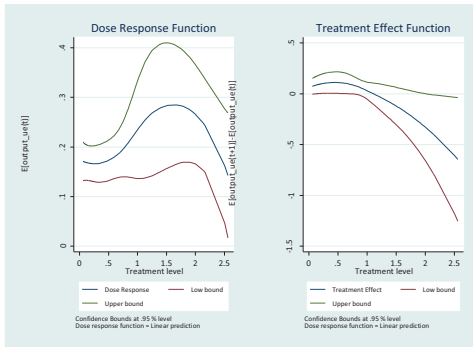


Fig. 1 Estimates without interference

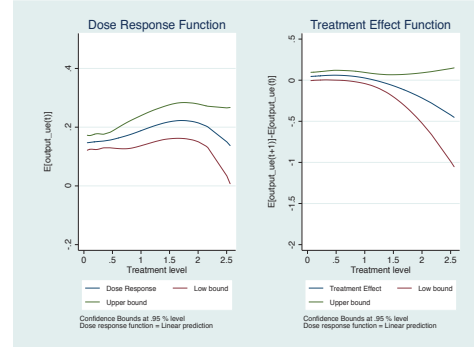


Fig. 2 Estimates with interference

References

1. Bia, M., and Mattei, A. A Stata package for the estimation of the dose–response function through adjustment for the generalized propensity score, *The Stata Journal*, 8, 3, 354–373, (2008).
2. Bia, M., and Mattei A. Assessing the effect of the amount of financial aids to Piedmont firms using the generalized propensity score. *Statistical Methods & Applications*: 21, 485-516, (2012).
3. Cerulli, G. Identification and estimation of treatment effects in the presence of (correlated) neighborhood interactions: Model and Stata implementation via ntreatreg. *The Stata Journal*, 17 (4): 803-833, (2015).
4. Hirano, K. and Imbens, G. W. The propensity score with continuous treatments. In *Applied Bayesian Modeling and Causal Inference from Incomplete-data Perspectives* (eds A. Gelman and X. Meng). New York: Wiley, (2004).
5. Hong, Guanglei, and Stephen W. Raudenbush. Heterogeneous agents, social interactions, and causal inference. *Handbook of causal analysis for social research*. Dordrecht: Springer Netherlands, 331-352, (2013).
6. Imai, Kosuke, and David A. Van Dyk. Causal inference with general treatment regimes: Generalizing the propensity score. *JASA* 99.467: 854-866, (2004).
7. Kluge, J., Schneider, H., Uhlendorff, A., & Zhao, Z. Evaluating continuous training programmes by using the generalized propensity score. *J R Stat Soc Ser A: Statistics in Society*, 175(2), 587-617, (2012).
8. Pieńkowski J. and Berkowitz P. Econometric assessments of Cohesion Policy growth effects: How to make them more relevant for policy makers? Regional Working Paper 2015, European Commission, WP 02/2015, 1-16, (2015).
9. Rosenbaum, P.R., Rubin, D.B., The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70, 1, 41-55, (1983).
10. Wu, Xiao, et al. Matching on generalized propensity scores with continuous exposures. *JASA* 119.545, (2024): 757-772.

The Effect of Covid-19 on Risk Aversion: Evidence from the SHARE Survey

Desiré De Luca and Giorgio Tassinari

Abstract Traditionally, risk preference is assumed to be stable over one's life, while recent studies have reported that individuals' risk tolerance can be altered by exogenous shocks, such as natural disasters: but with discordant results about the direction of the effect, increase/decrease in risk aversion or tolerance. In this study, we investigated the impact of Covid-19 on financial risk preferences by elderly Europeans in the context of household finance. The analysis uses data from the Survey of Health, Ageing and Retirement in Europe (SHARE) combined with the history of Covid-19 collected with a special survey during the outbreak of disease, the SHARE Corona survey. To identify the causal effect of the virus on risk preferences we apply a difference-in-differences strategy. We document that individual who experienced Covid-19 became more risk-tolerant.

Key words: Risk Preferences, Covid-19, Household Finance, Europe, SHARE

1 Introduction

Traditional economic theories assume that individuals' risk preference is stable over time, although there is growing evidence that such stability is a mere theoretical assumption. Indeed, a growing economic literature finds that individuals' risk tolerance can be altered by exogenous shocks, such as natural disasters, violent conflicts, and financial crises [1]. In this vein, numerous studies have examined the impact of the Covid-19 outbreak on risk tolerance [2]. However, the results of previous studies are mixed and inconclusive. Therefore, the lack of consensus in the Covid-19 literature both indicates the continued usefulness of studies similar to ours. The aim of this paper is to contribute to this literature by analyzing the impact of

Desiré De Luca
University of Calabria, e-mail: deluca@unical.it
Giorgio Tassinari
University of Bologna, e-mail: giorgio.tassinari@unibo.it

exposure to Covid-19 on financial risk perceived by older Europeans as they control a large fraction of society's resources and thus their investment decisions can have broader macroeconomic implications.

In order to estimate the causal effect of the Covid-19 incidence on individuals' risk preferences, we use data from the Survey of Health, Ageing and Retirement in Europe (SHARE), a multidisciplinary and cross-national panel study, which is conducted to collect data about the health and living situation of the 50+ population in Europe. We combine questions from the waves from the pre- and post-pandemic with the history of Covid-19 collected by a special survey during the outbreak of the pandemic. The specific information on the Covid-19 history makes our study unique and allows us to construct an accurate measure of exposure to the virus, compared with previous studies, that have used the mortality rate, as a measure of exposure to the disease [5]; or regional variation in infection rates [4].

With the goal to study the causal effect of Covid-19 virus exposure on individuals' risk preferences, we apply a difference-in-differences (DiD) method. This approach removes biases in post-Covid-19 period comparisons between the treatment (those who have experienced virus) and control group (those who have not experienced virus) that could be the result from permanent differences between these groups, as well as biases from comparisons over time in the treatment group that could be the result of trends due to other causes. Our results suggest that exposure to Covid-19 virus influences individuals' risk preferences, whereby those who experienced the disease became more risk tolerant after the pandemic.

2 Data

The study was conducted on a panel dataset covering the period from 2013 to 2022, and data were obtained from wave 5 to wave 9 of the SHARE. From this data we construct our outcome variable, which measures individual risk preferences. In addition, taking advantage of the longitudinal dimension of the survey, we supplement SHARE with information on the contraction of the virus that we recover from a special questionnaire, SHARE Corona Survey (SCS), designed to collect information about the consequences of the pandemic in two rounds. The first SCS was fielded between June and August 2020, and the second SCS one year later, between June and August 2021. Therefore, we construct an accurate measure of exposure to the Coronavirus, which is equal to 1 if the respondent or someone close to him/her tested positive for the virus or had symptoms of the disease, and 0 otherwise.

3 Identification Strategy and Results

In order to estimate the causal effect of the Covid-19 on the individuals' risk behavior, we employ a generalized DiD framework. To this end, we fitted the following empirical model:

$$level_risk_{it} = \beta_0 + \beta_1 Time_t + \beta_2 Covid_19_i + \beta_3 (Time_t \cdot Covid_19_i) + \beta'_4 X_i + \gamma_i + \delta_c + \theta_t + u_{it} \quad (1)$$

where $level_risk_{it}$, denotes the individual i 's risk preferences, in year t ; no_risk is equal to 1 if respondents report taking no financial risk and 0 otherwise; $high_risk$ is equal to 1 if respondents declare to be willing to take a substantial or an above the average risk, and 0 otherwise; $medium_risk$, takes value 1 if respondents declare to be willing to take an average financial risk, and 0 otherwise. $Time_t$, is a dummy variable equal to 1 for year after the Covid-19 outbreak, and captures time effects; the variable $Covid_19_i$ (*treatment*) accounts for the exposure of the virus and switches on for the treated group, and captures constant differences in composition between the two groups; the coefficient β_3 associated with the interaction term $(Time_t \cdot Covid_19_i)$, indicates the estimated causal effect of Covid-19 virus on the outcome, and is the key coefficient of interest in the analysis. Then, X_i is a vector of the basic socio-demographic variables that may influence individuals' risk preferences (age, gender, marital status, level of education, occupation, income). The parameters γ_i , δ_c , θ_t , represent individual, country, and time-fixed effects, respectively; and u_{it} , is the error term. Before proceeding with the estimates, to ensure the validity of the results we verify that the parallel trend hypothesis is valid by exploiting visual inspection, which we omit for brevity. Results reported in Table 1 column 1 show that the interaction term $Time \cdot Covid_19$ is negative and statistically significant at the 10% level, indicating that exposure to the virus decreased risk aversion. Moreover, columns 2 and 3 suggest that Covid-19 modifies the individuals' risk tolerance; in particular, exposure to the virus tends to increase the probability that individuals begin to be inclined to invest and not simply save. In other words, the pandemic has made people more risk tolerant but not risk takers. In fact, we can see that the Covid-19 pandemic does not have a statistically significant impact on the propensity to choose very risky investments.

Table 1 Effect of exposure to Covid-19 on Financial Risk Preferences: DiD

	(1) No risk	(2) High Risk	(3) Medium Risk
Time	-0.338*** (0.126)	1.041*** (0.223)	0.171 (0.137)
Covid_19	-0.111*** (0.0395)	0.173** (0.0728)	0.0968** (0.0465)
<i>Time</i> • <i>Covid_19</i>	-0.236* (0.126)	0.0335 (0.230)	0.298** (0.151)
Constant	0.0370 (0.202)	-1.572*** (0.430)	-0.306 (0.245)
Obs	21,791	17,042	20,734

Notes. Table 1 displays the DiD results. All regressions control for socio-demographic variables and include individual, country, and time FE. Robust standard errors, clustered at the individual level are in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To check the robustness of our results, we use a different specification for the *treatment* variable, namely the $Symptoms_i$ variable, which is equal to 1 if the

respondent or someone close to him/her had symptoms of the disease, and 0 otherwise. This specific indicator allows us to capture the influence of disease, regardless of the outcome of the test. Indeed, symptoms are a manifestation of disease evident to the patient himself, while a test is a manifestation of disease perceived by others. The results obtained are very similar and confirm the positive effect of virus exposure to individual risk propensity.¹

4 Conclusions

In conclusion, our results suggest that elderly Europeans who have directly experienced Covid-19 virus modulate attitudes toward risk, increasing their individual risk tolerance.

These findings are in line with the economic literature on attitudes and risk-taking behaviors in relation to life-threatening events, which argues that particularly stressful experiences can alter the attitudes toward risk of those who experience them, who enact different behaviors than they would normally.

Overall, the analysis provides new and useful insights into the risk behavior of the older households in Europe, since this segment of the population is growing and controls a large fraction of society's resources, so their investment decisions may have broad macroeconomic implications.

References

1. Bäckman, S. B., Brown, M., Fisman, R., Heimer, R., Keloharju, M., & Pursiainen, V. (2020). Risk taking during a global crisis: Evidence from Wuhan. *Covid Economics*, 5, 106-146.
2. Gassmann, X., Malézieux, A., Spiegelman, E., & Tisserand, J. C. (2022). Preferences after pandemics: Time and risk in the shadow of COVID-19. *Judgment and Decision making*, 17(4), 745-767.
3. Guiso, L., Sapienza, P., & Zingales, L. (2008). Trusting the stock market. *the Journal of Finance*, 63(6), 2557-2600.
4. Mineyama, T., & Tokuoka, K. (2024). Does the COVID-19 pandemic change individuals' risk preference?. *Journal of Risk and Uncertainty*, 1-20.
5. Scherpenzeel, A., K. Axt, M. Bergmann, S. Douhou, A. Oepen, G. Sand, K. Schuller, S. Stuck, M. Wagner, A. Börsch-Supan (2020). Collecting Survey Data among the 50+ Population during the COVID-19 Outbreak: The Survey of Health, Ageing and Retirement in Europe (SHARE). *Survey Research Methods* 14 (2): DOI: 10.18148/srm/2020.v14i2.7738.
6. SHARE-ERIC (2024a). Survey of Health, Ageing and Retirement in Europe (SHARE) Wave [5-9]. Release version: 9.0.0. SHARE-ERIC. Data set. DOI: 10.6103/SHARE.[w5-w9].900

¹ Estimates are omitted for brevity, but are available upon request.

A non-parametric approach to employee performance in digital workplaces

Fabio Demaria, Maddalena Cavicchioli, Tommaso Fabbri, Ariadni Papan Dagiasis and Anna Chiara Scapolan

Abstract The digital transformation has enabled the detailed and real-time datafication of work activities, allowing organizations to analyze and understand digital work performance. This study introduces a data-driven methodology that leverages an unsupervised Random Forest-based algorithm to cluster observations, identify key features using tree topology metrics, and visualize results with optimized graphical tools. We applied the proposed framework to data from a digital consulting agency, incorporating metadata from Microsoft365 and survey responses on work attitudes. The analysis produced a novel metric for digital work performance, which was linked to employee attitudes using tailored visual tools to explore the relationships between work activities and attitudes in digital workplaces.

Key words: Unsupervised Random Forest, Clustering, Variable Importance, Variable Interaction, Visual tools, Digital work.

1 Introduction

The digitalization of work involves the reorganization of social and professional relationships through digital technologies, leading to *work datafication*, where every digital activity generates data and metadata. This process, further accelerated by the recent Covid-19 pandemic, enables the digital representation of work behaviors, making employee activities observable and analyzable through time-stamped logs [1]. These data can be utilized to develop appropriate metrics for tracking and monitoring employee behavior and to investigate how such metrics are influenced

Fabio Demaria

University of Modena and Reggio Emilia, e-mail: fabio.demaria@unimore.it

Maddalena Cavicchioli

University of Modena and Reggio Emilia, e-mail: maddalena.cavicchioli@unimore.it

Tommaso Fabbri

University of Modena and Reggio Emilia, e-mail: tommaso.fabbri@unimore.it

Ariadni Papan Dagiasis

Cleveland State University, e-mail: a.papanadagiasis@csuohio.edu

Anna Chiara Scapolan

University of Modena and Reggio Emilia, e-mail: annachiara.scapolan@unimore.it

by employees' attitudes. In fact, according to extant literature, attitudes are deemed relevant predictors of employee work behavior. Thus, in this work, we formulate two research questions (RQs):

RQ1. *How can employees' digital work performance be synthesized into a series of work-related metrics derived from the analysis of employee metadata?*

RQ2. *How does employees' digital work performance influence their work-related attitudes?*

This study employs a data-driven approach based on unsupervised Random Forests (RF), integrating inductive and deductive methodologies, to uncover patterns in digital work environments [2].

2 Data and methods

The sampling frame for this study encompasses the entire organizational workforce ($n=39$) of a small Italian firm operating in the field of AI solutions and applications for business. The company operates in a fully digital work environment where nearly all activities are conducted via the Microsoft365 platform. The final dataset comprises two primary sources of data: (1) 35 click variables from Microsoft365, collected between October 2021 and May 2022, and (2) 93 attitude variables obtained through a self-administered questionnaire distributed in May 2022. For the click variables (1), data were collected and anonymized from the Microsoft365 platform, which records time-stamped logs of employees' activities within the system. Examples of the extracted metrics include the "highest number of daily actions performed by the user outside working hours", "maximum number of projects a user engages with in a single day", and "total number of meetings attended by the user". The attitude variables (2) were measured through an online survey using a 7-point Likert scale, ranging from strongly disagree to strongly agree. The survey assessed various work-related attitudes, including job satisfaction, embeddedness, engagement, work-related stress, work-life interface, organizational communication, and innovative behavior. These dimensions were derived from established scales and validated frameworks in the literature [3, 4, 5].

2.1 Methods

Machine learning encompasses supervised and unsupervised approaches, with the latter focusing on discovering structures in data without predefined target variables [6]. By leveraging RF's ensemble learning techniques [7], unsupervised RF generates a proximity matrix that allows clustering, feature selection, and the identification of nonlinear interactions in a fully nonparametric way, outperforming conventional clustering methods [7, 8]. The sidClustering algorithm, introduced by Mantero and Ishwaran [8], extends Breiman's Random Forest (RF) methodology [7] to unsupervised learning by transforming raw data through "*sidification*". In this process, original features are transformed into main effects $\mathbf{Y} = (Y_1, \dots, Y_d)^T$ and interaction features $\mathbf{Z}$. The main effects are computed as $Y_j = \delta_j + X_j$ and $Y_k = \delta_k + X_k$, where $\delta_j, \delta_k > 0$ ensure positivity and distinctness. Interaction features $\mathbf{Z}$ are then derived

as pairwise products of the main effects ($X_j \star X_k = Y_j \times Y_k$). These features are used in a multivariate RF model to predict the main features $\{\mathbf{Y}_i\}_{i=1}^n$, and the resulting forest distance is computed using the tree topology. For two observations $\mathbf{Z}_i$ and $\mathbf{Z}_j$, the forest distance $D(\mathbf{Z}_i, \mathbf{Z}_j)$ is defined as:

$$D(\mathbf{Z}_i, \mathbf{Z}_j) = \frac{1}{B} \sum_{b=1}^B \frac{S(\mathbf{Z}_i, \mathbf{Z}_j, T_b)}{R(\mathbf{Z}_i, \mathbf{Z}_j, T_b)}, \quad (1)$$

where $S(\mathbf{Z}_i, \mathbf{Z}_j, T_b)$ and $R(\mathbf{Z}_i, \mathbf{Z}_j, T_b)$ represent the number of splits between the terminal nodes of $\mathbf{Z}_i$ and $\mathbf{Z}_j$, relative to a common ancestor and the root, respectively. Feature importance is assessed using *minimal depth*, which represents the *first-order* maximal subtree and measures the distance of a variable v from the root of the tree [9]. Variables with smaller minimal depths are considered more predictive. Interactions are quantified by constructing *second-order* maximal subtrees, where normalized minimal depths indicate the strength of interaction between variables. These results are aggregated into a $p \times p$ interaction matrix $\mathbf{\Gamma}$, with diagonal entries representing variable importance and off-diagonal entries quantifying pairwise interactions. Lastly, visualization tools like heatmaps and network plots are used to visualize the results. To improve their interpretability a *seriation* algorithm was applied to $\mathbf{\Gamma}$. The algorithm assigns a weight w_{ij} to each pair of objects $i, j \in n$, incorporating variable importance (θ_1) and interaction (s_{ij}), to determine the optimal arrangement that positions high-interaction variable pairs close to each other in the plot. The weighting scheme is defined as:

$$w_{ij} = \lambda_1 \theta_1 + \lambda_2 \min_{i \neq j} s_{ij}, \quad (2)$$

where λ_1 and λ_2 are scaling factors. This systematic reordering enhances the visualization of high-interaction variable pairs, significantly improving the interpretability of the visual tools.

3 Results

The sidClustering analysis identified two distinct employee clusters: the *Operational* group, characterized by higher scores in action-related variables reflecting technical roles, and the *Coordination* group, marked by greater engagement in meeting-related activities and relational centrality, indicative of managerial roles. Variable importance was assessed using the minimal depth criterion, identifying the 10 most important features using the mean of the minimal depth distribution as threshold [9]. Results are presented in Table 1. These variables were categorized into two dimensions: *Quantity* (e.g., number of actions, meetings attended) and *Complexity* (e.g., number of departments, centrality measures). Work quantity reflects the volume and intensity of tasks performed, while work complexity captures the heterogeneity and adaptability of activities. Key findings highlight the significance of action- and meeting-related variables in distinguishing employee behaviors. A weighted arithmetic mean, using importance scores as weights, was calculated for each dimension to construct composite indicators for further analysis. Lastly, as a final step, we investigated the relationship between employee attitudes and the digital work scores of Quantity and Complexity within each cluster, using the optimized visual tools to facilitate exploration and interpretation of the results.

Table 1 Minimal depth rank and variable weights.

Variable name	Category	Description	Min. depth	Weight
n.meet	Quantity	Total number of meetings the user attended.	4.322	1
avg.act	Quantity	Average number of actions taken by the user in a workday.	4.392	0.939
w_avg.meet	Quantity	Average number of weekly meetings in which the user participated.	4.414	0.920
n.out	Quantity	Total number of actions performed by the which user outside working hours.	4.420	0.915
d.out	Quantity	Average number of actions taken by the user in a working day outside working hours.	4.438	0.899
n.act	Quantity	Total number of actions (any type) taken by the user.	4.450	0.889
hrs.meet	Quantity	Total hours of meetings the user attended.	4.482	0.861
d_avg.meet	Quantity	Average number of daily meetings in which the user participated.	4.482	0.861
d.dept	Complexity	Average number of departments a user works with on a daily basis.	4.528	0.821
p.rank.rel	Complexity	Centrality measure from 'Pagerank' algorithm: average relational pattern score among users.	4.534	0.815

4 Conclusions

The digitalization of work and the resulting datafication of work activities enable the collection of digital traces (i.e., metadata) that provide unprecedented information with the potential to inform HR theory [2]. To address the need for analyzing and interpreting these digital records, this study introduces a data-driven, unsupervised, decision tree-based methodology. This approach enables researchers to cluster observations using a tree-based distance matrix, create digital work metrics, and visually organize the results for seamless integration with additional data sources. The derived metrics can assist HR practitioners in monitoring employees' digital work and tailoring strategies for specific groups to enhance their work attitudes.

References

1. Leonardi, P.M., and Treem, J. W. (2020). Behavioral Visibility: A new paradigm for organization studies in the age of digitization, digitalization, and datafication. *Organization Studies*, 41(12), 1601-1625.
2. Kitchin, R. (2014). Big data, new epistemologies and paradigm shifts. *Big Data & Society*, 1(1).
3. Schneider, B., Hanges, P. J., Smith, D. B., and Salvaggio, A. N. (2003). Which comes first: Employee attitudes or organizational financial and market performance? *Journal of Applied Psychology*, 88, 836-851.
4. Schaufeli, W. B., Bakker, A. B., and Salanova, M. (2006). The measurement of work engagement with a short questionnaire. *Educational and Psychological Measurement*, 66, 701-716.
5. Goldberg, D. P. and Williams, P. (1988). *A user's guide to the General Health Questionnaire*. NferNelson.
6. James, G., Witten, D., Hastie, T., and Tibshirani, R. (2021). *An Introduction to Statistical Learning*. Springer US.
7. Breiman, L. (2001). Random forests. *Machine Learning*, 45, 5-32.
8. Mantero, A. and Ishwaran, H. (2021). Unsupervised random forests. *Statistical Analysis and Data Mining: The ASA Data Science Journal*, 14, 144-167.
9. Ishwaran, H., Kogalur, U. B., Gorodeski, E. Z., Minn, A. J., and Lauer, M. S. (2010). High-dimensional variable selection for survival data. *Journal of the American Statistical Association*, 105, 205-217.

Italian Spatial Price Indices: using Web scraping in an experimental analysis for electricity

Cristina Dormi, Barbara Dramis and Agostina Zanolì

Abstract The Italian National Institute of Statistics (Istat) is running a project to compute Sub-national Spatial Price Indices (SSPIs). In this paper, we present an experimental analysis to estimate SSPIs for the electricity free market Basic Heading (BH) of the ECOICOP (European Classification of Individual Consumption according to Purpose) classification. Using a web scraping procedure, on the expenditure data for standard electricity consumption from a range of power company providers, different offers were collected. SSPIs were estimated using the Regional Product Dummy (RPD) model.

Key words: web scraping, electricity prices, Spatial Price Indices, Regional Product Dummy model

1 Introduction

Sub-national spatial price indices (SSPIs) measure the differences in price levels across regions within a country at a given point of time. They express how many currency units a given quantity of goods or services costs in different areas. SSPIs are essential for comparing real income and standards of living.

As part of the Istat project aimed at calculating SSPIs, results for 5 ECOICOP expenditure divisions were published [3] and the 4th division is currently under examination. This division concerns ‘Housing, Water, Gas, Electricity and Other

Cristina Dormi
ISTAT, e-mail: dormi@istat.it

Barbara Dramis
ISTAT, e-mail: dramis@istat.it

Agostina Zanolì
ISTAT, e-mail: zanolì@istat.it

Fuel', which is important in terms of consumer expenditure and characterized by the presence of tariffs that require special treatment in the SSPIs calculation.

Among the BHs of the 4th division, in this study the focus of the experimental analysis are the electricity prices in the liberalized market for the month of December 2024.

2 Data source

Since 2019, Istat has been collecting prices for electricity in the liberalized market through web scraping procedures to calculate CPI/HICP indices [2].

The free market nowadays represents a substantial part of the electricity market in Italy, thanks also to the changes in the regulatory legislation that have encouraged liberalization.

Prices are scraped on the Portal of Offers of the Italian Regulatory Authority For Energy, Networks and Environment (ARERA)¹, referring to tariffs applied to the domestic customers of the free market divided by region, by type of contract (resident or non-resident; variable or blocked price) and by type of time slot (single-hour or multi-hour). Eight profiles (items) are defined according to the following three variables:

- ✓ Type of household: residential/non-residential; some Italian regions have a greater tourist vocation, consequently, these are the regions with the largest share of non-residents;
- ✓ Type of rate: mono/dual hourly rate;
- ✓ Type of contract: fix/variable rate.

A sample of detection units identified with a cut-off criterion is selected among the main suppliers, based on the regional market shares derived from the regulated sector survey, carried out annually by ARERA. With a regional detail; the selection considers coverage ranging from 60% to 80% of the market shares for each region. In the sample selected for 2024 there are seventy-four suppliers (collection units) and five hundred and ninety-two layers (item per region per collection unit).

Free market electricity prices are uniform across the entire national territory at company level; regional differences are due to the operators selected and the weighting system adopted.

In December 2024 the procedure was adapted for SSPIs purposes, considering the same consumption in every region, 2.700 kW. In fact, the data used in SSPIs calculation have to be comparable among regions. About 163.900 prices were

¹The online Portal of Offers provided by the Law on Competition, resolution 51/2018/R/com implementing the Italian Law No. 124 of 2017, allows comparison between fixed and variable offers of the free market, as well as the PLACET offers, the offers that all the suppliers will have to give, with pre-established and uniform contractual conditions for all the users.

scraped, but considering only the selected company for each region about 2.400 prices have been used in this experimental analysis.

3 Methodological Approach

The method used is Regional Product Dummy (RPD) model at Basic Heading (BH) level [1]. The RPD model estimates the following regression equation [4]:

$$\ln p_{nr} = \sum_{r=1}^R a_r D_r + \sum_{n=1}^N b_n D_n^* + v_{nr} \quad (1)$$

where: p_{nr} is the price of an item n ($n=1\dots N$) belonging to the BH in a region r ($r=1\dots R$) D_r are dummies for the areas (regions), D_n^* are dummies for the items, a_r e b_n are the differences in the effects associated with the areas and the item type, respectively, v_{nr} are random errors normally distributed with a zero mean and variance σ^2 .

Parameters of this model can be estimated using ordinary least squares, imposing a restriction that a coefficient corresponding to a specific area is set equal to zero ($a_r=0$) or equivalently $SSPI_i=1$ thus considering it as the reference area to which the coefficient estimates are referred.

The SSPIs between an area r and the reference area is given by $\widehat{SSPI}_r = \exp(\widehat{a_r})$. Having expenditure or quantity weights for each item, the weighted RPD model can be written as:

$$\sqrt{w_{nr}} \ln p_{nr} = \sum_{r=1}^R a_r \sqrt{w_{nr}} D_r + \sum_{n=1}^N b_n \sqrt{w_{nr}} D_n^* + \sqrt{w_{nr}} v_{nr} \quad (2)$$

where w_{nr} are the weights in terms of expenditure share that reflect the economic importance of the different commodities consumed in the area.

For electricity data, the weighted RPD model was adopted, using weights defined in the HICP calculation based on the expenditure share of each product and region.

The preliminary data cleaning consisted in detecting outliers; the method used was the calculation of the 1st and 99th percentiles and the elimination of data lower than the value corresponding to the 1st percentile and data higher than the value corresponding to the 99th percentile. For every item and region, a company could have different offers, so the geometric mean of the offers for each company, item and region was computed to obtain the mean price per company. The mean price per item was calculated as a weighted mean of the prices per company using the market share of each company provided by ARERA as weights.

4 Results

The SSPIs are presented with references to the national average (100), so when the price level index of a region is greater than 100 it means that this region is relatively more expensive than the Italian average and vice versa. If the price level index of one region is

higher than that of another region, it means that this region is relatively more expensive than the other for the product categories considered and vice versa

For the electricity-liberalized market BH, the prices per kW of electricity recorded in the northern regions are higher than those in central and southern Italy, with the exception of Lombardia where consumer price level is lower than the national average (Figure 1). Lombardia together with Lazio are the least expensive regions while Valle d'Aosta is the most expensive one.

The group of regions in southern Italy is characterized by a similar level of prices per kW due to the presence of the same representative companies. The SSPIs are systematically lower than the national average.

The same analysis was carried out considering only the PLACET offers, those mandatory for each company, obtaining similar results.

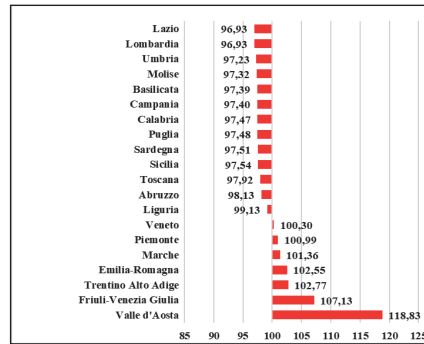


Fig. 1 SSPIs for electricity free-market BH – December 2024 – Italy=100. Source: Istat

5 Concluding Remarks

The web scraping data on electricity prices allowed us to calculate SSPIs for an important BH of the 4th Ecoicop division. The results show differences in price levels between different geographical areas.

The differences in importance of companies across geographic areas, as well as the varying weight of items at a regional level, are factors leading to this outcome. The reliability of these results will be improved by regularly collecting data via web scraping throughout 2025.

References

1. ICP: A Guide to the Compilation of Subnational Purchasing Power Parities (PPPs). World Bank (2021).
2. Istat: Indici dei prezzi al consumo: aspetti generali e metodologia di rilevazione. Edizione 2022
3. Istat: Consumer Spatial Price Indices – Year 2022, Statistica sperimentale, 21 ottobre, 2024.
4. Rao, D.S.P, Hajargasht, G.: Stochastic approach to computation of purchasing power parities in the International Comparison Program (ICP). *Journal of Econometrics*, 191(2), pp. 414-425 (2016).

Forecasting CO₂ emissions from electricity generation: comparison of methods

Pierdomenico Dutillo, Francesco Lisi and Marina Bertolini

Abstract Electricity generation strongly contributes to global carbon emissions, making accurate short-term forecasting essential for emission-based scheduling. This study compares classical and functional methods to predict short-term carbon emissions in northern Italy. Three model categories are examined: linear parametric models, such as SARIMA and SARIMAX, nonparametric and possibly nonlinear models, such as GAM, and functional models including the (S)FAR and FARX models. These models are applied to hourly carbon emission data from 2020 to 2022, with forecasts for 2023. Performance is evaluated using the hourly RMSE. The results show that the functional models perform best in the early hours, while the GAM outperforms others during the midday and evening.

Key words: CO₂ emissions forecasting, electricity generation, classical time series models, functional autoregressive models, generalized additive models

1 Introduction

Mitigating carbon emissions is a crucial challenge in the context of the green energy transition and requires considerable investments. To efficiently incorporate costs and benefits related to mitigation measures in the evaluation models, it is necessary to apply innovative approaches to model and forecast carbon emissions dynamics. In particular, accurate short-term forecasting of CO₂ is essential for emission-based

Pierdomenico Dutillo
University of Padua, e-mail: pierdomenico.dutillo@unipd.it

Francesco Lisi
University of Padua, e-mail: lisif@stat.unipd.it

Marina Bertolini
University of Padua, e-mail: marina.bertolini@unipd.it

scheduling and optimal management of energy storage systems [1, 2]. Emission-based scheduling involves shifting flexible electricity demand to periods of lower emissions. Flexible consumers can adjust their electricity use in response to carbon emissions forecasts. Moreover, by forecasting carbon emissions, energy storage systems, such as batteries, can be charged during low-emission periods and discharged during high-emission times. This approach also alleviates grid congestion, improving the efficiency of the electrical system [3, 4]. Consequently, carbon emission calculations can be included as an assessment tool to support incentive and taxation policies for businesses and consumers in general, particularly when evaluating flexibility strategies.

To optimise flexible electricity consumption, several methods have been proposed in the literature to model and forecast carbon emissions [5, 6]. This study compares classical and functional methods to forecast short-term carbon emissions in the northern Italian electricity market. Specifically, three categories of models are examined: linear parametric models, such as the seasonal autoregressive integrated moving average (SARIMA), with the possibility of incorporating exogenous variables (SARIMAX) to account for multiple seasonal patterns; nonparametric models, such as generalised additive models (GAM), which may capture nonlinear relationships; and parametric functional models, including the seasonal functional autoregressive (S)FAR and functional autoregressive with exogenous inputs (FARX) models. The functional approach treats the daily CO₂ profile as a continuous curve, providing a more detailed view of the dynamics of the emissions between the standard measurement intervals. The models were fitted to data covering the period from 1 January 2020 to 31 December 2022. The predictions were then analysed for 2023, with a day ahead horizon. Forecast accuracy was evaluated using the root mean square error (RMSE) at discretised 24-hour intervals. The rest of the paper is organised as follows: Section 2 introduces the emission data and the setup of the models, and Section 3 presents the forecast results.

2 Data and model setup

Carbon emissions from electricity generation [7], E_t , are calculated as follows

$$E_t = \sum_{i=1}^I E_{t,i}, \quad (1)$$

$$E_{t,i} = G_{t,i} \times EF_i \times O_i \times M,$$

where $E_{t,i}$ denotes the CO₂ at time t for fuel type i , $G_{t,i}$ represents the hourly electricity generation in the northern Italian day-ahead market at time t by fuel type i , EF_i is the country-specific emission factor for fuel type i , O_i is the oxidation rate for fuel type i , and M is the ratio of the molecular weight of CO₂ to the atomic weight of carbon. Electricity generation data are obtained from entsoe.eu, covering a 3-year period from 1 January 2020 to 31 December 2023. The data is recorded

with an hourly frequency over 24 hours and 7 days a week. Since E_t is affected by multi-seasonality, the following variables are considered: T_t representing a continuous time index for each time instant t ; W_t an indicator variable for the day of the week at time t ; D_t representing the specific day of the year at time t ; H_t is an indicator variable for the hour at time t .

The SARX(1)₂₄ model is specified as follows

$$E_t = \omega + \phi_1 E_{t-1} + \theta_1 E_{t-24} + \alpha_1 W_t + \alpha_2 D_t + \eta_t \quad (2)$$

where: ω represents the intercept, ϕ_1 is the autoregressive coefficient for lag 1, θ_1 is the seasonal autoregressive coefficient for lag 24, α_1 quantifies the impact of the day of the week on E_t , α_2 quantifies the impact the day of the year on E_t , and η_t represents the error term.

Let $\mathcal{H}$ be a real separable Hilbert space and consider the continuous-time carbon emissions process E_t defined in $\mathcal{H}$. The FARX(1) model is specified as:

$$E_t = \rho_1(E_{t-1}) + \alpha_1(W_t) + \alpha_2(D_t) + \varepsilon_t, \quad \text{for } t \in \mathbb{N}, \quad (3)$$

where: ρ_1 , α_1 , and α_2 are bounded linear operators in $\mathcal{H}$; W_t and D_t are continuous exogenous variables defined in $\mathcal{H}$; ε_t is a $\mathcal{H}$ -valued white noise process. The linear operator ρ_1 quantifies the influence of the lagged emission curve E_{t-1} , while α_1 and α_2 account for the effects of weekly and yearly seasonal variations, respectively.

The GAM model is defined by

$$E_t = \omega + f_1(T_t) + f_2(W_t) + f_3(D_t) + f_4(H_t) + f_5(E_{t-1}) + \varepsilon_t, \quad (4)$$

where: ω is the intercept; $f_1(T_t)$ is a smoothing spline function that models the long-term behavior over time; $f_2(W_t)$ and $f_4(H_t)$ are indicator functions accounting for the weekly and hourly seasonalities; $f_3(D_t)$ is a seasonal smoothing spline function that captures the seasonal variation across the year; $f_5(E_{t-1})$ models short term dependence on carbon emissions; ε_t is the error term. Additional models are also considered: AR(1), SAR(1)₇, SAR(1)₂₄, FAR(1), SFAR(1)₇, and TBATS.

3 Forecasting results

We used data from January 1, 2020, to December 31, 2022 to estimate models, while the whole of 2023 is left for out-of-sample predictions. The models are reestimated daily, incorporating the latest available data. Out-of-sample predictions are evaluated by calculating the hourly RMSE. The results are shown in Figure 1. The “M-shaped” pattern of the RMSE is supported by the daily pattern of the hourly sample standard deviation (SD). For the early hours (1 to 4), the FAR(1) and FARX(1) models consistently produce relatively lower RMSE. During the daytime, afternoon and evening hours (5 to 21), the GAM model outperforms others, yielding a lower RMSE. However, for the nighttime hours (22 to 24), the FAR(1) and FARX(1) mod-

els regain their leading position. Classical time series models are overtaken by functional and GAM models. This pattern highlights the importance of choosing the appropriate forecasting model based on the time of day, with FAR(1) and FARX(1) being strong contenders for early and late hours, while GAM performs better in the midday and evening periods. As a possible solution, forecast combinations could be explored to take advantage of the strengths of each model in different time intervals.

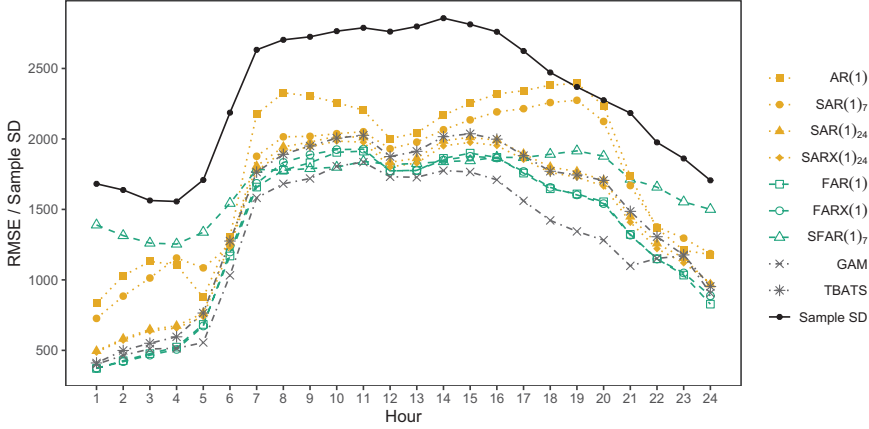


Fig. 1 Root mean square error (RMSE) of CO₂ emissions predictions in Northern Italy, with the solid black line representing the hourly sample standard deviation (SD) of CO₂ emissions.

Acknowledgements This study was funded by the European Union - NextGenerationEU, Mission 4, Component 2, in the framework of the GRINS - Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 - CUP C93C22005270001). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

References

1. Leerbeck, K., Bacher, P., Junker, R. G., Goranović, G., Corradi, O., Ebrahimi, R., Tveit, A., and Madsen, H.: Short-term forecasting of CO₂ emission intensity in power grids by machine learning. *Appl. Energy*. **277**, 115527 (2020).
2. Bokde, N. D., Tranberg, B., Andresen, G. B.: Short-term CO₂ emissions forecasting based on decomposition approaches and its impact on electricity market scheduling. *Appl. Energy*. **281**, 116061 (2021).
3. Geng, Z., Conejo, A. J., Chen, Q., and Kang, C.: Power generation scheduling considering stochastic emission limits. *Int. J. Electr. Power Energy Syst.* **95**, 374-383 (2018).
4. Zhang, D., Wang, Y., Xi, L., Deng, F., Deng, Z., Liu, J., and Wei, Z.: Low-carbon and economic flexibility scheduling of power system with multiple generation resources penetration. *Front. Energy Res.* **10**, 18 January 2023.
5. Lau, E.T., Yang, Q., Forbes, A.B., Wright, P., and Livina, V.N.: Modelling carbon emissions in electric systems. *Energy Convers. Manage.* **80**, 573-581 (2014).
6. Jin, Y., Sharifi, A., Li, Z., Chen, S., Zeng, S., and Zhao, S.: Carbon emission prediction models: A review. *Sci. Total Environ.* **927**, 172319 (2024).
7. Bertolini M., Dutillo P., and Lisi F.: Accounting carbon emissions from electricity generation: a review and comparison of emission factor-based methods. 2024. Available at: <https://arxiv.org/abs/2411.13663>.

Modelling inefficiency in multi-output spatial stochastic frontiers for cultural and creative industries: a methodological proposal

Silvia Emili and Federica Galli

Abstract: The aim of analyzing the significant role of some sustainability-related factors in determining the efficiency level of Italian cultural and creative sectors raises a set of methodological issues. In this proposal, we develop a system of simultaneous stochastic frontier models with inefficiency determinants, spatio-temporal effects and dependent error components.

Key words: Multi-output stochastic frontier models, Spatial and temporal dependence, Inefficiency determinants, Cultural and creative industry

1 Introduction

The cultural and creative sectors (CCS) are among Europe's most dynamic industries, significantly contributing to economic growth and stability (4.7% of the EU's GDP in 2022), job creation, and social cohesion. CCS is inherently marked by spatial and temporal dynamics [4] and has a distinct multi-sectoral, multi-product structure [3]. Unlike sectors like manufacturing or agriculture, CCS products and services are deeply rooted in the social and cultural attributes of specific regions, such as cultural sites, tourism amenities, and local characteristics, making them particularly unconventional in production and trade. This unique nature underscores the development of ad-hoc techniques for production analysis of CCS, particularly for identifying sustainable drivers of efficiency [3]. This study focuses on how eco-

Silvia Emili
University of Bologna, e-mail: silvia.emili2@unibo.it

Federica Galli
University of Bologna, e-mail: federica.galli14@unibo.it

nomic, social and environmental sustainable local factors influence the efficiency mechanisms of Italian CCS regional production, differentiating between core cultural and cultural and creative industries (CCI) (see Measuring CCS Consortium's Final Report, 2022, available at <https://www.measuring-ccs.eu/the-measuring-ccs-consortium-publishes-the-final-report>). To reach this goal, we propose a copula-based estimation approach for a system of dynamic spatial stochastic frontier (SF) models with inefficiency determinants and dependence between the inefficiency and/or the random error terms of the different frontiers.

2 Methodological Proposal

The multi-output SF system for R sectors is defined as

$$\mathbf{B}z_t = \Psi W z_t + \Gamma W z_{t-1} + \mathbf{P}z_{t-1} + (X_t \otimes I_M)\Pi + v_t - u_t \quad t = 1, \dots, T \quad (1)$$

with $v_t \sim \mathcal{N}(0_{Rn \times 1}, \Sigma_v \otimes I_n)$ and $u_t \sim \mathcal{N}_R^+((d_t \otimes I_R)\Upsilon, \Sigma_u \otimes I_n)$, for n units and T time periods. In Eq.(1) z_t represents the $(nR \times 1)$ vector of production outputs of the M sectors observed at time t , and W is an $(nR \times nR)$ matrix with R^2 $(n \times n)$ spatial weight matrices. Parameters associated with mutual impacts among the R output variables are collected in $\mathbf{B} = (B \otimes I_n)$, with block-diagonal entries equal the identity matrix. Matrices $\Psi = \Psi \otimes I_n$ and $\Gamma = \Gamma \otimes I_n$ are referring to simultaneous and temporal lagged spatial terms, and $\mathbf{P} = P \otimes I_n$ collects autoregressive effects. X_t is an $(n \times k)$ matrix of input factors with associated parameter vector Π ($Rk \times 1$). The system is specified such that intra-sectoral effects are collected in the main block diagonal of all parameter matrices, while off-diagonal blocks relate to inter-sectoral impacts. Moreover, following [1], the mean of the inefficiency error term (μ_t) is modelled as a function of m exogenous inefficiency determinants d_t collected in a $(n \times m)$ matrix with $(Rm \times 1)$ associated parameter vector Υ .

The joint PDF is derived based on two main assumptions: first, the independence between u_t and v_t , and second, the independence of the error components among the R equations. Then, the convolution of the two error terms is the product of u_t and v_t marginal distributions, restricting the covariance matrices to be diagonal. Covariance terms in Σ_v and Σ_u are handled separately from Σ_v and Σ_u through correlation parameters estimated by means of copula techniques. Under standard regularity conditions, the associated ML estimator is consistent, asymptotically efficient and normal. Results of Monte Carlo experiments with $R = 2$, $n = 20$, and $T = 30, 50$ indicate that all parameters are consistently estimated, with increasing precision as the temporal dimension increases.

3 Empirical Model

We consider balance sheets data on Italian core cultural and CCI industries (AIDA Bureau Van Dijk database) from 2013 to 2022 at the NUTS-2 level and different indicators from "Benessere equo e sostenibile" dataset of the Italian National Institute of Statistics (ISTAT). The existence of possible spatial clusters is tested by Moran's I tests on value added of core and CCI industries separately in 2021, finding significant (even if weak) correlation (0.09 for the core sector, 0.07 for CCI, and 0.10 for cross-sectoral dependence) at 1% significance level.

The empirical model is given by a system of two Cobb-Douglas production functions augmented by spatial and temporal terms, cross equation (inputs and mutual) effects and an inefficiency model. The outcome z_t is proxied by the logarithm of value added by region, while input factors L_t and K_t , collected in X_t in (1), are the logarithm of number of workers and fixed asset of the same (intra-sectoral) and other sector (inter-sectoral). The spatial weight matrix W is given by a combination of first and second-order binary contiguity row-normalized spatial matrices, the former on off-diagonal blocks of W , and the latter on the main diagonal (ensuring identification and leading to distinguish between intra and inter sectoral transmission channels [2]). The model for inefficiency mechanisms is defined as $\mu_t = (Eco_t \otimes I_2)Y_1 + (Social_t \otimes I_2)Y_2 + (Envir_t \otimes I_2)Y_3$ for $u_t \sim \mathcal{N}_2^+(\mu_t, \Sigma_u)$, where Eco_t is the average disposable income per capita, $Social_t$ is the percentage of municipalities with entirely online services, and $Envir_t$ the percentage of electricity from renewable sources.

4 Results

Estimated short and long-run marginal effects of input factors and inefficiency determinants are presented in Table 1.

The direct effects of the input variables indicate that, in the short run, the core group is influenced only by inputs from its own sector. In contrast, CCI is significantly and positively affected also by investments from the core group. This also applies to indirect effects, although with lower magnitude. The direct impacts of inefficiency determinants are all negative and significant in the short run, contributing to reduce the inefficiency levels of both groups, with the exception of the social sustainability factor. Focusing on indirect effects, instantaneous positive spillovers from the sustainability determinants of neighbouring regions tend to vanish in the long run for the core sector, while those for CCI shift to competition effects.

Considering the distribution and time trend of the technical efficiency scores by group, we observe a remarkable difference in the efficiency degrees of the two groups, with the core group reaching lower efficiency levels (0.87 on average, with a downturn during 2020), and the CCI excellent results (0.95, stable over time).

Table 1 Marginal effects of inputs (upper panels) and inefficiency determinants (lower panels).

		Core cultural		CCI	
		Direct	Indirect	Direct	Indirect
Short	L_{core}	0.33 ***	0.13 **	0.63 ***	0.04 ***
	L_{CCI}	-0.01	-0.00	0.29 ***	0.11 *
	K_{core}	0.13 ***	0.05 ***	0.32 ***	0.02 ***
	K_{CCI}	0.01	0.00	0.40 ***	0.15 ***
Long	L_{core}	0.10 ***	-0.06 ***	0.11 ***	-0.03 ***
	L_{CCI}	-0.00	0.00	0.09 ***	-0.05 ***
	K_{core}	0.04 **	-0.02	0.06 ***	-0.02 ***
	K_{CCI}	0.00	-0.00	0.12 ***	-0.07 ***
Short	Eco	-0.07 **	-0.03 **	-0.12 ***	-0.01 ***
	$Envir$	-0.09 **	-0.03 **	-0.16 ***	-0.01 ***
	$Social$	-0.01	-0.00	-0.04	-0.00
Long	Eco	-0.02 **	0.01	-0.02 ***	0.01 **
	$Envir$	-0.02 **	0.02	-0.03 ***	0.01 ***
	$Social$	-0.00	0.00	-0.01	0.00

Note: *:p-value $\leq$ 0.10; **:p-value $\leq$ 0.05; ***:p-value $\leq$ 0.01

5 Conclusion

We proposed a multi-output spatial SF with dependent errors and inefficiency determinants for modelling the regional production of Italian core cultural and CCI industries and their inefficiency mechanisms. Results depict significant cross-sectoral input effects (especially from core to CCI), and the key role of economic and environmental sustainability factors on the efficiency level of both sectors.

Acknowledgements This study was supported by Ministero dell'Università e della Ricerca PRIN 2022 grant 2022M87K4F: "Towards local development through a sustainable valorization of cultural heritage".

References

1. Battese, G.E., Coelli T.J.: A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empir Econ* 20(2), 325–332. (1995)
2. Elhorst, J.P., Emili, S. A spatial econometric multivariate model of Okun's law. *Reg Sci Urban Econ*, 93, 103756. (2022)
3. European Commission: Recovery and Resilience Scoreboard. url: <https://ec.europa.eu/economy-finance/recovery-and-resilience-scoreboard>. (2024)
4. Le Blanc, A.: Cultural districts, a new strategy for regional development? The south-east cultural district in Sicily. *Reg Stud* 44(7), 905–917. (2010)

Catastrophic Health Expenditure: heterogeneity among Regions and citizenship

Maria Rosaria Ferrante, Lorenzo Mori and Silvia Pacei

Abstract We analyze Catastrophic Health Expenditure (CHE) across Italian regions, distinguishing between Italians and foreigners. CHE serves as an indicator of a household's capacity to manage healthcare costs without financial hardship. Despite free public healthcare, long wait times frequently drive individuals to opt for private services, thereby increasing the risk of CHE. Our findings, based on a Beta zero-inflated SAE-GAMLSS model, reveal substantial disparities between Italians and foreigners, underscoring a paradox in Italy's universally accessible healthcare system.

Key words: Health Budget Share, GAMLSS, Out-of-Pocket Payments

1 Introduction

Healthcare systems often rely on household expenditure data to assess financial challenges faced by different population groups. One critical metric is Catastrophic Health Expenditure (CHE), which focuses on households that must divert resources from basic needs to cope with healthcare costs [1]. CHE is typically defined as occurring when Out-of-Pocket (OOP) healthcare payments exceed a certain percentage of a household's income or expenditure. This study focuses on estimating CHE across Italian regions, differentiating between native Italians and foreign res-

Maria Rosaria Ferrante
University of Bologna, e-mail: maria.ferrante@unibo.it

Lorenzo Mori
University of Bologna, e-mail: lorenzo.mori7@unibo.it

Silvia Pacei
University of Bologna, e-mail: silvia.pacei@unibo.it

idents. Understanding patterns for sub-national domains is crucial for identifying inequalities and informing targeted policy interventions in healthcare [2].

The Italian healthcare system, although universally accessible, has some critical issues. Long wait times in public healthcare services often push households towards private alternatives, increasing their financial burden and the likelihood of CHE [3]. Distinguishing CHE between Italians and foreigners provides insights into the inclusivity and effectiveness of the healthcare system, as foreign households may face additional barriers due to socio-economic, monetary and integration factors.

The estimation of the CHE at regional level using the Italian Household Budget Survey (HBS, 2019) distinguishing between Italians and foreigners requires us to use a Small Area Estimation (SAE) model given that direct estimates, obtained using sample weights, are not reliable for the considered domains. The SAE model that we adopt is based on the Generalized Additive Models for Location, Scale and Shape (SAE-GAMLSS) and assume a zero-inflated beta distribution [4, 5]. The necessity for a zero-inflated model is particularly relevant as a non-ignorable percentage of sample units has a OOP health expenditures equal to 0.

This study's findings offer valuable insights into the limitations and disparities within Italy's healthcare system, and may guide efforts to reduce inequities and improve access for all population groups.

2 Estimating the CHE through SAE Models

In small area estimation, a finite population Ω with N units is distributed into J sub-population $\Omega_1, \dots, \Omega_J$, called domains or areas of size $N_1, \dots, N_J$, where $N = \sum_{j=1}^J N_j$. We identify the target variable with Y_{ij} for unit $i = 1, \dots, N_j$ in area $j = 1, \dots, J$. The units belonging to the sample part of the population are denoted by $i \in s$ with an observed target variable y_{ij} for $i = 1, \dots, n_j$ and $j = 1, \dots, J$, where n_j is the sample size for the j -th area and $n = \sum_{j=1}^J n_j$. The units belonging to the non-sample part of the population are denoted by $i \in r$. The target small area parameter is denoted by $H_j = \zeta Y_j$ where $\zeta \cdot$ is a real measurable function and $Y_j^T = Y_{1j}, \dots, Y_{ij}, \dots, Y_{N_j,j}$.

Given the aim to compute the mean of CHE for a given area j ($\overline{CHE}_j$), the dependent variable Y_{ij} is the household budget share for health expenditure, and $\zeta \cdot$ is a function that computes the mean over a certain area of a transformation (t_{ij}) of Y_{ij} ,

$$\overline{CHE}_j = \frac{1}{N_j} \sum_{i=1}^{N_j} t_{ij} \quad \text{where} \quad t_{ij} = \begin{cases} 1 & \text{if } Y_{ij} \geq z \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where z is a threshold to be defined. Given the impossibility of knowing Y_{ij} and the unreliability of the Direct estimator, an estimate of $\widehat{\overline{CHE}_j}$ can be obtained using a SAE model. This involves estimating a mixed model with area specific random effects using y_{ij} for $i \in s$ and then predicting y_{ij} for $i \in r$. For the generic area j the CHE can be expressed as a weighted mean between the values of sampled units and

non-sampled ones:

$$\widehat{CHE}_j = \frac{1}{N_j} \left(\sum_{i \in s_j} t_{ij} \sum_{i \in r_j} \widehat{t}_{ij} \right), \quad (2)$$

where $\widehat{t}_{ij}$ s are obtained based on the predicted values for the non-sampled units, using the zero-inflated Beta model estimated from the observed values y_{ij} . Those values are obtained on the basis of the Monte-Carlo approximation defined for the SAE-GAMLSS by [5]. We use a zero-inflated SAE-GAMLSS model to estimate the CHE in the Italian Regions ($J = 20$) distinguishing between Italians and foreigners.

3 Catastrophic Health Expenditure: the Estimates

As previously mentioned, we consider data from the 2019 Italian HBS. Given the definition of OOP, for coherence, we decide to discard from the sample those individuals who have health insurance. By using a Direct estimator foreigners have a mean value of the Second-Order Coefficient of Variation (CV2, a version of the classical CV that is not influenced by values near 0) about 38.0% while for Italians the mean CV2 is near 7.1%. Therefore, for Italians the direct estimates are reliable while for foreigners there is the necessity for a SAE model. By using a Beta zero-inflated SAE-GAMLSS we are able to reduce the mean CV2 to 16.9%.

Figure 1 shows the regional estimates of the CHE distinguishing between Italians and foreigners. Within each group, differences among the 20 regions are present. We can immediately observe that the estimated $\widehat{CHE}$ is higher for Italians compared to foreigners. In the northern regions, the $\widehat{CHE}$ for foreigners is slightly higher than in the southern regions, whereas for Italians, there is no significant difference in $\widehat{CHE}$ between the northern and southern regions.

Among foreigners only one Region, Lazio, have a CHE higher than 10.0%, specifically 12.4%. Among Italians, no regions have a CHE smaller than 7.0%. Two of the most interesting situations are in Lazio and Calabria. Those Regions share similar situations in their health systems. As reported by the Italian Central Bank (2018), These regions, along with Molise, suffer from financial problems and a lack of efficiency in their health systems, which results in poor infrastructure, inadequate services, and long waiting times for citizens [6]. As noted in the document of the Italian Central Bank, when a Region has these types of problems, it is possible to request special help from the central state, called "Plans for Recovery in the Healthcare Sector." In Calabria around 7.0% of foreigners and 15.0% of Italians face the problem of CHE. In this case, the differences between the two groups are not negligible, and the high CHE is likely attributable to the healthcare issues faced by the region [7]. On the other hand, Lazio has, as mentioned, a very high CHE for foreigners (approximately 12.0%) and for Italians (around 15.0%). In Lazio, similarly to Calabria, the most probable reason for resorting to CHE is to bypass queues in the public sector and obtain faster healthcare in the private sector.

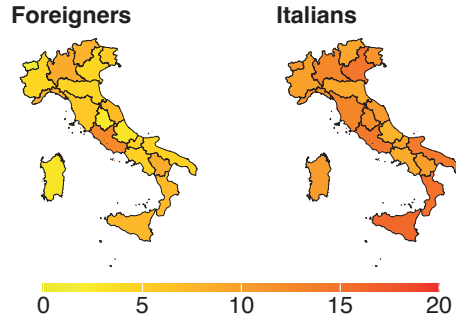


Fig. 1 Choropleth map of estimated regional CHE

References

1. Xu, K., Evans, D. B., Kawabata, K., Zeramdini, R., Klavus, J., and Murray, C. J. (2003). Household catastrophic health expenditure: a multi-country analysis. *The lancet*, 362:111–117.
2. Wang, X., Guo, Y., Qin, Y., Nicholas, S., Maitland, E., and Liu, C. (2023). Regional catastrophic health expenditure and health inequality in China. *Frontiers in Public Health*, 11:1193945.
3. Landi, S., Ivaldi, E., and Testi, A. (2021). The role of regional health systems on the waiting time inequalities in health care services: Evidences from Italy. *Health Services Management Research*, 34:136–147.
4. Rigby, R. A. and Stasinopoulos, D. M. (2005). Generalized additive models for location, scale and shape. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 54:507–554.
5. Mori, L. and Ferrante, M. R. (2024). Small area estimation of household economic indicators under unit-level generalized additive models for location, scale and shape. *Journal of Survey Statistics and Methodology*, page smae038.
6. Aimone Gigio, L., Alampi, D., Camussi, S. A., Ciaccio, G., Guaitini, P., Lozzi, M., Mancini, A. L., Panicara, E., and Paolicelli, M. (2018). The Italian healthcare system: The difficult balance between budget sustainability and the quality of services in regions subject to a financial recovery plan. Technical report, Bank of Italy Occasional Paper.
7. Lamberti-Castronuovo, A., Pine, J. A., Brogiato, G., and Kinkel, H.-F. (2021). Agricultural migrants’ health and ability to access care: A case study in southern Italy. *International Journal of Environmental Research and Public Health*, 18:12615.

A quantification of the costs and benefits of the “Green buildings” directive in two Italian regions

Lorenzo Forni, Filippo Fortuna, Elena Giarda, Francesco Giovanardi and Demetrio Panarello

Abstract This paper assesses the monetary costs and benefits of meeting the targets for 2030 and 2033 outlined in the Energy Performance of Buildings Directive (EPBD). We employ open-source microdata on Energy Performance Certificates (EPCs) for the Lombardy and Piedmont regions, which provide information on dwellings’ energy class and recommendations of the necessary retrofits to reach a higher energy class, as well as CO₂ emissions and energy consumption. We estimate a total expenditure of €118.9 billion to take Lombardy’s and Piedmont’s residential stock to at least energy class D, which is 20.2% of the two regions’ GDP and 5.6% of Italy’s GDP. Households are estimated to save yearly €3.3 billion in lower energy bills in the two regions, and CO₂-equivalent emissions are estimated to drop annually by 6.9 million tons.

Key words: Energy Performance Certificates (EPC), Energy Performance of Buildings Directive (EPBD), retrofit costs, energy efficiency

Lorenzo Forni
Prometeia and University of Padua, e-mail: lorenzo.forni@unipd.it

Filippo Fortuna
Prometeia and Pompeu Fabra University, e-mail: filofortu98@gmail.com

Elena Giarda
Prometeia and University of Modena and Reggio Emilia, e-mail: elena.giarda@prometeia.com

Francesco Giovanardi
Prometeia, e-mail: francesco.giovanardi@prometeia.com

Demetrio Panarello
Prometeia and Link Campus University, e-mail: d.panarello@unilink.it

1 Introduction

The aim of this paper is to quantify the costs and benefits associated with the implementation of energy efficiency measures in residential buildings in the North of Italy (Lombardy and Piedmont regions), by looking at the 2023 version of the Energy Performance of Buildings Directive (EPBD-2023) according to which all residential buildings have to achieve at least energy class E by 2030 and at least class D by 2033.

We provide an estimate of the costs of renovating low-efficient buildings to reach class E and then at least class D, and the associated benefits in terms of reduced CO₂ emissions and energy expenditure. This is particularly relevant since many European countries are taking action to contain their residential sector's energy usage and CO₂ emissions. In the economic literature there is limited evidence on the quantification of the costs implied by the EPBD, such as Borgarello et al. (2023) and Politecnico Milano et al. (2024).

2 The data

To perform our analysis, we employ novel open-source and almost unexploited microdata on EPCs provided by two Italian regions, Lombardy and Piedmont, covering the periods 2015-2022 and 2015-2023, respectively. The data refer only to properties with an EPC, that is, those that have been sold, rented out, have undergone major renovation, or the newly built ones, as set by the legislation.

The relevant variable for our analysis consists of the retrofit recommendations provided by the domestic energy appraiser. Recommendations contain: (i) a brief description and categorization of the recommended retrofit, (ii) the energy performance class and the global non-renewable energy performance index that the dwelling would obtain if the recommendation is implemented, (iii) an estimated return year of the investment, i.e. how many years of energy savings are needed to repay the investment required to implement the recommendation, and (iv) the performance class and the index that the dwelling would achieve if all the provided recommendations are implemented. We concentrate on four recommendations: 1. Opaque building envelope, 2. Transparent building envelope, 3. Climate control system (winter), and 4. Climate control system (summer). They make up around 90% of total recommendations.

3 The simulation exercise

Our aim is to compute the cost of switching from classes G and F to E and then to D. To this end, we look at the four selected recommendations provided by the energy appraiser

to each housing unit, and we impute the cost of the recommendations to each property belonging to the two least efficient classes. For this aim, we refer to the price listings of the first semester 2024 (the latest available) used by engineers, architects and surveyors to provide retrofit works estimates to homeowners (DEI, 2024) to which we add VAT to get final prices.

Since our objective is to estimate the overall cost of switching from classes G and F to E, and then from class E to at least class D, for the whole housing stock of Lombardy and Piedmont, we must impute a cost to the housing units not included in the EPC datasets (i.e., those for which an EPC is not available). The estimated total cost of taking Lombardy’s and Piedmont’s residential stock from classes G/F/E to at least class D is €118.9 billion, which corresponds to 20.2% of the two regions’ yearly gross domestic product (GDP) and 5.6% of Italy’s GDP. The size of this figure reveals that the financial burden of the EPBD-2023 could not be borne by the private sector only, but that it would require government intervention.

Now, we proceed to the estimation of the public and private benefits (reduction in CO₂ emissions and gains from lower electricity and gas expenditure). To this end, we look at CO₂ emissions (kg/year) and consumption of gas (m³/year) and electricity (kWh/year) associated to the buildings in the dataset. Specifically, we compare median emissions, gas consumption and electricity consumption among clusters of dwellings characterised by similar surface, construction year, dwelling type and climate zone, but with a different energy performance class. Thus, we consider the difference between the median values assigned to groups of similar dwellings at distinct levels of energy efficiency (G compared to E, F compared to E, and E compared to each higher class), determining the unitary benefits for the two regions and the three class switches (G to E, F to E, and E to at least D) as the weighted average of the calculated differences, in which the number of recommendations in each cluster for each considered class switch is taken as weight. We estimate annual savings in energy (electricity and gas) expenditure of €2.5 billion and €0.9 billion in Lombardy and Piedmont, respectively, while CO₂-equivalent emissions are estimated to drop yearly by a total of 6.9 million tons (5.2 million tons in Lombardy and 1.7 million tons in Piedmont). We also present a robustness exercise in which we assume different scenarios for electricity and gas prices.

Finally, we compare the costs and the private and social benefits to perform a simple cost-benefit analysis for an upgrade from class G to class E a class in Lombardy. The aim is to get an estimate of the breakeven year, that is how many years of future benefits are needed to compensate for the retrofit cost to be paid upfront. The private benefits are the discounted sum of the overall yearly monetary savings derived in the previous section, while the social ones are the discounted sum of the monetary value of the yearly reduction in CO₂ emissions, assuming a Social Cost of Carbon (SCC) of 805€/tonCO₂ in 2024. The

analysis shows that the social benefits dominate the private ones implying that a significant contribution of public funds would be necessary to achieve the targets of the directive. Finally, by comparing the sum of private and social benefits with the costs we estimate a breakeven year equal to 12.

4 Conclusions

In this paper, we estimate the costs and benefits associated with the implementation of the Energy Performance of Buildings Directive in two Italian regions (Lombardy and Piedmont). The 2023 version of the directive set that dwellings in energy classes G and F must switch to at least class E by 2030 and those in class E to at least class D by 2033.

The estimated total cost of implementing the directive for the two regions amounts to €118.9 billion, which is 20.2% of the total of the two regions' GDP and 5.6% of Italy's GDP. The size of this figure makes it clear that its financial burden cannot be borne by the private sector alone but requires government intervention.

The implementation of the EPBD-2023 is expected to lead to an annual reduction of CO₂-equivalent emissions of 6.9 million tons in the two regions (5.2 million tons in Lombardy and 1.7 million tons in Piedmont). Monetary private gains are computed by applying electricity and gas prices to savings expressed in kWh/year for electricity and in m³/year for gas: they amount to €2.5 billion yearly for Lombardy and to €0.9 billion for Piedmont yearly, for an annual total of over €3.3 billion.

Acknowledgments We acknowledge funding from the European Commission, Next Generation EU, Project "GRINS - Growing Resilient, INclusive and Sustainable", id code MUR PE00000018, CUP B33D22001700006 and CUP C93C22005270001.

Disclaimer The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The opinions expressed herein are our own and do not necessarily reflect those of the affiliated institutions.

References

1. Borgarello, M., Croci, L., Talamo, F., Brugnetti, E., D'Oria, F., Sabbatini, S.: Direttiva "case green": opportunità o asticella troppo alta? *Energia*, Vol. 2, pp. 62-67 (2023)
2. Politecnico Milano, Energy & Strategy, Osservatorio Energy Efficiency: Energy Efficiency Report 2024, (2024) Available at: <https://www.energystategy.it/es-download/>
3. DEI: Prezzi informativi dell'edilizia. Recupero, ristrutturazione, manutenzione. (2024) Available at: <https://www.build.it/prezzari/dei/>

Integration of statistical and administrative data for companies in the non-energy mineral extraction sector

Flora Fullone, Mirella Morrone and Donatella Vignani

Abstract The availability of statistics and indicators on the extraction of mineral resources is crucial to address the increasing scientific and institutional demand for statistical information. Non-energy mineral raw materials are essential inputs for the construction sector, industrial activities, and the transition to low-carbon energy production technologies, as outlined in key frameworks such as the UN 2030 Agenda (2015), the EU Green New Deal (2019), and the Critical Raw Materials Act (2024). The aim of this work is to assess the consistency of data for companies in the extractive sector across two Istat surveys using statistical business registers and administrative data from the Revenue Agency.

The goal is improving the quality of statistical information at the territorial level.

Key words: database interoperability, survey data, statistical business register, administrative data, integration

1 Statistical sources and administrative data

Istat produces statistical information on the extractive sector through: (i) The comprehensive Survey on Anthropogenic Pressure and Natural Risks (PSN IST 02559), which collects data on the physical extraction of minerals by lithotype and extraction site (quarries and mines). Data sources include administrative archives

Flora Fullone
ISTAT, e-mail: ffullone@istat.it

Mirella Morrone
ISTAT, e-mail: mimorron@istat.it

Donatella Vignani
ISTAT, e-mail: vignani@istat.it

from Regions, the Autonomous Provinces of Trento and Bolzano, the Provinces of Lombardy, the Mining Districts of Sicily, and local public institutions that issue authorizations for the exploitation of extraction sites. (ii) The Annual Survey on Industrial Production of manufactured goods (PSN IST 00070) which collects data on the production and marketing of a wide range of products defined annually at community level (Prodcom list).

The administrative archive Summary Reliability Indices (ISA) is acquired by the Revenue Agency. The compilation of a specific ISA form is required for companies carrying out mining activities and contains information relating to the quantities extracted and the quantities authorized for the company. There is also data from the local units. The Isa observation field does not include all extractive companies.

2 Integration analysis

The common unit of observation across the three examined sources is the extractive company. In the Cavmin Mining Database on Anthropogenic Pressure and Natural Risks, companies are identified by their VAT number, and company name. For each authorized company, data are collected at the local unit level, corresponding to extraction sites authorized by the Regions and surveyed annually by Istat. In the Prodcom Database, companies are identified with a statistical identification code, which has a one-to-one correspondence with the tax code. Data are collected for each local unit; however, in some cases, the data are provided at the company level. In the ISA, the unique identifier is the tax code which records information related to local units and reports the quantity extracted at the company level.

Micro Data Linkage procedures are applied between Istat survey microdata, administrative source, and Statistical Business Registers to obtain structural characteristics of extractive companies and to allocate the local units to the companies.

3 First results of the analysis

As mentioned above, the Cavmin survey observes the entire reference universe of extractive companies. The main objective of the experiment is to highlight the existence of declarations that are clearly contradictory between sources and to verify their degree of consistency at national and regional level. It is also useful to obtain information on extractive companies that are not currently included in the Cavmin survey database. The idea is to identify subgroups of extractive companies for each source and compare the data of individual companies for each subgroup. Specifically, each source is functionally distinguished by the subset of enterprises reporting zero or null extraction (Cavmin0; Prodcom0; Isa0) and the subset of enterprises reporting extraction activities (Cavmin1; Prodcom1; Isa1).

The subsets of most interest for integration are the intersection sets (*Cavmin1* $\cap$ *Isa1* and *Cavmin1* $\cap$ *Prodcom1*; *Cavmin0* $\cap$ *Isa1* and *Cavmin0* $\cap$ *Prodcom1*), and the difference sets (*Isa1* - *Cavmin* and *Prodcom1* - *Cavmin*).

The first step is to analyze the degree of coherence of the data provided by the enterprise declaring mining activity in the Istat surveys and in the administrative archive (*Cavmin1* $\cap$ *Isa1* and *Cavmin1* $\cap$ *Prodcom1*).

The second step is to analyze the data provided by enterprises that declare zero or null extraction in Cavmin and a not null quantity extracted in Isa or Prodcom (*Cavmin0* $\cap$ *Isa1* and *Cavmin0* $\cap$ *Prodcom1*). In addition, companies that are not included in the Cavmin survey, but which report a certain amount of minerals extracted in the other sources, appear in the difference sets (*Isa1* - *Cavmin* and *Prodcom1* - *Cavmin*).

Table 1 Comparison of subsets identified in Cavmin, Prodcom, Isa. Year 2020

Subset	Enterprises	Extracted amount	
		Source	10 ⁶ tons.
<i>Cavmin0</i>	985	Cavmin	-
<i>Cavmin1</i>	1,679 (*)	Cavmin	169.89
<i>Isa1</i>	1,449	Isa_stima1	87.4
		Isa_stima2	67.8
<i>Isa0</i>	5,761	Isa	0
<i>Cavmin</i> - <i>Isa</i>	1,508	Cavmin	108.03
		Cavmin	59.05
<i>Cavmin1</i> $\cap$ <i>Isa1</i>	790	Isa_stima1	56.2
		Isa_stima2	51.6
		Cavmin	-
<i>Cavmin0</i> $\cap$ <i>Isa1</i>	174	Isa_stima1	17.2
		Isa_stima2	15.4
<i>Isa1</i> - <i>Cavmin</i>	407	Isa_stima2	10.3
<i>Cavmin1</i> $\cap$ <i>Isa0</i>	75	Cavmin	2.6
<i>Cavmin0</i> $\cap$ <i>Isa0</i>	117	Cavmin/Isa	0
<i>Prodcom1</i> (**)	300	<i>Prodcom</i>	57.87 (***)
<i>Prodcom0</i>	0	<i>Prodcom</i>	0
<i>Cavmin1</i> $\cap$ <i>Prodcom1</i>	188	Cavmin	45.7
		<i>Prodcom</i>	48.2
<i>Cavmin0</i> $\cap$ <i>Prodcom1</i>	27	Cavmin	0
		<i>Prodcom</i>	2.4
<i>Prodcom1</i> - <i>Cavmin</i>	85	<i>Prodcom</i>	7.25

(*) Cavmin enterprises to which a statistical identifier has been assigned.

(**) Manufacturing enterprises in mining (products '08', '07') in the 2020 Prodcom survey sample.

(***) The quantities surveyed are not reported throughout the universe.

4 Conclusion

Non-energy minerals represent the most significant category in physical terms among raw materials extracted in Italy. Thematic analyses at the territorial level are crucial for designing and monitoring development policies with a focus on environmental sustainability. To adequately address these needs, this experimental data integration study aims to evaluate the benefits to the quality of statistical information on the extractive sector introduced by the interoperability of available information systems, considering their specificities (current Istat surveys and the AE Isa administrative source).

The ability to achieve complete coverage of authorized companies engaged in extractive activities will significantly enhance the territorial detail of the data.

References

1. Istat, Rilevazione Pressione antropica e rischi naturali (2024)
2. IstatData, Istat Rilevazione Annuale della Produzione Industriale Prodcop <https://www.istat.it/it/archivio/223053> (2024)
3. Agenzia delle Entrate, https://www.agenziaentrate.gov.it/portale/web/guest/modulistica_ia (2024)

Proposal of a Synthetic Measure of (E)Quality of Life Satisfaction: A Regional Perspective on Gender Disparities in Italy

Daniela Fusco, Paola Giordano, Maria A. Liguori and Margherita M. Pagliuca

Abstract. The relationship between gender and quality of life satisfaction is a complex issue with mixed findings. Some studies have found that women are more satisfied with their lives than men, whereas in others men are more satisfied. In this study, we investigated the gender disparities in quality of life satisfaction in the Italian regions. Using data from the multipurpose survey on households “Aspects of Daily Life” by Istat, this study builds a synthetic index of gender disparity in quality of life satisfaction through the AMPI methodology. This index facilitates spatial and temporal comparisons across Italian regions from 2018 to 2022, aiming to identify changes influenced by the COVID-19 pandemic. As we expected, the results showed important territorial features.

Key words: satisfaction, disparity, gender, AMPI, synthetic index

1 Introduction

Gender disparities in quality of life satisfaction are a critical topic that reflects the broader dynamics of social progress in a country. Understanding these differences

Daniela Fusco
ISTAT, e-mail: dafusco@istat.it

Paola Giordano
ISTAT, e-mail: pgiordano@istat.it

Maria A. Liguori
ISTAT, e-mail: liguori@istat.it

Margherita M. Pagliuca
University of Naples Parthenope, e-mail: margherita.pagliuca@uniparthenope.it

highlights inequalities that influence well-being, personal fulfilment, and overall societal development. As societies evolve, addressing such disparities becomes increasingly important to ensure equal opportunities and improve the quality of life for everyone. According to the Need Satisfaction Theory [7], subjective well-being is influenced by how effectively social systems and conditions meet physical and psychological needs. Given the persistent global state of gender inequality, women are expected, on average, to report lower subjective well-being than men. However, research on gender differences in satisfaction has yielded mixed results [4,5,8]. These discrepancies may be attributed to varying cultural, social, and economic contexts, which shape individuals' experiences differently. This study aimed to investigate the gender disparities in quality of life satisfaction in the Italian regions by analysing trends before and after the COVID-19 pandemic. The COVID-19 pandemic further amplified these dynamics, disproportionately affecting women due to increased caregiving responsibilities and job insecurities. As a result, understanding gender disparities in quality of life satisfaction became even more critical in the post-pandemic recovery phase [3].

2 Data source and methodology

Quality of Life Satisfaction is a complex, abstract, and multidimensional concept. Therefore, it was synthesized into a single composite index. Based on the availability of regional data, timeliness to enable time comparison, and thematic appropriateness feasibility, five simple indicators were chosen from Multipurpose survey on households "Aspects of daily life" by Istat: *Positive judgement of future perspectives*, *Leisure time satisfaction*, *Life satisfaction*, *Satisfaction with friends relations* and *Satisfaction with family relations*. The analysis covered the last 5 years (2018–2022), spanning both the pre- and post-COVID-19 periods. To synthesize the domain into a single composite index, a formative measurement model was used, where the indicators were viewed as causes of the gender gap. In line with previous studies [1,2], female-to-male ratios (R) were calculated instead of absolute levels of indicators: in this way, it was possible to capture the different forms of inequality rather than the single levels. A value $R = 1$ indicated perfect parity; a value $0 < R < 1$ indicated inequality favourable to men; a value $R > 1$ indicated inequality favourable to women. The Adjusted Mazziotta–Pareto Index (AMPI) was applied, allowing spatial and time comparisons across units [6]. It is based on a non-linear function that introduces a penalty for the units with unbalanced values of the indicators, starting from the arithmetic mean. The AMPI decomposed the score of each unit in two parts: mean level and penalty. The penalty was a function of the indicators' variability in relation to the mean value ('horizontal variability').

3 Results

On average for all indicators, men showed greater optimism than women in terms of satisfaction and positive judgment, except for family and friend relationships towards which the attitude was similar for both genders. To better analyze the phenomenon, a synthetic index for the Quality of Life Satisfaction was constructed (Fig. 1). Index values will fell approximately in the range 70-130, where 100 represented the reference value, i.e. the gender equality.

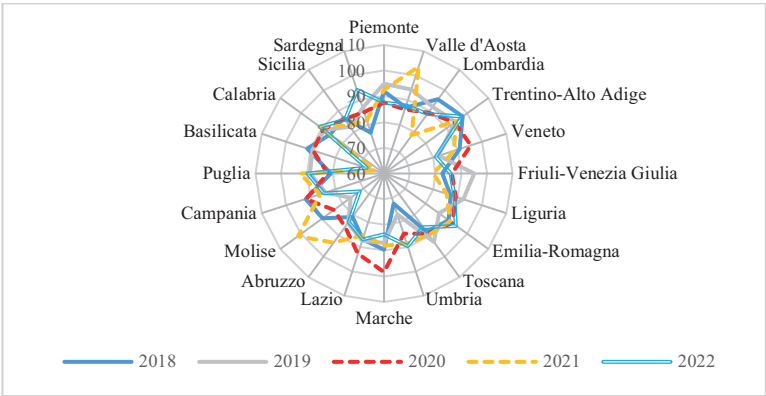


Fig. 1 Quality of Life Satisfaction Synthetic Index for Italian regions (Years: 2018-2022)

The results showed that the regions exhibited different behaviour towards COVID-19 effect. Trentino Alto Adige displayed an almost constant trend towards parity, with values ranging from 97.8 in 2018 to 97.5 in 2022. In this region, even the simplest indicators presented constant values. Trentino never reached the parity levels since women, in the period considered, had less optimism than men about their future. Emilia Romagna also reached a value close to parity (94.6) in 2022, starting from 91.1 in 2018. Marche in 2020, and only in that year, reached a value close to parity (98.4) due to a trend towards parity for all indicators. Similarly, Molise achieved a value close to 100 (101.3) in 2021, although it dropped to 71.8 in 2022 (the penultimate lowest value of 2022) due to the change in women's perspective on family and friendship relationships. Valle d'Aosta, which reached a near-equality value (103.6) in 2021, returned to its 2018 value (87.8) the following year. The value for 2021 was largely influenced by the significant satisfaction expressed by women regarding their friendship relationships. Basilicata was the region where women seemed to have suffered the most from the pandemic's impact, with the index dropping from 89.1 in 2020 to 63.8 in 2021 due to dissatisfaction with friendship and family networks. Although it recovered to 67.2 in 2022, Basilicata remained the region with the lowest index value for that year. Lombardia, where women were also more affected by COVID-19, saw its index decrease from 89.4 in 2020 to 78.3 in 2021, mainly due to the decline in the *Positive judgement of future perspectives* indicator. In Lazio, the index also decreased (from 92.8 in 2020

to 85.1 in 2021) due to greater dissatisfaction with friend and family relationships. Calabria displayed a constant trend with a moderate increase, reaching 90.9 in 2022, though still far from parity. Umbria, which had the lowest value of the equality index in 2018 (72.2), due to female dissatisfaction with life and friendship networks, showed a growth towards equality, but remained below parity (89.7 in 2022).

4 Conclusion

Considering the Quality of Life Satisfaction index, derived from its five indicators, from 2018 to 2022, consistent evidence showed that men had higher life satisfaction than women, with no significant changes during the COVID-19 pandemic.

Excluding certain cases, such as Basilicata, where women appeared to have suffered the most from the pandemic, the synthetic index results suggested a form of female resilience. Compared with other aspects of the gender gap, such as economic and job-related disparities, the Italian regions were not so far from equality during the period considered. While men remained more satisfied than women, these, despite lower wages, less executive power, and greater social burdens, were not highly dissatisfied with their lives.

References

1. Bericat, E. The European Gender Equality Index: Conceptual and Analytical Issues, *Social Indicators Research*, 108: 1–28 (2012).
2. Cascella C., Williams J., Pampaka M. An Extended Regional Gender Gaps Index (eRGGI): Comparative Measurement of Gender Equality at Different Levels of Regionality. *Social Indicators Research*, 159, 757–800 (2022).
3. Di Bella, E., Fachelli, S., López-Roldán, P., Suter, C. Measuring Gender Equality. *Social Indicators Research Series*, 87. Springer, Cham (2023).
4. Goldbeck L, Schmitz TG, Besier T, Herschbach P, Henrich G. Life satisfaction decreases during adolescence. *Qual. Life Res.* 16:969–979 (2007) <https://doi.org/10.1007/s11136-007-9205-5>
5. Jovanović V, Lazić M. Is longer always better? A comparison of the validity of single-item versus multiple-item measures of life satisfaction. *Appl Res Qual Life* (2019). <https://doi.org/10.1007/s11482-018-9680-6>
6. Mazziotta, M. Pareto, A. On a generalized non-compensatory composite index for measuring socio-economic phenomena, *Social Indicators Research*, 127, 983–1003 (2016).
7. Tay, L., & Diener, E. Needs and subjective well-being around the world. *Journal of Personality and Social Psychology*, 101(2), 354–365 (2011). <https://doi.org/10.1037/a0023779>
8. Tay L, Ng V, Kuykendall L, Diener E. Demographic factors and worker well-being: an empirical review using representative data from the United States and across the world. In: Perrewé PL, Rosen CC, Halbesleben JRB (eds) *The role of demographics in occupational stress and well-being*. Emerald Group Publishing Limited, Bingley, pp 235–283 (2014).

A decision-oriented approach to assess tourism sustainability in Italian regions

Elisa Fusco and Alessandro Magrini

Abstract We propose a two-step methodology to assess tourism sustainability in Italian regions. First, the Multi-Directional Benefit of Doubt model evaluates each region's potential for improvement in economic, social, and environmental dimensions. Second, the Directional Benefit of Doubt model incorporates the priorities of decision-makers, allowing comparisons between strategy scenarios. Unlike traditional approaches, our method: (i) derives region-specific preferences directly from the data, (ii) facilitates scenario-based assessments aligned with policy objectives, and (iii) uses longitudinal data to analyze both levels and trends of sustainability.

Key words: benefit of doubt, composite indicators, sustainable tourism

1 Introduction

Nowadays, tourism is an important driver of the economic development of territories, but its sustainability requires the implementation of effective policies to preserve natural resources and communities. For this reason, the measurement of tourism sustainability represents an essential support for decision-makers. Unfortunately, in the current literature, there are no shared agreements regarding its definition and measurement. Certainly, academic research has by now moved beyond the purely environmental perspective in favor of a holistic view, which also includes the economic and the social dimensions (see [1] for a review). The complexity of measuring tourism sustainability lies in the need for multiple indicators, whose relevance depends on the territorial scale. The local level allows for customized indicators and subjective data collection but struggles with objective data availability. Regional as-

Elisa Fusco
University of Florence, e-mail: elisa.fusco@unifi.it

Alessandro Magrini
University of Florence, e-mail: alessandro.magrini@unifi.it

assessments, while less precise due to territorial differences, offer more accessible data and greater usability for policy decisions, as national policies rely on regional data. This study evaluates tourism sustainability in Italy at the regional level, chosen for its suitability for longitudinal analysis. Italy's tourism sector, contributing over 6% to GDP, underscores the study's relevance. A Web of Science search found only four related studies in the past 15 years. All these studies have two common limitations: they assume compensability or even uniform weighting and rely on cross-sectional data. Therefore, they can neither reflect policy priorities nor assess the evolution of sustainability over time. To overcome these limitations, we consider a reasonably long temporal span, and apply a two-step methodology combining two Benefit of Doubt (BoD) models: the Multi-Directional BoD to assess each region's potential for improvement in the three dimensions of sustainability, and the directional BoD to incorporate the priorities of decision-makers.

2 Data and methodology

Data collection relied on the database of the Italian Statistical Office (ISTAT), with the objective of selecting the maximum number of indicators at the regional level that cover a reasonably long time span and all the three dimensions of sustainability: economic (ECO), social (SOC), and environmental (ENV). We obtained a dataset consisting of 14 indicators with yearly measurement in the period 2010-2019.¹ To assess tourism sustainability in Italian regions, a two-step methodology is proposed. This procedure combines two extensions of the BoD, introducing non-compensability by defining a preference structure among indicators. It allows decision-makers to explore expert-based scenarios while considering each region's efforts to reach specific empirical benchmarks. In particular, the first step involves assessing the potential improvements of each region within the economic, social, and environmental dimensions relative to an empirical benchmark, using the Multi-Directional BoD (MD-BoD - [2]) model. This method establishes a specific preference structure for elementary indicators based on the efforts required to achieve the benchmark for each indicator. The benchmark is set by proportionally adjusting each indicator to maximize potential improvement, following the principle of using the "most favourable weighting scheme in the desirable direction" ([2]). Therefore,

¹ Economic dimension: average length of stay in accommodation establishments (ECO1), gross domestic product at market prices per inhabitant (ECO2), added value of accommodation and catering services (ECO3), area of Community Importance Sites as a percentage of the regional area (ECO4). Social dimension: beds in residential social welfare and social health facilities per 10,000 inhabitants (SOC1), percentage of workers, pupils, and students aged 3 and over habitually using the train to commute to work, kindergarten, or school (SOC2), overnight stays in tourist accommodation per inhabitant (SOC3). Environmental dimension: robberies per 1,000 inhabitants (ENV1), perceived presence of degradation elements as a percentage of the living area (ENV2), perceived risk of crime (ENV3), PM2.5 concentration (ENV4), municipal waste per inhabitant (ENV5), percentage of electricity produced from renewable sources (ENV6), density of Special Protection Areas (ENV7). To account for negative polarities, we took the complement to 100 for ENV2, ENV3, and ENV4, and the reciprocal for SOC3, ENV1, and ENV5.

it provides not only an overall score but also individual scores for each indicator. This facilitates the identification of strong and weak dimensions for each unit, enabling the design of tailored improvement plans. In the second step, the decision maker's priorities concerning the dimensions considered in the final evaluation are integrated using the Directional Benefit of Doubt (D-BoD - [3]) model. This approach introduces a subjective prioritization strategy, enabling the comparison of multiple scenarios by aligning the evaluation process with the specific goals and strategic preferences of decision-makers.

3 Results

This section presents the key results of our study. In the first step, the overall score for the ECO, SOC, and ENV dimensions, along with those of the related elementary indicators, are calculated using MD-BoD. As an example, Figure 1 reports indicator-specific scores in 2019 for three regions: Umbria, Abruzzo, and Trentino-South Tyrol. Umbria is performing below the average for most economic and social indicators. This means that economic and social aspects of tourism sustainability should be a priority for the region, even if achieving the benchmark would require investing a substantial effort in a large number of indicators. Different considerations can be made for Abruzzo and Trentino-South Tyrol, as they are fully efficient in several areas. Consequently, to enhance their overall performance, these regions should aim at improving the areas where they are less efficient.

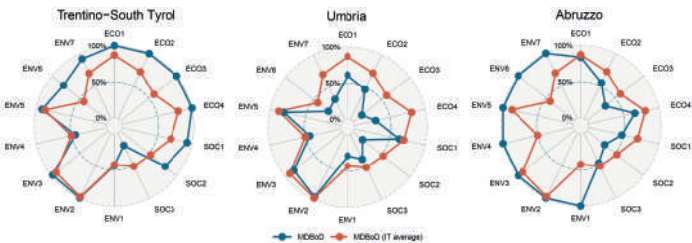


Fig. 1 MD-BoD scores for three regions in 2019. The average across all regions is shown in red

In the second step, two scenarios of interest for decision makers are compared: (a) the economic dimension has a strategic role in improving tourism sustainability while the other two are equally important; (b) the environmental dimension is the most relevant strategically, and the other two are equally important. Figure 2 shows the average score and the average annual change by region in the two scenarios. The main differences between the two scenarios can be seen in Apulia, Campania, Tuscany, and Veneto: when the environmental dimension is the priority for decision-makers, the average score of these regions drops significantly. This suggests that these regions may face greater challenges in improving their overall performance

when environmental sustainability becomes a priority. The situation is reversed for Calabria and Abruzzo.

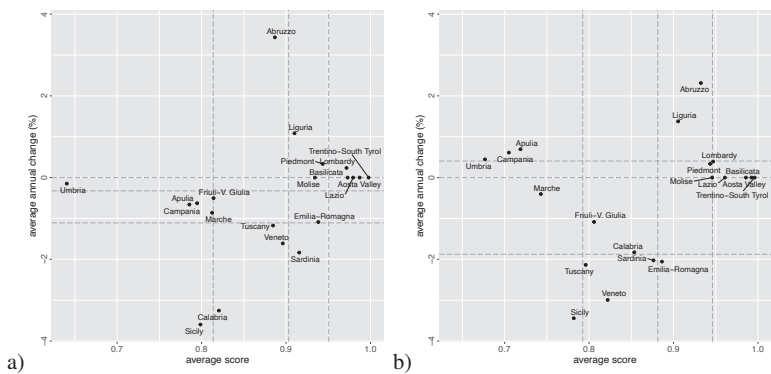


Fig. 2 Sustainability of regions by scenario. Dotted lines indicate quartiles

4 Concluding remarks

With this contribution, we have proposed an innovative approach to assess tourism sustainability in Italian regions. Our proposal has three main strengths: (i) it covers a 10-year period, allowing us to assess both levels and trends of sustainability, (ii) it considers the economic, social, and environmental dimensions, and (iii) its weighting scheme reflects policy priorities without relying merely on subjective opinions. The first limitation of our study is the small number of indicators, which is due to difficulties in collecting comprehensive data across multiple indicators and time points. A second limitation is represented by the low geographical detail, which could be deepened by considering provinces as units of observation, instead of regions. However, focusing on provinces could lead to an even lower number of indicators measured over fewer years. Future work could extend the analysis to recent years, making it possible to also assess the impact of COVID-19 on tourism sustainability.

References

1. Giambona, F., Magrini A., Fusco, E. (2024). Assessing tourism sustainability in European Union countries: A multi-directional benefit of the doubt composite indicator. *Socio-Economic Planning Sciences*, **95**: 102042.
2. Fusco, E. (2023). Potential improvements approach in composite indicators construction: The Multi-directional Benefit of the Doubt model. *Socio-Economic Planning Sciences*, **85**: 101447.
3. Fusco, E. (2015). Enhancing non-compensatory composite indicators: A directional proposal. *European Journal of Operational Research*, **242**: 620-630.

Spatial Dependence in the Dynamics of the 2020 Presidential Election Polls Trackers

Giampiero M. Gallo, Demetrio Lacava and Edoardo Otranto

Abstract This study investigates the spatial and political contagion dynamics influencing candidate polls for US swing states during the 2020 presidential election. By suggesting a Markov Switching Spatial-Temporal AutoRegressive model (MS-STAR), we achieve evidence of significant interdependence and regime-specific impact of spatial components, particularly in states with uncertain electoral outcomes. The model highlights the role of neighboring states during periods of greater political uncertainty.

Key words: Markov Switching, Political contagion, Presidential polls, Space-Time Autoregressive Model, Swing states

1 Introduction

The analysis of the US presidential election polling provides a valuable example of how political opinions may diffuse geographically. It reflects not only each candidate's popularity but also the sociopolitical dynamics across neighboring states, supposedly sharing similar values. Analyzing political contagion can thus offer key insights into the role of spatial interactions in shaping public opinion (see [2] for a survey on the economic determinants of the US presidential approval ratings).

In this paper, we explore the interdependence of presidential general election polling across US states through two dimensions: i) the political spillover, defined as how presidential polls in a given state are influenced by lagged results in other

Giampiero M. Gallo
New York University in Florence, e-mail: giampiero.gallo@nyu.edu

Demetrio Lacava
University of Messina, e-mail: dlacava@unime.it

Edoardo Otranto
Sapienza University of Rome, e-mail: edoardo.otranto@uniroma1.it

states identified by a selection algorithm, regardless of geographic proximity; and ii) a spatial component with contemporaneous contagion (with equal weights) from neighboring states.

To that end, we suggest a new Markov Switching Spatial-Temporal Autoregressive model (MS-STAR) on a dataset of presidential general election polling series recorded on the 13 swing states¹ in the 2020 presidential election campaign. The analysis shows that the model effectively captures a stronger spatial effect in the second regime, corresponding to higher political uncertainty, where presidential polls are more sensitive to exogenous factors and influences from neighboring states.

The rest of the paper is structured as follow: Section 2 presents the main features of the proposed model; the empirical application is discussed in Section 3; finally, Section 4 concludes the paper with some remarks.

2 The model

Our Markov Switching Spatial-Temporal Autoregressive (MS-STAR) model extends the class of Space-time Autoregressive models ([1]) with a regime-specific spatial parameter. It specifies the presidential polling for state i at time t , $y_{i,t}$ as an autoregressive function augmented by two terms: the spillover is $w'_{i,s}x_{t-1}$, that is a linear combination of all the other states' presidential polls at time $t - 1$ weighted by suitable weights $w_{i,s}$; the contagion is a linear spatial combination (with a regime switching parameter, γ_{s_t}) of all the other states' presidential polls at time t weighted by a weight $1/k_i$, where k_i is the number of neighboring states to state i . In detail:

$$y_{i,t} = \omega + \phi y_{i,t-1} + \beta(w'_{i,s}x_{t-1}) + \gamma_{s_t}(w'_{i,c}x_t) + \varepsilon_{i,t} \quad \varepsilon_{i,t} \sim N(0, \sigma_{s_t}^2). \quad (1)$$

The variable representing the regime at time t , $s_t = 1, 2$, follows a first order Markov chain via $Pr(s_t = j | s_{t-1} = h, s_{t-2} \dots) = Pr(s_t = j | s_{t-1} = h) = p_{hj}$. The model is estimated via Maximum-Likelihood with $|\phi| < 1$ for stationarity. The error term $\varepsilon_{i,t}$ has a regime-specific variance $\sigma_{s_t}^2$.

A novel recursive algorithm exploits significant partial correlations to select the most relevant states for y_i ; the weights $w_{i,s}$ are the squared loadings of the first Principal Component when the states' lagged polls are selected, and zero otherwise.

3 The Application to the 2020 Presidential Elections

The empirical analysis is based on presidential general election taking $y_{i,t}$ to be the polling data in favor of Biden, covering the period from February to November

¹ These are states where no candidate had a predominant support in 2020: Arizona-AZ, Florida-FL, Georgia-GA, Iowa-IA, Michigan-MI, Minnesota-MN, Nevada-NV, New Hampshire-NH, North Carolina-NC, Ohio-OH, Pennsylvania-PA, Texas-TX and, Wisconsin-WI.

Table 1 Estimation results ([3] robust standard errors in parenthesis) for the swing states. Sample period February - November 2020.

	AZ	FL	GA	IA	MI	MN	NV	NH	NC	OH	PA	TX	WI
ω	0.007 (0.008)	-0.003 (0.008)	-0.003 (0.005)	0.000 (0.008)	-0.001 (0.009)	-0.008 (0.010)	0.001 (0.005)	0.003 (0.010)	-0.002 (0.006)	0.005 (0.008)	0.003 (0.006)	-0.001 (0.001)	0.002 (0.008)
ϕ	0.126 (0.051)	0.322 (0.060)	0.255 (0.062)	0.296 (0.062)	0.164 (0.072)	0.526 (0.058)	0.070 (0.039)	0.296 (0.085)	0.284 (0.054)	0.325 (0.067)	0.284 (0.051)	0.004 (0.015)	0.224 (0.057)
β	-0.022 (0.028)	0.018 (0.028)	-0.119 (0.050)	0.003 (0.020)	0.096 (0.041)	-0.048 (0.035)	-0.067 (0.037)	-0.000 (0.045)	0.008 (0.024)	0.037 (0.025)	-0.004 (0.040)	0.003 (0.007)	-0.005 (0.030)
γ_1	0.653 (0.049)	0.566 (0.064)	0.706 (0.043)	0.392 (0.052)	1.396 (0.366)	-0.006 (0.062)	1.123 (0.036)	-0.025 (0.059)	0.604 (0.045)	-0.247 (0.097)	0.688 (0.047)	1.019 (0.012)	0.429 (0.059)
γ_2	0.093 (0.272)	1.316 (0.409)	0.639 (0.219)	0.968 (1.121)	0.110 (0.115)	0.375 (0.824)	0.309 (0.081)	-0.432 (1.245)	1.417 (0.253)	0.312 (0.452)	-0.005 (0.355)	0.507 (0.084)	1.231 (0.256)
p_{11}	0.881 (0.001)	0.858 (0.001)	0.922 (0.000)	0.965 (0.001)	0.714 (0.014)	0.904 (0.001)	0.916 (0.000)	0.963 (0.002)	0.900 (0.000)	0.893 (0.001)	0.897 (0.001)	0.895 (0.000)	0.920 (0.001)
p_{21}	0.173 (0.012)	0.251 (0.010)	0.129 (0.005)	0.284 (0.052)	0.148 (0.001)	0.245 (0.048)	0.075 (0.003)	0.382 (0.120)	0.133 (0.009)	0.293 (0.023)	0.179 (0.014)	0.089 (0.002)	0.146 (0.016)
σ_1^2	0.005 (0.005)	0.005 (0.005)	0.002 (0.002)	0.008 (0.008)	0.049 (0.049)	0.009 (0.009)	0.001 (0.001)	0.012 (0.012)	0.003 (0.003)	0.007 (0.007)	0.004 (0.004)	0.000 (0.000)	0.006 (0.006)
σ_2^2	0.063 (0.063)	0.045 (0.045)	0.028 (0.028)	0.121 (0.121)	0.007 (0.007)	0.277 (0.277)	0.033 (0.033)	0.119 (0.119)	0.058 (0.058)	0.076 (0.076)	0.084 (0.084)	0.018 (0.018)	0.060 (0.060)

2020.² To ensure stationarity, the MS-STAR model is estimated on transformed data, obtained by removing a weekly moving average from the original series.

Estimation results are reported in Table 1. Given that $\hat{\sigma}_1^2 < \hat{\sigma}_2^2$, we interpret the second regime (with an average duration, $\frac{1}{(1-p_{22})}$, approximately 6 days) as the period when Biden's support met greater instability: $\hat{\gamma}_2$ is significant in 6 out of 13 cases, pointing out to a regime-specific impact of the spatial component. Specifically, in states where the election outcome was more uncertain, $\hat{\gamma}_1 < \hat{\gamma}_2$ and the Biden's consensus in state i is more sensitive to the neighboring states' consensus. This is the case of FL (where Biden won 12 out of 27 districts), NC (5 out of 13) and WI (2 out of 6). Notably, GA and TX – traditionally considered Republican strongholds – show significantly higher spatial influence in regime 1.

Figure 1 shows the evolution of periods when the process is in regime 1 (thick solid black line) and the Political events (blue vertical lines). In the figure, each row represents a state, allowing for the observation of differences in how events and regimes are distributed over time. For example, on August 20, when the Democratic National Convention ended, regime 1 (stability) was observed in 10 out of 13 states. AZ and MI show more instability (regime 2, absence of lines), indicating a higher sensitivity to events. In contrast, influential states like FL, PA, and TX balance stable periods with unstable ones, but with a higher frequency of stability. Political events (blue vertical lines) are concentrated in stable periods; however, in most of the states they are associated to the regime switching, suggesting that key events have an impact on political preferences even during times of relative calm.

² Data are available at <https://projects.fivethirtyeight.com/polls/approval/>.

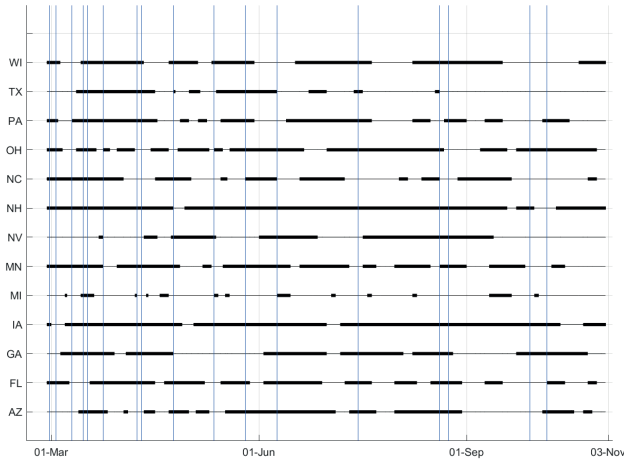


Fig. 1 Regime 1 periods (thick solid black line) and political events (blue vertical lines). Sample period February–November 2020.

4 Conclusion

We propose a new Markov Switching Spatial-Temporal Autoregressive (MS-STAR) model to evaluate political spillover and spatial contagion effects for US swing states in the 2020 presidential election. The findings support a critical role of spatial interactions in shaping presidential candidates' preferences, especially during volatile periods. The model effectively captures regime-specific sensitivities, offering valuable insights for political strategists and analysts into how candidate poll ratings propagate across states.

References

1. Luc Anselin. *Spatial econometrics: methods and models*, volume 4. Springer Science & Business Media, 2013.
2. Michael Berlemann and Sören Enkelmann. The economic determinants of us presidential approval: A survey. *European Journal of Political Economy*, 36:41–54, 2014.
3. Halbert White. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(4):817–38, 1980.

Cultural Capital and Economic Growth

Giorgio Garau, Andrea Karim El Meligi, Giuliana Altea, Antonella Camarda and Luca Poddighe

Abstract In this paper, we aim to evaluate how an intervention in cultural capital, such as the reopening of the Tavolara Pavilion, can impact not only the cultural growth of the primary target population but also serve as a catalyst for innovative activities, potentially generating economic effects over time. The theory of change and a regional social accounting matrix are presented, forming the foundation of our analysis to construct scenarios that capture both the short- and medium-term impacts.

Key words: cultural capital, theory of change, regional SAM accounting

1 Introduction

This paper presents an impact assessment of cultural capital interventions, specifically the reopening of the Tavolara Pavilion, on cultural growth and economic development in Sassari and its surrounding areas. Drawing on Bourdieu's [1] concept of capital, the study explores how cultural and social capital generate wealth and influence the economic system. Sen's [9] development framework highlights

Giorgio Garau

University of Sassari, e-mail: giorgio@uniss.it

Andrea Karim El Meligi

University of Sassari, e-mail: andreak.elmeligi@gmail.com

Giuliana Altea

University of Sassari, e-mail: altea@uniss.it

Antonella Camarda

University of Sassari, e-mail: acamarda@uniss.it

Luca Poddighe

University of Sassari, e-mail: l.poddighe2@phd.uniss.it

those expanding freedoms and opportunities is key to progress, with the removal of obstacles such as poverty and deprivation being essential for meaningful growth.

The research considers the Tavolara project as a local development initiative within district economies. Traditional cultural districts emphasize spatial clustering and direct economic effects, whereas Sacco's [8] model of systemic cultural districts promotes horizontal integration. This approach views culture as a bridge between sectors, fostering the accumulation of intangible assets such as human, social, and symbolic capital, which drive innovation and inclusive development.

The paper applies the Theory of Change (ToC) and a regional Social Accounting Matrix (SAM) to measure economic and social impacts, as outlined by Garau et al. [4]. This includes analysing income distribution among households and revisiting Sen's concepts of socio-economic cohesion. The contributions of visitors, including tourists and day-trippers, are integral to the analysis. The study employs surveys to reconstruct data for impact monitoring and proposes scenarios that align cultural and economic objectives, demonstrating how culture acts as a catalyst for sustainable development.

2 Methods: ToC and macroeconomic modelling

The ToC is a process that helps stakeholders articulate long-term goals and monitor progress [10]. The initiative to establish a museum of "Craft and Design" in Sassari is divided into three phases. In T1 the focus is on reopening the Tavolara Pavilion, emphasizing community engagement, artisan participation, and political satisfaction as Key Performance Indicators (KPIs). T2 involves setting up the museum to drive regional economic and cultural growth, with KPIs such as visitor numbers, job creation, and artisan product sales. Finally, T3 envisions a sustainable cultural ecosystem generating long-term economic, social, and cultural benefits.

Four key stakeholder groups are identified: Public, Artisans, Media and Policymakers. The complexity of stakeholder interactions necessitates tailored data collection methods. The first survey phase targeted visitors through voluntary questionnaires, while the second phase gathered feedback from artisans via email questionnaires and follow-up interviews based on the Nominal Group Technique [2].

In our impact assessment, the Regional Social Accounting Matrix (RSAM) is the chosen tool for analysing how the activities of the museum and its exhibitions generate effects on the production system. The accounting framework presented in this study is specifically constructed at the regional level and allows for the inclusion of induced effects—those arising from the transition from income generation to its redistribution and subsequent consumption. The macroeconomic analysis is based on a SAM framework developed at the regional level to capture the potential gravitational area of tourists visiting the Tavolara Pavilion. The regional scale of the framework also allows for generalizing the Theory of Change (ToC) approach, extending the results from the local level to encompass the entire island of

Sardinia, thereby scaling up the impacts. Previous studies related to the development of a local-based approach for Sardinia include [3] and [5], both of which assess the impacts of tourist attractions and the indirect socio-economic effects on the regional economy.

3 Build scenarios by Integrating ToC with Macroeconomic Modeling

To align ToC analysis with macroeconomic modelling, it is essential to connect changes in Key Performance Indicators (KPIs) to the reference macroeconomic model. In the project's second phase (T2), the Museum's establishment aims to drive both cultural and economic growth. Increased local visitor engagement fosters cultural identity, potentially boosting tourism as visitors return as tourists, further promoting the region's heritage.

The interplay between cultural and economic development is evident, as cultural shifts influence employment and economic expansion. Bourdieu's theories suggest that economic benefits—such as higher artisanal product sales and job creation—can help artisans overcome cost barriers and enhance the use of Sardinian materials. Additionally, the Museum can strengthen cultural tourism by integrating Sassari with nearby coastal areas, appealing to tourists seeking cultural experiences. A rising interest in modern art among non-local visitors signals shifting preferences, presenting an opportunity for tourism planners to enhance the region's cultural tourism offerings.

Let's assume, following the ISTAT survey *Viaggi & Vacanze*, that in Sardinia, 14.8% of tourists are interested in cultural itineraries. The expenditure on cultural tourism is calculated by multiplying this share by the number of visits (3,478,891), the length of stay (13 nights), and the median expenditure (80 euros). Multiplying the result (534,208,229) by the expenditure shares derived from the Satellite Tourism Account allows us to build the exogenous shock vector, from which we observe the indirect and induced effects. In the short term, we observe the following effects: a. Direct effects determined by the cost structure of productive activities (matrix A). b. Indirect effects that arise from the cost structure and, consequently, from the level of integration of different productive activities (Leontief inverse matrix). c. Induced effects observed when the Value Added generated by productive activities becomes income, enters the redistribution circuit, and is eventually consumed or saved.

As shown in the figure below (Figure 1), induced effects are particularly significant in the trade, accommodation, and real estate sectors. Over the next five years (medium-term impact), the museum is expected to contribute to local cultural growth and economic development, with artisan sales and related professions projected to increase by 20%. While stakeholder behaviours remain unchanged, the integration of the cultural product supply chain will strengthen, enhancing backward linkages. This means that an update of the accounting model will be needed to

recalculate new SUT and SAM multipliers, as the values in the figure will likely increase. In the long term, shifts in stakeholder behaviours should further integrate cultural tourism with broader economic activities, reinforcing backward linkages. A Computable General Equilibrium (CGE) model will be necessary to assess these behavioural changes. Strengthening cultural identity and sustainable tourism is expected to increase museum visits, cultural site loyalty, and cultural spending as a share of personal income. For artisans, greater use of local production inputs will enhance resource utilization and further strengthen economic linkages. Additionally, media will play a key role in promoting Sardinia’s image as a cultural destination, while policymakers can drive economic growth by investing in the integration of coastal and inland tourism and promoting cultural tourism routes.

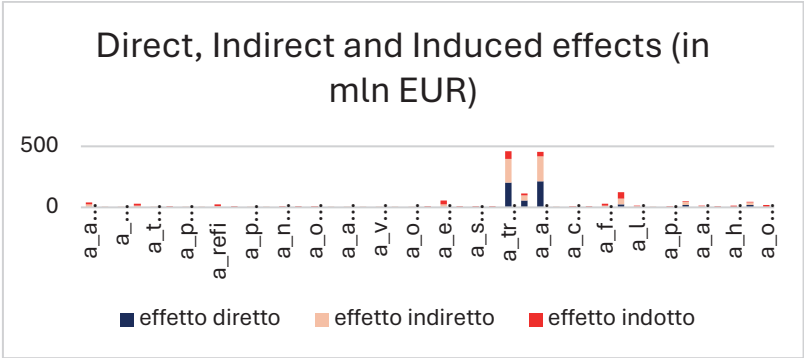


Fig.1 Direct, Indirect and Induced effects

References

1. Bourdieu, P.: *The Forms of Capital*. In *Handbook of Theory and Research for the Sociology of Education*, ed. John Richardson. New York: Greenwood (1986)

2. Delbecq A. L., Van de Ven A. H. and Gustafson D.: *Group Techniques for Program Planning; a guide to nominal group and Delphi processes*. Glenview IL, Scott Foresman and Company (1975)

3. El Meligi A. K., Carboni D., Garau G.: Perceived crowding and physical distance rules: a national account perspective, *National Accounting Review*, doi: 10.3934/NAR.2021017, (2021).

4. Garau G., El Meligi A. K., Altea G., Camarda A. and L. Poddighe: Estimation of the economic and social impact of a museum activity, a case study: the Tavolara Pavillon in Sassari, *Networks, Markets & People, Lecture Notes in Networks and Systems*, Springer (2024)

5. Garau, G., Carboni, D., El Meligi, A. K.: Economic and environmental impact of the tourism carrying capacity: A local-based approach. *Journal of Hospitality & Tourism Research*, 46(7), 1257-1273 (2022)

6. Robinson, S., Cattaneo, A., & El-Said, M.: Updating and estimating a social accounting matrix using cross entropy methods. *Economic Systems Research*, 13(1), 47-64 (2001)

7. Robinson, S., & McDonald, S., SAMEST: An Information-Theoretic Approach to Estimating National Accounts. DRAFT. (2023)

8. Sacco, P. L., Ferilli, G., Blessi, G. T.: *Culture as an Engine of Local Development Processes: System-Wide Cultural Districts I: Theory. Growth and Change*, 44(4), 555-570 (2013)

9. Sen, A.: *Development as Freedom*. Oxford University Press (1999)

10. Taplin D. H. and H. and Clark: *Theory of Change Basics*, ActKnowledge, New York (2013)

Italian Social Security System Sustainability: a statistical study based on INPS Data Bank

Massimiliano Giacalone, Maria Longobardi, Stefano Marra and Gianfranco Piscopo

Abstract The aim of this paper is to evaluate the sustainability of the Social Security System for the Italian economy, by examining the current demographic situation and trends in Italy, as well as their consequences on welfare resources and the quality of life of its citizens. The data were collected from the INPS Data Bank “*Open Data*”, an online database providing information free of charge and free from licensing restrictions. These resources are shared among other important national institutes, such as ISTAT. The study, by implementing regression models, highlights how, in recent decades, the number of retired workers has grown faster than the number of new workers, leading to an increase in the financial resources required to sustain welfare services. Finally, the paper proposes some potential solutions to address or at least mitigate the negative effects associated with Italy's ageing population.

Key words: Welfare, Social Security System, Sustainability, INPS Database, Open Data

Massimiliano Giacalone
University of Campania Luigi Vanvitelli, e-mail: massimiliano.giacalone@unicampania.it

Maria Longobardi
University of Naples Federico II, e-mail: maria.longobardi@unina.it

Stefano Marra
University of Campania Luigi Vanvitelli, e-mail: stefanomarra95@gmail.com

Gianfranco Piscopo
University of Naples Federico II, e-mail: gianfranco.piscopo@unina.it

1 Introduction

The topic of sustainability has assumed a central role in recent decades, reflecting a growing awareness of the importance of balancing economic development, social progress, and environmental protection.

This concept has been extended to all areas of human activity and trends, including national welfare and population demographics.

The Italian population has experienced significant changes, leading to two major consequences: a rise in the average age of the population and a marked decline in birth rates.

Given the multitude of factors involved [12,13], it was necessary to focus on those with the greatest potential impact on the phenomena of interest and that could be effectively measured and observed in both the short and long term. Consequently, labor market dynamics were highlighted, as they have significant implications for both welfare and household resources [9].

Another important aspect to consider is the taxonomy adopted in the records, which determines whether a worker fits or doesn't fit in a determined profession. These indicators were incorporated into a regression model to better understand their interrelations and to comprehensively evaluate their impact on sustainability.

Once this impact was quantified, it was deemed important to propose solutions to address the potential decline of the Italian welfare system. A sustainability-oriented approach could involve implementing new policies aimed at better integrating and managing immigrants, as well as supporting families through childcare services and related initiatives.

2 The methodology and the main implications

The analysis was conducted with a mainly statistical approach, leaving aside the Italian legal context. The objectives of this investigation are exploratory in nature; therefore the preliminary results should not be intended as definitive, but more like a foundation for a follow-up analysis. To build the indicators, data has been selected from online database "Open Data", come from INPS census on the current workforce [10,11].

The indicators represent different workers categories, differentiating between independent workers, employees both in public and private businesses and other kinds of employment situations. They also include several economic indicators, such as the number of workers for each profession, how many weeks do they work and how much each single category earns every year.

The research enabled a comparison between different job and employment categories, considering factors such as the number of workers, the total number of work weeks, and the overall income generated by each category.

To build a regression model, the dependent variable chosen is “Income”, while the independent variables are “Workers” and “Weeks”. These two factors are considered of major interest due to their potential impact on the welfare system, as they are related to the gatherable resources for pensions. The higher the number of workers, the higher the monetary contributions for welfare. The same can be said for the number of weeks worked, as they allow workers to increase their income as well as their social security contributions. In the Table 1 is possible to observe part of the results obtained from the regression between “Income” and “Workers”:

Table 1 Coefficients of the Regression Model based on Income and workers

	Estimate	Std. Error	t value	Pr(> t)
Intercept	-2.633e+07	4.197e+09	-0.006	0.995
Workers	2.287e+04	9.518e+02	24.025	7.42e-11 ***

Source: Own elaboration based on data from “Open Data [10]”

Both quantitative and visual analysis (Fig. 1) confirm a positive correlation between the Income perceived from the several workers’ categories and the number of workers for each category. The same outcome was found for the other indicator, “Weeks”. The obtained model equation is the following:

$$Y = -26,330,000 + 22.87 \cdot X$$



Fig. 1 Graphic representation of standardized regression model. Source: Own elaboration based on data from “Open Data [10]”

The results obtained at the end of the analysis process highlight a strong positive correlation between the dependent variable and the independent variables. However, more in-depth is required to better understand why some categories perceive a far superior income than the rest of the workers and what factors contribute to such a degree of polarization [6].

3 Final Remarks

In conclusion, the work market is of great interest for the sustainability of the social security system as it represents the main source of financial support for the INPS.

The current working generation acts as a pillar for the retired generation, however such balance risks to break as the average population age keeps rising. To avoid economic and social instability it is of uttermost importance to implement sustainable policies on the short and long term, capable of sustaining workers and retired at the same time.

For example, improving the integration of immigrants can have huge benefits on both the overall work market and welfare. Not only they can contribute to higher financial resources, but they can also increase the birth rates, lowering the population average age.

Another important aspect worth of the attention is the retirement procedures [1,2], as they will need to fit in the new social context where the population keeps ageing and will have different needs and behaviours [3,4,16] than their predecessors. It is necessary to extend the workers' career as life expectancy and quality keeps improving over time, so that the balance can be maintained between workers and retired [5,7]. The topic is complex and will require further studies to better understand all the dynamics involved in the demographic [8] and economic aspects [11] of the society.

References

1. Bassoli, E., & Brilli, Y. (2023). Women's retirement behavior and pension wealth: the unintended effect of a recent pension reform.
2. Belloni, M., & Alessie, R. (2009). The importance of financial incentives on retirement choices: New evidence for Italy. *Labour Economics*, 16(5), 578-588.
3. Boeri, T., Garibaldi, P., & Moen, E. R. (2022). In medio stat victus: Labor Demand Effects of an Increase in the Retirement Age. *Journal of Population Economics*, 35(2), 519-556.
4. Brugiavini, A., & Peracchi, F. (2003). Social security wealth and retirement decisions in Italy. *Labour*, 17, 79-114.
5. Carta, F., & De Philippis, M. (2024). The forward-looking effect of increasing the full retirement age. *The Economic Journal*, 134(657), 165-192.
6. Checchi, D., Jappelli, T., Marino, I., & Scognamiglio, A. (2024). Inequality trends in a slow-growing economy: Italy, 1990–2020. *Fiscal Studies*, 45(3), 377-392.
7. Del Prato, F., Nardotto, M., Huremovic, K., Cassiman, B., & Zaccchia, P. (2023). Essays on the Economics of Labor Markets and Retirement Policies.
8. Fluchtmann, J., V. van Veen and W. Adema (2023), "Fertility, employment and family policy: A cross-country panel analysis", OECD Social, Employment and Migration Working Papers, No. 299, OECD Publishing, Paris, <https://doi.org/10.1787/326844f0-en>
9. Francesca, D. P. (2023). Essays on the Economics of Labor Markets and Retirement Policies.
10. INPS Open Data: <https://servizi2.inps.it/servizi/osservatoristatistici/99/o/465>
11. ISTAT (2024), "Rapporto annuale 2024 – La situazione del paese"
12. Mazzaferro, C. (2023). The transition to NDC in Italy: assessing distributive and financial effects. *Journal of Pension Economics & Finance*, 22(1), 116-131.
13. OECD (2023), "Pensions at a Glance 2023: OECD and G20 Indicators", OECD Publishing, Paris <https://doi.org/10.1787/678055dd-en>.
14. Paiella, M. (2023). The Italian Gender Gap in Pensions: A Cohort of Birth Approach. *Ubezpieczenia Społeczne. Teoria i praktyka*, (3 (158)), 101-122.
15. Rocca, A., Marletta, A., Marini, C., Giambona, F. A., & Fabrizi, E. (Eds.). (2024). 2nd Italian Conference on Economic Statistics (ICES 2024), Statistical Analysis of Complex Economic Data: Recent Developments and Applications, Book of Short Papers.
16. Serrano-Alarcón, M., Ardito, C., Leombruni, R., Kentikelenis, A., d'Errico, A., Odone, A., ... & IWGRH. (2023). Health and labor market effects of an unanticipated rise in retirement age. Evidence from the 2012 Italian pension reform. *Health Economics*, 32(12), 2745-2767.

The effect of energy efficiency upgrades on residential property prices: evidence from Italy

Elena Giarda and Demetrio Panarello

Abstract This paper examines the relationship between energy efficiency in residential buildings and house market prices in Italy, using novel data from Energy Performance Certificates across three regions: Emilia-Romagna, Lombardy and Piedmont. By combining this data with house prices and socio-economic and climate variables, we estimate the relationship using hedonic OLS and quantile regression models. Our findings indicate a price premium for energy-efficient homes, with regional differences and variations along the price distribution. Factors such as newer construction, higher housing market mobility and greater income levels positively influence prices, while heat waves are associated with lower prices.

Key words: Energy Performance Certificates, Energy Performance of Buildings Directive, House prices, Hedonic regression, Quantile regression

1 Introduction

Energy efficiency is key to reducing consumption and achieving the EU's climate goals while improving affordability. In the EU, the Energy Performance of Buildings Directive (EPBD) and the Energy Efficiency Directive (EED) aim to enhance buildings' energy performance. A key EPBD requirement is the introduction of Energy Performance Certificates (EPCs), which rate buildings from G (least efficient) to A4 (most efficient) based on expected energy consumption. The EPBD was recast in 2021 with stricter goals, requiring residential buildings to achieve at least class E by 2030 and class D by 2033. The revised directive,

Elena Giarda

Prometeia and University of Modena and Reggio Emilia, e-mail: elena.giarda@prometeia.com.

Demetrio Panarello

Prometeia and Link Campus University, e-mail: d.panarello@unilink.it.

approved in 2024, aims for a 16% energy use reduction by 2030 and 20-22% by 2035, with 55% of such reductions obtained through renovating the worst-performing buildings.

This paper investigates whether higher energy efficiency in residential buildings leads to higher market prices in Italy. We use novel biannual data on Energy Performance Certificates from Emilia-Romagna, Lombardy and Piedmont (2016-2022), combined with micro-area house prices, socio-economic factors and climate-related variables. The relationship between house prices and energy efficiency is estimated using hedonic OLS and quantile regression models.

Understanding this relationship is important for several reasons: higher prices increase household wealth, incentivising property renovations; energy efficiency can offset retrofit costs; and evolving attitudes towards environmental issues may influence price premiums.

There is extensive literature on the relationship between buildings' energy performance and their prices, driven by increased awareness of climate and energy issues and the EU's focus on energy-efficient buildings, which are expected to make homebuyers willing to pay higher prices for more energy-efficient homes.

However, evidence from Italy is limited, mainly due to the lack of combined data on EPCs and house prices. A recent study [3] shows that listing prices increase with better energy labels, with a 25% price premium for top-rated homes. Other studies [1,2] find smaller premiums in specific cities (Bolzano/Bozen and Turin).

2 Data and Methods

Energy performance is measured through the Energy Performance Certificates, which attribute an energy efficiency label to dwellings on a scale from G (the least efficient) to A4 (the most efficient) based on dwellings' expected (theoretical) energy consumption. The energy performance of a building depends on how well it performs compared to a reference one, where the reference building has the same geometric characteristics, exposure and location of the building to be certified but with energy performance parameters equivalent to class A1. The energy class of each dwelling is based on the ratio between its own global non-renewable energy performance index and the reference standard one.

To estimate the price premium of energy efficiency, we need house prices. However, we do not have access to granular prices, but only to those provided by Italy's Revenue Agency through its Real Estate Market Observatory (Osservatorio Mercato Immobiliare – OMI). The Observatory provides prices by micro area (OMI area), defined as portions of the municipal territory reflecting a homogeneous segment of the local real estate market, where there is uniformity in the economic and socio-environmental conditions. The semestral prices provided by the Observatory are verified minimum and maximum values by micro area in which at least five transactions have occurred within one semester.

We employ novel bi-annual microdata on Energy Performance Certificates from three Italian regions (Emilia-Romagna, Lombardy and Piedmont), which provide information on dwellings' current energy class, and merge them, by means of geocoding techniques, with house prices by micro area and with a set of local socio-economic and environmental characteristics such as income, population density and altitude.

We estimate the relationship between house prices and energy efficiency by applying hedonic OLS models and quantile regression models. We concentrate on residential buildings. The datasets cover the period 2016H1-2022H2 (14 data points). After cleaning the data, we are left with 558,163 observations in Emilia-Romagna, 1,118,162 in Lombardy and 395,465 in Piedmont, which represent 21.9%, 20.0% and 14.2% of all residential buildings in the three regions – as assessed by the 2021 Census. We collapse the datasets so that the new unit of analysis is the micro area: from almost 2 million individual observations, we are left with 84,821 total obs. (16,975 Emilia-Romagna, 39,392 Lombardy, 28,454 Piedmont). In our models, the outcome variable is the average price by micro area (in logs). As regressors, we employ:

- energy class (classes A4-D reference category), share of sold properties, share of rented out dwellings, share of second homes, construction year by class (“Before 1945” reference category) – all at the micro area level;
- quartiles of average individual net income (1st quartile reference category), population density, climate zone (zones D-E reference category), altitude, heat waves – all at the municipality level;
- province dummies (Bologna is the reference province for Emilia Romagna, Milan for the pooled model and for Lombardy, Turin for Piedmont) and a dummy identifying the post-2020 period (2021H1-2022H2) in interaction with the energy class.

3 Results and Discussion

The results unveil the existence of an energy efficiency price premium. The coefficients for energy class are significant, negative and increasing in absolute value: compared to the reference energy class A4-D, the price of less energy-efficient dwellings is lower, and the price reduction is more pronounced the less efficient a property is. For an average dwelling, the loss of value from class A4-D to class G is 20.0%, while for a dwelling in class F it is 11.3% and for a property in class E it is 4.9% (see Table 1).

Dwellings in areas with higher mobility – captured by higher shares of home purchases and rentals – experience a positive effect on their prices. A higher population density is associated with a higher price and municipalities in which the average income level is higher exhibit higher prices. The price premium for higher energy efficiency is heterogenous across regions and it seems to be stronger in Emilia-Romagna than in Lombardy and Piedmont.

Table 1 Estimated energy class coefficients from hedonic OLS models.

	Pooling	E-R	Lombardy	Piedmont
Energy class: E	-0.049***	-0.219***	-0.045**	-0.030***
Energy class: F	-0.113***	-0.222***	-0.136***	-0.060***
Energy class: G	-0.201***	-0.355***	-0.191***	-0.137***
Constant	6.984***	6.895***	7.064***	6.669***
Observations	84,821	16,975	39,392	28,454
R-squared	0.655	0.711	0.672	0.582

Notes: *** $p < 0.01$, ** $p < 0.05$; other regressors not displayed for the sake of brevity.

Moving on to the quantile regression models, there is evidence of an energy-efficiency price premium in all the quartiles of the house price distribution and the premium increases along the price distribution. For instance, the price loss of the reference dwelling in class G (compared to class A4-D) is 7.4% in the first quartile, 14.1% in the second and 20.0% in the third.

The presence of an energy efficiency price premium suggests that market mechanisms may incentivise energy-efficient investments, but this effect is highly variable across regions and price segments: regional differentiation in policy design may be necessary to account for the observed local dynamics. The most recent EPBD recast set that energy use of residential buildings must be reduced by 20-22% by 2035 (compared to 2020 levels) and that at least 55% of this reduction must be achieved through the renovation of the worst-performing buildings: it is relevant to know how much residential properties would be valued after renovation, to compensate, at least partially, for the retrofit costs.

The heterogeneity in price responses should guide the allocation of public resources: targeting financial incentives more effectively – by focusing on regions or price segments with lower responsiveness – could enhance policy efficiency and reduce the fiscal burden. Other factors, such as population density and income levels, also significantly affect property values: policymakers may consider integrating energy efficiency policies with urban planning and economic development strategies to maximise their effectiveness.

Acknowledgments We acknowledge funding from the European Commission, Next Generation EU, Project “GRINS - Growing Resilient, INclusive and Sustainable”, id code MUR PE00000018, CUP B33D22001700006.

References

1. Bisello, A., Antoniucci, V., Marella, G.: Measuring the price premium of energy efficiency: A two-step analysis in the Italian housing market. *Energy & Buildings* 208, No. 109670 (2020)
2. Fregonara, E., Rolando, D., Semeraro, P.: Energy performance certificates in the Turin real estate market’. *Journal of European Real Estate Research* 10(2), 149-169 (2017)
3. Loberto, M., Mistretta, A., Spuri, M.: The capitalization of energy labels into house prices. Evidence from Italy. *Bank of Italy Occasional Papers*, No. 818 (2023)

Inner Areas in Lombardy: An Analysis of Vulnerability

Chiara Gigliarano, Annamaria Bianchi, Sara Maiorino and Rashad Mammadli

Abstract This study examines socio-economic vulnerability in the inner areas of Lombardy, Italy, using data from the MYPEOPLE project. Adopting a multidimensional approach with small area estimation techniques, the research explores sixteen indicators across four domains and compares the results between inner and non-inner areas of Lombardy. Findings show that while poverty levels are similar in both areas, inner areas face greater financial vulnerability, particularly in managing unexpected expenses. However, health and leisure indicators generally show better outcomes in inner areas. Internet connectivity remains a significant challenge, but overall, disparities in access to service are less pronounced than expected.

Key words: inner areas, vulnerability, small area estimation, Fay-Herriot models

1 Introduction

The inner areas of Lombardy, as defined by the National Strategy for Inner Areas (SNAI), are characterized by significant distances from major centers offering essential services such as healthcare, education, and mobility. Despite these challenges, they possess rich environmental and cultural resources. In Lombardy, 488 municipalities with more than 1.16 million population fall under this framework.

Chiara Gigliarano
LIUC C. Cattaneo University, e-mail: cgigliarano@liuc.it

Annamaria Bianchi
University of Bergamo, e-mail: annamaria.bianchi@unibg.it

Sara Maiorino
PoliS-Lombardia, e-mail: sara.maiorino@polis.lombardia.it

Rashad Mammadli
LIUC C. Cattaneo University, e-mail: rmammadli@liuc.it

A related concept is that of inner peripheries, referring to vulnerable rural areas in Europe that face challenges such as depopulation, limited economic potential, and weak territorial cohesion [2]. According to De Toni et al. [1], these inner peripheries are shaped by connectivity gaps, whether geographic, economic, or relational. Defining marginality solely by geographic distance has its limitations. Studies like those by Vendemmia et al. [6] show that while remoteness often correlates with lower income, education, and population decline, it does not fully explain socio-economic fragility. Some peripheral areas exhibit better socio-economic situation than more central ones, emphasizing the need for a more nuanced approach.

This study contributes to this discourse by analyzing socio-economic vulnerability from a multidimensional perspective in the inner areas of Lombardy, Italy. It examines economic and material conditions, as well as access to services such as healthcare, transportation, and internet.

2 Materials and Methods

The data for this study is drawn from probability-based sample surveys conducted in 2024 as part of the MYPEOPLE project [5], focusing on the impact of recent crises on household living conditions. Using a multidimensional approach, the study analyzes vulnerability in Lombardy’s inner areas and compares them with non-inner areas. Sixteen elementary indicators across four domains are identified (Table 1).

Table 1 Domains, elementary indicators and deprivation cut-offs

Domain	Elementary Indicator	A household is deprived if (deprivation cut-off):
Financial Well-being	Income Deprivation	Its annual equivalent disposable income is less than €12,841.84 (60% of median income in the sample).
	Financial Difficulty	It can't afford to make ends meet.
	Inability to Cover Unexpected Expenses	It is unable to cover unexpected expenses of €3,000.
	Bill Payment Difficulty	It has had difficulties to pay household bills over the past 12 months.
	Medical Expense Payment Difficulty	It has had difficulties to pay medical bills within the past 12 months.
Health	Foregone Health Visits	Any family member has foregone health service visits in the past 12 months due to high cost.
	Food Consumption Reduction	It has reduced food consumption at least a couple of times in the past 12 months due to economic difficulties.
	Healthy Diet Reduction	It has had to forgo a healthy and varied diet over the past 12 months because of economic difficulties.
Leisure and Social Participation	Vacation Affordability Difficulty	It has been unable to afford a vacation of at least one week in the past 12 months.
	Cultural Activity Participation Difficulty	It has been unable to attend cultural activities at least twice a month in the past 12 months.
	Eating Out Difficulty	It has been unable to eat out at least twice a month in the past 12 months.
Access to Services	Access to Services: Healthcare	It has difficulties in reaching emergency rooms, hospitals, or other National Health Service facilities.
	Access to Services: Pharmacy	It has difficulties in reaching pharmacies.
	Access to Services: Culture & Sport	It has difficulties in reaching places for recreational, cultural, or sporting activities.
	Access to Services: Transport	It has difficulties in reaching public transportation.
	Access to Services: Internet	It has difficulties or problems in accessing the internet.

The survey has not designed to yield precise estimates for inner areas, as reliable direct estimates require larger sample sizes or oversampling. To address this

limitation, small area estimation (SAE) techniques are applied, allowing for precise estimates in small domains with limited or even zero sample sizes. Given that auxiliary data is available only at the area level rather than the unit level, this study applies the area-level SAE models introduced by Fay and Herriot [3] (FH models).

3 Results

FH model-based estimates show a significant improvement in efficiency compared to direct estimates, with nearly all coefficients of variation below 33.3%. Figure 3 illustrates various deprivation indicators estimated using the FH models for inner areas in Lombardy, compared to direct estimates for both inner and non-inner areas.

Regarding the financial well-being domain, some inner areas experience higher income deprivation and financial difficulties than the inner-area average, while non-inner areas show slightly lower deprivation in income but higher deprivation in financial difficulties. Inner areas struggle more with covering unexpected expenses, whereas non-inner areas are more resilient. In contrast, non-inner areas face greater challenges with bill payments and medical expenses, likely due to higher living costs in central areas.

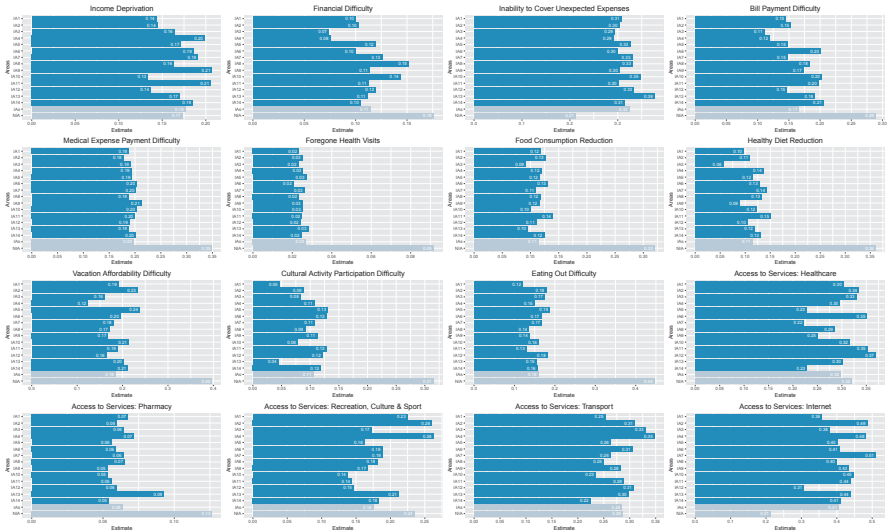


Fig. 1 Deprivation in the inner areas of Lombardy
IA1: Alto Lago di Como e Valli del Lario, *IA2:* Appennino Lombardo – Alto Oltrepò Pavese, *IA3:* Laghi Bergamaschi e Sebino Bresciano, *IA4:* Lario Intelvese e Valli Lario Ceresio, *IA5:* Lario Orientale – Valle S.Martino e Val, *IA6:* Lomellina, *IA7:* Oltrepò Mantovano, *IA8:* Piombello e Valli del Verbano, *IA9:* Valcamonica, *IA10:* Valchiavenna, *IA11:* Valle Brembana e Valtellina di Morbegno, *IA12:* Valle Seriana e Val di Scalve, *IA13:* Valsabbia Alto Garda, *IA14:* Valtrompia, *IAS:* All Inner Areas (direct), *NIA:* Non-inner Areas (direct)

In the health domain, inner areas show consistently lower levels of deprivation for all three indicators including foregone health visits, food consumption reduction, and healthy diet reduction, suggesting better health outcomes. In leisure and social participation, deprivation in activities like cultural participation and eating out is 2-3 times higher in non-inner areas. Regarding access to services, inner areas face challenges in healthcare and transport, with deprivation rates comparable to those in non-inner areas. Contrary to expectations, access to pharmacies, as well as recreational, cultural, and sports facilities, is not significantly constrained in inner areas. However, internet connectivity remains a major issue in many inner areas, with deprivation in this indicator considerably higher compared to non-inner areas.

4 Conclusion

The findings of this study reveal both expected and nuanced patterns of socio-economic vulnerability across Lombardy. In inner areas, the poverty rate is similar to that in non-inner areas; however, residents face greater difficulty managing unexpected expenses. Conversely, challenges related to making ends meet and specific expenses are less pronounced in inner areas. Access to services, including healthcare, transport, and cultural facilities, is generally equal across both inner and non-inner areas, although internet access remains more problematic in inner areas.

These patterns may be influenced by factors such as the different family compositions across areas, with fewer couples with children in inner areas; a lower cost of living in inner areas compared to metropolitan regions; and subjective perceptions of service accessibility that may differ from objective measures.

Acknowledgements The authors acknowledge financial support by the Italian Ministry of University and Research (MUR) under the PRIN PNRR 2022 [project MYPEOPLE (“Measuring inequality, Poverty and living conditions for Planning Local strategies”)].

References

1. De Toni, A., Vizzarri, M., Di Febbraro, M., Lasserre, B., Noguera, J., Di Martino, P.: Aligning Inner Peripheries with rural development in Italy: Territorial evidence to support policy contextualization. *Land Use Policy*. **100**, 104899 (2021) doi: 10.1016/j.landusepol.2020.104899
2. European Observation Network for Territorial Development and Cohesion (ESPON): Inner Peripheries in Europe. (2018)
3. Fay, R., Herriot, R.: Estimates of Income for Small Places: An Application of James-Stein Procedures to Census Data. *J. Am. Stat. Assoc.* **74**(366a), 269–277 (1979)
4. Henderson, C.R.: Best Linear Unbiased Estimation and Prediction under a Selection Model. *Biometrics*. **2**(31), 423–447 (1975)
5. MYPEOPLE (“Measuring inequality, Poverty and living conditions for Planning Local strategies”) (2024) Available via DIALOG. www.mypeople-unibg.it. Cited January 4th, 2025
6. Vendemmia, B., Pucci, P., Beria, P.: An institutional periphery in discussion. Rethinking the inner areas in Italy. *Appl. Geogr.* **135**, 102537 (2021) doi: 10.1016/j.apgeog.2021.102537

Forecasting Italian daily electricity generation disaggregated by geographical zones and energy sources using coherent forecast combination

Daniele Girolimetto and Tommaso Di Fonzo

Abstract A novel approach is applied for improving forecast accuracy and achieving coherence in forecasting the Italian daily energy generation time series. In hierarchical frameworks such as national energy generation disaggregated by geographical zones and energy sources, independently generated base forecasts often result in inconsistencies across the constraints. We deal with this issue through a coherent balanced multi-task forecast combination approach, which combines unbiased forecasts from multiple experts while ensuring coherence. Applied to the daily Italian electricity generation data, our method shows superior accuracy compared to single-task base and combined forecasts, and a state-of-the-art single-expert reconciliation technique, demonstrating to be an effective approach to forecasting linearly constrained multiple time series.

Key words: Italian electricity generation, Linearly constrained multiple time series, Forecast combination, Forecast reconciliation

1 Introduction

Selecting an effective forecasting method among many options presents a complex and resource-intensive challenge, as inherent uncertainties often prevent any method from achieving the best accuracy across all scenarios. This complexity becomes even more significant when dealing with multiple interrelated variables that must satisfy linear constraints, as in National Accounts [6] and in hierarchical time series like electricity demand segmented by regions and sources [1]. Such settings

Daniele Girolimetto
University of Padua, e-mail: daniele.girolimetto@unipd.it

Tommaso Di Fonzo
University of Padua, e-mail: difonzo@stat.unipd.it

require appropriate forecasting approaches ensuring coherence across interrelated variables. Traditional univariate forecast combination methods [2, 3] focus on individual time series. In contrast, global forecast combination methods leverage shared information across multiple series to improve accuracy [9]. Similarly, forecast reconciliation approaches search for coherence by adjusting forecasts to satisfy some *a priori* constraints [10], with significant empirical advantages in various fields [1].

In this paper, we exploit a recently developed linear framework [5], that joins single-variable forecast combination [2] and the least squares reconciliation procedure to produce optimal (in the least squares sense) coherent forecasts. The remainder of the paper is structured as follows. Sect. 2 presents the optimal coherent forecast combination procedure for incoherent base forecasts. Sect. 3 presents the main findings of a forecasting experiment on 76 daily time series of the Italian electricity generation disaggregated by geographical zones and energy sources.

2 Optimal coherent multi-task forecast combination

Let $\mathbf{y} = [y_1 \dots y_i \dots y_n]^\top \in \mathbb{R}^n$ represent the target forecast vector for a linearly constrained time series $\mathbf{Y}_t$, such that $\mathbf{C}\mathbf{Y}_t = \mathbf{0}_{(n_u \times 1)}$, where $\mathbf{C} \in \mathbb{R}^{n_u \times n}$ is a predefined matrix describing the (homogeneous) linear constraints valid for the single component series of $\mathbf{Y}_t$, i.e., $\mathbf{C}\mathbf{y} = \mathbf{0}_{(n_u \times 1)}$. We assume that $p \geq 2$ experts independently produced a base forecast for every one of the n individual components of $\mathbf{y}$, yielding $m = np$ base forecasts overall¹.

Denote $\hat{y}_i^j$ the unbiased base forecast of the i -th individual variable of $\mathbf{y}$ produced by the j -th expert, and let $\varepsilon_i^j = \hat{y}_i^j - y_i$ the zero-mean base forecast error. Let $\hat{\mathbf{y}}^j \in \mathbb{R}^{n_j}$, $j = 1, \dots, p$, be the vector of base forecasts produced by the j -th expert, with error given by $\varepsilon^j = \hat{\mathbf{y}}^j - \mathbf{y}$, $\hat{\mathbf{y}} = \text{vec} [\hat{\mathbf{y}}^1 \dots \hat{\mathbf{y}}^j \dots \hat{\mathbf{y}}^p] \in \mathbb{R}^m$, and $\varepsilon = \text{vec} [\varepsilon^1 \dots \varepsilon^j \dots \varepsilon^p] \in \mathbb{R}^m$. The linear relationship linking all the available base forecasts $\hat{\mathbf{y}}$ and the unknown target forecast vector $\mathbf{y}$ can be expressed through the multiple regression model $\hat{\mathbf{y}} = \mathbf{K}\mathbf{y} + \varepsilon$, where $\mathbf{K} = (\mathbf{1}_p \otimes \mathbf{I}_n)$, $E(\varepsilon) = \mathbf{0}_{(np \times 1)}$ and $\mathbf{W} = E(\varepsilon\varepsilon^\top) \in \mathbb{R}^{m \times m}$ is a p.d. matrix.

We are looking for a coherent forecast vector $\tilde{\mathbf{y}}^c$, i.e., $\mathbf{C}\tilde{\mathbf{y}}^c = \mathbf{0}_{(n_u \times 1)}$, which exploits all the available base forecasts and improves their accuracy. Forecast combination and reconciliation can be simultaneously dealt with through an optimization-based technique that combines multiple individual experts' base forecasts $\hat{\mathbf{y}}^j$:

$$\tilde{\mathbf{y}}^c = \arg \min_{\mathbf{y}} (\hat{\mathbf{y}} - \mathbf{K}\mathbf{y})^\top \mathbf{W}^{-1} (\hat{\mathbf{y}} - \mathbf{K}\mathbf{y}) \quad \text{s.t.} \quad \mathbf{C}\mathbf{y} = \mathbf{0}_{(n_u \times 1)}. \quad (1)$$

By extending the well known least squares adjustment procedure for a single vector of preliminary incoherent estimates (i.e., base forecasts) to the case of $p \geq 2$ vectors,

¹ A complete discussion of the optimal coherent combination approach, including the extension to the general case where the experts may produce base forecasts only for a subset of the totality of variables, can be found in [5].

the coherent combined forecast vector $\tilde{\mathbf{y}}^c$ can be expressed as $\tilde{\mathbf{y}}^c = \mathbf{M}\mathbf{\Omega}^\top\hat{\mathbf{y}}$, where $\mathbf{M} = \left[\mathbf{I}_n - \mathbf{W}_c \mathbf{C}^\top (\mathbf{C} \mathbf{W}_c \mathbf{C}^\top)^{-1} \mathbf{C} \right]$, $\mathbf{\Omega} = \mathbf{W}^{-1} \mathbf{K} \mathbf{W}_c$, and $\mathbf{W}_c = (\mathbf{K}^\top \mathbf{W}^{-1} \mathbf{K})^{-1}$ (see [5] for details). It is worth noting that this result is obtained under the commonly assumed hypotheses that the base forecasts are unbiased, and that the joint dispersion matrix of the p forecast experts is known.

3 Forecasting Italian daily electricity generation

We consider a forecasting experiment for 76 Italian daily electricity generation time series (01/01/2023-31/12/2023) from the ENTSO-E Platform. The market follows a grouped structure: a generation sources hierarchy with renewable (Biomass, Hydro, Solar, Wind, Geothermal) and non-renewable (Fossil, Waste) categories, and a geographic hierarchy with 7 bidding zones.

In order to assess the forecast accuracy of the various approaches, we perform a rolling forecast experiment with an expanding window (01/01/2023 – 21/5/2023 first training set). One- to seven-step-ahead forecasts were generated leading to $Q_1 = 225$ one-, ..., and $Q_7 = 119$ seven-step-ahead daily forecasts for evaluation. Each series was independently modeled using three different approaches [7]: stlf, arima, tbats. Moreover, we consider the following eleven forecasting procedures:

1. *Single best model and its reconciled counterpart*: two approaches. For the best base forecast expert (tbats), the reconciled forecasts are obtained through the shrunk MinT approach by [10] (tbats_{shr}).
2. *Single-task combination*: three approaches. Equal weights (ew) and the optimal weighting schemes proposed by [2] and [8], called respectively ow_{var} and ow_{cov}.
3. *Coherent combination*: six approaches. A sequential reconciliation-then-equal-weight-combination (src), three sequential combination-then-reconciliation (scr_{ew}, scr_{var}, scr_{cov}), and finally two optimal coherent combination approach, occ_{wlsv} and occ_{be}, with diagonal and block-diagonal shrunk in-sample covariance matrix, respectively (see [5] for details).

The forecast accuracy is evaluated in Table 1 using the Average Relative Mean Absolute (AR-MAE) and Squared (AR-MSE) Error [4] computed as, respectively,

$$AR-MAE_h^{app} = \left(\prod_{i=1}^{76} \frac{MAE_{h,i}^{app}}{MAE_{h,i}^{ew}} \right)^{\frac{1}{76}} \quad \text{and} \quad AR-MSE_h^{app} = \left(\prod_{i=1}^{76} \frac{MSE_{h,i}^{app}}{MSE_{h,i}^{ew}} \right)^{\frac{1}{76}}, \quad \text{with}$$

$$MSE_{h,i}^{app} = \frac{1}{Q_h} \sum_{q=1}^{Q_h} (y_{i,h,q} - \bar{y}_{i,h,q}^{app})^2 \quad \text{and} \quad MAE_{h,i}^{app} = \frac{1}{Q_h} \sum_{q=1}^{Q_h} |y_{i,h,q} - \bar{y}_{i,h,q}^{app}|, \quad \text{where } h = 1, \dots, 7 \text{ is the forecast horizon, } i = 1, \dots, 76 \text{ denotes the variable, } Q_h \text{ is the test set dimension, } app \text{ is the approach used, } y_{i,h,q} \text{ is the observed value and } \bar{y}_{i,h,q}^{app} \text{ is the forecast value using the } app \text{ approach (coherent or incoherent). The equal weights (ew) single-task combination is used as benchmark.}$$

Looking at Table 1, single-task combination and single-expert reconciliation strategies consistently improve forecasting accuracy compared to the three base

Table 1 AR-MAE and AR-MSE with equal weights combination approach (ew) as benchmark.

Approach	AR-MAE						AR-MSE					
	1	2	3	5	7	1:7	1	2	3	5	7	1:7
<i>Base (incoherent forecasts) and single model reconciliation</i>												
tbats	1.038	1.042	1.041	1.034	1.031	1.036	1.072	1.078	1.073	1.056	1.041	1.059
tbats _{shr}	1.008	1.009	1.018	1.016	1.017	1.014	1.004	1.005	1.029	1.022	1.018	1.018
<i>Combination (incoherent forecasts)</i>												
ew	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ow _{var}	0.988	0.987	0.991	0.994	0.996	0.992	0.978	0.978	0.986	0.991	0.997	0.989
ow _{cov}	1.021	1.015	1.021	1.017	1.006	1.015	1.022	1.020	1.036	1.039	1.039	1.035
<i>Coherent combination</i>												
src	0.980	0.982	0.987	0.992	0.995	0.989	0.959	0.962	0.977	0.985	0.994	0.981
scr _{ew}	0.983	0.985	0.992	0.996	0.998	0.993	0.965	0.969	0.986	0.991	0.997	0.987
scr _{var}	0.974	0.978	0.986	0.993	0.995	0.988	0.950	0.958	0.977	0.989	0.998	0.982
scr _{cov}	1.008	1.009	1.014	1.015	1.005	1.011	0.994	1.003	1.024	1.035	1.037	1.026
occ _{wls}	0.984	0.982	0.986	0.991	0.992	0.988	0.970	0.970	0.978	0.985	0.992	0.983
occ _{be}	0.970	0.973	0.979	0.988	0.992	0.983	0.940	0.946	0.966	0.981	0.993	0.974

Bold entries identify the best performing approaches, italic entries identify the second best.

models. However, tbats_{shr} tends to perform less effectively when compared to the more advanced single-task combination approaches. In contrast, coherent combination approaches consistently outperform all the other forecasting strategies.

Acknowledgements The authors acknowledge financial support from project PRIN 2022: PRICE – “A New Paradigm for High-Frequency Finance” – 2022C799SX.

References

1. G. Athanasopoulos, R. J. Hyndman, N. Kourentzes, and A. Panagiotelis. Forecast reconciliation: A review. *International Journal of Forecasting*, 40(2):430–456, 2024.

2. J. Bates and C. W. Granger. The combination of forecasts. *Operations Research Quarterly*, 20(4):451–468, 1969.

3. R. T. Clemen. Combining forecasts: A review and annotated bibliography. *International Journal of Forecasting*, 5(4):559–583, 1989.

4. A. Davydenko and R. Fildes. Measuring forecasting accuracy: The case of judgmental adjustments to sku-level demand forecasts. *International Journal of Forecasting*, 29(3):510–522, 2013.

5. D. Girolimetto and T. Di Fonzo. Coherent forecast combination for linearly constrained multiple time series. *arXiv*, 2024.

6. D. Girolimetto and T. Di Fonzo. Point and probabilistic forecast reconciliation for general linearly constrained multiple time series. *Statistical Methods & Applications*, 33(2):581–607, 2024.

7. R. J. Hyndman, G. Athanasopoulos, C. Bergmeir, G. Caceres, L. Chhay, M. O’Hara-Wild, F. Petropoulos, S. Razbash, E. Wang, and F. Yasmeen. forecast: Forecasting functions for time series and linear models. *R package*, 2023.

8. P. Newbold and C. W. Granger. Experience with forecasting univariate time series and the combination of forecasts. *Journal of the Royal Statistical Society, A*, 137(2):131–146, 1974.

9. R. Thompson, Y. Qian, and A. L. Vasnev. Flexible global forecast combinations. *Omega*, 126:103073, 2024.

10. S. L. Wickramasuriya, G. Athanasopoulos, and R. J. Hyndman. Optimal forecast reconciliation for hierarchical and grouped time series through trace minimization. *Journal of the American Statistical Association*, 114(526):804–819, 2019.

Economic complexity, technological innovation, and co-location of activities

Annamaria Giuffrida, Alessio Bumbea, Giuseppe Espa and Andrea Mazzitelli

Abstract The study explores the relationship between Italian industrial districts and technological innovation, employing the framework of economic complexity, a data-driven approach rooted in complex systems and network theory. By analyzing Italian patent data from 2020 to 2023, we focus on firms' patent portfolios and innovative capabilities within and outside industrial districts. The work provides new insights into the dynamics of the geography of innovation in Italy, using the metrics of Economic Fitness and Complexity (EFC) and Relatedness.

Key words: Economic Fitness and Complexity, Exogenous Fitness, Relatedness, Industrial districts

1 Introduction

The study seeks to delve into technological innovation, through the patent activity developed by companies. The performance of firms holding patent portfolios is assessed using the Economic Fitness and Complexity (EFC) methodology [1]. Studies such as that by Boix et al. [2], which compare the impact of innovation in industrial districts in Spain and Italy, highlight how geographical location can influence the intensity of patenting activity. Moreover, innovation involves continuous col-

Annamaria Giuffrida
Universitas Mercatorum, e-mail: annamaria.giuffrida@studenti.unimercatorum.it

Alessio Bumbea
Universitas Mercatorum, e-mail: alessio.bumbea@studenti.unimercatorum.it

Giuseppe Espa
University of Trento, e-mail: giuseppe.espa@unitn.it

Andrea Mazzitelli
Universitas Mercatorum, e-mail: a.mazzitelli@unimercatorum.it

laboration and interaction between neighboring actors [3]. Relatedness, a key tool within the Economic Complexity framework, measures the similarity between two economic activities or between an activity and an economic actor [4]. We aim to combine the Economic Fitness and Complexity (EFC) method with a Relatedness metric to assess the different level of patent activities of firms located both inside and outside industrial districts. Specifically, we investigate whether firms with similar patents and close geographical locations are predominantly located within industrial districts—where shared resources and economic activity promote innovation—or whether they emerge as distinct innovation hubs outside these districts.

2 Data and methods

2.1 Data

The study focuses on the patent activities of Italian firms between 2020 and 2023, using data from the Orbis Intellectual Property Database. The data was enhanced by linking firms with the National Business Registry (ASIA) via their tax codes, resulting in a sample of 98,817 patenting firms.

The dataset was refined to include only relevant IPC (International Patent Activity) categories, leading to the identification of 6,144 firms (both inside and outside industrial districts) associated with 441 IPC categories. We define the incidence matrix M to represent this relationship. Each element M_{ij} in the matrix is defined as:

$$M_{ij} = \begin{cases} 1, & \text{if firm } i \text{ has filed at least one patent in IPC category } j, \\ 0, & \text{if firm } i \text{ has not filed any patent in IPC category } j. \end{cases}$$

2.2 Complexity measures

The EFC approach evaluates a firm's fitness and the complexity of IPCs using the incidence matrix. Fitness measures a firm's ability to engage in advanced technological activities, reflecting its innovative potential based on the sophistication and diversity of its patent portfolio. On the other hand, the complexity of a patent is determined by how specialized is the knowledge required to file it.

A challenge in the Economic Complexity (EC) literature is the difficulty of analyzing systems across varying geographical scales. To tackle this problem, we computed the Exogenous Fitness using the patents of all the firms, and computed the complexity of all IPCs categories. We only considered the patents that appear at least once within an industrial district. The concept of Exogenous Fitness involves applying the Fitness-Complexity algorithm in a context with abundant information, such as data from all Italian regions or provinces, to determine the complexity of

patents. Hence the algorithm is then utilized to estimate the Fitness of geographical areas in a different context, such as fine partition of the territory, namely industrial districts, where data availability can be more limited [5].

2.3 Relatedness

To investigate the similarities between firms, namely the co-location of the activities, we employ the concept of relatedness derived from the bipartite network linking firms to their patents via IPC codes. Relatedness measure is based on the assumption that firms specializing in a particular activity have developed a set of capabilities that can facilitate diversification into activities that are closely related. Intuitively, activities requiring similar inputs are positioned near each other in the network, where proximity indicates a higher likelihood of transitioning from one activity to a neighboring one [6].

3 Results

The results suggest that industrial districts play a key role in promoting innovation. Firms within these areas show high levels of technological fitness due to the concentration of resources and collaborative networks. However, we also see a promising trend toward innovation by firms in functional urban areas, namely Labor Market Areas (LMAs), mainly localized in highly specialized local urban systems, such as Milan and Rome [7]. In these areas, firms show similar or even higher fitness levels than firms located within the districts, showing encouraging signs of the development of technologically advanced goods.

Fig. 1 shows the geographic distribution of firms, aggregated by municipality, and the color gradient within each municipality represents the average fitness of the firms located there. Fig. 2 illustrates the geographical distribution of industrial districts in Italy, highlighting sectoral specialization.

4 Conclusion

Using patent data, in the future, we propose to test the hypothesis that co-localized technologies are more likely to become correlated over time. Our approach involves the use of spatial point processes methodology, which we apply to solve the problem of spatial inhomogeneity also [8]. This approach allows us to explore the development of spatial relatedness between technologies and their different complexities by studying the co-location of technologically advanced firms. To this end, we will analyze both spatial concentration and agglomeration of economic activities using K-

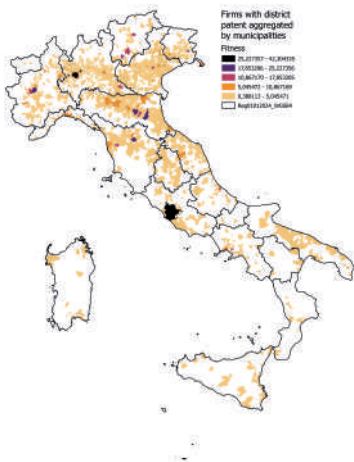


Fig. 1 Average fitness score of firms

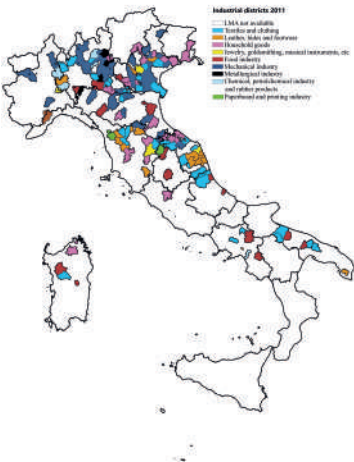


Fig. 2 Industrial districts

Ripley and apply test functions of spatial independence and joint spatial distribution [9].

References

1. Cristelli, M., Gabrielli, A., Tacchella, A., Caldarelli, G., Pietronero, L.: Measuring the intangibles: A metrics for the economic complexity of countries and products. PLOS ONE 8(8), e70726 (2013)

2. Boix-Domenech, R., Capone, F., Galletto, V.: Searching for “rare diamonds”? Industrial districts and innovation in Spain and Italy. Compet. Rev. 32(5), 728–742 (2022)

3. Arbia, G., Espa, G., Giuliani, D., Mazzitelli, A.: Detecting the existence of space-time clusters of firms. Reg. Sci. Urban Econ. 40, 311–323 (2010)

4. Albora, G., Zaccaria, A.: Machine Learning to Assess Relatedness: The Advantage of Using Firm-Level Data. Complexity (2022)

5. Pugliese, E., Tübke, A.: Economic complexity to address current challenges in innovation systems: a novel empirical strategy for regional development. Ind. R&I – JRC Policy Insights (2019)

6. Caldarola, B., Mazzilli, D., Napolitano, L., Patelli, A., Sbardella, A.: Economic complexity and the sustainability transition: a review of data, methods, and literature. J. Phys. Complex. 5, 022001 (2024)

7. Istat: Forme, livelli e dinamiche dell’urbanizzazione. Roma (2017).

8. Arbia, G., Espa, G., Giuliani, D., Mazzitelli, A.: Clusters of firms in an inhomogeneous space: The high-tech industries in Milan. Econ. Model. 29(1), 3–11 (2012)

9. Diggle, P. J.: Statistical Analysis of Spatial and Spatio-Temporal Point Patterns. Routledge (2014).

Leveraging Data Integration for Effective Revenue Management

Andrea Guizzardi, Ercolino Ranieri and Federico Zardo

Abstract In this study, we seamlessly integrate micro-level data from both internal and external sources to revolutionize last-minute occupancy forecasting across the advance booking horizon. By utilizing a sophisticated beta regression framework coupled with a robust variable selection methodology, we highlight the importance of feature engineering raw data. This approach delivers actionable insights that drive revenue optimization and elevate performance in the hospitality sector.

Key words: Hospitality sector, Occupancy forecasting, Advance bookings, Feature engineering, Beta regression

1 Introduction

Forecasting demand in the hotel industry poses a significant challenge for revenue managers due to irregular fluctuations driven by promotions, events, and environmental changes, which affect sales processes. This study highlights the importance of integrating Property Management Systems (PMS) with external sources of information to increase the accuracy of occupancy prediction models. We acknowledge that for many small and medium-sized hotels, system integration requires a mindset shift that is often difficult to implement due to limited financial, technical, and human capital resources. However, this is a necessary change for effective pricing

Andrea Guizzardi
University of Bologna, e-mail: andrea.guizzardi@unibo.it

Ercolino Ranieri
Xenia Spa, e-mail: ercolino.ranieri@xeniahs.com

Federico Zardo
Xenia Spa, e-mail: federico.zardo@xeniahs.com

and resource allocation decisions, in light of the growing use of digital tools by consumers in choosing their destination and accommodation [3].

By examining a medium-sized, four-star hotel in central Italy that offers two specific room types—*classic* and *superior*—we demonstrate that reliable forecasts can be achieved through accurate feature engineering of raw data using relatively simple methods like beta regression, rather than complex statistical methodologies that are harder to implement for many small and medium-sized hotels.

2 Data Description and Methodology

In this work, we suggest a feature engineering approach to the specification of a new type of independent variables with the idea that this could significantly influence the accuracy in predicting the daily pick-up curve. We consider daily data spanning from August the 12th 2022, marking the end of the COVID period, to December the 3rd 2024. Our dependent variable ($O_{t,k}$) represents the proportion of occupied rooms to the total available rooms on the arrival day t , with advance booking $k = 0$. We forecast $O_{t,0}$ at two horizons, $k = 5$ and $k = 10$ days ahead, a critical timeframe for decision-making due to high last-minute volatility [2]. As independent variables, we consider a combination of micro- and macro-level data, providing a holistic perspective that accounts for both internal and external determinants of tourism demand. Micro-level variables ($O_{t,k}$ and pricing strategies $P_{t,k}$) capture the temporal dynamics influenced by management choices, while macro-level data, such as monthly domestic and inbound tourism demand at the destination, reflect the destination's market size.

Micro-level data are synthesized using averages and standard deviations, across four predetermined booking intervals: $[5, 10)$, $[10, 19)$, $[19, 38)$, $[38, 345)$. This aggregation approach is justified by the consistent dynamics observed between adjacent booking days. Notably, statistics from the $[5, 10)$ interval are excluded for the 10-day ahead forecasts. We also include average cancellation rates calculated over longer intervals: $[5, 345)$ for the 5-day forecast and $[10, 345)$ for the 10-day forecast.

Borrowing common practices from financial markets, we perform feature engineering proposing technical-analysis indicators. Moving averages are particularly valuable for enhancing the revenue management practice of using the same day's performance from the previous year as a benchmark for current performance. Specifically, we define the moving average as $MA(y_t) = \frac{1}{2k+1} \sum_{j=-k}^k y_{t-j-365}$, where $k = 5$ corresponds to a 10-day window. This formulation allows us to better capture seasonality in prices and occupancy rates by smoothing short-term fluctuations. We also capture the variables 'momentum' with the following Stochastic-like and MACD-like oscillators: $Stoch(X) = \frac{X_{t,0} - X_{t,\min}}{X_{t,\max} - X_{t,\min}}$, $MACD(Z) = \frac{Z_{[a,b]}}{Z_{[a,c]}}$, where $X_{t,0}$ is the most recently observed price or occupancy, $X_{t,\min}$ and $X_{t,\max}$ are the minimum and the maximum observed values, respectively. Here, $Z_{[i,j]}$ may denote the mean or the standard deviations of both ($O_{t,k}$ or $P_{t,k}$) in the advance booking interval $[i,j)$ (e.g., $[5, 10)$). These indicators are computed for both 'classic' and 'complementary'

room types. After this preprocessing phase, we obtained 47 and 52 explanatory variables for the forecasts at horizons $k = 5$ and $k = 10$, respectively.

In our Beta regression approach $y_t \sim \text{Beta}(\mu_t, \phi)$, $\mu_t \in (0, 1)$ represents the mean and $\phi > 0$ denotes the precision. μ_t is linked to explanatory variables X_t via a logit link function. $\mu_t = \frac{\exp(X_t \beta)}{1 + \exp(X_t \beta)}$.

Model parameters are estimated using maximum likelihood [1]. Significant variables are selected by fitting the model across 100 random partitions of the dataset (80% training, 20% testing). For each partition, a stepwise selection procedure guided by the AIC criterion identifies significant variables. The frequency of each variable’s inclusion across the 100 regressions ranks their importance. For the final model, the top 20 most important variables are selected, a choice that does not significantly impact our results. Forecast accuracy is assessed using a distribution representing the Mean Absolute Error (MAE) from 1000 random dataset partitions (80% training, 20% testing), with occupancy rates converted back to the number of rooms for interpretability.

3 Results and conclusion

We report aggregate results for both *Classic* (32 rooms) and *Superior* (25 rooms), totaling 57 rooms. The histograms below represent 1,000 MAEs associated with each partition of the dataset. They clearly show that accuracy decreases as we move further from the check-in date, influenced by late cancellations and last-minute bookings. Considering the high market volatility in the last minute, the performance appears satisfactory, with a maximum error of less than 5% of the available rooms for the 10-day forecasts.

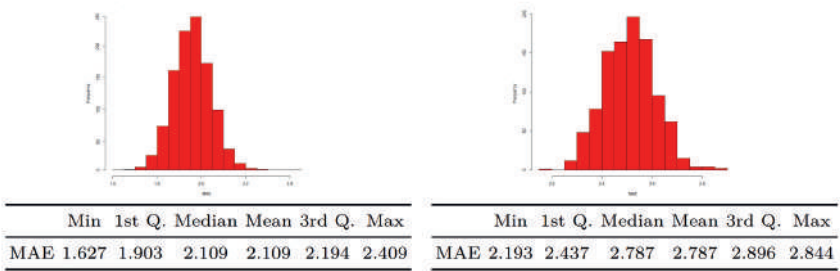


Fig. 1. MAE distributions: 5-day Forecast (left) - 10-day Forecast (right)

Table 1 provides a structural overview of the results, grouping the 20 variables that are most frequently significant in the 1,000 estimates into macro-categories. Notably, occupancy-related variables are the most informative, with 9 out of them

in the ‘top 20’ significant variables at the 5-day horizon and 6 at the 10-day horizon. Occupancy-related metrics also show high relevance: on average, they appear significant in 79% of the estimated models for the 5-day horizon and in 84% for the 10-day horizon.

Table 1 Structural determinants

By macro categories	5-day Forecast		10-day Forecast	
	N°	(%)	N°	(%)
Occupancy	9	79%	6	84%
Prices	6	57%	7	57%
Context	2	60%	4	51%
Moving Averages	1	100%	1	89%
Oscillators	2	52%	2	50%

Price-related indicators and contextual factors are influential across both forecast horizons (although they are fewer). The moving average measure achieves an impressive 100% score on the 5-day forecasting horizon, highlighting the relevance of our ‘fuzzy’ measure of the previous year’s occupancy.

Overall, Table 1 shows that integrating macro and micro data sources enhances forecast accuracy. However, the specified data generation process is mostly autoregressive, as occupancy metrics (both recent and those referring to the previous year) play a central role in capturing booking dynamics. This autoregressive component became stronger in the 5-day ahead forecasts, while 10-day ahead forecasts rely more on broader trends and macro-level factors. From a managerial point of view, this result suggests that real-time pricing adjustments are more effective in the short term, offering actionable insights for implementing techniques to refine pricing and inventory decisions.

References

1. Ferrari, S., Cribari-Neto, F. (2004). Beta regression for modelling rates and proportions. *Journal of Applied Statistics*, 31(7), 799–815.
2. Guizzardi, A., Angelini, G., Pons, F.M.E. (2020). Does advance booking matter in hedonic pricing? A new multivariate approach. *International Journal of Tourism Research*, 22(3), 277–288.
3. Webb, T., Schwartz, Z., Xiang, Z., Altin, M. (2022). Hotel revenue management forecasting accuracy: The hidden impact of booking windows. *Journal of Hospitality and Tourism Insights*, 5(5), 950–965.

Examining the Impact of Geopolitical Risk, Climate Policy Uncertainty, Waste Management, and Financial Efficiency on Renewable Energy Investment in the USA: A Novel Dynamic Simulated ARDL Approach

Aamir Javed and Agnese Rapposelli

Abstract The aim of this work is to examine the impact of geopolitical risk, climate policy uncertainty, waste management, environmental policy stringency, financial integration and financial institutions efficiency on renewable energy investment in the USA. To this purpose, we apply a novel dynamic simulated ARDL model by focusing on time series data for the period 1990-2022. The results obtained show that geopolitical risk negatively affects renewable energy investment, while climate policy uncertainty, environmental policy, financial integration and efficiency have a positive impact on it. Based on these findings, the USA should implement strict environmental policies to stimulate renewable energy investment.

Key words: renewable energy investment, geopolitical risk, climate policy uncertainty, waste management, financial efficiency, dynamic ARDL.

1 Introduction

The extensive digging of fossil fuels has not only resulted in choking environmental damages but also in several economic shocks, energy poverty, geopolitical concerns, and climate changes [7]. Investments in renewable energy sources provide energy

Aamir Javed
University of Chieti-Pescara G. D'Annunzio, e-mail: aamir.javed@unich.it
Agnese Rapposelli
University of Chieti-Pescara G. D'Annunzio, e-mail: agnese.rapposelli@unich.it

security, protect the biodiversity of the ecosystem, reduce environmental degradation, and preserve the planet for future generations [7]. Investment in renewables is the key to sustainable development as it represents the two key indicators of sustainability and sustainable development goals (SDGs). SDG 7, in particular, focuses on the provision of clean energy, which has a consequent impact on other SDGs, such as SDG 13 - as clean energy is the pedestal of climate action -, SDGs 14 and 15 - as clean energy promotes eco-sustainability [4]. Besides, clean and accessible energy sources are the strategic commodities that ensure sovereign stability and the prerequisite to sustainable economic growth which has widespread influence on the well-being of the masses.

However, the ratio of renewable energy to total energy consumption is far less. Global renewable energy capacity is expected to increase by 2400 GW by 2027, mainly due to energy security (due to the Russia-Ukraine war) and energy crises [1]. Another report by the World Bank on tracing SDG 7 indicates that the current pace to chase the 2030 Agenda for Sustainable Development is not sufficient and requires significant investments in renewables, rigorous policy formulation and implementation, as well as sovereign commitment [2,6]. It is important to mention that the heavy cost of renewable energy generation and deployment hinders its use as compared to conventional methods. Authentic policy promotion and system involvement are therefore necessary to incentivize renewable energy investment [7]. Being a strategic commodity, energy investment is affected by many national and international dynamics, the most important of which are related to geopolitical risk, climate policy uncertainty, environmental policy, financial integration, and financial institutions efficiency. Furthermore, to develop sustainable energy policies, policymakers require rigorous empirical justifications, and this paper serves well to the notion.

In this context, our aim is to investigate how renewable energy investment is affected by geopolitical risk, climate policy uncertainty, waste management, environmental policy stringency, and financial integration and efficiency. We decided to extract empirical evidence from the USA economy for various reasons. Firstly, there are important environmental reasons as the USA produced 4.7 billion metric tons of CO₂ emissions in 2020 and became the second largest emitter of carbon emissions (per capita CO₂ emissions in the USA are higher than the global average). To achieve Agenda 2030 goals, the USA committed to curtailing half of the emissions that need clean energy investment [4]. Secondly, the USA energy utilization amounts to 17% of the global primary energy consumption to back household needs, industrial activities, transportation, etc. [3]. The US produces 18% of the world's oil production, thus becoming the first country on the list of oil-producing countries [5]. Finally, the political, economic, and military interests of the US spread all over the world, making it the country most affected by geopolitical risk and climate policy uncertainty.

2 Estimation approach

This work employs a novel dynamic ARDL model (DYARDL), an appropriate new econometric approach, to examine the long- and short-run influences of the explanatory variables on the explained variable (renewable energy investment, REI).

Before implementing the DYARDL model, we must implement a unit root test to verify the stationarity and cointegration order of the examined series. Variables only integrated at $I(0)$ and $I(1)$ can be utilized in the DYARDL model. Furthermore, we utilized the frequency domain causality approach to evaluate the long-, medium- and short-term causality connections between the variables considered.

The relationships between the research variables are examined using the following empirical model:

$$REI_t = \beta_0 + \beta_1 GPR_t + \beta_2 CPU_t + \beta_3 WM_t + \beta_4 EP_t + \beta_5 FI_t + \beta_6 FIE_t + \beta_7 OP_t + \beta_8 GDP + \varepsilon_t$$

where GPR denotes the geopolitical risk, CPU denotes the climate policy uncertainty, WM denotes the waste management, EP denotes the environmental policy stringency, FI denotes the financial integration/globalization, FIE denotes the financial institutions efficiency, OP denotes the oil prices, and GDP denotes the economic growth. This study uses US data for the period 1990–2022.

3 Estimation results

We examined each variable stationarity with regard to $I(0)$ and $I(1)$ by applying Dickey and Fuller and Phillips and Perron tests. The unit root tests suggest that the underlying series are non-stationary at the level. Both tests indicate that the variables under analysis are stationary at first difference. Next, we utilized the ARDL cointegration test to evaluate the existence of long-term relationships among the variables. The estimated results confirm the existence of long-run connection between the REI and the variables considered (GPR, CPU, WM, EP, FI, FIE, OP, GDP).

The DYARDL results suggest that an increase in the geopolitical risk has a substantial adverse effect on REI. This implies that the growth of geopolitical conflicts hinders renewable energy investment in the USA. In addition, our findings reveal that REI has a positive significant connection with climate policy uncertainty, waste management, and environmental policy. Similarly, we observe that financial integration positively affects the level of REI both in the short- and in the long-run. Moreover, the results demonstrate that financial institutions efficiency has a beneficial impact on REI only in the short-run, while the long-run relationship is not significant. In addition to this, the empirical findings show that there is a substantial positive correlation between oil price and the amount of dollars invested in the renewable energy sector, as well as a significant positive association between GDP

and REI. Finally, we performed several diagnostics test such as heteroscedasticity, serial correlation, and model stability. The findings of these tests confirm that our model is free from these issues and that the estimated model is stable.

4 Conclusion and policy recommendation

The present work has been conducted to analyse the role of geopolitical risk, climate policy uncertainty, waste management, environmental policy stringency, and financial integration and efficiency on renewable energy investment in the USA. We adopted a modern econometric technique - the novel dynamic simulation ARDL approach - to reach the study goals by focusing on the period 1990-2022.

Based on the results obtained, it is suggested that though the paths to renewable energy investment are being developed still it is not enough to meet the enormous energy challenges. Environmental governance needs to ensure the restructuring of the environmental policies and their execution as well as penalizing polluting activities and rewarding environmentally friendly projects. Environmental management is required to establish a strict and consistent environmental policy to lower the uncertainty regarding the environmental concerns of governance that would directly boost renewable energy investment. Furthermore, an awareness campaign to create public awareness regarding renewable energy investment opportunities is required to create “energy literacy” in the general public.

Acknowledgments This work was funded by EU – NextGenerationEU – Call Prin 2022 PNRR, D.D. 1409 14.9.2022, National Recovery and Resilience Plan (PNRR) Mission 4 - Component 2, Investment n. 1.1 (project code P2022XME5P titled “Circular Economy from the Mathematics for Signal Processing prospective”, grant number E53D23018040001).

References

1. IEA: Renewables 2022 (2022a). www.iea.org
2. IEA: World Energy Outlook 2022 (2022b). www.iea.org/t&c/
3. IEA: World Energy Outlook 2023 (2023). www.iea.org/terms
4. Liu, X., Yuan, S., Yu, H., Liu, Z.: How ecological policy stringency moderates the influence of industrial innovation on environmental sustainability: The role of renewable energy transition in BRICST countries. *Renew. Energy* 207, 194--204 (2023)
5. Sweidan, O.D.: The geopolitical risk effect on the US renewable energy deployment. *J. Clean. Prod.* 293, 126189 (2021)
6. World Bank: TRACKING SDG7 A joint report of the custodian agencies (2022). www.worldbank.org
7. Zhou, D., Siddik, A. B., Guo, L., Li, H.: Dynamic relationship among climate policy uncertainty, oil price and renewable energy consumption - findings from TVP-SV-VAR approach. *Renewable Energy*, 204, 722--732 (2023)

Digital skills of citizens, enterprises and local PA

Valeriana Leporanico and Cira Acampora

Abstract To measure the degree of digitalization in Italy, Istat documents the development of the information society through surveys on information and communication technologies (ICT) among citizens, businesses and public administration. The estimates produced are used by the European Commission to evaluate the progress of Member States in digitalization and, from 2021, are part of the monitoring system of the European strategic program "Digital Decade 2030". The aim of this work is to analyze the digital skills of these 3 Targets, their characteristics and discriminating factors by comparing indicators in time and space.

Key words: Digitalization, Innovation, ICT, AI

1 Citizens' digital skills

One of the objectives of the European program is to increase the share of the population aged between 16-74 years with at least basic digital skills in all five domains to 80% by 2030 (*communication and collaboration, information and data literacy, security, problem solving, digital content creation*) defined by the current Digital Competence Framework.

In 2023, in Italy, only 45.7% have at least basic digital skills, a stable value compared to 2021, while at a European level it is 55.5%. Of these, more than half (51.7%) live in the North while just over a quarter are resident in the South (26.8%). As in other European countries, also in Italy digital skills are associated with the socio-cultural characteristics of the population: in 2023, 61.7% of Italian children aged 20-24 have at least basic digital skills. This share decreases rapidly with age to 42.2% among 55–59-years old and reach 19.3% among 65–74-years old. This level

Valeriana Leporanico
ISTAT, e-mail: valeriana.leporanico@istat.it
Cira Acampora
ISTAT, e-mail: acampora@istat.it

of skills is characterized by a strong gender disparity in favor of men in almost all European countries (in Italy, equal to 3.1 percentage points). It should be noted, however, that at least up to the age of 34 a female advantage is recorded and then reversed the mark from 45 years. The main discriminating factor along with age is education; in fact, 77.6% of people aged 25-54 with tertiary education have at least basic digital skills compared to 26.4% of the same people with low educational qualifications (up to average license).

Adequate digital skills are also a prerequisite for access to employment. In Italy, 56.9% of the employed reach a level at least basic, below the EU27 average of 8 percentage points (64.7%). From the analysis of individual Italian regions, a strong gap emerges between North-Central and South & Islands, except for Sardinia which shows an average value. The regions in the best position in this area are the Autonomous Province of Trento (56.5%), Lombardy (53.1%), Lazio (51.4%) and Emilia Romagna (51.3%). At the bottom of the ranking are Calabria (32.2%) and Campania (32.3%). The highest share of employees with at least basic digital skills is observed in Information and communication services and in Financial and insurance activities (around 80%), while the sectors lagging are agriculture, forestry and fisheries (32.5%) of the construction industry (43.8%).

2 Digital skills of enterprises

The level of digitalization of enterprises is assessed against 12 indicators that make up the Digital Intensity Index (DII)¹. Referring only to small and medium-sized enterprises (SMEs) with a "basic" DII level in the "Digital Compass 2030" program, the target to be achieved by 2030 is 90%. In 2023, 60.7% of SMEs are at a basic level of digitization using at least 4 out of 12 digital activities (57.7% in the EU27). In contrast, 91.1% of enterprises with at least 250 employees reach a level of at least basic. In 2023, Italian enterprises are more dependent than European ones on external service providers such as IT security and web sales: About 6 out of 10 Italian enterprises selling online use platforms or apps of online trade intermediaries compared to an EU average of 42.9%, demonstrating the lack of IT skills of those employed. The second concrete objective of the strategic program "Digital Decade" is to reach 1.7 million ICT specialists by 2030 and to increase the number of women in these professions. In Italy, according to the Labor Force Survey, in 2023 there are 970 thousand people employed in occupations that fall within the aggregate of ICT specialists. The various elements that contribute to define a weak picture of the

¹ Digital Intensity Index (DII) 2023: a microdata-based index measuring the use by enterprises of 12 different digital technologies: 1. percentage of connected employees >50%; 2. percentage of enterprises using AI technologies; 3. percentage of enterprises connecting to fixed broadband internet at download speeds $\geq$ 30 Mbit/s; 4. percentage of enterprises analysing data internally or externally; 5. percentage of enterprises purchasing cloud computing services; 6. percentage of enterprises purchasing sophisticated or intermediate cloud computing services; 7. percentage of enterprises using social media; 8. percentage of enterprises using ERP; 9. percentage of enterprises using CRM; 10. percentage of enterprises using at least two social media; 11. percentage of companies with online sales value at least equal to 1% of total revenues (on total turnover); 12. percentage of companies that have web sales greater than 1% of revenues and web sales to private consumers (B2C) more than 10% of total web sales. The value for the index therefore ranges from 0 to 12. The index identifies four digital intensities according to the number of activities carried out by enterprises: up to 3 activities (very low level), 4 to 6 (low level), 7 to 9 (high level), 10 to 12 (very high level). The basic intensity consists of at least four activities.

Italian position are: *the low diffusion of ICT specialists in enterprises with at least 10 employees*: (in 2022 it had 13.4% against an average value of 21.0% for the EU27) *a small proportion of specialists with university degrees*: Italy is the last in the EU; in 2023, these were 42.1% against an average level of 66.7%; *few ICT specialists under 35 years old*, 29.3% against 37.3% of the EU27 average; also in this case, Italy is the last among the EU27 countries and *a persistently low female presence in an employment context* characterized by a male predominance: in 2023, women accounted for 15.7% of the EU27 population, compared to 19.4% of the EU27 average. One of the European Commission's recommendations in its first report on the Digital Decade is to increase the share of graduates in science, technology, engineering and mathematics (STEM). The majority of graduates in STEM disciplines are concentrated between Engineering and Architecture (14.2%), followed by subjects in the Science and Mathematics group (3.2%) while only 1.5% have graduated in ICT disciplines, with a distance from the EU27 average of 3 percentage points.

In the context of corporate training in 2022, 19.3% of Italian enterprises with at least 10 employees have implemented digital skills training activities, a value that has grown strongly compared to 2017 (+6.4 percentage points), although less than 224% of the EU27 where, however, the increase was much smaller (+1.7 points). The spread of training grows with the increase in the size of the company: from 16.1% among small enterprises, to 65.4% among those with 250 employees and more. However, this investment is not sufficient to bridge the gap with the EU27 average, which increases with size, reaching up to 4.1 percentage points for large enterprises.

In 2023, 5% of Italian enterprises with at least 10 employees (excluding the financial and insurance sector) use Artificial Intelligence (AI) technologies that are analyzed indicating a certain stability compared to last year (6.2%); Enterprises with 50-99 employees, which amounted to 5.6% (9.4% in the previous year). The share of large enterprises remains stable at around 24%.

3 Digital skills of local PA

In 2022, the services offered online are no longer mainly aimed at businesses, for which they are confirmed, as in 2018, values over 80%, but increases the offer of services to households: 86.4% of the regions and 70.4% of the municipalities. These are mainly the services of registration which in the Municipalities increased from 65.5% to 83.9%, the identity card (from 58.8% to 70.8%) and the request for disability cards (from 46.1% to 60.0%), school meal services (from 55.1% to 66.0%) and fines (from 30.8% to 45.5%). The online healthcare offer by the Regions also increases, as for the choice of primary care physician, from 36.4% to 68.2%, and the request for exemptions (from 22.7% to 31.8%). 76.6% of local PAs declare that users can access online services through the SPID Digital Identity (it was 20.5% in 2018), for the regions this share rises to 100% and for larger Municipalities to 99%

(respectively 72.7% and 58.2% in 2018); there are territorial differences between the municipalities of the North with percentages over 80% and those of the South (67.5%). 43.9% (21.9% in 2018) of local PAs use the national services card (CNS), and for electronic identity cards this figure increases from 5.5% in 2018 to 59.6%. 74.0% of local PAs access the internet through fast connections (at least 30 Mbps, megabit per second), while doubling (35.8%) compared to 2018 (17.4%) the spread of ultra-fast ones (at least 100 Mbps).

Despite the development of digitalization, 89.1% of local PAs still use analogue instruments (stamps, signatures, initials) in their registration. The most advanced activities for networked computerization are the management of other receipts (PagoPA application) equal to 70.0% (56.4% in 2018), the management of tenders (53.6% compared to 44.1% in 2018) and the management of competitions (23.5%, 16.2% in 2018). 5.1% of local PAs (81.8% of the Regions) have invested in artificial intelligence or big data analysis or have planned to do so in the three-year period 2022-2024. At the dimensional level, the municipalities of greater size emerge with more than 60 thousand inhabitants (36.7%) and among the regions are those of the Molise region (11%). The provincial administrations of the North reach higher shares (about 13%) than those of the Centre (5.0%) and of the South of Italy (5.7%). To organize ICT activities, the Municipalities that have chosen to provide themselves with an autonomous office of information technology are those belonging to the metropolitan cities of Cagliari (70.6%), Venice (65.9%) and Naples (65.2%); on the other hand, the metropolitan municipalities of Bologna prefer an associated organization of computer offices (90.9%), while those of Florence prefer both internal management (48.8%) and in an associate form (31.7%).

In 2022 there is an increase in the number of public sector training providers on digital skills, although this is related to the size and organizational complexity of the institution. The main topics covered by training are specific applications and software (71.4%), ICT security (49.4%), web (42.2%) and use of platforms offering online services (58.7% telematics payments, 44.9% digital identity and 20.2% cloud computing).

References

1. Istat, Indagine Multiscopo sulle famiglie: aspetti della vita quotidiana (parte generale) - The survey hosts the module: L'uso delle tecnologie della comunicazione e dell'informazione da parte delle famiglie e degli individui
2. La rilevazione sulle tecnologie dell'informazione e della comunicazione (Ict)
3. La Rilevazione sulle tecnologie dell'informazione e della comunicazione nella PA locale
4. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/europes-digital-decade-digital-targets-2030_it
5. <https://digital-strategy.ec.europa.eu/en/factpages/digital-decade-2024-report-country-fact-pages>
6. Strategia nazionale per le competenze digitali. <https://docs.italia.it/italia/mid/strategia-nazionale-competenze-digitali-docs/it/1.0/index.html>

Exploring Occupational Mismatch in European Labor Markets: Measures, Determinants, and Implications

Sergio Longobardi and Margherita Maria Pagliuca

Abstract This study investigates occupational mismatch in the labor force across selected European countries, focusing on overeducation, overskilling, and severe mismatch. The analysis employs statistical and subjective approaches to measure mismatch, utilizing recent OECD data, revealing significant cross-country variation. In addition, a multinomial logistic analysis highlights that factors such as gender, age, and educational background influence mismatch probabilities. The findings underline the need for targeted policies to align education systems with labor market demands.

Key words: occupational mismatch, overeducation, overskilling, labor market

1 Introduction

Occupational mismatch, the misalignment between workers' qualifications or skills and those required by their jobs, is a multifaceted phenomenon with far-reaching implications for individuals and society. As early as the 1970s, Richard Freeman (1976) introduced the concept of overeducation in his studies on American college graduates. Later, Duncan and Hoffman (1981) explored the relationship between educational mismatch and wages, providing analytical tools to measure these disparities within the framework of the Mincer earnings equation. Over the past few decades, however, attention has shifted from educational mismatch to skill mismatch (overskilling), reflecting their distinct nature and policy implications (Desjardins and Rubenson, 2011). While some degree of mismatch is inevitable—particularly for

Sergio Longobardi

University of Naples Parthenope, e-mail: sergio.longobardi@uniparthenope.it

Margherita Maria Pagliuca

University of Naples Parthenope, e-mail: margherita.pagliuca@uniparthenope.it

young workers or those entering or re-entering the labor force—it is crucial to minimize its impacts through targeted policies. Over the past decades, empirical evidence reveals that occupational mismatches are widespread and persistent in Europe, imposing real costs on individuals, businesses, and society (Cedefop, 2010). Educational systems often fail to equip individuals with skills aligned with labor market demands, exacerbating the problem. For instance, a significant portion of the workforce reports being overqualified (educational mismatch) but not simultaneously overskilled (skills mismatch), highlighting inefficiencies in the alignment of education with job market requirements. At an individual level, mismatches can lead to lower job satisfaction and reduced wages. At a broader level, they undermine productivity, devalue investments in human capital, and weaken economic competitiveness (McGowan and Andrews, 2015). The impacts of mismatch extend beyond wage dynamics. Overqualified workers often face lower wages than expected based on their education, reduced job satisfaction, diminished productivity, and psychological stress (Tsang and Levin, 1985). These individual challenges aggregate into broader societal costs, including reduced productivity and higher turnover rates. Moreover, as major educational investors, governments face the challenge of ensuring that these investments yield meaningful economic and social returns. Unaddressed mismatches can lead to substantial losses in productivity, undermining national economic growth (Dolado et al., 2002). Tackling occupational mismatch requires strategic interventions that improve the allocation of workers, enhance the alignment of education and skills with labor market needs, and ensure a more efficient use of human capital. Such efforts are essential for boosting competitiveness, fostering economic growth, and improving individual well-being.

2 Data and methods

To measure and analyze occupational mismatch, we utilize the recent data from the Programme for the International Assessment of Adult Competencies (PIAAC), made available by the OECD in 2024. This dataset provides a unique opportunity to simultaneously measure mismatch using education-related variables (overeducation) and individual competency levels (overskilling). Two distinct approaches are adopted to measure overeducation and overskilling: a Statistical Approach and a Subjective Approach. The Statistical Approach classifies individuals as overeducated if their education level exceeds the modal level for their occupation (based on ISCO 1-digit classification) and country. Overskilling is identified when an individual's numeracy score is more than one standard deviation above the average for their ISCO 1-digit occupation and country. The Subjective Approach relies on self-assessment. Individuals are overeducated if their highest qualification surpasses the level they consider necessary for their job. Overskilling is determined by identifying “matched” workers who report neither excess skills nor the need for additional training. An individual is then classified as mismatched if their numeracy score exceeds the 95th percentile of the skills distribution among matched workers within the same ISCO 1-

digit occupation and country. The analysis focuses on employed individuals from nine European countries, excluding the self-employed, using survey data to assess the prevalence of education and skills mismatches.

3 Main results

Statistical matching and subjective assessment identify three types of occupational mismatch: overeducated, overskilled, and severely mismatched (both overeducated and overskilled). Using the statistical approach (Figure 1, panel a), Poland has the lowest mismatch rates, followed by Slovakia (76.11%) and Belgium (75.30%). Conversely, Spain records the highest overeducation (25.67%) and severe mismatch (7.79%), indicating potential inefficiencies in its education system or labor market. Italy (16.91%) and Hungary (15.87%) also show notable overeducation and severe mismatch levels. Finland and Portugal exhibit better alignment between education and labor market demands. The subjective approach reveals that workers in some Eastern European countries (Czech Republic, Hungary, Poland) perceive themselves as more overeducated than statistical measures suggest. However, differences in overskilling and severe mismatch rates remain minimal across the two methods, reinforcing the reliability of statistical classifications.

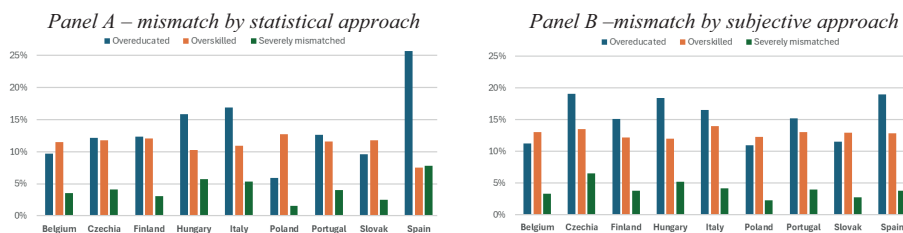


Fig.1 Percentage of overeducated, overskilled and severely mismatched workers by country

Subsequently, a multinomial regression model estimates the likelihood of falling into one of the mismatch categories, using “matched” workers as the baseline. Results (table 1) indicate that females are less likely than males to be overskilled or severely mismatched. Regarding the occupational level, workers in high-skill professions face lower mismatch probabilities than those in elementary occupations. Semi-skilled workers (white-collar and blue-collar jobs) experience a reduced, but sometimes not significant, mismatch likelihood. On average, and as intuitively expected, having more years of education increases the probability of overqualification. However, this significant effect is substantially weaker when mismatch is measured through a subjective approach. Focusing on the age of workers, individuals in the oldest age group (55–65 years) show a lower probability of being mismatched. This finding is expected since workers need time to find skill-matched jobs, while younger, new labor market entrants face higher mismatch risks.

Table 1 Multinomial logit model estimates

covariates	Mismatch by statistical approach						Mismatch by subjective approach					
	overeducat.		overskilled		sever. mism.		overeducat.		overskilled		sever.mism.	
	coeff.	sig.	coeff.	sig.	coeff.	sig.	coeff.	sig.	coeff.	sig.	coeff.	sig.
female	0.030		-0.596	***	-0.545	***	-0.118		-0.703	***	-0.431	***
Skilled occ	-6.811	***	-0.388	**	-7.237	***	-3.095	***	-0.709	***	-3.965	***
white-coll.	-1.704	***	0.026		-2.101	***	-1.448	***	-0.173		-2.003	***
blue-collar	-0.963	***	-0.201		-1.425	***	-1.246	***	-0.437	**	-1.456	***
educ.lev1	-30.39	***	-1.377	**	-30.61	***	-0.749	**	-1.318	**	-3.410	***
educ.lev2	-5.728	***	-0.643	***	-6.469	***	-1.059	***	-0.761	***	-2.125	***
age 36-45	-0.085		-0.049		0.110		-0.095		0.019		-0.013	
age 46-55	-0.094		-0.084		-0.110		-0.201	**	-0.054		-0.280	*
age 56-65	-0.285	**	-0.422	***	-0.654	***	-0.382	***	-0.485	***	-0.610	***
STEM	-0.035		0.235	***	0.296	**	-0.259	***	0.298	***	0.351	**
Fixed term contract	-0.117		-0.181		-0.307		0.270	**	-0.128		0.067	
Part time employed	-0.055		0.006		-0.545		0.536	***	-0.009		0.567	***
firm size 11-250	-0.043		-0.001		-7.237		-0.262	***	-0.008		-0.141	
firm size 250-999	0.190		0.064		-2.101	***	-0.333	**	0.201		-0.185	
firm size >1000	0.156		-0.122		-1.425	*	-0.255		0.105		-0.140	
constant	4.106	***	-1.041	***	-30.61		1.182	***	-0.597	**	0.672	*
country fix. effects	yes		yes		yes		yes		yes		yes	

*p<0.1 ; ** p<0.05; *** p< 0.01

Workers with STEM educational backgrounds are significantly more likely to be overskilled or severely mismatched. On the other hand, the type of employment contract (e.g., fixed-term) and firm size do not appear to influence mismatch significantly. These findings underline the complex interplay between education, labor market structures, and demographic factors in shaping occupational mismatch. Addressing these challenges requires tailored policies to align education systems with labor market demands, particularly for younger workers and STEM professionals.

References

1. Adalet McGowan, M., Andrews, D.: Labour market mismatch and labour productivity: Evidence from PIAAC data, OECD Economics Department Working Papers, No. 1209, OECD Publishing, Paris, (2015)
2. CEDEFOP: The Skill Matching Challenge: Analysing Skill Mismatch and Policy Implications. Luxembourg: Publications Office of the European Union (2010).
3. Desjardins, R., Rubenson, K.: An Analysis of Skill Mismatch Using Direct Measures of Skills. OECD Education Working Papers. OECD Publishing, Paris, (2011).
4. Dolado, J. J., García-Serrano, C., Jimeno, J.F.: Drawing Lessons from the Boom of Temporary Jobs in Spain. The Economic Journal (2002)
5. Duncan, G. J., Hoffman D.S.: The Incidence and Wage Effects of Overeducation. Economics of Education Review 1 (1): 75–86 (1981)
6. Freeman, Richard B.: The over-Educated American. New York: Academic Press (1976)
7. Tsang, M. C., Levin, H.M: The Economics of Overeducation. Economics of Education Review 4 (2): 93–104 (1985)

Cointegrated Matrix Auto-Regressive Model

Emanuele Lopetuso and Massimiliano Caporin

Abstract Traditionally, econometric models have treated observations as vectors, even though the data collection process often generates more complex structures. For instance, when data are collected at the intersection of two classifications, representing them as matrices is more natural. Building on recent advancements in matrix AutoRegressive (MAR) models, this paper introduces an error correction representation tailored to such matrix-structured data. By comparing our model with existing approaches, we demonstrate how it enhances the economic interpretability of coefficients while preserving and extending the insights provided by standard cointegrated models.

Key words: Matrix AutoRegression, Cointegration

1 Introduction

This study explores recent advancements in cointegration, specifically the integration of cointegrated models with autoregressive structures for matrix-valued time series (see [?]). To our knowledge, the only prior work on cointegration for matrix-valued time series is [?], which introduced the Cointegrated Matrix AutoRegressive Model (hereafter C-MAR). The C-MAR model is expressed in the following Matrix Error Correction form (hereafter MECM):

$$\Delta X_t = \Lambda X_{t-1} \Psi' + E_t, \quad (1)$$

Emanuele Lopetuso
University of Padua, e-mail: emanuele.lopetuso@unipd.it

Massimiliano Caporin
University of Padua, e-mail: massimiliano.caporin@unipd.it

where X_t is an $m \times n$ matrix of $I(1)$ observations (i.e., ΔX_t is stationary), Λ and Ψ are square matrices of dimensions m and n , respectively, and E_t is an $m \times n$ white noise matrix. Both Λ and Ψ have reduced ranks, $r_\Lambda < m$ and $r_\Psi < n$, allowing them to be decomposed as:

$$\Delta X_t = \alpha \beta' X_{t-1} \theta \varphi' + E_t, \quad (2)$$

where α and β are $m \times r_\Lambda$ matrices, and φ and θ are $n \times r_\Psi$ matrices.

By applying the vec operator, the MECM form can be expressed as a standard Vector Error Correction Model (VECM):

$$\text{vec}(\Delta X_t) = (\varphi \theta') \otimes (\alpha \beta') \text{vec}(X_{t-1}) + \text{vec}(E_t) = \Pi \text{vec}(X_{t-1}) + \varepsilon_t. \quad (3)$$

In general, if a matrix A admits a Kronecker product decomposition, the matrix $A + I$ does not necessarily admit a similar decomposition. Hence, although $\Pi = \Psi \otimes \Lambda$, the VAR form of (3) does not admit a MAR representation.

In this paper, we examine the interpretation of the C-MAR model and argue that the proposed representation may not fully capture the subtleties of economic dynamics. We then propose an alternative structure for the cointegrated MAR model, starting from its VAR form rather than the error correction representation. We demonstrate that focusing on the decomposition of the VAR coefficient, rather than Π , leads to a model that better captures the equilibrium dynamics typically emphasized in economic theory.

2 Adjustment Dynamic in the C-MAR Representation

From (3), it follows that $(\theta' \otimes \beta') x_t \sim I(0)$. It is well established that the condition $(\theta' \otimes \beta') x_t = 0$ represents an equilibrium state. When $(\theta' \otimes \beta') x_t \neq 0$, Δx_t adjusts to restore equilibrium. The speed of this adjustment is captured by the matrix $\varphi \otimes \alpha$. Extending this reasoning to the matrix model, the system is in equilibrium when $\beta' X_t \theta = 0$, and an adjustment occurs when this condition is violated.

Given (2), equilibrium is achieved when either $\beta' X_t = 0$, $X_t \theta = 0$, or both. Therefore, $\beta' X_t \neq 0$ and $X_t \theta \neq 0$ do not represent two distinct disequilibrium conditions, as it is sufficient for one to be zero to ensure a steady state. Hence, the decomposition of the cointegration matrix into $\beta' X_t \theta$ is based on the mathematical properties of the coefficient, without direct economic interpretations of θ and β .

To illustrate, consider an example where the data represent savings (S) and investments (I) for two countries, the UK and the US (denoted by subscripts). The data are structured in matrix form as follows:

$$X_t = \begin{bmatrix} S_{UK} & S_{US} \\ I_{UK} & I_{US} \end{bmatrix}. \quad (4)$$

Assume the data follow the model in (2), with the following specification:

$$\alpha = \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \quad \beta = \begin{bmatrix} 1 \\ -1 \end{bmatrix}, \quad \varphi = \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \quad \theta = \begin{bmatrix} 1 \\ -0.5 \end{bmatrix}. \quad (5)$$

At first glance, this representation might suggest two equilibrium relationships: one between savings and investments, and one comparing the measures of the two countries. Specifically, equilibrium appears to occur when $S = I$ and when US values are double those of the UK. However, equilibrium is achieved even when only one of these conditions is satisfied.

Consider the following observations at time t : $X_t = \begin{bmatrix} 5 & 10 \\ 2 & 4 \end{bmatrix}$. Here, the relations $S_{UK} = 0.5 \cdot S_{US}$ and $I_{UK} = 0.5 \cdot I_{US}$ hold, yet the economic condition $S = I$ does not. Despite this, the system remains in equilibrium because $X_t \theta = 0$ (hence, $\beta' X_t \theta = 0$), and the one-step-ahead value for ΔX_t is exclusively given by E_t .

This example demonstrates that the interpretation of the matrices β and θ is not a straightforward extension of the classical cointegration matrix. The steady-state conditions are not represented by $\beta' X_t = 0$ or $X_t \theta = 0$, as equilibrium can be reached even if only one of these holds. The decomposition primarily reflects the mathematical properties of the cointegration matrix. For instance, in the example, the decomposition holds because the first two entries of the cointegration matrix are twice the size of the third and fourth entries.

3 An Alternative Representation

In this section, we present an alternative way to represent a C-MAR model. We start with the basic VAR form $x_t = \Phi x_{t-1} + \varepsilon_t$ and assume that the matrix Φ can be decomposed into the Kronecker product of two other matrices.

In this section, we present an alternative way to represent a C-MAR (Cointegrated Multivariate Autoregressive) model. We start with the basic VAR form $x_t = \Phi x_{t-1} + \varepsilon_t$, and then assume that the matrix Φ can be decomposed into the Kronecker product of two other matrices.

Assume that $\Phi = \Psi \otimes \Lambda$, where Λ and Ψ are square matrices of appropriate dimensions (say m and n , respectively). If both Λ and Ψ have eigenvalues less than or equal to 1 in absolute value, and at least one of their eigenvalues equals 1, then the vectorized model is a cointegrated VAR and admits a VECM representation. Moreover, the decompositions $\Lambda = I + \alpha \beta'$ and $\Psi = I + \varphi \theta'$ are admitted. It follows that the Matrix AutoRegressive model has the error correction form:

$$\Delta X_t = \alpha \beta' X_{t-1} + X_{t-1} \theta \varphi' + \alpha \beta' X_{t-1} \theta \varphi' + E_t. \quad (6)$$

This alternative MECM representation differs from (2) by the inclusion of the terms $\alpha \beta' X_{t-1}$ and $X_{t-1} \theta \varphi'$. In this case, the steady state is reached only when both $\beta' X_t = 0$ and $X_t \theta = 0$. If only $\beta' X_t = 0$, the first and last terms vanish, but the second term persists, driving the system towards the equilibrium $X_t \theta = 0$.

To illustrate, consider the example from the previous section with $S_{UK} = 5$, $S_{US} = 10$, $I_{UK} = 2$, and $I_{US} = 4$, and the coefficients of (6) given in (5). After computation, we find that the expected future value of X is $\begin{bmatrix} 2 & 4 \\ 2 & 4 \end{bmatrix}$. Unlike the MECM presented in the previous section, this adjustment mechanism brings the system to equilibrium where $S = I$ and $US = 2 \cdot UK$.

To understand the role of the term $\alpha\beta'X_{t-1}\theta\phi'$, consider an initial state where both equilibria are violated. For instance, let $S_{UK} = 5$, $S_{US} = 8$, $I_{UK} = 3$, and $I_{US} = 2$. In this case, both $S \neq I$ and $US \neq 2 \cdot UK$. Then:

$$\Delta X_t = \begin{bmatrix} -2 & -6 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} -1 & 0 \\ -2 & 0 \end{bmatrix} + \begin{bmatrix} -1 & 0 \\ 0 & 0 \end{bmatrix} + E_t. \quad (7)$$

The first term pushes the system towards the equilibrium $S = I$: adding $\alpha\beta'X_{t-1}$ to X_{t-1} , we obtain $S = I$. Similarly, the second term drives the system towards equilibrium between countries: adding $X_{t-1}\theta\phi'$ to X_{t-1} results in $US = 2 \cdot UK$. However, these two terms do not coordinate perfectly, as the adjustment for one equilibrium may interfere with the other. The third term reconciles these dynamics. Adding all three terms gives $\begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix}$ where both $S = I$ and $US = 2 \cdot UK$ hold.

The MECM representation (6) ensures that the system adjusts towards both $\beta'X_t = 0$ and $X_t\theta = 0$, allowing an interpretation of the coefficients β and θ . In contrast to (2), both $\beta'X_t = 0$ and $X_t\theta = 0$ represent steady states and long-run solutions.

4 Conclusions

We propose a novel matrix representation of an error correction model that differs from those previously introduced in the literature. Unlike earlier formulations, our MECM ensures that the matrix structure is preserved in the autoregressive representation as well. We demonstrate that the classical economic interpretation of the cointegration matrix, as established in standard vectorized models, can be seamlessly extended to our MECM. In contrast, this extension is not possible when using earlier MECM formulations.

References

1. Breiman L.: Random Forests. *Machine Learning* **45**, 5–32 (2001)
2. OECD: How's Life? 2020: Measuring Well-being. OECD Publishing (2020) doi: 10.1787/9870c393-en
3. Torgo L.: Data Mining with R: Learning with Case Studies (2nd ed.). Chapman and Hall/CRC, Boca Raton (2017)

A study on the impact of “Reddito di Cittadinanza” using a multivariate linear mixed model

Paolo Maranzano, Laura Marcis, Gianluca Monturano, Maria Chiara Pagliarella and Renato Salvatore

Abstract A Multivariate Linear Mixed Model (MLMM), a Multivariate Spatial Linear Mixed Model (Spatial MLMM) with Time-Varying Fixed-Effects and a Multivariate Spatial State Space Linear Mixed Model (Spatial State Space MLMM) are used to analyze the impact of the “Reddito di Cittadinanza” (RdC) on the share of poverty, the Income inequality, and the average per capita income, treated as target variables. The analysis covers the years preceding the introduction of the social policy measure and those following it. Although we did not find a statistically significant impact of RdC at the global Italian level on these variables, at the regional level - and especially for the Southern Italy Regions and the Islands - the analysis shows an effective reduction in the share of poverty in these Regions.

Key words: reddito di cittadinanza, guaranteed minimum income, poverty, multivariate linear mixed model, spatial model, state space model

Paolo Maranzano
University of Milano-Bicocca, e-mail: paolo.maranzano@unimib.it

Laura Marcis
University of Cassino and Southern Lazio, e-mail: laura.marcis@unicas.it

Maria Chiara Pagliarella
University of Cassino and Southern Lazio, e-mail: mc.pagliarella@unicas.it

Renato Salvatore
University of Cassino and Southern Lazio, e-mail: lr.salvatore@unicas.it

Gianluca Monturano
University of Bari and University of Modena and Reggio Emilia,
e-mail: gianluca.monturano@unimore.it

1 Introduction

In 2019, the Italian government introduced a measure aimed at reducing poverty and encouraging reintegration into work, called "Reddito di Cittadinanza" (RdC)¹. It is a monthly economic benefit provided to people and low-income families who meet specific requirements. It was possible to access the RdC until the end of 2023; after this date, the RdC was replaced by social and work inclusion measures [6]. There were two primary purposes of the RdC: to bring many families out of a state of absolute poverty and to reintegrate as many people as possible into the world of work. The validity of the RdC is still a topic of political debate in Italy today. The economic literature shows that either with regards to the requirements necessary to access the RdC, but also due to territorial and welfare disparities, the results of this social policy measure are heterogeneous ([1], [5]). Busilacchi et al. ([2]) have instead found that, although the impact of the RdC on the employment rate is not statistically significant, in some Italian Regions characterized by low demand and supply of work, it seems that the RdC has contributed to decreasing active job searching. The work of Tonutti et al. ([8]) presented a first study on the targeting at the local level of the RdC anti-poverty policy in Italy, showing a heterogeneous targeting performance of this socio-economic measure, with a general lower targeting affecting northern regions and rural areas. Given this evidence, this paper proposes an application based on a multivariate linear mixed-effects model (MLMM). Traditionally, a MLMM is an extension of linear mixed-effects models (LMM) that have a more complex, multilevel, hierarchical structure concerning the classical linear regression model ([3]). Observations between clusters are independent in these models, but observations within each cluster are dependent because they belong to the same subpopulation. Moreover, in a mixed effects model there are two sources of variation: the within-cluster variation, and the between-cluster variation. The multivariate model is instrumental in using more response variables and exploiting the information from the link between them. Using the Income inequality, the Average per capita income, and the share of poverty as dependent variables, the number of RdC-perceiving households is one of the covariates of the model, together with the measure of quality of the local institutions, as well as the local employment rate. To account for both spatial and temporal autocorrelation, a Multivariate Spatial Linear Mixed Model (Spatial MLMM) - with Time-Varying Fixed-Effect and a Multivariate Spatial State Space Linear Mixed Model (Spatial State Space MLMM) [4] were also used, respectively. In the next section, the models will be presented briefly. The application to real data shows that although at the global Italian level there is no statistically significant impact of the RdC on the dependent variables used; at the regional level - and especially for the Regions of Southern Italy and the Islands - the analysis exhibits a reduction in the share of poverty for these particular Regions.

¹ Note that, despite its name, RdC is not a universal basic or citizens' income, but it is configured as a minimum income measure.

2 Model, application, and conclusion

For the sake of space, it is not possible to present the three models in detail, so please refer to the literature ([3], [4]). MLMMs describe the relationship between several response variables and independent variables, with coefficients varying concerning one or more grouping variables. The matrix multivariate extension of the LMM is $\mathbf{Y} = \mathbf{XB} + \mathbf{ZU} + \mathbf{E}$, and it is a model made of: fixed effects - $\mathbf{XB}$ - and random effects - $\mathbf{ZU}$. This means that, for a given data matrix $\mathbf{Y}$, the elements of $\mathbf{U}$ are realized (but unobservable [7]) values of random variables. As usually happens in a multivariate context, the model is vectorized by stacking vectors. The multivariate random effects covariance matrix used in the application is a heterogeneous compound symmetry matrix. To take into account also the spatial and the temporal autocorrelations we used a Multivariate Spatial State Space Linear Mixed Model (Spatial State Space MLMM): the "spatial" state-space LMM is then: $\mathbf{y}_t = \mathbf{X}_t\boldsymbol{\beta}_t + \mathbf{Z}\mathbf{v}_t + \mathbf{e}_t$, $\mathbf{y}_t = \underset{1 \leq i \leq m}{col} (y_{it})$ where

$$\begin{aligned}\boldsymbol{\theta}_t &= \mathbf{X}_t\boldsymbol{\beta}_t + \mathbf{Z}\mathbf{v}_t, & \mathbf{Z} &= \text{diag}(\mathbf{Z}_1, \dots, \mathbf{Z}_m)(\mathbf{I} - \rho_s \mathbf{W})^{-1}, \\ \mathbf{v}_t &= \rho_t \mathbf{v}_{t-1} + \boldsymbol{\eta}_t, & \boldsymbol{\eta}_t &\overset{iid}{\sim} N(\mathbf{0}, \sigma_v^2 \mathbf{I}_m)\end{aligned}$$

The ρ_s and the ρ_t are the spatial and the temporal correlation parameters, respectively. When $\rho_t = 0$, and $\alpha_t = \alpha_t + \mathbf{A}\zeta_t$, $\mathbf{A} = \mathbf{I}_{p+m}$, we obtain the third model used in this work, the Multivariate Spatial Linear Mixed Model (Spatial MLMM) - with Time-Varying Fixed Effects. In our study, we consider the years 2015-2022 to have a comparison between the situation before the introduction of the RdC measure and after its introduction. In particular, the dependent variables are the share of poverty (share of the population with an income of fewer than 10,000 euros), the income inequality (the Gini index on declared income obtained by aggregating data from different Region income groups), and the average per capita income (computed as the ratio between the total amount of income declared in each Region and the total number of taxpayers). The MLMMs can simultaneously capture the impact of the RdC on economic variables of high relevance. The nature of the MLMMs allows us to see the impact of the RdC from two different points of view. Firstly, it concerns the national scenario, and secondly, what happens in each region of Italy. From the evaluation of the fixed effect estimates, the analysis does not show a significant impact of RdC on the $\mathbf{Y}$ variable at the national level. Nevertheless, some random effects predictions are statistically significant in the local (administrative Region) context. This points out that the RdC had an impact at the regional level. Nevertheless, this did not lead to a global improvement of the three target variables in the years 2015-2018 (before the introduction of RdC) and 2018-2022 (after the introduction of the measure studied). The results for the model covariance parameters are in Table 1. Even using the temporal and spatial correlation, the results are very similar to that of model MLMM, this might be because random effects by region already capture spatial correlation. Future works will focus on diagnostic measures to understand whether RdC influences the estimate of random effects and which

Table 1 The table reports the results for the model covariance parameters for the three models and the p-values wrt a set of Wald Likelihood ratio tests for the models covariance parameters; the Moran and Geary's tests for the spatial correlation, and the Durbin-Watson test for the time autocorrelation. All the parameters are significant.

	MLMM		Spatial MLMM		Spatial State-Space MLMM	
Covariance parameter	value	p-value	value	p-value	value	p-value
ρ (spatial)	-	-	0,5088	< 0,0001	0,5679	< 0,0001
ρ (UCH Covariance matrix)	-0,5000	< 0,001	-0,4124	< 0,001	-0,4044	< 0,001
σ^2 (Gini)	0,0001	< 0,001	0,0142	< 0,001	0,0305	< 0,001
σ^2 (Per Capita Income)	5,6316	< 0,001	3,9991	< 0,001	4,1262	< 0,001
σ^2 (Share of Poverty)	0,0019	< 0,001	0,0092	< 0,001	0,034	< 0,001
ρ (time)	-	-	-	-	-0,01265	< 0,0001
σ^2	0,0035	< 0,001	0,0460	< 0,001	0,0955	< 0,001

variables can improve the measure and ensure that all target people can benefit from it, this also with respect the new measure introduced by the Italian Government after the RdC.

References

1. Almeida, Vanda, Silvia De Poli, and Adrián Hernández. The effectiveness of Minimum Income schemes in the EU. No. 09/2022. JRC Working Papers on Taxation and Structural Reforms, (2022)
2. Busilacchi, Gianluca, and Alessandro Fabbri. "Does the unemployment trap still exist? The case of the Italian minimum income scheme." *Social Policy & Administration* 58.5 (2024): 750-770.
3. Demidenko, Eugene. *Mixed models: theory and applications with R*. John Wiley & Sons, (2013)
4. Durbin, J., and Koopman, S. J. (2012). *Time series analysis by state space methods* (Vol. 38). OUP Oxford.
5. Guimarães, Luis, and Diogo Lourenço. "The imperfections of conditional programs and the case for universal basic income." (2024)
6. Ministero del Lavoro e delle Politiche sociali <https://www.redditicittadinanza.gov.it/>
7. Robinson, George K. "That BLUP is a good thing: the estimation of random effects." *Statistical science* (1991): 15-32.
8. Tonutti, Giovanni, et al. "Disaggregation of poverty indicators by small area methods for assessing the targeting of the "Reddito di Cittadinanza" national policy in Italy." *Socio-Economic Planning Sciences* 82 (2022): 101327.

Forecasting short social time series with Theta method: an application to worldwide human development

Raffaele Mattera, Germana Scepi and Parmjit Kaur

Abstract Forecasting short time series is essential in many economic and social contexts. A notable empirical example is human development, measured annually since 1990. However, forecasting these series presents significant challenges due to limited data, making sophisticated statistical methods less appropriate than simpler models. In this paper, we evaluate the Theta method as a forecasting tool for short time series. We benchmark the performance of the Theta method against established approaches and apply the framework to forecast global human development indicators from 1990 to 2022.

Key words: predictive modelling, short time series, forecasting, decomposition, human development

1 Introduction

Forecasting short time series is a critical task in many economic and social domains, where data availability is often limited. A notable example in this context is the Human Development Index (HDI), an aggregate measure introduced by the United Nations Development Programme in 1990. The HDI combines indicators of life expectancy, education, and per capita income to evaluate and compare the level of human development across nations. While its annual measurement provides valuable insights to policymakers worldwide, the relatively short span of its recorded

Raffaele Mattera

University of Campania Luigi Vanvitelli, e-mail: raffaele.mattera@unicampania.it

Germana Scepi

University of Naples Federico II, e-mail: scepi@unina.it

Parmjit Kaur

London Metropolitan University, e-mail: p.kaur@londonmet.ac.uk

history makes long-term forecasting highly challenging. For these reasons, sophisticated forecasting methods are unsuitable while methods with simple structures and low number of parameters are better suited for this task. Examples of such simple methods include simple exponential smoothing, low-order ARIMA models, and the random walk.

The Theta method is a relatively simple yet powerful approach to time series forecasting. Its strength lies in its ability to decompose a time series into two components [1]: a long-term trend and short-term fluctuations. The long-term trend is extrapolated, while the short-term component is forecasted using a relatively simple method, often the simple exponential smoothing. The final forecast is obtained by averaging the two forecasts for long and short-run components. Despite its simplicity, the Theta method gained significant attention in the M3 competition, where it emerged as one of the most effective approaches for forecasting across a wide range of time series. However, its performance in forecasting short time series remains less explored and understood.

In this paper, we benchmark the Theta method against alternative forecasting approaches to evaluate its effectiveness in predicting global human development trends over the period from 1990 to 2022. To this end, we analyze over 700 time series spanning various dimensions of human development across multiple countries. With this comprehensive evaluation we aim to highlight the value of simple yet powerful forecasting tools in addressing the statistical challenges posed by short time series in the social sciences.

2 Theta method

The Theta method [1] is a relatively simple model, which performed very well in the M3-Competition [4]. Therefore, it is commonly considered a benchmark in more recent forecasting competitions. The Theta method decomposes the seasonally adjusted data into two “theta lines”, the first removing the curvature of the data to estimate the long-term trend component and the second approximating its short-term behaviour. Therefore, the Theta method can be considered as a forecasting with decomposition approach.

The Theta method can be briefly outlined as follows. Considering $i = 1, \dots, N$ time series, we refer to an i -th univariate time series as $\{X_{i1}, \dots, X_{it}, \dots, X_{iT}\}$. Then, [1] define the following transformed time series $\{Y_{i1,\theta}, \dots, Y_{it,\theta}, \dots, Y_{iT,\theta}\}$ such that for $t = 3, \dots, T$ it holds

$$\nabla^2 Y_{it,\theta} = \theta \nabla^2 X_{it}, \quad (1)$$

with ∇ indicating the difference operator, so that $\nabla X_{it} = X_{it} - X_{it-1}$. The (1) is a second difference equation with solution [3]

$$Y_{it,\theta} = (1 - \theta)(a + bt) + \theta X_{it}, \quad (2)$$

where a and b are constants and $t = 1, \dots, T$. Therefore, the series $Y_{it,\theta}$ – called the θ -line – is an additive function of the series X_{it} and a linear trend.

In the original Theta method adopted in the M3 competition, [1] selected two θ lines, that is, $\theta = 0$ and $\theta = 2$, leading to $Y_{it,0} = a + bt$ and $Y_{it,2} = 2X_{it} - (a + bt)$. We remark that the parameters a and b are the minimum square coefficients of a simple linear regression of $\{X_{i1}, \dots, X_{it}, \dots, X_{iT}\}$ over $\{1, \dots, t, \dots, T\}$, thus having known closed-form solutions. Therefore an estimate of the first theta line is $\hat{Y}_{it,0} = \hat{a} + \hat{b}t$, while the second is $\hat{Y}_{it,2} = 2X_{it} - \hat{a} - \hat{b}t$ given that X_{it} is known. The forecast at time $t + 1$ is obtained as

$$\hat{X}_{it+1} = \omega \hat{Y}_{it+1,0} + (1 - \omega) \hat{Y}_{it+1,2}, \quad (3)$$

hence a linear ω -combination of the forecasts obtained for the two theta lines, where the first is simply obtained by extrapolation of the linear trend, that is $\hat{Y}_{it+1,0} = \hat{a} + \hat{b}(t + 1)$, while the second is obtained with Simple Exponential Smoothing (SES). Originally, [1] assumed equal combination weights, i.e. $\omega = 0.5$, while more recently [2] developed an approach, called OTM, for optimal weights ω selection.

3 Data and results

We consider data on human development from the United Nations Development Program (UNDP) website¹. Our aim is to forecast the Human Development Index and its components, that is, health, education and standard of living dimensions. To forecast the health dimension we consider the life expectancy at birth variable, while for education we forecast the average of "Expected Years of Schooling" and "Mean Years of Schooling" variables, as defined by UNDP. Finally, we forecast the GNI per capita to predict the future economic standard of living. Given the four human development variables to be predicted, we have a number of 780 time series. To evaluate the accuracy of the forecasting methods, we adopt a rolling-window approach considering the first $M = 15$ years as estimation window. As a result we obtain a series of $T - M = 18$ years of out-of-sample testing where we evaluate the accuracy of alternative forecasting methods according to RMSE.

Table 1 shows out of sample forecast accuracy for the Human Development Index, Life Expectancy, the Education Index, and the GNI Index. These results are averaged over 195 countries, covering 780 short social time series, making the findings robust and highly representative. The results highlight the outstanding performance of the Theta method, which consistently provides the most accurate forecasts across all four dimensions of human development. Interestingly, the OTM, where the weights for the short-run and long-run components are optimally selected, does not outperform the simpler Theta method. This result underscores an important insight, that is, for short time series, sophisticated approaches do not necessarily yield

¹ Data associated with this paper is available at the following link: <https://hdr.undp.org/data-center/documentation-and-downloads>.

Table 1 Average out-of-sample forecast accuracy (RMSE) over the $N = 195$ countries. The model providing the best results is highlighted in bold font.

Human Development Index		Life Expectancy	
Forecasting method	Accuracy	Forecasting method	Accuracy
RW	68.7490	RW	55.1099
ARIMA	61.1430	ARIMA	54.9521
SES	69.1237	SES	55.5731
Theta	57.9163	Theta	50.5321
OTM	60.1228	OTM	53.5212
Education Index		GNI Index	
Forecasting method	Accuracy	Forecasting method	Accuracy
RW	16.0151	RW	744.8543
ARIMA	14.1424	ARIMA	724.2517
SES	16.0546	SES	752.6969
Theta	13.6763	Theta	705.2294
OTM	14.6243	OTM	716.0989

better results than simpler models. This could be attributed to the inherent limitations in the data length, which may not fully benefit from the additional complexity of optimization techniques.

However, there is room for future advancements. Notably, ARIMA is more competitive than Simple Exponential Smoothing (SES) in forecasting human development, suggesting that exploring alternative methods for modeling the short-run component could enhance the forecasting performance of the Theta method further. Future research could also investigate combining different approaches for the short-run component, leveraging the strengths of alternative models to achieve even greater accuracy, or to consider alternative Theta decompositions.

References

1. Assimakopoulos, V., Nikolopoulos, K.: The theta model: a decomposition approach to forecasting. *International Journal of Forecasting* **16**(4), 521–530 (2000)
2. Fiorucci, J.A., Pellegrini, T.R., Louzada, F., Petropoulos, F., Koehler, A.B.: Models for optimising the theta method and their relationship to state space models. *International Journal of Forecasting* **32**(4), 1151–1161 (2016)
3. Hyndman, R.J., Billah, B.: Unmasking the theta method. *International Journal of Forecasting* **19**(2), 287–290 (2003)
4. Makridakis, S., Hibon, M.: The m3-competition: results, conclusions and implications. *International Journal of Forecasting* **16**(4), 451–476 (2000)

Towards the balancing of Italian quarterly national accounts

Filippo Moauro

Abstract The paper provides main lines for balancing the current estimates of Italian quarterly national accounts within a system of supply and use tables. In a first step, a preliminary estimate of change of inventories split by product is implemented. Then, based upon simplified assumptions, the commodity flow approach is expanded towards a full system of preliminary estimates of quarterly supply and use tables. Finally, these tables are balanced applying an algorithm able to respect both temporal and sectional constraints provided by the annual set of tables. The algorithm operates by product, setting a state space form of multivariate constrained regressions, whose statistical treatment is based upon the Kalman filter and smoothing. A pre- and post-balancing comparison of seasonal adjusted GDP components in volumes is presented.

Key words: quarterly national accounts, supply and use tables, commodity flow approach, temporal disaggregation and reconciliation, constrained multivariate regression, Kalman filter and smoothing

1 Introduction

Istat has been publishing quarterly national accounts (QNA) for Italy since 1983 and nowadays these data are subject to the European Union regulation ESA 2010 [3].

Main aggregates of the current accounting system refer to [8] for evaluation and type of adjustment. Supply side components concern imports, value added, taxes and subsidies. The demand side distinguishes final consumption expenditure of households, of non-profit institutions serving households (NPISH) and of the general government, gross fixed capital formation (GFCF), net acquisition of valuables and

Filippo Moauro
ISTAT, e-mail: moauro@istat.it

exports, but it lacks for change of inventories. Therefore, Gross domestic product (GDP) results from the supply side only (value added + taxes net of contributions).

The current schemes of QNA are wide enough and well in line with the international guidelines as split into both 45 branches of economic activity and 50 products of the ATECO [7] and the CPA classifications [5] respectively. However, the resulting estimates are still incomplete, not fully integrated within supply and use tables (SUT), [4], and unbalanced between the supply and the demand side.

The work describes the modelling setup of a fully integrated system of quarterly SUT and provides a first comparative view of pre- and post-balanced estimates.

2 Modelling setup and the relative state space form

Let $\hat{l}_t$ be a $p \times s$ matrix of preliminary estimates of economic flows over the quarters $t=1, \dots, n$, of an unknown system of supply and use tables $\tilde{l}_t$ of fully balanced estimates. We denote $x_t = \text{vec}(\hat{l}_t)$, $y_t = \text{vec}(\tilde{l}_t)$ and $X_t = \text{diag}(x_t)$.

The balancing of the matrix of preliminary estimates $\hat{l}_t$ into $\tilde{l}_t$ can be approached by a generalized multivariate regression model, appropriately augmented for the treatment of both sectoral and temporal constraints. Appropriately modifying the univariate model by [9], a suitable unrestricted state space form can be the following:

$$y_t = X_t b + \mu_t, \quad (1)$$

$$\mu_t = a + T\mu_{t-1} + \epsilon_t, \quad \epsilon_t \sim NID(0, \sigma^2 \Sigma_t), \quad (2)$$

where a is a vector of constant terms and b of regression coefficients, both of sp elements, μ_t a sp-stochastic vector of elements modelled as the first order Markov process of equation (2), with error term the sp-vector ϵ_t of normally and independently distributed white noises with covariance matrix $\sigma^2 \Sigma_t$. The transition matrix T is generally set in such a way that the process (2) is stationary. Feasible restrictions set T as diagonal, i.e. $T = \text{diag}(\varphi_1, \dots, \varphi_{sp})$, with φ_i such that $-1 < \varphi_i < 1$ for $i = 1, \dots, sp$, or even scalar, i.e. $T = \varphi I$ with $-1 < \varphi < 1$. Σ_t is usually set as diagonal with values reflecting the mutual reliability of the preliminary estimates x_t at each quarter. Non-zero elements of Σ_t outside the principal diagonal could be also considered, taking into accounts the contiguity between single flows of x_t , but are once again exogenous. The state space form (1)-(2) is in general of large dimension with unknown parameters provided by unknown elements into T , the regression coefficients a , b and the scalar σ^2 .

Sectoral constraints of the supply and use setup take a time-varying form such that

$$r_t = R_t y_t, \quad (3)$$

where r_t is the k -vector of constraints and R_t is a $k \times np$ matrix which allows the link of the constraints to the supply and use variables y_t .

Temporal constraints arise for example when the elements of y_t are unobserved at the quarterly time span, but observed in terms of annual totals Y_t available at time $t=4, 8, \dots, 4[n/4]$, where $[n/4]$ is the integer part of the ratio $n/4$, such that

$$Y_4 = y_1 + y_2 + y_3 + y_4, \quad Y_8 = y_5 + y_6 + y_7 + y_8, \quad \dots$$

Following [6], it requires the definition of a cumulator variable y_t^c such that

$$y_t^c = \psi_t y_{t-1}^c + V_t y_t, \quad \psi_t = \begin{cases} 0, & t = 1, 5, \dots, \\ 1, & \text{otherwise}, \end{cases} \quad (4)$$

where $y_t^c = Y_t$ for $t=4, 8, \dots$. V_t is a diagonal matrix that, for modelling current price values, is such that $V_t = I$, whereas for modelling data expression of volumes, it takes values of ratios able to transform chain-linked values into previous-year price values. Similarly to y_t^c , a cumulator r_t^c for the constraints r_t is defined.

Therefore, following [2], defining an augmented state vector α_t as a variable which joins μ_t , the cumulator variables y_t^c and r_t^c such that $\alpha_t = (\mu_t' y_t^{c'} r_t^{c'})'$ and the regression coefficients $\beta = (a' b')'$, the system (1)-(2) is adjusted as follows:

$$\begin{pmatrix} y_t^c \\ r_t^c \end{pmatrix} = Z_t \alpha_t, \quad t = 1, \dots, n, \quad (5)$$

$$\alpha_t = W_t \beta + T_t^* \alpha_{t-1} + H_t \epsilon_t, \quad \epsilon_t \sim NID(0, \sigma^2 1), \quad t = 2, \dots, n, \quad (6)$$

where the system matrices Z_t , W_t , T_t^* and H_t result respectively from

$$Z_t = \begin{bmatrix} 0 & I & 0 \\ 0 & 0 & I \end{bmatrix}, \quad W_t = \begin{bmatrix} I & 0 \\ V_t & V_t X_t \\ R_t V_t & R_t V_t X_t \end{bmatrix}, \quad T_t^* = \begin{bmatrix} T & 0 & 0 \\ V_t T & \psi_t I & 0 \\ R_t V_t T & \psi_t R_t & 0 \end{bmatrix}, \quad H_t = \begin{bmatrix} I \\ V_t \\ R_t V_t \end{bmatrix} \Gamma_t,$$

with Γ_t such that $\Sigma_t = \Gamma_t \Gamma_t'$. The initial conditions derive directly from (5)-(6) as

$$\alpha_1 = W_1 \beta + H_1 \epsilon_1, \quad \alpha_1 \sim NID(0, \sigma^2 P_1). \quad (7)$$

Statistical treatment of the form (5)-(7) can be carried out by the diffuse Kalman filter and smoothing [1] for maximum likelihood (ML) estimation of unknown parameters, the distribution of annual totals among quarters and the balancing.

3 Implementation and first experimental results

A first experimental balancing exercise has been applied to an unbalanced system of seasonal and calendar adjusted estimates in volume at previous year prices $\hat{I}_t$ for $p=50$ products and $s=106$ variables, 53 from both the supply and demand sides relative to the quarters t from 1995q1 to 2024q3. Both the data of production and intermediate consumption by product are split into 45 branches of economic activity and add up to imports and exports split by goods and services, 5 types of margins (4 for trade and 1 for transport), net taxes, 3 types of consumption expenditure (households, NPISH and general government), gross fixed capital formation, net acquisition of valuables and change of inventories. Figure 1 shows a summary view of results for main aggregates.

The implementation is carried out separately for each of the 50 products. Therefore in the notation above $p=1$ and $s=106$. Values of X_t are chain-linked values. Constraints of equation (3) are such that $r_t = 0$ and $R_t = (1 \dots 1, -1 \dots -1)$, where the 1s are for the supply and the -1s for the demand components. All the variables presenting zero, sparse or low values are excluded by the system. In other terms, the balanced estimates are posed equal to the preliminary ones and the constraints are adjusted accordingly. The coefficients V_t of equation (4) are based on annual data of previous year. Finally, to ensure coherence to the estimates, margin products are balanced in the last steps.

The matrix T of equation (2) is restricted into $T = \phi I$ and, depending on the circumstances, the covariance matrix Σ_t either to $\Sigma_t = |CX_t|$, or to $\Sigma_t = \Sigma = |CX_t|$,

with $\bar{\tau}$ relative to a predefined quarter and C a diagonal matrix of positive exogenous coefficients reflecting the reliability of the preliminary estimates for each variable.

The statistical treatment allows to obtain the ML-estimates of $\tilde{\varphi}$, $\tilde{\sigma}^2$, $\tilde{a}$ and $\tilde{b}$ of the system parameters for each product and finally the balanced estimate $\tilde{I}_t$.

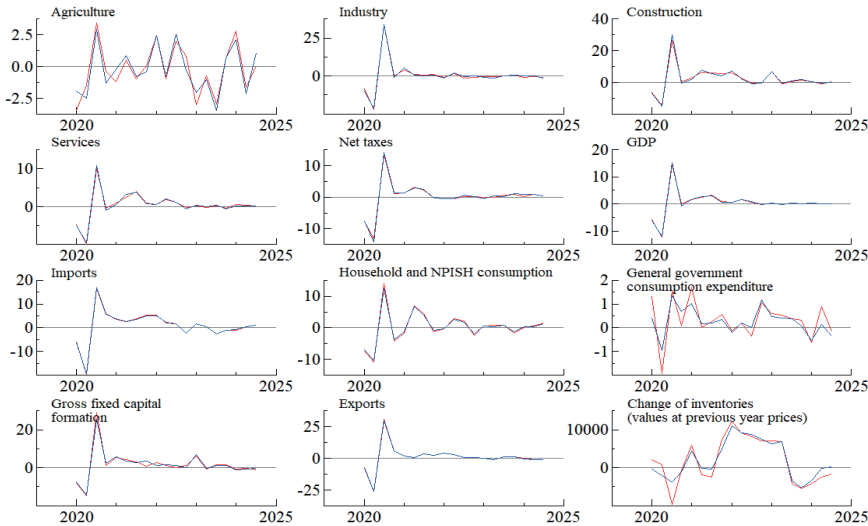


Fig. 1 Comparative view of pre- (in red) and post-balancing quarterly growth-rate estimates (in blue) of main supply and demand components of GDP.

References

1. De Jong P.: The diffuse Kalman filter, *The Annals of Statistics*, (1991), vol. 19, no. 2, 1073-1083;
2. Doran, H.E.: Constraining Kalman Filter and Smoothing Estimates to Satisfy Time-Varying Restrictions, *The Review of Economics and Statistics*, vol. 74(3), pages 568-572, August (1992).
3. Eurostat: European system of accounts - ESA 2010, (2013), <https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-02-13-269>
4. Eurostat: Eurostat Manual of Supply, Use and Input-Output Tables, (2008), <https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-ra-07-013>
5. Eurostat: Statistical classification of products by activity CPA, (2023), <https://ec.europa.eu/eurostat/statistics-explained/SEPDF/cache/2695.pdf>
6. Harvey A.C.: *Forecasting, structural time series models and the Kalman filter*, (1989), Cambridge University Press
7. Istat: Classificazione delle attività economiche ATECO 2007, (2022), <https://www.istat.it/non-categorizzato/bozza-bis-classificazione-delle-attivita-economiche-ateco/>
8. Istat: I conti economici trimestrali. Principali elementi informativi, (2024), <https://www.istat.it/notizia/i-conti-economici-trimestrali-edizione-2024/>
9. Proietti T.: Temporal disaggregation by state space methods: Dynamic regression methods revisited, *The Econometrics Journal*, Vol. 9, No. 3 (2006), pp. 357-372

Forecasting VaR and ES from high-frequency quantiles and consistent loss functions

Antonio Naimoli, Ostap Okhrin and Giuseppe Storti

Abstract This paper presents alternative specifications for forecasting daily risk measures by scaling intraday quantiles. In particular, we propose a flexible approach to forecasting Value-at-Risk and Expected Shortfall introducing novel scaling factor estimation methods based on consistent loss functions and Multiplicative Error Models with a Generalized F distribution. The empirical analysis on 27 stocks of the Dow Jones Industrial Average shows that the proposed approach can lead to significant accuracy gains in tail risk forecasting.

Key words: High-frequency quantiles, Value-at-Risk, Expected Shortfall, consistent loss functions, Multiplicative Error Models

1 Introduction

Financial risk management requires advanced methodologies to address extreme risks, particularly in complex global financial systems. This paper presents an innovative approach to forecasting Value-at-Risk (VaR) and Expected Shortfall (ES) using high-frequency (HF) intraday financial data and scaling techniques based on consistent loss functions. By developing a framework that allows scaling factors to vary across quantiles and employing Multiplicative Error Models (MEM) with the Generalized F (GF) distribution, this study provides a very flexible approach for forecasting tail risks. Key contributions of this paper include: novel scaling factor estimation methods for relating intraday to daily quantiles; direct quantile-based risk

Antonio Naimoli
University of Salerno, e-mail: anaimoli@unisa.it

Ostap Okhrin
Technische Universität Dresden, e-mail ostap.okhrin@tu-dresden.de

Giuseppe Storti
University of Salerno, e-mail: storti@unisa.it

measure prediction using MEM; a modeling approach that allows distinct dynamics between VaR and ES. Empirical analysis on Dow Jones stock data highlights the effectiveness of this approach.

2 Scaling intraday quantiles

To estimate the quantiles of daily financial returns directly from HF data, the process involves several steps. First, a sampling framework is defined by fixing the number, c , of intraday returns to be sampled for each day in the period $t = 1, \dots, T$. Next, intraday log-returns are computed for each day, $\mathbf{r}_{c,t} = \{r_{1,t}, \dots, r_{c,t}\}$, with the daily log-return denoted by r_t . Accordingly, for a chosen risk level α , intraday quantiles, $\widehat{Q}_\alpha(\mathbf{r}_{c,t})$, and ES, $\widehat{ES}_\alpha(\mathbf{r}_{c,t})$, are estimated. Quantiles are derived using the empirical sample-quantile estimator, while the ES is calculated via the empirical sample-ES estimator:

$$\widehat{ES}_\alpha(\mathbf{r}_{c,t}) = \frac{1}{\alpha c} \sum_{i=1}^c r_{i,t} \times 1\{r_{i,t} \leq \widehat{Q}_\alpha(\mathbf{r}_{c,t})\}.$$

Then, the scaling index, H , is either fixed or estimated from the intraday log-return series to adjust intraday risk measures to a daily scale. The rescaling is applied to compute daily quantiles and ES for each day t at a given probability level α , by:

$$\widehat{RQ}_{c,\alpha,t} = c^H \widehat{Q}_\alpha(\mathbf{r}_{c,t}), \quad (1)$$

$$\widehat{RES}_{c,\alpha,t} = c^H \widehat{ES}_\alpha(\mathbf{r}_{c,t}). \quad (2)$$

Finally, forecasts for daily VaR and ES are obtained by applying suitable time series models to the rescaled daily quantiles and ES series.

3 VaR and ES forecasting

Instead of fixing the scaling parameter H , we propose estimating it through the Quantile Loss (QL). Specifically, recognizing that $c^H \widehat{Q}_\alpha(\mathbf{r}_{c,t})$ corresponds to $VaR_{\alpha,t}$, we can derive the optimal H , by minimizing the QL function:

$$\operatorname{argmin}_H QL_{\alpha,t}(H) = \left(\alpha - 1\{r_t \leq c^H \widehat{Q}_\alpha(\mathbf{r}_{c,t})\} \right) \left(r_t - c^H \widehat{Q}_\alpha(\mathbf{r}_{c,t}) \right). \quad (3)$$

An alternative approach to estimating H is to consider the class of strictly consistent joint loss functions for VaR and ES [4]:

$$\begin{aligned} \operatorname{argmin}_H FZ0_{\alpha,t}(H) = & \frac{1}{\alpha c^H \widehat{ES}_{\alpha}(\mathbf{r}_{c,t})} 1\left\{r_t \leq c^H \widehat{Q}_{\alpha}(\mathbf{r}_{c,t})\right\} \left(r_t - c^H \widehat{Q}_{\alpha}(\mathbf{r}_{c,t})\right) + \\ & \frac{c^H \widehat{Q}_{\alpha}(\mathbf{r}_{c,t})}{c^H \widehat{ES}_{\alpha}(\mathbf{r}_{c,t})} + \log\left(-c^H \widehat{ES}_{\alpha}(\mathbf{r}_{c,t})\right) - 1. \end{aligned} \quad (4)$$

Consequently, the quantiles in (1) and (2) can easily be obtained using H estimated in (3) and (4). To generate VaR and ES forecasts, the MEM [3] with innovations following a GF distribution is implemented on each RQ and RES series. The GF distribution increases the flexibility of the model by allowing a wider range of error term distributions, including Exponential, Weibull and Log-Logistic variants [6].

4 Empirical results

The proposed methodology is evaluated using a dataset of 27 stocks in the Dow Jones Industrial Average, based on equally spaced 1-minute intraday returns during regular NYSE trading hours, 9:30 a.m. to 4:00 p.m., while the sample period spans from January 1, 2001, to December 31, 2016. To generate VaR and ES forecasts, both the HAR model of [1] and MEM are implemented on each RQ and RES series, where $HAR(H_{0.5})$ denotes the specification proposed by [2]. Consistent with the Basel Accords, we assess model performance at the 1% VaR and 2.5% ES risk levels. The findings provide evidence that MEM models outperform competing HAR models in terms of both average losses and Model Confidence Set (MCS) [5] inclusion rates. Specifically, $MEM(H_{0.5})$ and $MEM(H_{QL})$ exhibit the highest average ranks in minimizing QL and FZ0. Furthermore, it is more difficult for models using the scale index H minimized by FZ0 to enter the MCS than those using H_{QL} .

Table 1 Summary results for the QL loss at $\alpha = 0.01$.

	$\alpha = 0.01$							
	$\overline{QL}_{rank}$	$\overline{QL}$	QL_{med}	$\%QL_{min}$	$\%QL_{SQ0.75}$	$\%QL_{SQ0.90}$	$\%QL_{R0.75}$	$\%QL_{R0.90}$
$HAR(H_{0.5})$	2.815	1.048	0.945	3.704	33.333	74.074	29.630	48.148
$HAR(H_{QL})$	4.389	1.094	0.982	0.000	7.407	44.444	7.407	29.630
$HAR(H_{FZ0})$	5.926	1.135	1.012	0.000	0.000	7.407	0.000	0.000
$MEM(H_{0.5})$	1.574	1.039	0.917	70.370	88.889	88.889	88.889	88.889
$MEM(H_{QL})$	2.296	1.049	0.946	25.926	77.778	96.296	77.778	88.889
$MEM(H_{FZ0})$	4.000	1.091	0.987	0.000	3.704	33.333	0.000	11.111

$\overline{QL}_{rank}$: average rank across 27 stocks; $\overline{QL}$: mean QL; QL_{med} : median QL; $\%QL_{min}$: percentage of QL minimization; $\%QL_{SQ0.75}$ and $\%QL_{SQ0.90}$: percentage of times a model enters in 75% and 90% MCS (Semi-Quadratic); $\%QL_{R0.75}$ and $\%QL_{R0.90}$: percentage of times a model enters in 75% and 90% MCS (Range).

Table 2 Summary results for the FZ0 loss at $\alpha = 0.025$.

	$\alpha = 0.025$							
	$\overline{FZ0}_{rank}$	$\overline{FZ0}$	$FZ0_{med}$	$\%FZ0_{min}$	$\%FZ0_{SQ0.75}$	$\%FZ0_{SQ0.90}$	$\%FZ0_{R0.75}$	$\%FZ0_{R0.90}$
$HAR(H_{0.5})$	3.222	-3.490	-3.557	0.000	22.222	44.444	18.519	29.630
$HAR(H_{QL})$	4.278	-3.472	-3.536	0.000	7.407	29.630	7.407	14.815
$HAR(H_{FZ0})$	5.889	-3.431	-3.491	0.000	0.000	3.704	0.000	3.704
$MEM(H_{0.5})$	1.611	-3.514	-3.574	66.667	85.185	92.593	85.185	88.889
$MEM(H_{QL})$	1.889	-3.511	-3.572	33.333	81.481	96.296	81.481	92.593
$MEM(H_{FZ0})$	4.111	-3.474	-3.537	0.000	7.407	33.333	3.704	7.407

$\overline{FZ0}_{rank}$: average rank across 27 stocks; $\overline{FZ0}$: mean FZ0; $FZ0_{med}$: median FZ0; $\%FZ0_{min}$: percentage of FZ0 minimization; $\%FZ0_{SQ0.75}$ and $\%FZ0_{SQ0.90}$: percentage of times a model enters in 75% and 90% MCS (Semi-Quadratic); $\%FZ0_{R0.75}$ and $\%FZ0_{R0.90}$: percentage of times a model enters in 75% and 90% MCS (Range).

5 Conclusions

This paper presents a novel framework for forecasting daily VaR and ES by using HF financial data. The proposed approach combines flexible distributional scaling factors, estimated through consistent loss functions, and quantile-based risk modeling using MEM with the GF distribution, allowing for distinct dynamic specifications for VaR and ES. Empirical analysis using 1-minute returns from 27 Dow Jones stocks demonstrates significant improvements in tail risk forecasting accuracy.

Acknowledgements Giuseppe Storti and Antonio Naimoli acknowledge financial support under the National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.1, Call for tender No. 104 published on 2.2.2022 by the Italian Ministry of University and Research (MUR), funded by the European Union – NextGenerationEU – Project Title: Methodological and computational issues in large-scale time series models for economics and finance (ID: 20223725WE) – CUP D53D 2300610 0006 - Grant Assignment Decree No. n. 967 of 30/06/2023.

References

1. Corsi, F.: A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics* **7**(2), 174–196 (2009)
2. Dimitriadis, T., Halbleib, R.: Realized quantiles. *Journal of Business & Economic Statistics* **40**(3), 1346–1361 (2022)
3. Engle, R.: New frontiers for arch models. *Journal of applied econometrics* **17**(5), 425–446 (2002)
4. Fissler, T., Ziegel, J.F.: Higher order elicibility and osband’s principle. *Ann. Statist.* **44**(4), 1680–1707 (2016)
5. Hansen, P.R., Lunde, A., Nason, J.M.: The model confidence set. *Econometrica* **79**(2), 453–497 (2011)
6. Naimoli, A., Storti, G.: Heterogeneous component multiplicative error models for forecasting trading volumes. *International Journal of Forecasting* **35**(4), 1332–1355 (2019)

Tourism and Energy Decoupling in Mountain Areas. Towards an Integrated Framework for Analysis and Forecasting

Consuelo Rubina Nava and Stefano Tedeschi

Abstract Tourism is a cornerstone of economic activity in many regions, yet its environmental and energy impacts pose significant challenges to sustainability. In fragile mountain ecosystems, such as Italy's Valle d'Aosta, balancing economic growth with ecological preservation is critical. This paper explores the concept of *energy decoupling* in tourism, analyzing strategies to disconnect tourism growth from energy consumption and greenhouse gas emissions. Using a combination of statistical forecasting models and agent-based simulations, we propose a methodology to examine the impact of policy interventions, such as the electrification of mobility, the use of energy-efficient technologies, and incentives for sustainable practices. Our aim is to offer practical insights to policy makers for achieving energy decoupling, thereby promoting a sustainable tourism model for mountainous regions.

Key words: Sustainable tourism, Energy decoupling, Mountain ecosystems, Forecasting models, Agent-Based Modeling

1 Introduction

Mountain areas are particularly vulnerable to environmental degradation due to their fragile ecosystems and limited resource capacities. Tourism, while being an economic boon, often intensifies the energy demands for heating, transport, and infrastructure. In the Valle d'Aosta region (Italy), which is renowned for its rich natural heritage and robust tourist inflow, addressing these challenges is urgent. Recent data highlights a record-breaking 1.34 million tourist arrivals and 3.71 million overnight

Consuelo Rubina Nava
University of Aosta Valley, e-mail: c.nava@univda.it

Stefano Tedeschi
University of Aosta Valley, e-mail: s.tedeschi@univda.it

stays in 2023, marking a significant growth in tourist activity, which contributed approximately 1% to the regional GDP [1]. However, this surge intensifies energy demands, stressing the region's limited energy infrastructure and increasing greenhouse gas emissions. In this context, *energy decoupling* [2, 5, 6] — i.e., the strategic goal of supporting tourism growth without proportionate increases in energy use and emissions — represents a critical pathway to balance economic development and environmental preservation. This paper explores this objective through a methodological proposal which integrates data analysis, policy evaluation, and simulation modeling. The aim of this research is to highlight the need for systemic approaches to align tourism growth with the efficient use of renewable energy sources, smart energy grids, and sustainable mobility solutions. By leveraging insights from interdisciplinary methods, the study contributes actionable strategies for the Valle d'Aosta region to position itself as a leading example of sustainable mountain tourism, ensuring long-term ecological and economic resilience while serving as a replicable model for similar regions worldwide.

2 Context and Challenges

The rise in tourism in Valle d'Aosta boosts employment, income, and the local economy while promoting cultural and natural heritage. However, it also drives up energy consumption in heating, lighting, mobility, and infrastructure, putting pressure on energy systems and the environment. This presents a key challenge: *how to sustain economic growth through tourism while ensuring environmental sustainability?*

Some key challenges hinder progress. These include the lack of systematic energy efficiency assessments in hospitality, high seasonal fluctuations in energy demand, ecosystem fragility exacerbated by climate change, limited renewable energy infrastructure, and fragmented and heterogeneous data sources that complicate informed decision-making.

To tackle these challenges, a strategy focused on energy decoupling is essential, aiming to sustain tourism without increasing energy consumption and emissions. This requires a multi-factorial approach, including advanced monitoring and simulation technologies for real-time data analysis, initiatives to encourage sustainable tourist behavior, and investment in renewable energy and resource-efficient infrastructure. Public bodies should implement data-driven policies to promote infrastructure upgrades. Measures such as improved thermal insulation, LED lighting, solar panels, heat pumps, and an expanded electric vehicle charging network can help reduce fossil fuel dependence.

By adopting an integrated and innovative approach, Valle d'Aosta can establish itself as a leader in sustainable mountain tourism, balancing economic growth with environmental preservation and long-term resilience.

3 Methodology

In order to effectively address the challenges identified above, we propose the adoption of a comprehensive framework for analysis and forecasting that leverages a combination of statistical and computational methods. We briefly introduce the main steps of the proposed approach:

1. **Data Collection and Analysis.** Integrated datasets on energy consumption, tourist flows, and environmental metrics will be sourced from ARPA¹ and regional tourist observatories. Additional data collection will involve stakeholder surveys and assessments of energy efficiency in hospitality and tourism infrastructures. These datasets will be then harmonized to overcome the heterogeneity of sources and ensure a comprehensive analysis.
2. **Forecasting Models.** Advanced econometric techniques, such as ARIMA and panel data regressions, as well as machine learning models, will be employed to predict future energy demands under varying tourism scenarios. These models can integrate multidimensional data, including environmental, infrastructural, and socio-economic variables, to simulate real-world conditions effectively.
3. **Agent-Based Modeling (ABM).** Simulations will be carried out to assess the impact of various policy interventions, such as subsidies for green technologies, dynamic pricing for energy-efficient accommodations, and electrification of mobility and heating systems. In fact, agent-based models can provide useful information on both the individual and systemic implications of proposed measures and can help identify the most effective strategies to achieve decoupling [3, 4].
4. **Integration of Renewable Energy Solutions.** The proposed approach will also encompass the potential of renewable energy solutions, such as solar panels, heat pumps, and smart grids, in reducing reliance on fossil fuels. A focus will be placed on the impact of interventions improving the energy efficiency of the existing infrastructure to support the electrification of transport and heating systems.
5. **Policy Development and Evaluation.** The developed forecasting and simulation models will be tested on a set of policy scenarios to evaluate their feasibility and potential impact. These scenarios include strategies for improving the energy infrastructure, promoting sustainable tourism practices and implementing energy-efficient hosting solutions.
6. **Stakeholder Engagement and Validation.** Regular workshops and consultations with policymakers, local operators, and community members will ensure the alignment of the research objectives with regional priorities. Feedback loops from these stakeholders will inform the refinement of both models and policies.

¹ Agenzia Regionale per la Protezione Ambientale, the Italian regional agency for environment protection.

4 Conclusion

Our proposal underscores the urgency of achieving energy decoupling in tourism, particularly in sensitive mountain ecosystems like Valle d'Aosta. By integrating statistical forecasting models and agent-based simulations we aim at providing a robust framework to guide sustainable tourism policies. The proposed framework can become a powerful tool for policy makers and local stakeholders, supporting the definition of data-driven decoupling strategies that balance economic growth with ecological preservation. The territory of Valle d'Aosta can become a replicable model of sustainable tourism, paving the way for other mountain regions to adopt similar approaches. Ensuring a collaborative and data-driven process, involving policymakers, industry stakeholders, and local communities, will be pivotal to the success of these interventions. Ultimately, an approach promoting convergence of technology, policy innovation, and sustainable practices marks a promising step toward harmonizing tourism development with environmental stewardship, fostering resilience in the face of future challenges.

Acknowledgements This paper is part of the project NODES which has received funding from the MUR – M4C2 1.5 of PNRR funded by the European Union – NextGenerationEU (Grant agreement no. ECS00000036).

References

1. Assessorato turismo, sport, commercio, agricoltura e beni culturali - Regione Autonoma Valle d'Aosta: Statistiche flussi turistici 2023. <https://www.regione.vda.it/asstur/statistiche/> (2024). Accessed: 2024-12-10
2. Ausserladscheider, V.: Decoupling climate change: winter tourism and the maintenance of regional growth. *New Political Economy* **29**(5), 693–708 (2024). DOI 10.1080/13563467.2024.2330486
3. Castro, J., Drews, S., Exadaktylos, F., Foramitti, J., Klein, F., Konc, T., Savin, I., van Den Bergh, J.: A review of agent-based modeling of climate-energy policy. *Wiley Interdisciplinary Reviews: Climate Change* **11**(4) (2020). DOI 10.1002/wcc.647
4. Moglia, M., Podkalicka, A., McGregor, J.: An agent-based model of residential energy efficiency adoption. *Journal of Artificial Societies and Social Simulation* **21**(3) (2018). DOI 10.18564/jasss.3729
5. Xu, Z., Li, Y., Wang, L., Chen, S.: Decoupling tourism growth from carbon emissions: Evidence from Chengdu, China. *Environmental Science and Pollution Research* **30**, 125,866–125,876 (2023). DOI 10.1007/s11356-023-30899-6
6. Zha, J., Dai, J., Ma, S., Chen, Y., Wang, X.: How to decouple tourism growth from carbon emissions? A case study of Chengdu, China. *Tourism Management Perspectives* **39** (2021). DOI 10.1016/j.tmp.2021.100849

Cluster-based Weighting Approach for Composite Indicators with an Application to Measuring Well-being in European Regions

Viet Duong Nguyen and Chiara Gigliarano

Abstract This paper introduces a novel weighting method for composite indicators that clarifies the match between variable importance and corresponding weights. The approach employs a combination of cluster analysis and predictive modeling to optimize the weights based on the capability of features in differentiating observations within the multidimensional context. To demonstrate the practical application of the weighting procedure, a composite index has been developed to measure well-being in European regions during the ten-year period from 2010 to 2019.

Key words: composite indicator, weighting method, cluster analysis

1 Cluster-based Weighting Approach

Cluster analysis refers to a family of techniques used for partitioning a set of units into distinct groups (called clusters) in such a way that units in the same group are more similar to each other than to those in other groups. Consider a sample matrix of n variables, the row observations can be partitioned into k cluster $c_1, c_2, \dots, c_k$ in the n -dimensional space using a proper clustering algorithm. From the cluster structure, there exists a hypothetical function $f : R^n \mapsto \{c_1, c_2, \dots, c_k\}$ that maps every data point to one of the k defined clusters.

The analytical form of f can be approximated by training a classifier that predicts the cluster labels from the sample matrix. The mean decrease in accuracy [1], so-called permutation feature importance, is a model-agnostic method that comes in handy for evaluating how useful each variable is in predicting cluster membership. This score is measured by the reduction in prediction accuracy when randomly per-

Viet Duong Nguyen
LIUC C. Cattaneo University, e-mail: vnguyen@liuc.it

Chiara Gigliarano
LIUC C. Cattaneo University, e-mail: cgigliarano@liuc.it

muting observations in each input feature. The more accuracy declines, the more the classifier relies on the variable for successful prediction.

The core of the proposed weighting approach is to train an approximation of f , measuring feature importance for each dimension, then normalizing to obtain “cluster-based” weights. These weights reflect the contribution of variables to classifying the units based on the partition patterns, i.e., the n -dimensional Voronoi diagram created by the chosen clustering scheme. Because each cluster differs from others in member characteristics, the dimension with a higher permutation importance score plays a more essential role in discriminating units within the multi-dimensional space. Therefore, it should be assigned with a greater weight in the aggregation process to establish the composite index.

2 Data

Table 1 provides the description of the dimensions employed to construct the well-being composite indicator for large (TL2) European regions. According to the OECD well-being framework [2], the dimensions of income and jobs pertain to material conditions that shape people’s economic sustainability. The aspects of health, education, environment, and safety refer to the fundamental measures of life quality. Civic engagement reflects the degree of public trust in government while the NEET rate is employed to gauge the level of social exclusion.

Table 1 Dimensions of well-being.

Dimension	Measuring indicator
Income	Household disposable income per capita (real USD PPP)
Jobs	Unemployment rate (%)
Health	Life expectancy at birth (years)
Education	Share of people aged 25-64 with at least secondary education (%)
Environment	Level of PM2.5 ¹ air pollution (µg/m ³)
Safety	Intentional homicide rate (per 100 000 population)
Civic engagement	Voter turnout to general elections (%)
Society	NEET ² rate for young people aged 18-24 (%)

¹ Fine particles that are 2.5 microns or less in diameter; ² Not in employment, education or training.

The data for the eight measuring indicators are gathered from the OECD database (<https://data-explorer.oecd.org>). To handle missing values, k -nearest neighbors (k -NN) imputation [3] was applied to replace unknown cells by a distance-weighted average of their closest neighbors’ values. Since the indicators are measured in different units, they were converted into the same scale $[0, 1]$ using the min-max normalization (with variables positively correlating with well-being) and the max-min normalization (with other variables). After the normalization process, a complete

2000 × 8 sample matrix of well-being scores was obtained, measuring across 200 European regions in the period 2010-2019.

3 Constructing Composite Indicator

To define the optimal number of clusters, the association between clustering outcomes and predictive performance was analyzed. Starting with the extraction of cluster allocations by *k*-means clustering for *k* = 2 to *k* = 10, the clustering results are subsequently used as the response variables to train multiple random forest classifiers. The model performances are given in Figure 1, where the prediction accuracy is calculated using the out-of-bag (OOB) estimate and 5-time repeated 5-fold cross-validation. According to both criteria, the three-cluster scheme yields the ensemble with highest accuracy, implying that *k* = 3 is the optimal number of clusters that should be extracted from the data to achieve the best prediction performance.

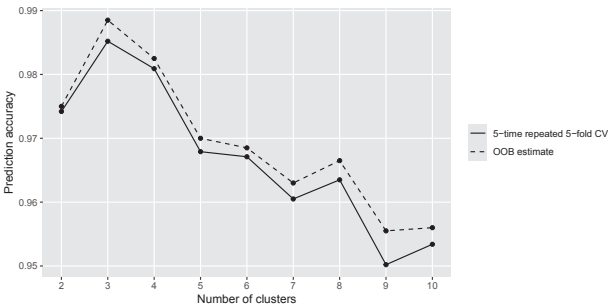


Fig. 1 Prediction accuracy of the random forest ensembles. All the ensembles grow the same size of 500 trees and randomly sample three well-being dimensions as candidates at each split.

Figure 2 presents the sets of weights for the well-being composite indicator, obtained from the cluster-based weighting procedure using the random forest ensemble trained with the three-cluster solution. According to each variable’s capacity to distinguish the regions in the multidimensional well-being space, health is the most prominent facet affecting the composite index while safety is considered the aspect yielding the smallest influence.

Figure 3 presents the average well-being composite scores for the European regions calculated using weighted arithmetic aggregation with the cluster-based weights. Northern Europe is the area that displays the highest average scores in well-being, followed by Western Europe and the British Isles. In Eastern Europe, the majority of territories show a welfare level below the continental average, and places in the southeast notably exhibit the most severe situation. In Southern Europe, a pronounced north-south gradient in well-being is visible, where the northern part produces mostly above-moderate scores while the southern part predominantly records subpar status.

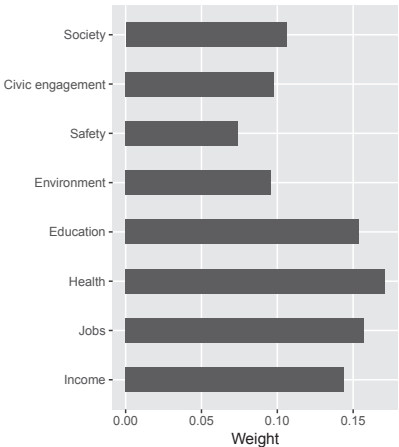


Fig. 2 Weights for the well-being composite indicator derived from the cluster-based weighting method.

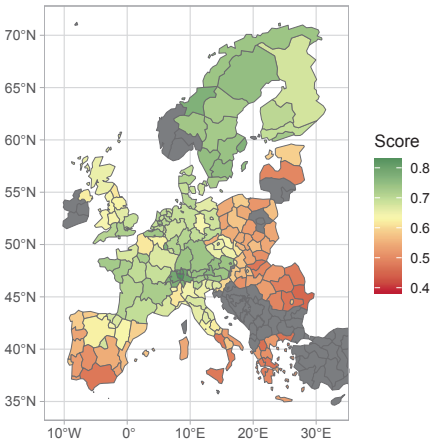


Fig. 3 Average well-being composite scores for European regions in 2010-2019. The grey areas denote territories with missing information.

4 Final Remarks

This paper introduces an innovative weighting method for composite indicators by investigating the underlying cluster structure in data and assigning weights based on the permutation importance of each dimension in predicting cluster allocation. The cluster-based weights obtained reflect the significance of constituents in explaining the multifaceted nature of the measuring context. Applying this method to measure multidimensional well-being in European regions, a comprehensive picture has been sketched with health being the most important factor while safety is the least influential dimension.

Acknowledgements The authors acknowledge the support from the Fondazione Cariplo, under the project “MultiLocal: Multi dimensional inequality and optimization in a local perspective” (Rif. 2022-1548).

References

1. Breiman L.: Random Forests. *Machine Learning* **45**, 5–32 (2001)
2. OECD: How’s Life? 2020: Measuring Well-being. OECD Publishing (2020) doi: 10.1787/9870c393-en
3. Torgo L.: Data Mining with R: Learning with Case Studies (2nd ed.). Chapman and Hall/CRC, Boca Raton (2017)

Sustainable Development Goals in Italian Regions: Temporal dynamics and spatial patterns

Giuseppe Notarstefano and Giuseppe Terzo

Abstract. This research uses a multivariate approach to analyse progress on the Sustainable Development Goals (SDG) in Italian regions, emphasizing the need for a holistic sustainability vision from the measurement stage. The aim is to provide analytical tools that interpret complex sustainability dynamics, support targeted regional policies, and reveal territorial disparities and opportunities.

Key words: Sustainability, multivariate analysis, local indicators

1 Introduction

This study assesses Italian regional sustainability from 2018-2022, using ISTAT's SDG indicators and multivariate analysis. Dynamic factor analysis (DFA) tracks convergence/divergence across 89 indicators. Given Italy's regional diversity, this analysis is crucial for understanding sustainability disparities.

Analysing regional sustainability is vital for targeted policies to address Italy's imbalances. While SDGs offer a broad framework, univariate analyses miss complex interrelationships (Alaimo and Maggino, 2020; D'Adamo et al. 2021; Perchinunno et al., 2023). This study employs a framework using active and passive sustainability to assess SDG progress (Notarstefano, 2022).

Giuseppe Notarstefano
LUMSA University, e-mail: g.notarstefano@lumsa.it

Giuseppe Terzo
LUMSA University and LUISS University, e-mail: gterzo@luiss.it

2 Methodology

In order to investigate the sustainability performance of Italian regions, we preliminarily develop composite indicators for the various goals following the scheme proposed by the Italian National Institute of Statistics (Istat) (we exclude Goals 13, 14, and 17 due to data unavailability). We finally consider 89 indicators, ensuring no redundancies by preliminarily checking for high correlations among elementary indicators.¹

We structure the composite indices for each goal using the AMPI (Adjusted Mazziotta-Pareto Index – Mazziotta and Pareto, 2018) methodology. This non-compensatory approach penalises geographical units showing higher horizontal variability, thus accounting for imbalances among elementary indicators. Consistent with analysing sustainable development, we assign a positive polarity to all indicators, ensuring that higher values indicate better performance.

To investigate convergence/divergence processes based on the previously created composite indices, we employ dynamic factor analysis (Model 1), which decomposes the variability of a cubic array into three components: average temporal variability (S_t), representing the average temporal evolution of variables; structural variability (S_i), depicting the average relationship between units and variables; and differential variability (S_{it}), capturing the specific dynamics of units over time. This approach allows us to isolate and quantify different sources of variation, providing a detailed view of convergence or divergence processes.

The first DFA model analyses data variability through two main phases. Initially, it employs principal component analysis (PCA) to examine both the average differences between units (structural variability) and how each unit deviates from the mean over time (differential variability). This analysis is performed on a matrix $\tilde{S}t$ that combines both types of variability. On the principal component plane, we can observe the average positions of units and their variations over time. By comparing each unit's path with its average position, it is possible to understand its specific dynamics. Additionally, to group units with similar patterns, we carry out a hierarchical cluster analysis (Ward's method). This analysis allows us to evaluate both the proximity of units at a given moment and the similarity of their changes over time, thus grouping units with similar trajectories (Corazziari, 1999).

3 Results

Table 1 illustrates the results of the cluster analysis, which reveals a clear three-part division of Italian territory, except for the Autonomous Province of Bolzano, which shows distinct characteristics that set it apart from other regions. This territorial segmentation reflects the varied challenges and opportunities that Italian regions face in achieving sustainability goals. The identified macro-areas likely share similar

¹ For further information on the selection of indicators, please contact the authors.

environmental, social, and economic performance traits, highlighting the need for targeted policies and strategies for sustainable development.

Table 1 Regional clusters

Cluster	Regions
1	Sicily, Basilicata, Calabria, Campania
2	Emilia-Romagna, Veneto, Friuli V.G., Trento, Lombardy, Liguria, Piedmont, Valle d'Aosta
3	Apulia, Molise, Lazio, Abruzzo, Marche, Tuscany, Umbria, Sardinia
4	Bolzano

The trajectories shown in Figure 1 indicate signs of convergence that appear to have been disrupted by the pandemic shock. Until 2019, there was evidence that all clusters, except for the one associated with Bolzano, were converging toward the centre. However, this trend of convergence has since halted, suggesting that the pandemic fundamentally changed the underlying dynamics.

This analysis uncovers critical insights into regional sustainability performance across Italy, highlighting both leading and lagging regions in achieving the SDGs and revealing the temporal evolution of sustainability metrics from 2018 to 2022. It emphasises the persistence of regional disparities, driven by socio-economic and environmental factors, while also assessing the tangible impact of policy interventions on sustainability outcomes. These findings provide a nuanced understanding of progress and challenges, offering valuable guidance for targeted policymaking and resource allocation to bridge gaps and accelerate sustainable development across all regions.

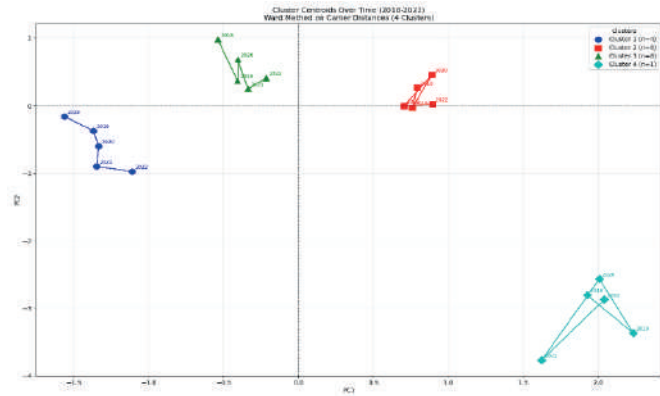


Fig. 1 Dynamic representation of clusters

Furthermore, our study highlights key challenges in adopting official statistics for territorial SDG monitoring, particularly concerning data management and regional contextualization. Issues of data availability and quality emerge through gaps in regional-level information, methodological inconsistencies, and delays in data collection processes. Additionally, the territorial dimension presents unique complexities, as regions exhibit distinct contexts and priorities, necessitating locally adapted indicators while maintaining cross-regional comparative capabilities. These

challenges underscore the importance of developing more robust and regionally sensitive monitoring frameworks for effective SDG assessment.

4 Conclusions

Our work demonstrates the value of dynamic multivariate methods in understanding complex sustainability challenges while emphasising the necessity of robust statistical frameworks for SDG monitoring. The complex nature of SDGs simultaneously requires multivariate assessment models and data with a wider spatial granularity (Phillips, 2024). This is also so that the trade-offs, synergies and contradictions that the achievement of objectives itself brings to the attention of policy makers emerge. The findings advocate for strengthened statistical capacity and enhanced inter-institutional collaboration to address regional disparities. Key recommendations focus on two main areas: first, improving data collection and management through enhanced regional statistical capabilities and standardized protocols; second, advancing policy integration by aligning regional strategies with SDG frameworks and fostering cross-regional cooperation. These targeted interventions aim to create a more cohesive and effective approach to sustainable development across Italian regions.

References

1. Alaimo, L. S., & Maggino, F. (2020). Sustainable development goals indicators at territorial level: Conceptual and methodological issues—The Italian perspective. *Social Indicators Research*, 147(2), 383-419.
2. Blanco, J., Coppi, R., and Corazziari, I. (1999). *Su alcuni sviluppi metodologici dell'analisi fattoriale dinamica*. Quaderni di ricerca n. 13. Dipartimento di Statistica, Probabilità e Statistiche applicate, Università la Sapienza di Roma.
3. Coppi, R., Zannella, F. (1978). *L'analisi fattoriale di una serie temporale multipla relativa allo stesso insieme di unità statistiche*. In Atti della XXIX Riunione della Società Italiana di Statistica SIS, Bologna, 20-22 marzo 1978.
4. Corazziari, I. (1999). *Analisi di dati Longitudinali Multivariati*. Tesi di Dottorato, XI ciclo, Università degli Studi di Napoli Federico II, aprile 1999.
5. D'Adamo, I., Gastaldi, M., Imbriani, C., and Morone, P. (2021). Assessing regional performance for the Sustainable Development Goals in Italy. *Scientific reports*, 11(1), 24117.
6. Mazziotta, M., & Pareto, A. (2018). Measuring well-being over time: The adjusted Mazziotta–Pareto index versus other non-compensatory indices. *Social Indicators Research*, 136, 967-976.
7. Notarstefano, G. (2022). Active and Passive Sustainability: Measuring the Anti-Fragility of Territories. *Pollutants*, 2(2), 172-179.
8. Perchinunno, P., Massari, A., L'Abbate, S., & Mongelli, L. (2023). Ecological Transition and Sustainable Development, A Multivariate Statistical Analysis to Guide the Policies of the National Recovery and Resilience Plan. *Social Indicators Research*, 1-15.
9. Phillips, J. (2024). Quantitative and dynamic scenario analysis of SDGs outcomes upon global sustainability 1990–2050. *The Anthropocene Review*, 11(1), 110-140.

Common Features in Volatilities: a New Multiplicative Error Model

Edoardo Otranto and Luca Scaffidi Domianello

Abstract Multivariate volatility models could consider the influence of each volatility series on the others (spillover effects). Furthermore, integrating financial markets provides similar dynamics (co-movements). We propose a new model for volatility vectors, belonging to the family of Multiplicative Error Models (MEMs), which incorporates spillover and co-movement effects captured in a separate component. Moreover, to reduce the number of coefficients for high-dimensional datasets, we propose a simple model-based clustering procedure. We apply the model to a set of 29 assets included in the Dow Jones Industrial index, providing the interpretation of spillover effects and co-movement. The proposed parameterization shows a satisfactory performance when compared to other vector MEMs.

Key words: high-dimensional time series, high-low range, model-based clustering, vector of volatility

1 Introduction

The increasing globalization of financial markets and their mutual dependence have favored the development of multivariate models for vectors of financial volatility series. The usual multivariate volatility models preclude the possibility of including spillover effects in the model specification, due to the so-called *curse of dimensionality problem*. Moreover, recent approaches to multivariate volatility models rely on the modelling of more precise measures of (co)variances based on the high-low daily range (HLR [4]) and the so-called realized (co)variance (RV- [1]), which is based on

Edoardo Otranto
Sapienza University of Rome, e-mail: edoardo.otranto@uniroma1.it

Luca Scaffidi Domianello
University of Catania, e-mail: luca.scaffidi@unict.it

ultra-high frequency data. The former is very simple to derive, being based on the difference between the maximum and the minimum value of the day, which are generally available for all indices and tickers. The vector Multiplicative Error Models (vMEMs), proposed by [2], are particularly suitable for modeling this type of time series: the vector of positive time series is the dependent variable, each one specified as the product of two factors representing the conditional mean of the series and the positive disturbance respectively. A very interesting extension has been proposed by [5]: they adopt a log-Normal distribution for innovations, modeling the logarithm of the conditional mean of volatility, with the advantage of not imposing restrictions on parameters to guarantee positiveness. Nevertheless, like other approaches, they face the curse of dimensionality problem. We propose a new diagonal log-vMEM with an additive common component, having an autoregressive dynamics, that captures spillover effects and co-movements in financial market volatility. Furthermore, we also address the problem of the high-dimensional vector of volatilities, proposing a reparameterization of the model coefficients, based on a model-based clustering algorithm. In the empirical application, we use the HLR of 29 components belonging to the Dow Jones Industrial (DJI) index. The proposed parameterization shows a satisfactory performance despite the small number of coefficients used. The paper is organized as follows: in the next section we present the new model, section 3 is mainly devoted to the empirical application; some final remarks (section 4) will conclude the paper.

2 The model proposed

Let us consider n volatility series collected in the vector $\mathbf{y}_t$. The proposed model is the log-vMEM [5], enriched by the presence of specific coefficients to consider spillover effects and by a common signal that drives all indices. Calling $\mathbf{x}_t$ the logarithm of $\mathbf{y}_t$ whose conditional mean is $\boldsymbol{\mu}_t$, the model proposed is:

$$\begin{aligned} \mathbf{y}_t &= \boldsymbol{\mu}_t \odot \boldsymbol{\varepsilon}_t & \boldsymbol{\varepsilon}_t &\sim \ln N(\mathbf{m}, \mathbf{V}) \\ \ln \boldsymbol{\mu}_t &= \boldsymbol{\varsigma}_t + \boldsymbol{\vartheta} \xi_t \\ \xi_t &= \delta p_{t-1} + \phi \xi_{t-1} \\ \boldsymbol{\nu}_t &= \mathbf{x}_t - \xi_t \boldsymbol{\iota} \\ \boldsymbol{\varsigma}_t &= (\mathbf{I}_n - \mathbf{A} - \mathbf{B}) \bar{\mathbf{x}} + \mathbf{A} \boldsymbol{\nu}_{t-1} + \mathbf{B} \boldsymbol{\varsigma}_{t-1} \end{aligned} \tag{1}$$

where $\odot$ indicates the element-by-element Hadamard product, $\boldsymbol{\iota}$ an n -dimensional column vector of ones, and $\mathbf{I}_n$ the $(n \times n)$ identity matrix. The vector of disturbances $\boldsymbol{\varepsilon}_t$ is a unit mean vector, log-normally distributed with parameters $\mathbf{m} = (m_1, \dots, m_n)'$ and the $n \times n$ symmetric positive definite matrix $\mathbf{V} = \{v_{ij}\}$, $(i, j = 1, \dots, n)$. To satisfy the unit mean property, it is imposed the constraint $m_i = -v_{ii}/2$ ($i = 1, \dots, n$). As a consequence, $\mathbf{y}_t \sim \ln N(\ln \boldsymbol{\mu}_t + \mathbf{m}, \mathbf{V})$. The vector $\bar{\mathbf{x}}$ represents the sample mean of the log-volatilities $\mathbf{x}_t$.

In (1), $\ln \boldsymbol{\mu}_t$ is decomposed into the sum of two unobservable components: the idiosyncratic log-volatility $\boldsymbol{\varsigma}_t$ and a zero-mean common dynamic signal ξ_t , which

affects the i -th element of the full conditional log-volatility vector, $\ln \mu_t$, with a loading coefficient ϑ_i , contained in the n -dimensional vector ϑ . The unobservable common time-varying component ξ_t depends on its own lag and on p_{t-1} , the lagged first principal component of the n log-volatilities in x_t . In this way spillover and co-movements are included into the common component ξ_t . The $(n \times 1)$ vector ς_t represents the ‘proper’ dynamics of each volatility and follows a multivariate diagonal GARCH dynamics; it depends only on its own lag and the past value of ν_t . We call model (1) the vMEM with Spillover effects and Comovement (vMEM-SeC).

Parameter estimation is performed using the Quasi Maximum Likelihood Estimator. Robust standard errors can be obtained by applying a sandwich estimator of the covariance matrix [6].

The number of unknown coefficients (including the covariance matrix element V) in (1) is $n(n+1)/2 + 3n + 2$ and, if n is large, we face the curse of dimensionality problem. The reduction in the number of coefficients could be based on the idea of identifying groups of series that follow the same dynamics and assigning them the same parameters α_i and β_i in the last equation of (1) and the same loading coefficient ϑ_i in the second equation. This could be achieved with a simple algorithm.

Algorithm 1 *Grouping the coefficients of the vMEM-SeC*

1. Derive the first principal component of the set of log-volatilities and estimate an ARMA(1,1) model; get the residuals $\hat{\eta}_t$;
 2. derive the series $\xi_t^* = p_t - \hat{\eta}_t$;
 3. derive the vector series $\nu_t^* = x_t - \xi_t^* \nu$;
 4. for each element $\nu_{i,t}^*$ of ν_t^* estimate a univariate log-MEM obtaining the coefficients (α_i^*, β_i^*) ;
 5. group the n pairs (α_i^*, β_i^*) into k_1 clusters with similar value, adopting a clustering algorithm that uses the ARMA distance between series i and j as:
$$d_{ARMA} = \left[\frac{\alpha_i^{*2}}{1-\beta_i^{*2}} + \frac{\alpha_j^{*2}}{1-\beta_j^{*2}} - 2 \frac{\alpha_i^* \alpha_j^*}{1-\beta_i^* \beta_j^*} \right]^{1/2}$$
 6. derive the vector series ς_t^* with each element $\varsigma_{i,t}^* = \bar{x}_i + \alpha_i^* (\nu_{i,t-1} - \bar{x}_i) + \beta_i^* (\varsigma_{i,t-1}^* - \bar{x}_i)$;
 7. estimate the auxiliary regression for each $x_{i,t} = \varsigma_{i,t}^* + \vartheta_i^* \xi_t^*$ obtaining the n parameters ϑ_i^* ;
 8. group the n parameters ϑ_i^* into k_2 clusters with similar values, adopting a clustering algorithm that uses the Euclidean distance: $d_\vartheta = |\vartheta_i^* - \vartheta_j^*|$.
-

3 Empirical Application

The dataset considered includes 29 components of the Dow Jones Industrial (DJI) index. We calculate for each asset the daily HLR as the square of the difference between the logarithms of the highest and the lowest value of the day, and by taking into account the correction proposed by [4]. The sample period spans from March 19, 2008, to April 22, 2024. We consider six competing models belonging to the vMEM-SeC family with three alternative parameterizations, that is, the scalar, the diagonal and the clustered one proposed in section 2. Furthermore, we consider the

three classical vMEM, obtained by imposing $\vartheta = \mathbf{0}$ and not considering the third equation in (1). To save space, we do not report the estimates of the parameters, the information criteria and the two loss functions employed (MSE and QLIKE). AIC slightly favors the diagonal models, while BIC, as expected, prefer the most parsimonious models. More interestingly, all vMEM-SeC models, including the scalar model, outperform all vMEMs, with c-vMEM-SeC being the best in terms of BIC. Finally, the Model Confidence Set (MCS) test [3] shows a clear preference for vMEM-SeC models.

4 Conclusion

An important strand of statistical and econometric literature aims to include the dependence on movements of other markets in volatility models generating various multivariate approaches, such as spillover effects. The vMEM seems an excellent candidate to include the latter, adopting the flexible dynamics GARCH to model the volatility and, via the proposed extension, having the possibility to specify an unobservable common component. To provide the ability to handle a large set of volatility series, we propose a model-based clustering algorithm, which shows a satisfactory performance, to dramatically reduce the number of unknown coefficients. It might be interesting to adopt alternative methods for grouping the parameters in this model, such as the fuzzy clustering approach or using other techniques for detecting co-movements, like Independent Component Analysis (ICA).

Acknowledgements Edoardo Otranto acknowledges financial support from the Italian PRIN 2022 grant “Methodological and computational issues in large-scale time series models for economics and finance” (20223725WE). Luca Scaffidi Domianello acknowledges financial support from the “PIAno di inCEntivi per la RIcerca di Ateneo 2024/2026” (UPB 28722052159) and starting grant BA-GRAPH (UPB 28722052144) of the University of Catania

References

1. Andersen, T., Bollerslev, T.: Deutsche mark-dollar volatility: intraday volatility patterns, macroeconomic announcements and longer run dependencies. *The Journal of Finance* **53**, 219–265 (1998)
2. Engle, R.F., Gallo, G.M.: A multiple indicators model for volatility using intra-daily data. *Journal of Econometrics* **131**, 3–27 (2006)
3. Hansen, P.R., Lunde, A., Nason, J.M.: The model confidence set. *Econometrica* **79**(2), 453–497 (2011)
4. Parkinson, M.: The extreme value method for estimating the variance of the rate of return. *The Journal of Business* **53**, 61–65 (1980)
5. Taylor, N., Xu, Y.: The logarithmic vector multiplicative error model: an application to high frequency NYSE stock data. *Quantitative Finance* **17**, 1021–1035 (2017)
6. White, H.: Maximum likelihood estimation of misspecified models. *Econometrica* **50**, 1–25 (1982)

Corporate Sustainability: a Technical Rehearsal for the Construction of a Composite Index

Luca Patelli and Daniele Toninelli

Abstract This study outlines a framework for constructing composite indexes to assess corporate sustainability, linking theoretical concepts to measurable variables. Key considerations include defining a theoretical framework, selecting variables, normalizing indicators, and aggregating the selected indicators. During the aggregation phase, the hierarchy is taken into account and discussed applying Ultrametric Composite Indicator models. This is a promising solution for enhancing the dimensionality reduction, including a phase of hierarchy testing, and it also aims to obtain an interpretable sustainability assessment.

Key words: sustainability, enterprises, composite indexes, PCA, Ultrametric Composite Indicators

1 Introduction

The new paradigm regarding the concept of sustainability has been widely discussed since the introduction of its first formal definition in the Brundtland Report [6]. Following the adoption of the Millennium Development Goals (MDGs), in 2000, and the Agenda for Sustainable Development (SDGs), in 2015, [7], the concept of sustainability has been declined in virtually every aspect of life.

Given their relevant role in the economy, enterprises have become a focal point for discussions and studies about sustainability. Beyond financial sustainability, which has traditionally been a primary concern for corporate survival, sustainability in firms has been increasingly addressed through various approaches. One of the most common is the Environmental, Social and Governance (ESG) one. ESG

Luca Patelli
University of Bergamo, e-mail: luca.patelli@unibg.it

Daniele Toninelli
University of Bergamo, e-mail: daniele.toninelli@unibg.it

criteria allow stakeholders to highlight specific corporate dimensions that are worthy of attention, particularly when investors evaluate a company for potential investments. Corporate sustainability, therefore, has been defined as a multifaceted concept [8], based on the principles of sustainable development. This concept emphasizes that businesses should anticipate and fulfil the needs of future customers and stakeholders by fostering innovation and creating value in areas such as social change, environmental protection and, enhanced business performances.

In order to quantify the overall sustainability of enterprises, whether the focus is on the adhering to ESG criteria or not, or if the sustainability assessment focus has been set on the whole company or if singular aspects of corporates' life (e.g., production, personnel management or other internal practices) are evaluated individually, composite indexes can be utilized. These indexes provide a well-established and tested framework for measuring and evaluating corporate sustainability, particularly for dimensions that are not directly measurable and rely on multiple data sources or on the combination of more than one variable.

However, the construction of a composite index for corporate sustainability is a complex process that involves addressing several methodological challenges. One key decision, for example, is defining a theoretical framework that identifies the macro groups of variables necessary to capture the multifaceted nature of corporate sustainability. This includes determining the number and the types of variables to be selected for building up the final composite index.

A critical yet unresolved issue pertains to the selection of a hierarchical structure for aggregating the individual indicators. The implementation of this approach is functional to attain statistically significant levels, thereby facilitating the construction of a composite index. This, in turn, enables a multi-level examination of sustainability performance, thereby enhancing the interpretability of results and their practical usage.

The objective of this study is to discuss the key decisions that must be taken for the construction of a composite index for assessing corporate sustainability including a hierarchical structure.

2 Construction of the composite indicator

The first key decision to be made in order to construct a composite index involves the definition of the model that links the theoretical unobserved concept of sustainability to the observable variables of corporate activity. In this framework, the variables, represented by X , constitute a set of dimensions P (where $j = 1, \dots, P$) and are treated as the causes of the sustainability level, which is the latent variable of interest. To formalize this relationship, a formative model can be defined for a generic variable j as follows:

$$R = \sum_j \beta_j X_j + \varepsilon \quad (1)$$

where β_j is a coefficient capturing the effect of X_j on R , and ε is a residual error term. In this model, the response variable R is determined by the observed value of the variable X_j , linked to it through the coefficients β_j . These coefficients indicate the polarity of the variables, reflecting their positive or negative theoretical effect on the latent variable of sustainability.

The second critical question concerns which and how many variables should be included in the model. Examples from the literature demonstrate that composite indicators designed to quantify the overall sustainability of a business entity often consider multiple pillars. These extend beyond traditional financial indicators to consider dimensions such as environmental protection, often in combination with the resource management, social responsibility (both toward employees and external stakeholders), and corporate governance [2,5].

The third issue is the variables normalization and the treatment of polarities, and for which numerous different approaches are proposed by the literature [4].

The last open question pertains to how the composite index should model the hierarchical structure of the multidimensional phenomena under study. Several attempts (e.g., 2,5) faced this issue by exploiting experts and literature by creating theoretically based structures, but how it is possible to understand if these are efficient and not redundant. Consider, for example, the case of a dataset containing a set of companies belonging to the same sector and of the same typology (e.g., public companies); $P = 9$ variables are selected. How is it possible to understand which is the most appropriate aggregation hierarchy? In Fig. 1, the original variables, X_p , are aggregated at a first level obtaining L_1 , that is a unique aggregation. But moving to the second level of aggregation in the left panel (a) the aggregation follows the theoretical segmentation of the selected variables, whereas in the right panel (b) one aggregation is avoided once obtaining a lower number of intermediate levels. In both the cases, the final composite index L_3 is reached.

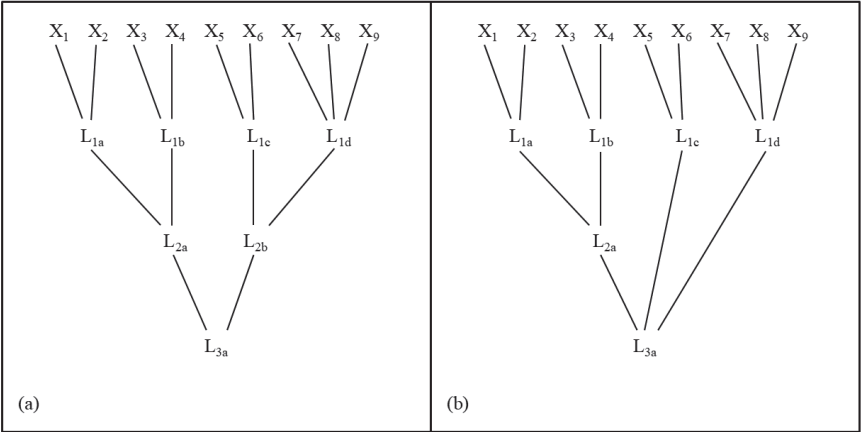


Fig. 1 Example of hierarchies.

3 Future directions

Future research will explore and compare alternative methods for aggregating selected variables while accounting for their intrinsic relationships. One approach is the use of Principal Component Analysis (PCA), which has been shown to address dimensionality reduction effectively. However, as highlighted by [3], PCA may not be ideal for formative models where assumptions of non-redundancy and non-interchangeability of indicators must hold, as it risks excluding critical individual indicators.

In order to overcome these limitations, our future work will focus on developing synthesis methods enabling to account for statistically significant higher-level composite indexes. These methods aim to support multi-level analyses of corporate sustainability while minimizing redundancy in the hierarchy of levels to be inspected. For example, the Ultrametric Composite Indicator model proposed by [1] in the framework of studying waste management in Italian municipalities offers a promising approach. This model leverages ultrametric correlation matrices to construct efficient hierarchical structures based on the relationships among selected variables.

Additionally, we aim to design a composite index allowing to compare corporate sustainability across countries. This approach will enable cross-national comparisons even when using data sources from multiple geographical regions. It will also foster a broader understanding of corporate sustainability practices.

References

1. Cavicchia, C., Sarnacchiaro, P., Vichi, M., Zaccaria, G.: A model-based ultrametric composite indicator for studying waste management in Italian municipalities. *Comput Stat.* 39, pp 21—50 (2024)
2. Kocmanová, A., Pavlákova Dočekalová, M.: Environmental, Social, Governance and Economics Model of a Company's Sustainable Development as a Base for Investment Decision Making. In: *Proceedings of the 21st World Multi-Conference on Systemics, Cybernetics and Informatics (WMSCI 2017)*. 2, pp 7—12. (2017)
3. Mazziotta, M., Pareto, A.: Principal component analysis for constructing socio-economic composite indicators: theoretical and empirical considerations. *SN Soc Sci.* 4, pp 114 (2024)
4. OECD: *Handbook on constructing Composite indicators. Methodology and user guide*. OECD, Paris. (2008)
5. Pavlákova Dočekalová, M., Kocmanová, A.: Composite indicator for measuring corporate sustainability. *Ecological Indicators*. 61, pp 612—623 (2016)
6. United Nations: *Report of the World Commission on Environment and Development: Our Common Future*. (1987)
7. United Nations: the 17 goals, Sustainable Development (2024) <https://sdgs.un.org/goals>
8. Zu, L.: Sustainable Enterprise Development. In *Springer eBooks* pp. 2449—2458. (2013)

Unveiling Underemployment Through a Fuzzy Approach: A Comparison of Fuzzy and Official Employment Rates in Italy (2021–2023)

Andrea Regoli, Bruno Cheli and Alessandra Coli

Abstract This paper applies a fuzzy approach to redefining and analysing employment. Rather than categorising individuals strictly as employed or unemployed, this method assigns a degree of employment based on the number of hours worked and the level of satisfaction associated with those hours. This approach addresses the limitations of the standard definition of employment adopted by Official Statistics, which treats individuals working only a few hours in the same way as those working full-time. The proposed method is applied to data from the Italian Labour Force Survey (2021–2023), and the resulting fuzzy employment rates are compared to the official rates published by Eurostat.

Key words: fuzzy approach, employment rate, underemployment

1 Introduction

The 13th International Conference of Labour Statisticians (ICLS) [1] established the widely used definitions of employment and unemployment, classifying individuals as employed if engaged in paid work during a short reference period and as unemployed if unable to work despite actively seeking employment. This framework has been criticised for overlooking aspects like underemployment, personal fulfilment and

Andrea Regoli
University of Naples Parthenope, e-mail: andrea.regoli@uniparthenope.it

Bruno Cheli
University of Pisa, e-mail: bruno.cheli@unipi.it

Alessandra Coli
University of Pisa, e-mail: alessandra.coli1@unipi.it

income adequacy, which significantly affect well-being. Hauser [2] and Clogg [3] addressed these gaps by introducing the Labour Utilization Framework, which accounts for low-paid employment and underemployment. Building on these ideas, the 18th ICLS [4] proposed a more comprehensive employment concept, recognising a continuum between employment, unemployment, and inactivity.

This paper adopts a fuzzy approach [5] to redefine employment [6] and unemployment [7, 8], integrating hours worked and satisfaction levels. Applied to the Italian Labour Force Survey for the 2021-2023 years, the methodology offers a nuanced classification of employment status and compares fuzzy employment rates with Eurostat's official figures.

2 Methodology

The core assumption of our proposal is that workers can be employed to varying degrees, according to a membership function μ_E in the fuzzy set E of the employed individuals. This function varies on a scale from 0 to 1, where 1 indicates full membership in the set E , 0 indicates complete non-membership, whereas values strictly between 0 and 1 denote a partial belonging to E . To determine the membership value for any individual, it is essential to establish an upper threshold based on the number of hours worked. This threshold serves as a reference standard which approximates the average weekly hours worked by full-time employees.

Denoting by x the number of hours worked and by t the threshold, the membership function μ_E is defined as follows:

$\mu_E = 1$ for:

- full-time workers who work a number of hours equal to or greater than the threshold ($x \geq t$);
- full-time workers who do not wish to work additional hours, even if they work fewer hours than the threshold ($0 < x < t$);
- voluntary part-time workers ($0 < x < t$);

$\mu_E = 0$ for the individuals classified either as unemployed or inactive based on ILO criteria, that is $\mu_E(x) = 0$ for $x = 0$;

$0 < \mu_E < 1$ for:

- involuntary part-time workers;
- full-time workers who work below the threshold and wish to work additional hours.

This segment of the labour force represents the most vulnerable group of workers. Their membership function μ_E is calculated as the ratio of the number of hours worked to the threshold value, as follows:

$$\mu_E(x) = \frac{x}{t} \text{ for } 0 < x < t$$

The fuzzy employment rate (FER) is the weighted arithmetic mean of individual membership values $\mu_{E,i}$ over the population in working age, where w_i is the sample weight for the i -th individual:

$$FER = \frac{\sum_{i=1}^n \mu_{E,t} \cdot w_i}{\sum_{i=1}^n w_i} \quad [1]$$

3 Main findings

This paper is based on the Eurostat Labour Force Survey (LFS)¹. The analysis refers to Italian yearly data for 2021 to 2023. For each year, we calculated the fuzzy employment rate according to formula [1] following the methodology summarised in section 2 above for the total population and the breakdown by gender, age group, migration status, and area of residence. The threshold t for defining the membership function is set at the median value of the weekly hours usually worked by full-time workers, separately for employees in the public sector, employees in the private sector and self-employed. The threshold is constant over time and is set equal to 36, 40, and 44 hours, respectively, for the three groups mentioned above.

Table 1 shows the results of the comparison between the official and the fuzzy employment rates.

One of the strengths of the fuzzy approach applied to employment quantification is that it accounts for the nuances in the different conditions of workers concerning their work intensity and their level of satisfaction with the hours worked. Specifically, the fuzzy approach considers those who work fewer hours than they would like to belong partially to the fuzzy set of the employed. Consequently, the presence of time-related underemployment (essentially involuntary part-time workers but also full-time workers who would like to work more hours) causes the fuzzy rate to be lower than the official rate.

Over time, the official rate in the total population increased from 58.2% in 2021 to 60.1% in 2022 and 61.5% in 2023. The fuzzy rate also increased from 55% in 2021 to 57.3% in 2022 to 58.8% in 2023. However, the fuzzy measure showed higher growth rates than the official one: while in 2021 the fuzzy rate was lower than the official one by 3.2 percentage points, in 2023 the difference narrowed to 2.7 percentage points. This different dynamic results from the combined effect of the reduction in time-related underemployment, the simultaneous increase in voluntary part-time work, and the increase in the lowest percentiles of the distribution of hours worked.

The rates calculated for the subpopulations by gender, age, migration background, and area of residence show a trend similar to that observed for the total population. However, the disaggregated analysis unveils disadvantaged situations for specific categories. Women, younger people, and residents in the South and the Islands regions display the lowest values of both rates and the largest differences between official and fuzzy rates. For these categories, therefore, a lower share of employment and a higher incidence of underemployment can be observed. In particular, in 2023, the difference

¹ We used data from Eurostat 2024 release of LFS scientific use files for the reference years 1983-2023, based on the new legal framework (Regulation EU 2019/1700 of the European Parliament and of the Council of 10 October 2019). The responsibility for all conclusions drawn from the data lies entirely with the authors.

between the official and fuzzy rates is 3.8 percentage points for women compared to 1.6 percentage points for men.

In contrast, results disaggregated by migration background show that foreign-born individuals have higher employment rates than natives but are more affected by time-related underemployment than native-born individuals.

Table 1 Official and fuzzy employment rate. Population between 15 and 64 years

	2021		2022		2023	
	Official	Fuzzy	Official	Fuzzy	Official	Fuzzy
Total	58.2	55	60.1	57.3	61.5	58.8
<i>By gender</i>						
Female	49.4	45.1	51.1	47.1	52.5	48.7
Male	67	64.9	69.2	67.4	70.4	68.8
<i>By age class</i>						
15-34 years	40.9	38.1	43.7	41	45	42.4
35-50 years	73.4	69.6	75.1	71.8	76.3	73.2
51-64 years	58.9	56	60.6	58	62.5	60
<i>By country of birth</i>						
Foreign-born	59.1	53.9	62.6	57.8	64	59.6
Native-born	58	55.2	59.7	57.2	61	58.6
<i>By area of residence</i>						
North-West	65.8	62.8	67.5	64.9	68.6	66.1
North-East	67.2	64.5	69	66.7	70.5	68.3
Center	62.4	58.7	64.7	61.3	65.9	62.6
South	45.1	42	47.1	44.3	48.5	45.8
Islands	44.1	40.5	45.6	42.1	47.7	44.3

Source: Authors' elaborations from EU LFS data

References

1. ILO Statistics of labour force, employment, unemployment and underemployment, Report II of the 13th International Conference of Labour Statisticians, Geneva (1982).
2. Hauser, P.M., The measurement of labour utilisation, *Malaysian Economic Review*, 19(1), 1–15 (1974).
3. Clogg, C.C., *Measuring underemployment: Demographic indicators for the United States*, Academic Press, (1979).
4. ILO, Beyond unemployment: Measurement of other forms of labour underutilisation, working group on labour underutilisation, 18th International Conference of Labour Statisticians, Geneva, 24 November–5 (2008).
5. Zadeh, L.A., Fuzzy sets, *Information and Control*, 8, 338–353 (1965).
6. Cheli, B., Coli, A., Regoli, A., A fuzzy approach to the measurement of the employment rate, In: Pollice, A., Salvati, N., Schirripa Spagnolo, F. (Eds.), *Book of short papers SIS 2020*, 893-897, Pearson (2020).
7. Cheli, B., Coli, A., Regoli, A fuzzy approach to the measurement of employment and unemployment. In: Betti, G. & Lemmi, A. (Eds.), *Analysis of socio-economic conditions. Insights from a fuzzy multidimensional approach* (pp. 256–263), *Routledge Advances in Social Economics*, Routledge (2021)
8. Cheli, B., Coli, A., Regoli, Measuring employment and unemployment from a fuzzy perspective. A comparative analysis across European countries, *Soc Indic Res* 175, 467–486 (2024).

Beyond the Multidimensional Poverty Index (MPI): a fuzzy approach based on proximity measures to investigate household deprivation in three Italian regions

Andrea Regoli and Giuseppe Verdoliva

Abstract This paper examines the application of fuzzy logic to multidimensional poverty assessment, providing an alternative to traditional poverty metrics like the Multidimensional Poverty Index (MPI). Using data from a household survey in three Italian regions, proximity-based membership functions are employed to create composite poverty indicators. These are then evaluated for robustness and compared with the MPI through statistical modeling, revealing nuanced insights into deprivation measurement.

Key words: fuzzy logic, multidimensional deprivation, proximity measures

1 Introduction

Since the seminal work of Sen (1985), a broad consensus has developed that poverty should be analyzed and measured as a multidimensional phenomenon and not only linked to the lack of monetary resources. In this framework, the relevant key points are the selection of the dimensions and indicators to be used, the definition of poverty thresholds delimiting poor/non-poor states, and the choice of weights assigned to each dimension. From this point of view, the most relevant indicator is the Multidimensional Poverty Index (MPI), developed since 2010 by the Oxford Poverty and Human Development Initiative (OPHI, Alkire and Foster, 2007).

Andrea Regoli

University of Naples Parthenope, e-mail: andrea.regoli@uniparthenope.it

Giuseppe Verdoliva

University of Naples Parthenope, e-mail: giuseppe.verdoliva001@studenti.uniparthenope.it

As early as the 1990s, the fuzzy approach to measuring monetary and non-monetary poverty aimed to overcome the use of poverty thresholds and the resulting rigid dichotomy between poverty and non-poverty status (Cheli and Lemmi, 1995; Betti et al., 2006). This approach defines a poverty membership function, measured on a continuous scale from 0 to 1 - where 1 means full membership in the set of poor and 0 full non-membership - thus allowing for a grey area in which households and individuals are neither completely poor nor completely non-poor.

This paper introduces membership functions constructed from proximity measures to assess the robustness of the resulting poverty indicators to the choice of the metrics and compare the fuzzy indicators with the Multidimensional Poverty Index.

We used data from a household survey conducted in three Italian regions (Lombardy, Tuscany, and Campania) as part of a project² aiming at deriving indicators of vulnerability and deprivation at the local level.

2 Methodology

The proximity between two generic units, i and j , is a function of the values taken by the characteristics observed in the two units. The specific function to be applied depends on the type of variables being considered for comparison. In this sense, metrics for quantitative data and metrics for qualitative data are considered. The former measure the distance between two units, while the latter measure their similarity. To determine the poverty membership of the units of analysis, the proximity to a maximum deprivation status is considered. By indicating the most deprived unit as h , it is possible to quantify the degree of deprivation of a generic unit i by calculating the proximity between i and h . The choice of status h for comparisons depends on the variables available. Suppose it is possible to identify modes that can objectively describe the maximum deprivation for each characteristic. In that case, h can be defined as the unit for which these values of the variables are observed. Alternatively, if the deprivation varies monotonically with respect to the observed characteristics, then it is possible to consider one of the extremes of each variable.

For subsequent analyses, the following metrics are considered: Gower's index (Gower, 1971), Euclidean distance and Manhattan distance (Deza & Deza, 2009). The first of these can take values between 0 and 1. Distances, on the other hand, can take positive values outside this range. In addition, the greater the difference between the values compared, the greater the final distance. For the reasons discussed, the membership functions related to distances are defined as follows:

$$F(i) = 1 - \frac{P_D(i, h)}{P_D(h, r)} \quad [1]$$

$F(i)$ expresses the membership to poverty of the i -th unit, $P_D(i, h)$ is the proximity (in terms of distance) between the i -th unit and status h and $P_D(h, r)$ is the distance

²Measuring inequality, Poverty and living conditions for Planning Local strategies (MYPEOPLE), PRIN Call 2022 PNRR, Ministry of University and Research, <https://www.mypeople-unibg.it/mp/index.php>

between the most deprived and the least deprived units. The status r can be determined similarly to what was previously described for h .

Two requirements need to be met for Equation [1]: i) the variables monotonically influence deprivation; ii) information on the status of minimum possible deprivation is available. If, in fact, condition (ii) is not met, it is not possible to calculate $P_D(h, r)$, therefore, it is not possible to apply equation [1]. Furthermore, if (i) is not met, there is no guarantee that the final value of $F(i)$ is between 0 and 1. However, if (i) and (ii) are observed, then $P_D(h, r)$ is the maximum possible distance. The values of the membership function must be aggregated into composite indices. These are constructed as weighted arithmetic averages using sample weights.

Once the synthetic indices have been calculated, it is necessary to verify whether they can be considered valid substitutes for the MPI. In particular, it is important to analyze the relationship between the measures and a number of other relevant variables. To this end, the following procedure is carried out: 1) the synthetic indices are calculated at the provincial level for each measure; 2) models are built with indices as the response; 3) comparisons are made between the estimated coefficients. To accomplish what is described in (2), for each of the fuzzy proximity-based measures, consider the following system of equations:

$$\begin{aligned} Y_1 &= X\beta_1 + \epsilon_1 \\ Y_2 &= X\beta_2 + \epsilon_2 \end{aligned} \quad [2]$$

Y_1 and Y_2 are, respectively, the index constructed with a fuzzy approach and the MPI, both calculated on a provincial basis. Predictors must be chosen from the most relevant in the analysis of living conditions. The median household equivalent income on a provincial basis and the region to which the province belongs are considered. The models are estimated separately for each of the previous covariates and controls are included. Estimates are made by applying the Seemingly Unrelated Regression (SUR) methodology (Zellner, 1962). The coefficients of the different equations are then compared with those of the MPI equation. The comparison is made both in terms of significance and sign and by applying a Wald test (Wald, 1943).

3 Results and Conclusions

For the calculation of the measures, a household is considered deprived if: 1) is unable to meet unexpected expenses (850 or 3000 euro); 2) has suffered loss of employment or reduction of working hours by any members (yes, no); 3) has received financial assistance (yes, no); 4) has reduced the amount of food in meals/given up a healthy diet (often, sometimes, never); 5) has had difficulties in meeting expenses for bills/medical treatment/mortgage or rent/loans/transport (often, sometimes, never); 6) could not afford a one-week holiday/cinema or theatre twice a month/eating out twice a month (often, sometimes, never); 7) has had difficulties in meeting expenses for children or family members in need of assistance (often, sometimes, never).

For the calculation of the MPI, the natural poverty thresholds are applied for each variable (e.g. Often/Sometimes/Never becomes Yes/No). For each of the distances, equation [1] is applied to three transformations of the data: 1) replacement of the values with their respective ranks; 2) binary deprivation (application of the MPI poverty thresholds); 3) replacement of the values with the distribution functions of the inverted ranks of the variables. On the other hand, Gower's metric is applied to the original data and to the transformation described by point (2) of the previous list.

Table 1 shows the results of the comparisons through the systems of equations [2]. As can be seen, the estimates obtained show the same signs between the measures and very similar levels of significance and are comparable in magnitude. Wald tests also allow us to say that (at $\alpha = 1\%$) the impact of income is not statistically different between the proximity-based indices and the MPI (with few exceptions). This is generally not the case for regions, whose impact, although not identical, is nevertheless very similar. Considering these results, it can be safely said that poverty indices constructed from proximity-based membership functions can be considered sufficiently robust substitutes for MPI and can, consequently, represent a valid alternative to it when the definition of poverty thresholds is not obvious.

Table 1 Coefficients and Wald tests

<i>Indices</i>	<i>Coefficients</i>			<i>Wald tests (p-values)</i>		
	<i>Income (*)</i>	<i>Lombardy</i>	<i>Tuscany</i>	<i>Income</i>	<i>Lombardy</i>	<i>Tuscany</i>
MPI	-0.13745**	-0.09978***	-0.09777***	-	-	-
Gower (original)	-0.09902**	-0.06587***	-0.05977***	0.09583	0.00116	0.00016
Gower (2)	-0.10954**	-0.08336***	-0.07821***	0.06168	0.03360	0.00870
Euclidean (1)	-0.06485**	-0.04796***	-0.04492***	0.00916	0.00005	0.00002
Euclidean (2)	-0.07293*	-0.05788***	-0.05509***	0.00532	0.00020	0.00009
Euclidean (3)	-0.06871*	-0.05295***	-0.05034***	0.00584	0.00006	0.00003
Manhattan (1)	-0.09668**	-0.06513***	-0.05938***	0.07721	0.00096	0.00015
Manhattan (2)	-0.10954**	-0.08336***	-0.07821***	0.06168	0.03360	0.00870
Manhattan (3)	-0.09352**	-0.06880***	-0.06498***	0.01783	0.00040	0.00010

(*) The coefficient is multiplied by 1000

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

References

1. Alkire S., Foster J.E. (2007), Counting and Multidimensional Poverty Measurement, Oxford Poverty and Human Development Initiative, Oxford Department of International Development, University of Oxford, "Working Paper" No. 7
2. Betti G, Cheli B, Lemmi A, Verma V (2006a) On the construction of fuzzy measures for the analysis of poverty and social exclusion, *Statistica & Applicazioni*, Vol. IV, numero speciale 1, pp. 77-97.
3. Cheli B, Lemmi A (1995) A "Totally" Fuzzy and Relative Approach to the Multidimensional Analysis of Poverty. *Economic Notes* 24:115-134
4. Deza, M.M., & Deza, E. (2009). "Encyclopedia of Distances". Springer
5. Gower, J. C. (1971). A General Coefficient of Similarity and Some of Its Properties. *Biometrics*, 27(4), 857-871.
6. Sen A. (1985) *Commodities and Capabilities*, North-Holland, Amsterdam, New York, Oxford
7. Wald, A. (1943). Tests of Statistical Hypotheses Concerning Several Parameters When the Number of Observations is Large. *Transactions of the American Mathematical Society*, 54(3), 426-482.
8. Zellner, A. (1962). An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias. *Journal of the American Statistical Association*, 57(298), 348-368.

Testing the convergence hypothesis on per capita GDP across European provinces from 1997 to 2023

Giulia Sacchetti, Bruno Paolo Bosco and Paolo Maranzano

Abstract We use a panel of NUTS-3 European provinces to test the hypothesis of convergence in the levels of individual wealth across Europe. Through a club convergence analysis based on the log-t test, we provide new empirical evidence of absence of global convergence during the period 1997-2023, while identifying five non-overlapping and internally-convergent clubs. The cluster analysis indicated that European countries strongly suffer from a polarization between highly attractive areas and rural provinces with poor economic capacity. The gap can be attributed to the historical East-West and North-South divides, as well as to the enlargement of the gap between urbanized provinces and the countryside.

Key words: European provinces NUTS-3, Gross Domestic Product, Real labor productivity, Club convergence analysis

1 Introduction

In the last 30 years significant changes in the growth patterns of European areas have occurred. Economic growth has been markedly different across European Union (EU) regions and across EU and non-EU country members. The fastest-growing regions of the EU between 2003 and 2015 were located in Bulgaria, Poland, Romania, Slovakia, in the three Baltic countries and in the southern part of Ireland. On the other end, Greece experienced a particularly dramatic recession,

Giulia Sacchetti

University of Milano-Bicocca, e-mail: bruno.bosco@unimib.it

Bruno Paolo Bosco

University of Milano-Bicocca, e-mail: g.sacchetti1@campus.unimib.it

Paolo Maranzano

University of Milano-Bicocca, e-mail: paolo.maranzano@unimib.it

while most regions of Italy and many regions in France, Spain and the United Kingdom are still among the slowest growing regions. These differences question the effectiveness of the EU's cohesion policy and make it difficult to conclude whether this policy has positive long-term impacts, or a positive but only short-term impacts, or even negative impacts. Understanding the true extent of the above convergence-divergence process across European areas is the goal of the present paper.

2 Empirical strategy: club convergence analysis on NUTS-3 data

We adopt the perspective of the Eurostat NUTS-3 provincial level and refer to the time sample going from 1997 to 2023. NUTS-3 data availability permits analysing convergence with respect to several macroeconomic indicators at a very disaggregated level. Here, we focus on a widely-used measure of average individual wealth, that is, the per capita Gross Domestic Product (GDP) at constant 2015 prices. The time period includes several world-leading events, such as the introduction of the Euro as official currency (2000-2002), the sub-prime financial crises (2008-2011), Brexit (2018-2019), and the COVID-19 pandemic (2020-2022). Data were collected from the ARDECO database (Auteri et al., 2024), which provides detailed annual information about EU and non-EU countries since 1980. In particular, we considered a panel spread over 27 years for 1492 provinces belonging to the EU states plus United Kingdom, Turkey, Northern Macedonia, Albania, Montenegro, Serbia, and Switzerland.

We use the methodology of Phillips and Sul (2007, 2009), which allows either detection of overall convergence or endogenous identification of groups (or clubs), to test the convergence hypothesis across European Provinces. Accordingly, the European provinces are divided into convergence clubs based on the observed trajectories of per capita GDP. The resulting clubs are analyzed and characterized on the basis of geographical and structural socio-economic factors.

We stress that the existing literature on convergence in Europe mostly used national (Monfort et al., 2013) or regional data (Postiglione et al., 2013; Postiglione et al., 2010). Although such papers reach relevant results and permits important insights into the convergence phenomenon, yet we trust that our more disaggregated analysis conducted using data from the NUTS-classification system over a longer time span (encompassing at least two exogenous shocks) allows to obtain more robust results. It permits to enrich the conclusions of the previous studies and offers a richer overview of the economic dynamics within the European territory.

3 Results and discussion

The Phillips and Sul's log-t convergence test applied to the overall sample clearly leans toward a rejection of the hypothesis of global convergence; thus, allowing for

Testing the convergence hypothesis on per capita GDP across European provinces from 1997 to 2023

the presence of several potential convergence clubs. Provinces are then aggregated by iteratively applying the log-t test for a new candidate member for each subgroup and assigning it to a cluster based on the significance of the regression statistics. The resulting clubs are displayed in the right panel of Figure 1, whereas in the left panel we show the average provincial per capita GDP observed between 1997 and 2023.

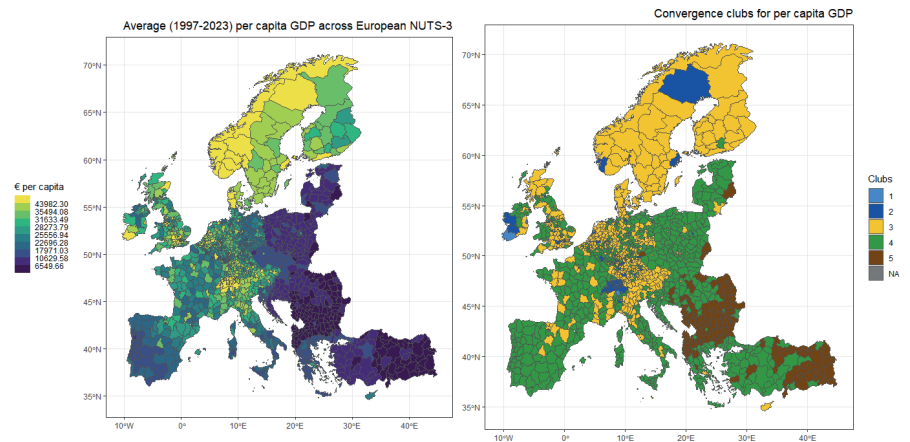


Fig. 1 Empirical results from the club convergence analysis for per capita GDP at the NUTS-3 level (right panel) and average provincial per capita GDP between 1997 and 2023.

Table 1 Summary averages (1997-2023) by cluster/club

Club/Cluster	Per capita GDP	Wage per employed	Hours worked per employed	GVA per employed
1	98027 €	59993 €	1531 hours	113520 €
2	60919 €	50781 €	1497 hours	87533 €
3	34519 €	39330 €	1549 hours	62918 €
4	19208 €	29156 €	1711 hours	45968 €
5	4923 €	7804 €	1737 hours	10455 €
Non converged	442275 €	64029 €	1669 hours	75334 €
Glob. Avg.	26809 €	33121 €	1638 hours	52963 €

Empirical findings suggest that Europe clearly presents either a East-West and North-South divides, in which, on the one side, a large number of provinces belonging to the historical core of the EU countries benefitted from major increases in the overall and individual wealth (thus, the average per capita GDP) after the II World War and are stably above the other (Clusters 2 and 3); on the other side, former Soviet Union areas (e.g., Poland, Baltic and Balcanic countries) realized strong and persistent growth rates since the join to the EU, but yet present poor levels of individual wealth (Cluster 5). Another finding is that the gap between urban centers (Clusters 1 and 2) and rural-agricultural suburbs (Cluster 4) is enlarging. Clusters 1 and 2 are mainly composed of Swiss regions, European capital (e.g., Paris, London, Bruxelles) or large urban centers with attractive opportunities (e.g., Milano and western German cities), notoriously benefit from high salaries from international institutions and financial companies and high-quality services.

From Table 1, we can infer that for provinces belonging to the upper clusters the average number of yearly per capita hours worked is much lower than the global average, yet registering much higher GDP per capita, and higher salary and GVA per employee and worked hour. Eventually, the club convergence also reveals an intermediate subgroup, namely Cluster 3, which acts as a buffer between highly attractive and rural areas, and where all values are in line with the global average, but remain well below urbanized provinces and well above rural provinces.

4 Conclusions

Our result showed the absence of an overall convergence process for per capita GDP within European provinces during the period 1997-2023. Therein, we were able to identify five non-overlapping and internally-convergent clubs and a small group of non-convergent provinces. The cluster analysis indicated that European countries strongly suffer from a polarization between highly attractive areas and rural provinces with poor economic capacity. The current work is subject to several limitations and can be extended in several ways. First, wealth is only one of the economic dimensions of interest; thus, other indicators, such as labor market, investments or capital stock could be included in the analysis. Second, one could consider different methodologies to cluster the temporal trajectories of the European areas and check the similarity across the time series (see, for instance, the hierarchical spatio-temporal clustering algorithm by Morelli et al., 2025 aiming at clustering time series under geographical constraint).

Reference

1. Auteri, D., Attardo, C., Berzi, M., Dorati, C., Albinola, F., Baggio, L., Bucciarelli, G., Bussolari, I., & Dijkstra, L. (2024). The annual regional database of the European Commission (ARDECO): Methodological note.
2. Monfort, M., Cuestas, J. C., & Ordóñez, J. (2013). Real convergence in Europe: A cluster analysis. *Economic Modelling*, 33, 689-694. <https://doi.org/https://doi.org/10.1016/j.econmod.2013.05.015>
3. Morelli, C., Boccaletti, S., Maranzano, P., & Otto, P. (2025). Multidimensional Spatiotemporal Clustering – An Application to Environmental Sustainability Scores in Europe. *Environmetrics*, 36(2), e2893. <https://doi.org/https://doi.org/10.1002/env.2893>
4. Phillips, P. C. B., & Sul, D. (2007). Transition Modeling and Econometric Convergence Tests. *Econometrica*, 75(6), 1771-1855. <https://doi.org/https://doi.org/10.1111/j.1468-0262.2007.00811.x>
5. Phillips, P. C. B., & Sul, D. (2009). Economic transition and growth. *Journal of applied econometrics*, 24(7), 1153-1185. <https://doi.org/https://doi.org/10.1002/jae.1080>
6. Postiglione, P., Andreano, M. S., & Benedetti, R. (2013). Using Constrained Optimization for the Identification of Convergence Clubs. *Computational Economics*, 42(2), 151-174. <https://doi.org/10.1007/s10614-012-9325-z>
7. Postiglione, P., Benedetti, R., & Lafratta, G. (2010). A regression tree algorithm for the identification of convergence clubs. *Computational Statistics & Data Analysis*, 54(11), 2776-2785. <https://doi.org/https://doi.org/10.1016/j.csda.2009.04.006>

Corruption and sustainable development

Fabrizio Sbicca

Abstract The UN Agenda 2030 highlights how corruption is one of the factors hindering sustainable development. However, to prevent and combat corruption, it is essential to deeply understand this latent phenomenon, which is not easy to measure. The goal of this work is to examine the main methodologies and recent developments on the topic of measuring corruption. These include the “Statistical Framework to Measure Corruption” by UNODC and the “Measuring Corruption” portal implemented by Anac, which provides the public with 70 indicators of corruption risk across Italian territories.

Key words: Corruption, Indicators, Sustainability Analysis, Development, Public Procurement, Social Capital

1 Measuring Corruption and Sustainable Development

The UN 2030 Agenda emphasizes that sustainable development cannot be achieved without peace and security. Among the main factors contributing to violence, insecurity, and injustice, the agenda identifies corruption, which is the focus of a specific goal: “16.5 Substantially reduce corruption and bribery in all their forms”. There is now a widely shared consensus that corruption is one of the main obstacles to economic, political, and social development, as well as a factor that exacerbates inequalities and distorts the implementation of public policies. Achieving any goal, however, must necessarily be based on the most accurate possible understanding of the phenomenon it targets. At the international level, there is a lack of structured data on corruption that goes beyond measuring the so-called “perception” or ad hoc scientific studies, the content and results of which are often difficult to generalize. Corruption is largely elusive and hidden, comparable to an iceberg, of which we see

Fabrizio Sbicca
Autorità Nazionale Anticorruzione, e-mail: f.sbicca@anticorruzione.it

only the tip [2, 8]. To improve the understanding of corruption, the UN itself has sought to develop a statistical framework to guide states in implementing national information systems on the phenomenon [19]. In particular, the United Nations Office on Drugs and Crime (UNODC) recently published the “Statistical Framework to Measure Corruption”, which includes 146 indicators deemed suitable to enable countries to gain a deep understanding of the extent of corruption and monitor the effectiveness of preventive policies. The framework identifies the various types of corruption (based on the United Nations Convention against Corruption) and the type of measurement: 1) direct measures (experiences of corruption); 2) indirect measures, divided into: a) perception indicators; b) risk indicators; c) response indicators.

2 The Risk Indicators developed by ANAC

A step forward in understanding the phenomenon has been made by the National Anti-Corruption Authority (ANAC), which in July 2022 launched a section of its portal called “Measuring Corruption” (<https://www.anticorruzione.it/en/il-progetto>). This section provides the public with 70 indicators capable of measuring the risk of corruption across the territory. These risk indicators can be considered as warning signals highlighting potentially anomalous situations, helping to determine whether a given area is more or less exposed to corrupt practices. The aim is to guide investments in prevention and/or investigation and to direct the attention of civil society, fostering civic interest and participation. The 70 indicators calculated and displayed on the portal are divided into three dashboards: Context, Tender, Municipal.

2.1 The Tender Dashboard and the Municipal Dashboard

The Tender Dashboard contains 17 risk indicators that provide information related to the public procurement activities of administrations at the provincial level, identified based on international literature on the subject [2, 4, 5, 6, 7, 14, 17]. An innovative aspect of the dashboard system is its ability to calculate summary indicators based on different risk thresholds. Specifically, for each indicator, all or a subset chosen based on a homogeneous dimension of the phenomenon, a red flag is triggered in a given province if its value exceeds that of a certain percentage of provinces with lower-risk values. This system of indicators can, on the other hand, represent a first step toward developing more sophisticated tools suitable for preventing and combating phenomena that harm the effective and efficient allocation of resources in public procurement. The increasing availability of large amounts of data, meanwhile, is shifting attention toward the development of advanced algorithms, complementing traditional statistical analyses with artificial

intelligence techniques, in line with the provisions of the NGUE community regulations and cohesion policies [1, 3, 9, 13, 15, 16, 18, 20]. The Municipal Dashboard considers 5 indicators calculated for the 745 Italian municipalities with populations of 15,000 or more. These 5 indicators are derived from statistical analysis of the relationships between variables potentially linked to corruption and incidents that have actually occurred at the level of individual administrations.

2.2 The Context Dashboard

The Context Dashboard draws inspiration from the methodology used in recent years for measuring complex multidimensional phenomena, such as that adopted for the *Report on Equitable and Sustainable Well-being* (Bes) [11]. Its indicators also align closely with those used for measuring sustainable development in the aforementioned UN 2030 Agenda [12]. Specifically, it involves the structuring of domains (pillars) and the calculation of composite indicators to simplify the interpretation of complexity. This methodology has also been recently applied in constructing the *Municipal Fragility Index* and the *Educational Poverty Index* [10]. The context indicators consider 18 provincial-level indicators grouped into four thematic domains: *Criminality*, *Education*, *Economy*, *Social Capital*. The selection of domains and their respective indicators was guided by relationships between corruption and a range of cultural, legal, economic, social, and political-institutional factors that influence its spread and persistence, as identified primarily in economic literature [2]. A composite index is calculated for each domain, and the four thematic indicators are combined into an overarching “composite of composites” index. Additionally, 25 other indicators outside the domains are considered, including the *Gini Index* of Economic Inequality, which measures a phenomenon linked to violence, insecurity, and injustice as identified in the UN Agenda. Its reduction is a goal of “Objective 10: Reduce inequality within and among countries”. Regarding the domains, it is notable that two of the dimensions analyzed - human capital (education) and social capital - are considered by modern economic literature as key determinants of both economic growth and social well-being. Social capital, in particular, encompasses concepts such as community cohesion, reliability, loyalty, mutual trust among social actors, and factors essential for effective economic transactions and relationships between citizens and institutions. Specifically, the five social capital indicators describe phenomena such as tendencies toward opportunistic behaviour in Invalsi school tests (cheating index), socio-economic segregation in schools (variance between classes and deviation in Economic, Social, and Cultural Status), and, conversely, altruism (blood donations) and gender equality (women's participation in political life). Notably, the last two indicators are included in the BES report, with one also appearing in the UN 2030 Agenda as part of “Objective 5: Achieve gender equality and empower all women and girls”.

3 Conclusion

Social capital is thus a useful indicator of the context in which corruption occurs. However, the relationship is also reciprocal: the harm caused by corruption exceeds immediate monetary waste, introducing distortions in both public and private spheres, such as the loss of trust it generates among citizens. For this reason, corruption undermines the very fabric of civil life and can reduce social capital, thereby depressing growth and well-being, as well as hindering sustainable development. This is why ANAC's system of indicators aims to raise collective awareness of the severe social damage caused by corruption. While its prevention and suppression are necessary conditions for reducing the phenomenon, they are not sufficient. The most effective long-term lever is the growth of social capital.

Disclaimer The opinions expressed in this paper are the author's own and do not reflect the view of ANAC

References

1. Adam I., Fazekas M.: Are emerging technologies helping in the fight against corruption? A review of the state of evidence. *Information Economics and Policy*, Vol. 57 (2021)
2. ANAC: Relazione Annuale (2021; 2022; 2023; 2024)
3. De Blasio G., D'Ignazio A., Letta M.: Gotham city. Predicting 'corrupted' municipalities with machine learning. *Technological Forecasting & Soc. Change*, 184, pp. 1-21 (2022)
4. Decarolis F., Giorgiantonio C.: Corruption red flags in public procurement: new evidence from Italian calls for tenders. *EPJ Data Sci.* 11/16 (2022)
5. Fazekas M., Kocsis G.: Uncovering high-level corruption: Cross-national objective corruption risk indicators using public procurement data. *Br. J. of Political Sci.*, 50(1), pp. 155-164 (2017)
6. Ferwerda J., Deleanu I., Unger B.: Corruption in Public Procurement: Finding the Right Indicators. *European J. of Crim. Policy and Res.*, 23, pp. 245-267 (2017)
7. Gara M., Iezzi S., Siino, M.: Corruption risk indicators in public procurement: A proposal using Italian open data. *Quaderni dell'antiriciclaggio*, n. 23, Banca d'Italia - UIF (2024)
8. Gnaldi M., Ponti B. (eds): *Misurare la corruzione oggi*, Franco Angeli, Milano (2018)
9. James G., Witten D., Hastie T., Tibshirani R., Taylor J.: *An Introduction to Statistical Learning: with Applications in Python*, Springer, Berlino (2023)
10. Istat: Rapporto Annuale (2024)
11. Istat: Rapporto Bes 2023 (2024)
12. Istat: Rapporto SDGs 2024. Informazioni statistiche per l'agenda 2030 in Italia (2024)
13. Lopez-Iturriaga F. J., Sanz I. P.: Predicting Public Corruption with Neural Networks: An Analysis of Spanish Provinces. *Soc. Indicators Res.*, 140(3), pp. 975-998 (2018)
14. Mirenda L., Mocetti S., Rizzica L.: The economic effects of mafia: firm level evidence. *American Economic Rev.*, 112(8), pp. 2748-73 (2022)
15. Odilla F.: Unfairness in AI Anti-Corruption Tools: Main Drivers and Consequences. *Minds and Machines*, Vol. 34 (2024)
16. OECD: Generative AI for anti-corruption and integrity in government. Taking stock of promise, perils and practice. *Artificial Intelligence Papers*, n. 12 (2024)
17. Sbicca F.: La misurazione del rischio di corruzione negli appalti. *Rivista economica del Mezzogiorno*, 3-4/2023, pp. 549-600 (2024)
18. Sbicca F.: Artificial Intelligence and Anti-Corruption. <https://ceur-ws.org/Vol-3762> (2024)
19. UNODC: Statistical framework to measure corruption (2023)
20. Wachs J., Fazekas M., Kertesz J.: Corruption risk in contracting markets: a network science perspective. *International J. of Data Sci. and Analytics*, 12, pp. 45-60 (2021).

Spatial Spillovers and Tourism: The Impact of Sustainable Initiatives in Italian Provinces

Riccardo Gianluigi Serio, Diego Giuliani, Giuseppe Espa and Maria Michela Dickson

Abstract This study examines the impact of environmental sustainability policies on tourism flows across Italian provinces using a Spatial Durbin Error Model (SDEM) within a gravity framework. Corporate-led initiatives and public measures exhibit significant spatial spillovers, extending their influence beyond local boundaries. These findings emphasize the interconnectedness of regional tourism systems and the need for coordinated sustainability policies. The study offers valuable insights for policymakers to promote sustainable tourism and foster regional collaboration in environmental efforts.

Key words: Sustainability, Tourism flows, Spatial spillovers, Environmental policy

1 Introduction

Tourism represents a fundamental pillar of economic development, deeply intertwined with the cultural and social fabric of contemporary societies. Its significant contributions to global GDP—10.4% in 2019—and its critical role in generating employment are well-documented. In Italy, tourism accounts for approximately 7% of the national GDP and 7.1% of total employment, underscoring its strategic importance for regional economies [1]. Modern tourism is shaped by multidimensional dynamics and an integrative analytical approach that incorporates

Riccardo Gianluigi Serio
University of Trento, e-mail: riccardo.serio@unitn.it

Diego Giuliani
University of Trento, e-mail: diego.guliani@unitn.it

Giuseppe Espa
University of Trento, e-mail: giuseppe.espa@unitn.it

Maria Michela Dickson
University of Padua, e-mail: mariamichela.dickson@unipd.it

both demand and supply dimensions is essential. Competition among destinations has intensified, leading to a growing emphasis on differentiation [2].

Furthermore, environmental sustainability has emerged as a cornerstone of destination development strategies, aligning with global efforts to promote sustainable growth [3]. However, there remains considerable debate regarding the tangible impacts of the new strategies [4].

Recent research highlights the spatial interdependencies of tourism flows, wherein the success of one region may influence neighbouring areas through spillover effects. These effects, whether positive underscore the interconnected nature of regional tourism systems (e.g., [5]). Notably, spatial interactions extend beyond origin-destination pairs, involving multi-regional influences that require advanced econometric techniques for proper analysis [6].

This study investigates the relationship between sustainable tourism practices and demand at the provincial level in Italy, with a particular focus on spatial spillovers. Utilizing a Spatial Durbin Error Model (SDEM), we explore how environmental commitment, through both public and private sector initiatives, influences tourism flows and fosters the diffusion of sustainable practices across neighbouring areas.

2 Literature review and statistical framework

The gravity model has proven instrumental in analysing tourism flows [7], by relating tourism demand to the economic “masses” of origin and destination and the geographical distance between them as a resistance force. Recent advancements [8], have expanded its scope, incorporating variables like travel costs, bilateral agreements, and destination-specific attributes. While traditional gravity models focus on demand-side factors, scholars [9] have debated whether tourism flows are more effectively explained by push factors or pull factors. Similarly, environmental considerations have gained prominence in tourism studies, with works [10] highlighting the sector’s contribution to carbon emissions and the need for eco-efficiency metrics. Environmental certifications reflect increased awareness, but their impact on tourism flows remains uncertain [11].

The gravity model framework adopted here incorporates spatial econometrics to account for inter-regional dependencies. Using origin-destination matrices, tourism flows are modelled as a function of push factors, pull factors, and bilateral characteristics. The basic gravity model is expressed as:

$$nv = \alpha n + O\beta_O + D\beta_D + OD\beta_{OD} + \varepsilon,$$

where nv represents log-transformed tourism flows, O and D capture origin and destination characteristics, and OD reflects bilateral attributes. To address spatial dependencies, the SDEM is employed:

$$nv = \alpha n + O\beta_O + D\beta_D + OD\beta_{OD} + W_D D\theta_D + W_D OD\theta_{OD} + u,$$

with $u = \lambda W_D u + \varepsilon$. Here, W_D denotes the spatial weight matrix capturing inter-regional proximity, while θ_D and θ_{OD} estimate local spillover effects.

3 Data and Results

Tourism inbound flows are measured using the count of overnight stays across accommodations in 107 Italian provinces for 2019, sourced from ISTAT. These flows are analysed using data from 32 European countries to ensure consistency within shared legislative and socio-economic contexts. Key independent variables include GDP per capita and population density, capturing economic capacity and travel propensity, alongside distance, calculated in Cartesian space, which typically exerts a negative influence on flows. Additional variables encompass accessibility metrics, and unemployment rates, as well as environmental indicators grouped into public (Blue Flags and EMAS certifications) and corporate (Ecolabel, Green Key, and Bio Hotels certifications) sustainability initiatives. Spatial patterns reveal that public green initiatives are more widely distributed, while corporate measures are concentrated in Northern Italy and the capital region. Two increasingly complex models are estimated (Table 1), beginning with a baseline incorporating GDP and distance. Variables such as sustainable initiatives and environmental certifications are included to evaluate their direct and spatial spillover effects on tourism demand.

Table 1 Maximum likelihood estimates of SDEM for the determinants of tourism flows.

	Model 1	Model 2
(Intercept)	-14.22*** (4.30)	-4.49 (7.79)
log (Distance)	0.54 (0.54)	-0.80 (0.36)**
GDP _D	0.47*** (0.16)	0.57 (0.15)***
GDP _D	3.77*** (0.16)	0.42 (0.17)**
Unemployment _D	—	-2.65 (0.82)***
Domestic flows	—	4.97 (0.62)***
No. tourism firms _D	—	1.38 (0.03)***
Air pollution _D	—	-1.53 (0.10)***
Corporate sustainability measures _D	—	0.22 (0.04)***
Public sustainability measures _D	—	0.08 (0.08)*
W _D log (Distance)	-1.28** (0.55)	0.44 (0.39)
W _D GDP _D	-1.79*** (0.35)	1.22 (0.63)*
W _D Unemployment _D	—	7.48 (3.04)**
W _D No. tourism firms _D	—	-0.31 (0.12)**
W _D Air pollution _D	—	-0.99 (0.40)**
W _D Corporate sustainability measures _D	—	1.14 (0.15)***
W _D Public sustainability measures _D	—	0.75 (0.36)**
λ	0.74*** (0.01)	0.82 (0.01)***
Num. obs.	3424	3424
Parameters	8	19
Log Likelihood	-6522.50	-5213.21
AIC (Linear model)	15061.43	13475.19
AIC (Spatial model)	13060.99	10464.43
LR test: statistic	2002.43	3012.76
LR test: p – value	0.00	0.00

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Values in parenthesis are the standard errors.

Results highlight significant spatial dependencies in tourism flows, with the autoregressive parameter consistently positive and significant across all models.

Distance exhibits a negative elasticity, while spatial lags reveal complementary effects among neighbouring provinces, supporting multi-destination travel. GDP in origin countries positively influences flows, confirming tourism as a normal good, whereas destination GDP shows a negative direct effect, potentially reflecting saturation or price sensitivity in wealthier provinces. Spatial lags for destination GDP are strongly positive, highlighting regional complementarities. Socioeconomic factors such as the number of tourism firms positively contributes, though spatial lags reveal competition among neighbouring provinces. Environmental sustainability measures significantly enhance tourism demand and spatial spillovers amplify these effects. Air pollution negatively impacts tourism both directly and through spatial spillovers, reinforcing the need for coordinated regional environmental policies.

4 Conclusions

This study underscores the intricate relationship between environmental sustainability and tourism flows across Italian provinces, leveraging the SDEM within a gravity framework. Incorporating public and corporate environmental initiatives reveals their direct effects on tourism demand and significant spatial spillovers, highlighting how sustainability efforts influence not only the implementing province but also its neighbours. These insights emphasize the importance of sustainability as both a local and regional issue for tourism policy.

References

1. WTTC: Travel & tourism: Economic impact 2021. World Travel and Tourism Council (2021)
2. Cracolici, M. F., Nijkamp, P.: The attractiveness and competitiveness of tourist destinations: A study of Southern Italian regions. *Tour. Manag.* (2009) doi: 10.1016/j.tourman.2008.07.006
3. Hall, C. M.: Policy learning and policy failure in sustainable tourism governance: From first-and second-order to third-order change? *J. Sustain. Tour.* (2011) doi: 10.1080/09669582.2011.555555
4. Guo, Y., Jiang, J., Li, S.: A sustainable tourism policy research review. *Sustainability* (2019) doi: 10.3390/su11113187
5. Drakos, K., Kutun, A.: Regional effects of terrorism on tourism in three Mediterranean countries. *J. Confl. Resolut.* (2003) doi: 10.1177/0022002703258198
6. Khadaroo, J., Seetanah, B.: The role of transport infrastructure in international tourism development: A gravity model approach. *Tour. Manag.* (2008) doi: 10.1016/j.tourman.2007.09.005
7. Morley, C., Rossello, J., Santana-Gallego, M.: Gravity Models for Tourism Demand: Theory and Use. *Ann. Tour. Res.* (2014) doi: 10.1016/j.annals.2014.05.008
8. Santana-Gallego, M., Paniagua, J.: Tourism and migration: Identifying the channels with gravity models. *Tour. Econ.* (2022) doi: 10.1177/135481662097259
9. Zhang, J., Jensen, C.: Comparative advantage: explaining tourism flows. *Ann. Tour. Res.* (2007) doi: 10.1016/j.annals.2006.08.004
10. Gössling, S., Scott, D., Hall, C. M., Ceron, J.-P., Dubois, G.: Consumer behaviour and demand response of tourists to climate change. *Ann. Tour. Res.* (2012) doi: 10.1016/j.annals.2011.11.002
11. Mycoo, M.: Sustainable tourism, climate change and sea level rise adaptation policies in Barbados'. *Natural Resources Forum*. Vol. 38. 1. pp. 47–57. Wiley Online Library (2014)

Caveat about non-normality in relative importance estimation from tourism surveys

Annalisa Stacchini and Andrea Guizzardi

Abstract Through a simulation exercise, we illustrate the consequences of not checking if tourism survey data can be appropriately modelled through a linear specification, to estimate the relative importance of a multidimensional construct's dimensions. Highlighting the most common misunderstandings, this example should be easier for practitioners to grasp, than theoretical demonstrations.

Key words: linearity, selection bias, social desirability bias, relative importance

1 Introduction

For planning and managing tourism, it is crucial to estimate the relative importance (weight) of each dimension, on which the expected effectiveness of an intervention depends [1]. Quantifying the weight of each aspect of multidimensional constructs is critical also because composite indices are very sensitive to the weighting system. The estimation of relative importance is also pivotal in the importance-performance analysis. Weights can be opinions-based or data-driven ('derived'). The main advantage of deriving importance based on statistical models is the possibility to check for estimates' significance and amount of total variance explained. Nonetheless, estimates can be biased or inefficient if the assumptions underpinning the model do not hold. Linear specifications are the most common to derive importance (e.g., [4]). However, in tourism analyses, the data used are frequently

Annalisa Stacchini
University of Bologna, e-mail: annalisa.stacchini2@unibo.it
Andrea Guizzardi
University of Bologna, e-mail: andrea.guizzardi@unibo.it

ordinal in nature, as they are typically collected through tourist/resident/stakeholder surveys, asking to rate questionnaire items on a Likert-type scale.

The possible unsuitability of a linear specification to tourism survey data is often overlooked not just by practitioners, but also by researchers (e.g., [2]). It is frequently believed that linearity should hold asymptotically, by virtue of the central limit theorem (CLT). The CLT applies only if sample observations are independent and either identically distributed or the contribution of extreme values to the variance decreases as the sample size (n) augments. In practice, a common misunderstanding is that these conditions regard the dependent variable marginally (e.g., [4]) instead of conditionally. It is often neglected that all the conditional samples sizes (not just n) must be sufficiently large. Moreover, though interviewees have been selected through simple random sampling, they themselves decide whether to (sincerely) answer. Thus, sample observations can be non-independent, due to self-selection and social desirability bias. Though this has long been proven, a practical example should help practitioners to understand it more clearly and grasp the criticality of verifying the suitability of linear models for relative importance estimation. To achieve such an objective, we propose the simulation exercise described in the next section.

2 Simulation exercise

We run two simulations. For the sake of simplicity, parsimony and for avoiding multicollinearity and conceptualization issues, we consider the three factors models of hotel service quality shown in table 1. We compare the predictive power of the ordinary least squares (OLS) estimates of the relative importance of the perceived quality of the three hotel service factors with that of the estimates obtained through two non-linear models. The latter are a cumulative logit model with parallel assumption (CLM) and a multilayer feed-forward perceptron neural network (MLP) with hyperbolic tangent activation function [3]. The CLM is tailored to the non-linearity of ordinal responses and does not require homoskedasticity. The MLP is considered an efficient universal approximation for non-linear data, especially appreciated for forecasting.

As measures of predictive power, we compute: exact classification rate (ECR), mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE). We test the significance of differences in predictive power through a Wilcoxon signed-ranks test for paired samples and the Harvey-Leybourne-Newbold test.

Table 1 Specifications considered¹

Method	Rel. Importance	Overall service quality (OS_i) models
<i>OLS</i>	β_j	$OS_i = \alpha + \sum_{j=1}^J \beta_j P_{i,j} + \varepsilon_i$
<i>CLM</i>	β_j	$\ln\left(\frac{\Pr[OS_i > k]}{1 - \Pr[OS_i > k]}\right) = \alpha_k + \sum_{j=1}^J \beta_j P_{i,j}$
<i>MLP</i>	$\beta_j^{(1)} \beta^{(2)}$	$OS_i = \frac{e^{\sum_{j=1}^J \beta_j^{(1)} \beta^{(2)} P_{i,j} + \alpha} - e^{-\sum_{j=1}^J \beta_j^{(1)} \beta^{(2)} P_{i,j} + \alpha}}{e^{\sum_{j=1}^J \beta_j^{(1)} \beta^{(2)} P_{i,j} + \alpha} + e^{-\sum_{j=1}^J \beta_j^{(1)} \beta^{(2)} P_{i,j} + \alpha}} + \varepsilon_i$

2.1 Data and bootstrap settings

Survey data were collected from September 2013 to January 2016 through SurveyMonkey.com from business travellers who stayed in one of 1,370 hotels worldwide. The dataset includes 3,341 observations. The sample composition is shown in table 2.

Table 2 Sample composition

Variable	Percentage	Variable	Percentage	Variable	Percentage
Female	29.70%	Employee	40.90%	Never Displaced	98.80%
Age25-34	12.50%	Lower Manager	22.00%	Rarely Displaced	0.80%
Age35-44	31.40%	Executive	12.50%	Always Displaced	0.40%
Age45-54	38.60%	Officer	22.80%	Respected Conditions	95.70%
Age55-65	17.20%	CEO	0.10%	Bank	55.80%
Age-24	0.20%	Manager	1.60%	Public Administration	14.70%
Age65+	0.10%	Overnights5	29.40%	Corporate	29.50%

To exemplify the irrelevance of n for the CLT to hold (as opposite to conditional samples sizes), we draw 1,000 samples with n equal to 100, 300, 600 and 1000 (totalling to 4,000 samples) through non-parametric bootstrap with replacement. We show the effects of selection and social desirability bias on the estimation of relative importance with a two-step procedure. First, we run a non-parametric, stratified bootstrap with replacement. Stratification variables (CEO vs non-CEO; aged 65 or more vs others; displaced to another hotel vs not) are identified through a CHi-squared Automatic Interaction Detection. Each replica includes 1,000 observations, randomly selected with replacement from each of the non-empty intersections of stratification variables, in varying proportions. From each replica, we draw 1,000 simple random samples with $n=300$. We iteratively test the predictive power of OLS, CLM and MLP estimates on 1/3 observations randomly chosen from each sample, leaving the remaining for estimation.

¹ $P_{i,j}, j=3$, are the ratings (on a Likert scale from 1: ‘very bad’, to 7: ‘excellent’) of: room and bathroom; exterior and location; and personnel.

2.2 Results

CLM-based estimates display the best predictive power (see table 3). ECR, MAE, MAPE and MSE values do not significantly change as n shrink from 1000 to 100. CLM and MLP-based estimates perform similarly on the 4,000 ‘random replicas’, while the former are significantly more accurate and efficient on the samples by construction affected by selection and social desirability bias. In fact, unlike the MLP, the CLM is robust to heteroschedasticity. The linear model is the worst predictor, not just on the ‘biased samples’, where the non-representativeness of the selected respondents induces heteroschedasticity, but also in the ‘random replicas’, due to the highly negative skew and positivity bias of the residuals.

Table 3 Out-of-sample predictive power: descriptive measures and inferential tests

Method	Bootstrap Cross Validation			
	ECR	MAE	MAPE	MSE
CLM	60.1%	0.45	14.30%	0.486
OLS	60.5%	0.53	17.30%	0.503
MLP	60.4%	0.52	16.60%	0.499

Signed-Rank test			Harvey-Leybourne-Newbold test		
95% bootstrap	% samples <i>CLM</i>		95% bootstrap	% samples <i>CLM</i>	
conf.int. for TW	<i>significantly</i>		conf.int.	<i>significantly</i>	
	($\alpha=5\%$) outperforms:			outperforms:	
23,990	24,647	63%	-0.008	-0.001	68%
26,306	27,188	99%	-0.081	-0.074	100%

The capability of predicting OS_i as a function of estimated importance is decisive. Hotel managers concentrate resources and efforts to improve the aspect that results the most important and make cost-saving cuts on irrelevant ones, aiming to attain the greatest augment in overall quality. Clearly, inaccurate or inefficient importance estimates mislead managers and can seriously damage the business.

Through this simple exercise, we have illustrated that deriving weights based on linear models when tourism survey data are used can yield wrong results in the presence of selection or social desirability bias. We have also exemplified that n is irrelevant for the CLT to apply, as the related assumptions must be verified on the model residuals and on all conditional samples.

References

1. Carrillo, M., Jorge, J.M: Multidimensional Analysis of Regional Tourism Sustainability in Spain. *Ecol. Econ.* **140**, 89-98 (2017)

2. Fallon, P., Schofield, P.S.: The dynamics of destination attribute importance. *J. Bus. Res.* **59**(6), 709-713 (2006)

3. Mikulić, J., Paunović, Z., Prebežac, D.: An Extended Neural Network-Based Importance-Performance Analysis for Enhancing Wine Fair Experience. *J. Travel Tour. Mark.* **29**(8), 744-759 (2012)

4. Pulido-Fernández, J., Rivero, M.: Measuring Tourism Sustainability: Proposal for a Composite Index. *Tourism Econ.* **15**, 277-296 (2009)

Green Tourism Competitiveness in Italian Provinces

Furio Urso, Martina Aronica, Salvatore Costantino, Davide Piacentino and Maria Francesca Cracolici

Abstract This study examines changes in green tourism competitiveness across Italian provinces between 2017-2019 and 2021-2023. Using spatial Shift-Share analysis and a Continuation Ratio Mixed-Effect Model, the research identifies shifts in provincial performance and the factors influencing competitiveness. Results highlight a decline in well-known destinations and improvements in lesser-known areas. The analysis reveals that both demand and supply factors, such as reduced air pollution and the presence of protected areas, positively influenced green tourism competitiveness, while provinces with high foreign tourism flows faced challenges in improving their position.

Key words: Green tourism, Spatial Shift-Share, Continuation Ratio Mixed model

1 Introduction

Green tourism has recently emerged as a sustainable alternative to traditional tourism, promoting ecological preservation and fostering socioeconomic development (Huynh et al., 2022; Zhang et al., 2015). From a policymaker's perspective,

Furio Urso
University of Palermo, e-mail: furio.urso@unipa.it

Martina Aronica
University of Palermo, e-mail: martina.aronica@unipa.it

Salvatore Costantino
e-mail: salvatore-costantino@virgilio.it

Davide Piacentino
University of Palermo, e-mail: davide.piacentino@unipa.it

Maria Francesca Cracolici
University of Palermo, e-mail: mariafrancesca.cracolici@unipa.it

supporting sustainable tourism development hinges on understanding a region's competitiveness relative to both the national economy and competing regions in offering eco-friendly, nature-based services. In this regard, Shift Share Analysis (SSA) (Dunn, 1960; Esteban-Marquillas, 1972) has been used to evaluate regional competitiveness by decomposing changes in an economic variable into national growth, industrial mix, and competitive effects. Here, we propose to use a spatial SSA formulation to analyze the competitiveness of Italian destinations in attracting foreign green tourists by incorporating spatial spillover. We use data on inbound green tourism from the International Tourism Survey of the Bank of Italy. Specifically, we focus on the number of bed nights spent by tourists taking a green vacation during the two periods of 2017–2019 and 2021–2023 in order to compare growth trends before and after the pandemic. The spatial SSA formulation allows us to decompose foreign tourism growth into national, regional, and local contributions and rank provinces. Subsequently, we apply a Continuation Ratio Mixed Effects Model (CRMEM) (Agresti, 2012) to examine how factors such as environmental certifications, cultural assets, and infrastructure influence improvements in ranking between the two periods. In the second phase, we used data about Arrivals and Presences, Environmental data, and Accommodation Establishments from ISTAT and ISPRA.

2 Methods

In order to identify the sources of changes of green tourism in the Italian provinces, we rely on a Spatial Shift-Share decomposition proposed by Costantino et al. (2021), that distinguishes net competitiveness and allocation effects incorporating spatial dependencies. Especially, the growth is decomposed into National-Share (NS) and Industrial-Mix (IM) as for the classic SSA, and Neighbour-Nation Competitive Effect (NNCE) and Neighbour-Nation Allocation Effect (NNAE), alongside the Region-Neighbour Competitive Effect (RNCE) and Region-Neighbour Allocation Effect (RNAE), allowing a more comprehensive analysis of regional green competitiveness growth. The decomposition is given by:

$$\Delta y_r = \underbrace{\sum_{i=1} y_{irt} g_n}_{\text{NS}} + \underbrace{\sum_{i=1} y_{irt} (g_{in} - g_n)}_{\text{IM}} + \underbrace{\sum_{i=1} \hat{y}_{irt} (\tilde{g}_{ir} - g_{in})}_{\text{NNCE}} + \underbrace{\sum_{i=1} (y_{irt} - \hat{y}_{irt}) (\tilde{g}_{ir} - g_{in})}_{\text{NNAE}} + \underbrace{\sum_{i=1} \hat{y}_{irt}^* (g_{ir} - \tilde{g}_{ir})}_{\text{RNCE}} + \underbrace{\sum_{i=1} (y_{irt} - \hat{y}_{irt}^*) (g_{ir} - \tilde{g}_{ir})}_{\text{RNAE}} \quad (1)$$

where $\hat{y}_{irt}$ and $\hat{y}_{irt}^*$ are homothetic values based on national and neighboring industrial structures, and $\tilde{g}_{ir}$ is the spatially weighted growth rate for sector i . This decomposition highlights whether regional growth is driven by local competitiveness (RNCE) or sectoral allocation (RNAE), while considering national and neighboring effects. Looking at RNCE and RNAE, we classify the provinces into four cate-

gories: *Worst*, *Potential Worst*, *Potential Best*, and *Best* performers. That enables us to rank provinces and consequently to explore by means of CRMEM how provincial characteristics influence the likelihood of moving to higher green competitiveness classes before and after the COVID-19 pandemic. The model is specified as:

$$\text{logit} [\Pr(C_{it} = k \mid C_{it} \leq k)] = \alpha_k + \beta^\top \mathbf{X}_{it} + \gamma_i, \quad (2)$$

where C_{it} represents the competitiveness category for province i at time t (the two periods), α_k is the category-specific intercept, β is a vector of covariate effects ($\mathbf{X}_{it}$), and γ_i captures random effects. The covariates matrix $\mathbf{X}_{it}$ include environmental factors such as air pollution (i.e., amount of Nitrogen Dioxide) and the density of protected areas, and tourism infrastructure (e.g., share of agritourism over total number of accommodations and foreign arrivals over total arrivals). The time-period variable allows us to explore how covariates' effects change before and after the pandemic.

3 Results

The analysis reveals significant changes in the competitiveness of green tourism in Italian provinces between 2017-2019 and 2021-2023. Using a spatial shift-share approach, in Figure 1 we observe a general decline in green tourism competitiveness, especially in the North-East and Centre of Italy, where many provinces transitioned to lower competitiveness categories. Best Performers, such as Aosta, Rimini, and Modena, lost their positions, while lesser-known destinations such as Catanzaro, Cosenza, and Crotone emerged as new leaders post-pandemic. The number of Potential Best Performers decreased, with 34% becoming Worst Performers, emphasizing a reshuffling of competitiveness. Spatial spillovers show a shift, with regions like Sardinia and parts of Calabria benefiting from neighboring advantages, while negative spillovers diminished, suggesting a reduced regional disadvantage effect. The CRMEM results show that the interaction of environmental factors with the post-pandemic period highlights the evolving dynamics: the air pollution variable alone is not significant, but its interaction with the post-pandemic period reduces competitiveness (odds ratio: 0.9081). Protected areas show a slight positive post-pandemic effect (odds ratio: 1.0359), and high agritourism concentration negatively impacts competitiveness, particularly in saturated markets (odds ratio: 0.361). Foreign tourism dynamics reveal challenges, with moderate to high tourist inflows (1stQ-3rdQ) negatively affecting post-pandemic competitiveness (odds ratios: 0.129 and 0.241).

By combining SSA and CRMEM, this work provides a comprehensive understanding of Italian provinces' changes regarding green tourism competitiveness before and after the pandemic periods showing significant spillover effects. In addition, results show that improvements in the regional competitiveness ranking are affected by changing tourist preferences, such as tourists' attention to environmental quality

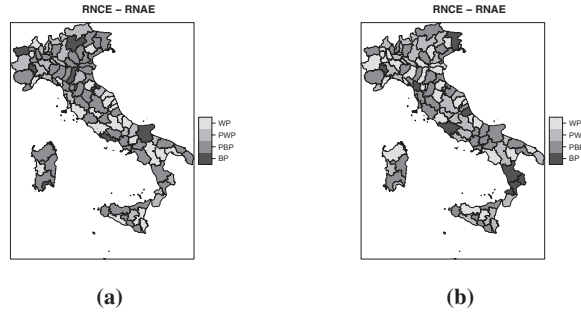


Fig. 1 Green Tourism. Province/Neighbourhood competitiveness and allocation components: (a) Period 2017 - 2019, (b) Period 2021 - 2023.

and destination's popularity (i.e., overcrowding). Summing up, the analysis points out that the protection and maintenance of sustainable environments and the balance of tourist flows across neighboring destinations are key factors for fostering regional competitiveness in green tourism.

Acknowledgements This work was carried out within the two projects: GRINS (Growing Resilient, Inclusive and Sustainable) funded by the European Union Next-GenerationEU (*National Recovery and Resilience Plan*, NRRP, Mission 4, Component 2, Investment 1.3 – D.D. 1558 11/10/2022, PE00000018, Spoke 7 Territorial Sustainability); and GREENGO (Competitiveness for a stronger and more sustainable Italian economy) funded by the Ministry of University and Research, PRIN 2022 – D.D. 104, 02/02/2022. This manuscript reflects only the authors' views and opinions, neither the European Union, the European Commission nor the Ministry of University and Research can be considered responsible for them.

References

1. Agresti, A.: *Categorical Data Analysis*. John Wiley & Sons, 2012.
2. Costantino, S., Cracolici, M.F., Piacentino, D.: A new spatial shift-share decomposition: An application to tourism competitiveness in Italian regions. *Geogr. Anal.* **53**(4), 708–735 (2021).
3. Dunn Jr, E.S.: A statistical and analytical technique for regional analysis. *Papers in Regional Science* **6**(1), 97–112 (1960).
4. Esteban-Marquillas, J.M.: Shift-and share analysis revisited. *Regional and Urban Economics* **2**, 249–261 (1972).
5. Huynh, T.L.D., Ngo, Q.T., Vu, N.T.T.: Predicting e-commerce customer behavior using advanced machine learning techniques. *Ann. Bus. Res.* **138**, 105–115 (2022)
6. Zhang, Y., Zheng, X., Li, X.: Hidden Markov models in customer behavior analysis: A review and new insights. *J. Mark. Anal.* **3**(2), 78–90 (2015)

Firm Resilience to Exogenous Shocks: The Impact of Gender Diversity in Leadership

Furio Urso, Cristina Leone, Pasquale Massimo Picone and Maria Francesca Cracolici

Abstract The study examines the resilience of European-listed firms to exogenous shocks focusing on the impact of gender diversity in the board and executive leadership. Using a Dynamic Panel Model for the period 2014–2023, we analyze the effect of U.S. and China trade war (2017–2018) and the COVID-19 pandemic (2020–2023) shocks, and we measure firm resilience as deviations between observed and counterfactual price trends.

Key words: Firm Resilience, Gender Diversity, Exogeneous Shocks, Dynamic Panel model

1 Introduction

Nowadays, firms have frequently to cope with exogeneous shocks requiring time-liness capabilities to maintain or improve their performance. Hence, *firm resilience* has become an important topic in management and organizational research (Iftikhar et al., 2021; Conz & Magnani, 2020). Literature has focused on main factors at supply chain (e.g., Iftikhar et al., 2021) and firm level (e.g., Ortiz- de-Mandojana & Bansal, 2016). As concerns the firm level, a stream of literature accounts for the role of leadership in shaping resilient firms, considering aspects such as the gender

Furio Urso
University of Palermo, e-mail: furio.urso@unipa.it

Cristina Leone
University of Palermo, e-mail: cristina.leone@unipa.it

Pasquale Massimo Picone
University of Palermo, e-mail: pasqualemassimo.picone@unipa.it

Maria Francesca Cracolici
University of Palermo, e-mail: mariafrancesca.cracolici@unipa.it

diversity in the board (Azeem et al., 2023; Triana et al., 2014) and executive leadership (e.g., in CEOs' roles; Shropshire et al., 2021). In line with this literature, our study aims to explore whether gender diversity in board and executive leadership impacts firm resilience. Using closing prices as a measure of firms' performance, we estimate a dynamic panel model (DPM) to capture firm-specific and industry-level dynamics. Resilience has been measured as the difference between the actual closing prices and the counterfactual trends. On the basis of the time plot graph on closing prices, we identified three phases: i) a first crisis phase in the 2017-2018 period; ii) a subsequent recovery phase in the 2018-2020 period corresponding to the U.S.-China trade war; and iii) a second crisis phase in the 2020-2023 period corresponding to the COVID-19 pandemic. The analysis has been performed on a sample of 485 European-listed firms for the period 2014-2023.

2 Models

We examine the impact of gender diversity in the board and executive leadership on firm resilience through a counterfactual analysis, following a step-wise approach: (1) estimating closing prices using a Dynamic Panel model; (2) computing *counterfactual* closing prices based on post-shock average growth rates by NACE sectors; and (3) measuring resilience as the difference between actual and counterfactual closing prices, linking it to firm-specific gender diversity.

In the first step, closing prices Y_t are estimated using the Difference Generalized Method of Moments (GMM) (Hansen, 1982). Specifically, it has been assumed that the difference in logarithm of closing price depends on its lagged differenced value, as well as key financial ratios, such as Operating Margin (OM_{it}) and Assets Turnover (TO_{it}), which reflect the firm's operational efficiency. The model is specified in Equation 1 as:

$$\Delta \ln(Y_{it}) = \alpha \Delta \ln(Y_{i,t-1}) + \beta_1 \Delta OM_{it} + \beta_2 \Delta TO_{it} + \Delta \varepsilon_{it} \quad (1)$$

where Y_{it} is the closing price at time t for firm i , OM_{it} is the Operating Margin, and TO_{it} is the Assets Turnover at time t . The error term ε_{it} is decomposed as $\varepsilon_{it} = \mu_i + \eta_{it}$, where μ_i is the time-invariant firm-specific effect removed through the difference specification and η_{it} is the idiosyncratic error term. The DPM is particularly appropriate for our data, where the closing price is expected to exhibit persistence over time, and we need to account for both individual effects and potential endogeneity arising from the lagged dependent variable and other covariates.¹ In the second step, to estimate the closing prices in the absence of the 2017–2018 shock, we simulate the model covariates under a no-shock scenario. Specifically, we hold values from 2014 to 2017 constant and project post-2017 values using the median sector-specific growth rates for EBIT, Net Sales, and Total Assets. The coun-

¹ The model satisfies Hansen test for instrument validity (p-value = 0.166) and Arellano-Bond test for absence of autocorrelation in errors (p-value = 0.074)

terfactual covariates are used to compute new values for Operating Margin (OP^*) and Assets Turnover (TO^*) that allow to obtain the counterfactual closing prices through the DPM:

$$\ln \hat{Y}_{it} = (1 + \alpha) \ln \hat{Y}_{i,t-1} - \alpha \ln \hat{Y}_{i,t-2} + \beta_1 \Delta OP_{i,t}^* + \beta_2 \Delta TO_{i,t}^* + \Delta \varepsilon_{i,t} \quad (2)$$

This provides an alternative growth path for each firm, represented by the counterfactual closing price time series.

As concerns the third step, we analyze firm resilience during the three distinct periods: the first crisis period (2017–2018), the recovery period (2018–2020), and the second crisis period (2020–2023). This measure is computed in Equation 3 as followed:

$$R_i = \frac{\Delta \hat{Y}_{it} - \Delta Y_{it}}{Y_{i0}} \quad (3)$$

Where, for each firm i , ΔY_{it} is the variation of the actual closing price in period t and $\Delta \hat{Y}_{it}$ is the variation of the counterfactual closing Price. The resilience R_t in each period is modeled using linear regressions.

$$R_t = \gamma_0 + \gamma_1 X_t + \varepsilon_t \quad (4)$$

where X_t represents a vector of covariates for each period, which includes a score of gender diversity among executive managers (EGD); a score of gender diversity in the Board of Directors (BGD); the Social Pillar Score representing the firm's social responsibility (SPS); a binary variable indicating the presence of a succession plan for executive leadership in the event of unforeseen circumstances (SP); the proportion of independent members on the Board IBM ; the total number of members on the Board of Directors (BS); a dummy variable of Industry Profitability (measured as Return On Investment) indicating that a firm is more profitable than the median value of the reference sector ($IndProf$); a dummy variable of Industry Productivity (measured as the ratio of net sales to full-time employees) indicating that a firm is more labour intensive than the median value of the reference sector ($IndProd$).

3 Results and Discussion

Table (1) presents OLS estimates of resilience models (Eq(4)). The results indicate a significant positive impact of gender diversity on firm resilience during the US-China trade war, with both Board Gender Diversity (BGD) and Executive Leadership Diversity (EGD) enhancing resilience. In the recovery phase, only BGD remained significant, while board size and productivity emerged as critical factors. During the pandemic, gender diversity had no significant effect, with succession planning and financial stability playing a more decisive role.

These findings underscore that gender diversity strengthens resilience in times of economic uncertainty, but its impact varies by shock type and hierarchical level.

Additionally, robust financial performance and succession planning are essential for managing recurring exogenous shocks.

Table 1 Regression Results

Variable	Crisis 2017–2018			Recovery 2018–2020			Crisis 2020–2023		
	Estimate	Std. Error	p-value	Estimate	Std. Error	p-value	Estimate	Std. Error	p-value
Intercept	0.131574	0.160869	0.4143	0.627967	0.224637	0.00564**	0.461286	0.581708	0.42880
BGD	0.251720	0.130724	0.0554	0.460559	0.201781	0.02341*	-0.427748	0.548604	0.43656
EGD	0.176582	0.105105	0.0943	-0.047547	0.141105	0.73646	0.266756	0.291351	0.36107
SP.TRUE	0.001661	0.069436	0.9809	-0.061273	0.089311	0.49340	0.555926	0.168700	0.00118**
IBM	0.001065	0.001450	0.4636	-0.003932	0.002090	0.06128	-0.001348	0.004068	0.74072
BS	-0.022217	0.010127	0.0293*	-0.036032	0.014064	0.01108*	0.023733	0.028237	0.40171
SPS	-0.001011	0.001539	0.5120	0.001034	0.002093	0.62178	-0.005527	0.003897	0.15771
IndProf	0.068387	0.062260	0.2732	-0.129797	0.081177	0.11126	0.017296	0.167503	0.91787
IndProd	-0.066257	0.063627	0.2988	-0.154454	0.084141	0.06775	-0.349164	0.168906	0.04010*

Acknowledgements The authors acknowledge that this work has been financed within the projects: “GRIS - Growing Resilient Italian SMEs” (No. 2022X9YPZJ) within the PRIN 2022 program by the European Union - Next Generation EU and the Italian Minister of University and Research (MUR); GREENGO (Competitiveness for a stronger and more sustainable Italian economy) funded by the Ministry of University and Research, PRIN 2022 – D.D. 104, 02/02/2022; GRINS (Growing Resilient, INclusive and Sustainable) funded by the European Union Next-GenerationEU (National Recovery and Resilience Plan), NRRP, Mission 4, Component 2, Investment 1.3 – D.D. 1558 11/10/2022, PE00000018, Spoke 7 “Territorial Sustainability” and Spoke 8 “Social Sustainability”. This manuscript reflects only the authors’ views and opinions, neither the European Union, the European Commission nor the Ministry of University and Research can be considered responsible for them.

References

1. Azeem, N., Ullah, M., & Ullah, F.: Board gender diversity and firms’ financial resilience during the Covid-19 pandemic. *Finance Research Letters* **58**, (2023).
2. Conz, E., & Magnani, G.: A dynamic perspective on the resilience of firms: A systematic literature review and a framework for future research. *European Management Journal* **38**(3), 400–412 (2020).
3. Hansen, L.P.: Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society* **50**(4), 1029–1054 (1982).
4. Iftikhar, A., Purvis, L., Giannoccaro, I.: A meta-analytical review of antecedents and outcomes of firm resilience. *Journal of Business Research* **135**, 408–425 (2021).
5. Ortiz-de-Mandojana, N., & Bansal, P.: The long-term benefits of organizational resilience through sustainable business practices. *Strategic Management Journal* **37**(8), 1615–1631 (2016).
6. Shropshire, C., Peterson, S., Bartels, A. L., Amanatullah, E. T., & Lee, P. M.: Are female CEOs really more risk averse? Examining economic downturn and other-orientation. *Journal of Leadership & Organizational Studies* **28**(2), 185–206 (2021).
7. Triana, M. D. C., Miller, T. L., & Trzebiatowski, T. M.: The double-edged nature of board gender diversity: Diversity, firm performance, and the power of women directors as predictors of strategic change. *Organization Science* **25**(2), 609–632 (2014).

Reconstructing climate change awareness survey data using socio-economics and geographical information

Gianpaolo Zammarchi

Abstract Spatially clustered regression is a recently developed methodology that combines clustering and regression in order to provide region-specific predictions. In this work, we applied spatially clustered regression to predict climate change awareness in countries not included in a survey conducted across approximately 110 countries or world areas. We are using socio-economics and geographical information to train models capable of estimating awareness after assessing the underlying relationships at regional level. Estimating a global level of awareness about climate change is crucial to assess the knowledge of this problem across the world before policies, collaborations and plans can be effectively implemented.

Key words: spatially clustered regression, climate change, awareness imputation

1 Introduction

Linear regression is a simple yet powerful tool for analyzing the relationship between a dependent variable and one or more independent variables. In this work we will focus on cluster regression and specifically on spatially clustered regression (SCR).

Generally speaking, cluster regression is a statistical modeling technique that takes into consideration the existence of groups of homogeneous observations in the data. The relationship between the dependent and independent variables may differ according to the subgroups to which the data points belong to. Finding these groups and estimating distinct regression models for each group is the aim of cluster regression. SCR is a method that combines regression models with clustering, under the assumption all the geographical locations that are close in space can share the

Gianpaolo Zammarchi

University of Cagliari, e-mail: gianpaolo.zammarchi@unica.it

same cluster. Therefore, the regression coefficients obtained for a cluster are valid for all countries in the same cluster [1].

In our study, we decided to use a large-scale survey promoted by Yale researchers in collaboration with Meta that originally provided data for 110 countries in the world [2]. Unfortunately, some countries were not involved in the survey and therefore the levels of awareness were not available. However, it is possible to use SCR to estimate the potential awareness values for countries not involved in the survey. Assessing and possibly monitoring people's levels of awareness about climate change is of fundamental importance to continue to pressure governments and supranational organizations to adopt measures to reduce greenhouse gas emissions and encourage virtuous behavior also by individuals. Since awareness levels for some countries might not be available for several years, the aim of this work is to provide reliable estimates of what these values could be in order to understand the current situation within these countries.

2 Background

SCR divides data into clusters based on shared characteristics in order to create regression models that account for spatial heterogeneity. Several approaches have been proposed in the literature to address the challenge of capturing spatial heterogeneity by estimating local models on subsets of data centered around a specific location. For instance, Lee and colleagues [3] proposed a method based on geographically weighted regression and applied it to a cancer mortality data set.

Li & Sang [4] proposed a computationally efficient method for detecting spatially clustered patterns in regression coefficients using a combination of spatial neighborhood information and regularization techniques.

Lastly, Fu and colleagues [5] used a smoothing method to obtain the asymptotic covariance matrices of the parameter estimators and prove the asymptotically unbiasedness of the induced estimating functions. Their approach consisted in the creation of covariance matrices for both between cluster estimators and within cluster estimators, along with a combined estimator of the within-cluster correlations. When applied to a data set of randomized clinical trials, the method showed good computational efficiency and stable results.

3 Methodology

In this section we illustrate how we created the data set for the analysis and provide an explanation of the methods used to carry out these analysis.

3.1 Data set

The awareness levels were obtained by collecting the answers given to a survey administered in 2022 by researchers at Yale University in collaboration with Meta [2]. The outcome variable was obtained as the number of respondents who answered positively to the question on awareness of climate change in the survey. The socio-economics and geographical information used as predictors in the regression models were collected from the following sources: Our World in Data, Penn World Table, Global Carbon Atlas, and Climate Change Knowledge Portal.

3.2 Spatially clustered regression

SCR is a modeling approach that finds clusters in geographically-related data, where the relationship between predictors and the response variable is assumed to be the same within each cluster. The main goal is to fit different regression models for each of the K clusters. Notationally, consider a response variable Y_i and p predictors $\mathbf{X}_i = (X_{i1}, X_{i2}, \dots, X_{ip})^\top$ observed at location i . In SCR's formulation the relationship between Y_i and $\mathbf{X}_i$ is the same as that of a linear regression model:

$$Y_i = \mathbf{X}_i^\top \beta_{C(i)} + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma^2)$$

where $C(i)$ indicates the cluster for location i , β is the vector of regression coefficients specific of cluster $C(i)$, and ε_i is the error term. The clustering is obtained by minimizing an objective function that combines within-cluster error and spatial heterogeneity as in Equation 1:

$$\mathcal{L} = \sum_{k=1}^K \sum_{i \in C(i)} (Y_i - \mathbf{X}_i^\top \beta_{C(i)})^2 + \phi \sum_{i < j} w_{ij} \mathbb{I}[C(i) = C(j)], \quad (1)$$

where ϕ is a parameter controlling for the strength of spatial correlation.

4 Results

The analysis is still in a preliminary phase. Figure 1 shows a clustering of the countries based on the climate change awareness level. A three cluster solution shows a strong effect of geographical proximity, with a purple cluster mainly including European countries, a green cluster including South American and Asian countries and a yellow cluster mostly including South American and African countries. SCR analysis is ongoing and will allow to compare clusters obtained using both geographically-related and socioeconomic predictors, as well as to obtain country-specific predictions.

Updating the estimate of transport costs in Europe: a focus on insularity

Gianpaolo Zammarchi and Paolo Mattana

Abstract In this work we present the preliminary results of a larger study to create time series of accessibility indices across Europe by updating and expanding the work of Persyn et al. [6]. The aim is to create indicators that reflect the relative efficiency of each NUTS-2 region in terms of transport costs. First, we updated the transport costs calculated in 2016 using a price index that accounts for national transport inflation rates. We included all the costs required to move a standard quantity of goods between European regions (specifically, a representative 40t vehicle). Second, costs were compared with the physical distances between NUTS-2 regions to determine whether transport costs were justified by the distance and to classify regions as efficient or inefficient based on the cost/distance ratio.

Key words: accessibility index, transport cost, insularity, efficiency

1 Introduction

The concept of “insularity” goes beyond the geographical aspect and also includes the consideration of social and economic elements that characterize places far from the mainland. Geographically speaking, isolation usually refers to the physical separation from larger landmasses, which affects how easy (and expensive) it is to move people and products. When the territory is very small or has little infrastructure, natural obstacles such as seas or oceans can make communications and transportation more expensive and difficult, and this has repercussions at the economic and cultural level

Gianpaolo Zammarchi
University of Cagliari, e-mail: gianpaolo.zammarchi@unica.it
Paolo Mattana
University of Cagliari, e-mail: mattana@unica.it

[3]. Because of their isolation, these places often face higher or specific challenges compared to similar places on the mainland. For example, higher exposure to the effects of climate change, lack of high levels of health care and educational opportunities, lack of economies of scale, limited access to labour markets and supply chains, heavy reliance on imported goods and services, and higher transportation costs are responsible for the deterioration of the economy, life expectancy and quality of life of the isolated places [1, 7]. Isolation, however, can also be a positive aspect, for example when it serves as an attractive element for tourism or for the preservation of language, local customs and traditions.

In this work, we consider an insular territory as a geographically isolated Nomenclature of Territorial Units for Statistics (NUTS-2) region that is entirely or mostly surrounded by water, such as, the Balearic Islands (Spain) or the Sardinia Island (Italy). The main aim of this work is to evaluate the efficiency of insular territories by assessing if isolated territories performed better than the average (or similarly to the mainland region) when correcting for the distance with respect to the other NUTS-2 regions.

2 Data sources

The main data source for this work is the public available dataset provided by Persyn and colleagues [6]. This dataset was created by estimating the transportation costs between each pair of NUTS-2 regions. The authors used the real European road network to establish a possible route between two regions that went beyond the simple consideration of the major population centers, but a simulation of possible centroids. Once the distance was determined, the cost of a typical transportation vehicle was evaluated considering various sources of cost, from the driver to factors related to the specific road section (e.g. toll) [6].

The NUTS classification system is a standard classification for subregions of the European Union. The EU's statistical agency, Eurostat, is the primary source of NUTS-2 data and provides information on a wide range of topics, including social and economic indicators. To enable researchers to carry out in-depth investigations into a wide range of issues, official data are released continuously over time [4]. The NUTS nomenclature was developed to divide the whole European Union into areas based on a numbering system able to identify countries (e.g. Scotland), regions (e.g. Bretagne) or smaller areas (e.g. individual provinces).

In general, NUTS-2 regions correspond to areas with a population between 800,000 and 3 million residents [5]. This level of granularity is important for instance for the evaluation of the European Union's cohesion policies, which aim to reduce social and economic inequalities across Europe and therefore require an accurate economic evaluation of the areas involved. Labour market statistics, such as employment and unemployment rates, can be used to illustrate regional differences in employment prospects and assess how well policies work to reduce unemployment.

3 Methodology

When considering the transport costs related to the movement of goods between hundreds of NUTS-2 regions, it is clear that greater distances correspond to greater costs. For this reason, we created an indicator that takes into account the distance between each possible pair of NUTS-2 regions and the costs incurred to move the goods between the regions. In this way, if the costs are lower than expected for a given distance, we can consider the transport as efficient, otherwise it will be considered inefficient. Naturally, the evaluation must be repeated for each possible connections from any NUTS-2 to all the others, and this is why we took the average values into consideration.

In this work we used the road distance computed by Persyn and colleagues [6] and updated the costs using the Harmonised Index of Consumer Prices (HICP). Next, we used the population of each NUTS-2 region as weight when computing the following indices:

$$A_i^T = \sum_{j=1}^N m_j C_{ij} \quad A_i = \sum_{j=1}^N m_j D_{ij} \quad (1)$$

where m is the importance of each destination, C is the cost incurred to move from NUTS-2 i to NUTS-2 j , and D is their distance [2]. Next, for each location we computed $N_i = \frac{A_i^T}{\bar{A}^T}$ and $V_i = \frac{A_i}{\bar{A}}$ as the ratio between a single cost and distance, respectively, and their mean. Lastly, we obtain I_i^T as:

$$I_i^T = \frac{N_i}{V_i} \quad (2)$$

which is the ratio between costs and distances already related to their mean.

4 Results

Figure 1 shows the EU maps according to the values of the A_i^T (a), A_i (b), and I_i^T (c) indices, respectively, where darker colors indicate lower values and lighter colors are higher values. The last map (Figure 1c) shows that many peripheral regions, such as the Scandinavian and Iberian peninsulas, can be considered as efficient, because their I^T values are lower than 1.

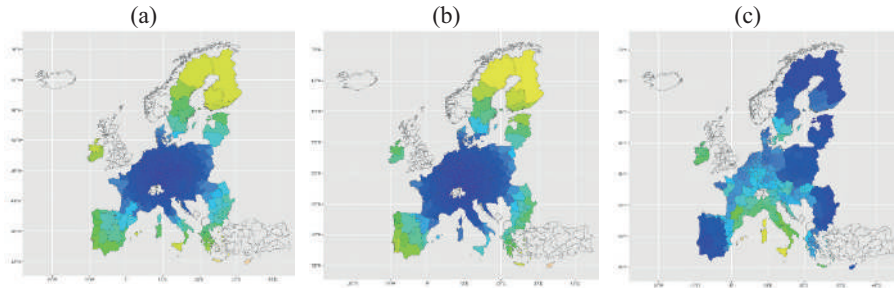


Fig. 1 (a) values of the $N_i = \frac{A_i^T}{A^T}$ index; (b) values of the $V_i = \frac{A_i}{A}$ index; (c) values of the $I_i^T = \frac{N_i}{V_i}$ ratio.

Acknowledgments This study was funded by the European Union - NextGenerationEU, Mission 4, Component 2, in the framework of the GRINS -Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 – CUP F53C22000760007). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

References

1. Agius, K., Theuma, N., & Deidun, A. So close yet so far: Island connectivity and ecotourism development in central Mediterranean islands. Case studies on transport policy, 9(1), 149-160. (2021)
2. Bucci, M., Ivaldi, G., Messina, G., Moller, L., & Gennari, E. I divari infrastrutturali in italia: una misurazione caso per caso. Banca d'Italia (Bank of Italy). Questioni di Economia e Finanza (Occasional Papers), (635). (2021)
3. Encontre, P. The vulnerability and resilience of small island developing states in the context of globalization. In Natural Resources Forum (Vol. 23, No. 3, pp. 261-270). Oxford, UK: Blackwell Publishing Ltd. (1999)
4. Eurostat. Road Freight Transport Methodology. Eurostat, Luxembourg, ISBN 9789279600685 2016
5. Eurostat. NUTS - Nomenclature of Territorial Units for Statistics. Retrieved from <https://ec.europa.eu/eurostat/web/nuts> 2024
6. Persyn, D., Díaz-Lanchas, J., & Barbero, J. Estimating road transport costs between and within European Union regions. Transport Policy, 124, 33-42, (2022)
7. Spilanis, I., Kizos, T., & Petsioti, P. Accessibility of Peripheral Regions: Evidence from Aegean Islands (Greece). Island Studies Journal, 7(2) (2012)

FINITO DI STAMPARE
NEL MESE DI APRILE 2025
DA ENZO ALBANO S.R.L.
VIA ENRICO FERMI, 17 - NAPOLI

Euro 20,00

