UNIVERSITY OF VERONA

Department of Economics

Doctoral Program in Economics and Management

36th Cycle

Nudges, Shocks, and Job Lock: Behavioral Responses in Environmental, Financial, and Labor Contexts

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Abstract

This dissertation examines how behavioral and psychological factors influence household decision-making and well-being across three distinct domains: environmental sustainability, financial portfolio choices, and labor market constraints.

The first study reports on a field experiment in a northern Italian municipality that tested whether text message nudges (the Know-As-You-Throw initiative) could improve residential waste sorting. We find that personalized self-comparison messages significantly reduced the frequency of unsorted waste disposal, while social-comparison messages had no detectable effect. Importantly, the positive impact on waste reduction persisted even one year after the intervention.

The second study investigates how past disaster experiences affect households' participation in risky financial assets, using panel data from the Survey of Health, Aging, and Retirement in Europe (SHARE) matched with the Emergency Events Database (EM-DAT). We show that a simple indicator of having experienced a disaster has no significant effect on risky financial decisions, while repeated exposure to natural or technological disasters lowers both the probability of holding risky assets and the share of wealth invested in them, and exposure that occurred six or more years earlier still reduces risky asset participation. Moreover, personality traits shape these responses: conscientiousness mitigates the adverse effect of disaster exposure on risky financial behavior, while there is weaker evidence that neuroticism amplifies it.

The third study explores the relationship between perceived job lock and life satisfaction among U.S. workers aged 50 and above, using longitudinal data from the Health and Retirement Study (HRS). We find that older workers who feel "locked" in their jobs due to financial and health insurance dependency report lower overall life satisfaction and lower satisfaction in specific life domains, especially financial and leisure domains. Furthermore, control beliefs moderate this relationship: the negative association between job lock and life satisfaction is weaker among individuals who already perceive greater constraints on their personal control, consistent with adaptation to constrained circumstances. Taken together, these three stud-

ies highlight the importance of behavioral interventions and contextual factors in shaping sustainable practices, financial resilience, and subjective well-being. The findings suggest that policymakers should leverage behavioral insights—such as tailored nudges and support for psychological resources—when designing programs to improve environmental outcomes, financial health, and the quality of work-life for older adults.

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Introduction

Understanding how external influences and internal predispositions shape people's decisions is central to economics and related social sciences. This dissertation unifies three empirical studies under the broad theme of behavioral responses in different contexts. Each chapter addresses a distinct domain but shares a common emphasis on how information, shocks, and constraints affect individual and household behavior. The first chapter (Chapter 1) focuses on environmental behavior: it examines whether sending tailored text-message nudges to households can improve waste sorting and reduce unsorted waste generation. The second chapter (Chapter 2) examines financial decision-making under shocks: it analyzes how households' past exposure to natural or technological disasters influences their willingness to hold risky assets and how personality traits moderate the magnitude of the effect. The third chapter (Chapter 3) turns to labor and well-being among older adults: it studies the phenomenon of job lock (when workers feel unable to leave a job due to dependence on income or health benefits) and its impact on overall and domain-specific life satisfaction, also considering how individual differences in perceived control moderate this relationship. In what follows, we briefly summarize the motivation, methodology, and key findings of each study and outline how they contribute to the broader literature on household decision-making and well-being.

In Chapter 1, we address the challenge of improving household waste separation as part of broader sustainability goals. Modern waste policies like door-to-door collection and pay-as-you-throw provide structural incentives, but behavioral interventions may further enhance outcomes. We conducted a natural field experiment in collaboration with a waste management company in the Veneto region of Italy. Households received periodic text messages (the Know-As-You-Throw initiative) that acted as nudges, with two different framings: self-comparison (feedback on one's past waste behavior) and social comparison (benchmarking against neighbors). Using difference-in-differences analysis, we find that receiving these messages significantly reduced the amount of unsorted waste each household generated. Notably, messages referencing the household's own past performance yielded a much larger decline in

unsorted waste than messages providing social comparisons. We also observe that the positive effect of the nudges persisted for at least a year after the intervention ended, suggesting lasting behavioral change. These results contribute to the literature on environmental nudges by demonstrating that personalized feedback can be more effective than social norms in promoting sustainable waste management and that low-cost messaging interventions can have enduring impacts on pro-environmental behaviors.

Chapter 2 shifts focus to household financial decision-making under uncertainty by examining how disaster experiences influence risky investment behavior. Drawing on the experience-based learning and behavioral finance literature, the chapter investigates whether exposure to natural and technological disasters affects households' participation in risky asset markets and the proportion of financial wealth allocated to risky assets. Using longitudinal data from the Survey of Health, Aging and Retirement in Europe (SHARE) linked with geo-coded disaster information from the Emergency Events Database (EM-DAT), the study considers multiple dimensions of disaster exposure, including binary disaster experience, cumulative disaster exposure, and the timing of exposure. The analysis further explores whether stable personality traits moderate households' financial responses to disaster-related shocks. The findings reveal that a simple binary measure of disaster exposure has limited effects on risky financial decisions, whereas repeated disaster experiences are associated with lower risky asset participation and smaller allocations of financial wealth to risky assets. The results also show that long-term disaster exposure is linked to lower risky asset participation, suggesting that the effects of adverse experiences may persist well beyond the immediate aftermath of a disaster. Personality traits play an important role in explaining heterogeneity in household responses to disaster exposure. Openness to experience is positively associated with risky financial participation, while conscientiousness and neuroticism are negatively associated with risky asset holding and risky asset share. More importantly, conscientiousness mitigates the adverse effect of disaster exposure on risky financial behavior, indicating that disciplined and forward-looking individuals are better able to maintain long-term investment strategies following adverse shocks. This chapter contributes to the literature on household finance and disaster exposure by demonstrating that the financial consequences of disasters

depend not only on the occurrence of adverse events but also on the frequency and timing of exposure and on underlying personality characteristics that shape responses to uncertainty.

Chapter 3 examines labor market constraints and life satisfaction among older U.S. workers. In recent years, many Americans have continued working beyond early retirement age because they rely on their job for income and health insurance. We define "job lock" as the self-reported condition of wishing to retire or leave one's job but feeling unable to do so due to these dependencies. Using seven waves (2008–2020) of the HRS, we analyze how perceived job lock relates to overall life satisfaction and satisfaction in specific domains (health, finances, family, leisure, city, and housing). We control for a rich set of demographics and personality traits, and we also investigate whether psychological resources—specifically, a sense of mastery and perceived constraints on personal control—buffer the impact of job lock. Our results indicate that older workers who report being job-locked have significantly lower general life satisfaction. This negative association is strongest for those who mention both financial needs and health insurance as reasons for staying versus only one. In domain-specific outcomes, job lock is most strongly linked to lower satisfaction with personal finances and leisure activities. Furthermore, we find that perceived constraints on personal control moderate this relationship: the negative correlation between job lock and life satisfaction is weaker among individuals who already perceive greater constraints, suggesting that those with lower expectations of control adapt more readily to an additional constraint.

These findings contribute to several works of literature: they add to the well-being literature by highlighting a particular stressor (job lock) faced by older workers, and they show that its well-being cost depends on individuals' control beliefs. They also inform labor economics by suggesting that policies addressing health coverage and pension timing could improve the well-being of those who feel unable to retire.

Each chapter stands on its own within its field, but together they illustrate a common insight: individuals' economic and environmental choices are deeply influenced by behavioral and contextual factors. In the environmental domain, informational nudges can shift ingrained habits. In the financial domain, life experiences and resulting psychological changes

shape risk-taking. In the occupational domain, institutional constraints on retirement can weigh on subjective well-being. By drawing on a field experiment and two empirical studies based on large-scale survey data, this dissertation highlights the importance of combining economic analysis with behavioral and psychological perspectives. In the conclusion, we discuss the broader implications of these findings for policy: for example, how municipalities can design effective communication for waste management, how financial education and counselling might account for clients' past traumas, and how retirement reforms might consider the psychological impact of job lock. Overall, the three studies underscore that improving outcomes in sustainability, finance, and employment requires attention not just to prices and policies, but also to the ways people think, feel, and respond to nudges and shocks.

CHAPTER 1.

Text Message-Based Nudging Interventions for Household Waste Sorting: A Field Intervention Study

1.1 Introduction

Economic development is typically associated with increasing levels of waste generation, making it a heightened environmental concern (Wang et al., 2021). In many cases, this increase in waste generation is coupled with insufficient logistics capacity to manage it properly. At the household level, increasing waste prevention and sorting can be crucial behavioral drivers for reducing overall waste and fostering recycling. To address the challenge of unsorted waste disposal practices, various waste management policies are implemented across the regions in Italy.

In the Veneto region of Italy, two major waste policies, namely Door-to-Door (DtD) and Pay-As-You-Throw (PAYT), have made substantial contributions to improving waste sorting. The DtD policy consists of designated waste bins with tags placed outside residential homes. It facilitates the separate collection of different waste streams directly from households. Household-level and curbside sorting systems can facilitate recycling by allowing waste to be separated at source rather than relying exclusively on subsequent sorting at specialized facilities (see, e.g., Czajkowski et al., 2019; Varotto & Spagnolli, 2017). Conversely, PAYT is a waste tariff charged proportionally to the volume of collected unsorted waste.

However, while these policies enhance separate waste collection, they inadvertently encourage undesirable behaviors such as illegal waste, waste tourism, etc. (see, e.g., Kirakozian, 2016; Olson Jr, 1971). Additionally, achieving the desired long-term goal of improved waste sorting quality remains a challenge. Therefore, exploring behavioral interventions, such as nudges, that can further engage households in waste-sorting activities is crucial. One such

intervention is the Know-As-You-Throw (KAYT) initiative, introduced by a municipality in Veneto, which utilizes chat messaging to provide personalized information and regular feedback on households' waste disposal behavior through smartphones. For this study, we utilized a portion of the KAYT information as nudges to evaluate their effectiveness on residential waste sorting.

The KAYT initiative allowed us to test two distinct types of informational nudges, each grounded in a different behavioral mechanism. The first, a self-comparison nudge, provides feedback on a household's own past waste performance. This approach is informed by goal-setting theory and the principle of self-regulation, which suggests that personalized, historical feedback can motivate improvement by making progress salient and fostering a sense of personal accountability (Locke & Latham, 2002). The second, a social-comparison nudge, benchmarks a household's performance against the average of similar neighbors. This design leverages social norms theory, which posits that behavior can be influenced by revealing descriptive norms and activating motives for conformity or social approval (Cialdini et al., 1990; Schultz et al., 2007). We hypothesize that both nudges would reduce unsorted waste compared to a control group. However, based on literature suggesting potential reactance to peer comparisons (e.g., Allcott, 2011; Beshears et al., 2015) and the potent effects of personal feedback loops, we further hypothesize that the self-comparison nudge would yield a stronger and more persistent effect on waste-sorting behavior than the social-comparison nudge.

This paper aims to examine the impact of nudging interventions on reducing unsorted waste at the household level. In particular, we assess whether the provision of text message-based nudges can modify households' waste-sorting behavior. Furthermore, we investigate whether the nudges employed exhibit sustained impact beyond the treatment period, indicating persistence in behavioral change. To conduct our analysis, we collaborated with a waste management company in a municipality in northern Italy, obtaining experimental data.

Our empirical results show a significant positive effect of the chat messages on households' bin emptying. Notably, the treatment exhibits a substantial annual decline in unsorted waste

bins ranging from 13.3 percent to 17.1 percent. Regarding the specific type of treatment messages received by each group, self-comparison messages contribute to a reduction of 16.4 percent to 22.6 percent in the number of emptying dedicated to unsorted waste. However, we find no significant effect of treatment messages comparing participants' performance relative to their neighbors. Intuitively, the provision of regular KAYT messages serves as an incentive, influencing households' actual behaviors towards proper waste separation and waste reduction. Furthermore, our analysis indicates persistence in the impact of nudges on households' waste sorting behavior, with post-treatment effects showing an even greater impact on bin emptying.

This study contributes to the literature on the influence of nudges on individuals' waste disposal practices and sustainable waste management. It complements previous studies by demonstrating the efficacy of self-comparison messages over social-comparison messages. While prior research has explored nudges in the context of energy consumption (Allcott, 2011) and tax evasion (Hallsworth et al., 2017), among others, this paper is the first to test the effectiveness of the KAYT messages employed as nudges in ensuring proper residential waste sorting and reduction of household waste in the Bassano del Grappa municipality in northern Italy. Moreover, we show evidence of the sustained impact of nudges in a field where persistent intervention is crucial. In the Bassano experiment, a chat system was designed to provide real-time messages about waste disposal practices to some domestic users. Two treatment groups were formed, with each group receiving different nudging messages: one group received self-comparison messages based on their waste disposal history and current practices, while the other group received messages comparing their performance to that of their neighbors. We then evaluate how each group responds to the nudges. Lastly, we present results of behavioral factors that have the potential to influence household waste sorting behavior before the intervention (see Appendix 1.B for a detailed discussion).

The remainder of this study proceeds as follows: Section 1.2 reviews the existing literature on nudges and waste disposal management. Section 1.3 presents the experimental setting and design. Section 1.4 describes the estimation strategy, reports the results, and discusses their implications. Finally, Section 1.5 concludes.

1.2 Literature Review

We structure this section into two subsections. The first subsection presents relevant literature on nudges toward sustainable ethical behavior in waste disposal, water conservation, and energy usage. The second subsection reviews studies on waste disposal management and the different pricing schemes.

1.2.1 Nudging Towards Sustainable Ethical Behavior

The concept of nudging, as theorized by Thaler & Sunstein (2009), is widely used in the field of behavioral economics to influence the behavior of individuals or groups to make better-informed decisions. Insights from nudges help us appreciate how the behavior of people looks distinct in varying contexts and situations and lessen any unconscious influence of irrational beliefs in our decision-making process. The adoption of nudging tools has aided in effectively enhancing the societal welfare of people, such as the promotion of environmental protection, encouraging charitable giving, etc. (see e.g., Sunstein, 2014; Chakravarty & Mishra, 2019), and the well-being of individuals, such as using nudges to encourage people to lose weight and to adopt pension plans for retirement (Thaler & Sunstein, 2009; Lai et al., 2019). The application of nudges to aid policy goals appears to be generally easy to implement, inexpensive, and effective in reducing the misuse of resources. As the House of Lords Science and Technology Select Committee (2011) posits, often, people are oblivious to how their actions are affected by available distinct options or alterations in the environment; nudges, in most cases, help alter facets of individuals' actions that are non-contemplative. Nudge instruments consist of sending messages, modifying features and layouts of distinct environments, defaults, emphasizing social norms, implementing various forms of warnings, prompting individuals about their choices, and changing behavior through the use of framing. Consistent with this, Beshears et al. (2015) find that exposure to peer information about their actions can generate an oppositional reaction. Thus, a constant reminder to employees of low economic status is more likely to discourage them from retirement savings. However,

Hallsworth et al. (2017) find that including social norm messages in standard reminder letters increases payment rates for overdue tax in the UK. Sunstein (2014) points out that coercive policy tools, including bans, regulations, laws, or fiscal and economic instruments such as subsidies or taxes to promote environmentally friendly behavior, are not considered nudges. Although the provision of information as a nudge is contested in the literature, Sunstein (2014) considers disclosure and information provision to be among the interventions that may qualify as nudges. In contrast, Hansen & Jespersen (2013) adopt a more restrictive behavioral account, under which the mere provision of factual information or rational argumentation does not, by itself, constitute a nudge.

As discussed by Thaler & Sunstein (2009), the concept of choice architecture explains that individual decision-makers make choices not in a vacuum but in an environment that is regarded as highly important, where many features, both observed and unnoticed, can alter their decisions. It is worth noting that regulations about the environment have not succeeded in their quest to significantly change the behaviors and habits of people toward sustainable lifestyles. Nonetheless, public authorities such as local governments could expedite the endorsement of environmentally friendly habits such as proper waste segregation and disposal, water conservation, and energy utilization through nudges, which could influence cognitive biases to achieve sustainable behaviors. Verplanken & Wood (2006) find that over 40 percent of the actions that people take every day are not active decisions but habits. In terms of achieving sustainable consumption, behavioral interventions may encourage more efficient use of vital resources like energy and water and aim to shift consumers towards choices that have a reduced impact on the environment. The role of nudging in controlling an environment is highlighted in vast literature and emerges as a favorable tool that activates behavioral change and effectively augments conventional environmental policy tools. Empirical evidence supports this assertion at least in the short run.

In a field experiment on electricity usage by Brülisauer et al. (2020), residents were provided with information regarding their electricity consumption and its comparison to their immediate neighbors, whom they could identify. The authors find that the provision of feedback reduced electricity consumption, particularly for high-energy-use electrical devices

such as an air conditioner, by about 17 percent on average (see also, Schultz et al., 2007).

Allcott (2011) reveals that home energy reports that the provision of information to households about their previous energy consumption, as well as juxtaposing it with the consumption by their neighbors, helped to reduce energy consumption by 2 percent on average. It is in this direction that our study investigates how expanding the knowledge base of waste differentiation can effectively alter the behavior of people within the pilot area under study. Moreover, social norms through the provision of information in connection with the behavior of other people emerge as a robust approach to encourage farmers to adopt environmentally friendly practices (Kuhfuss et al., 2016). Kallbekken & Sælen (2013) also reveal that hotel restaurants record a 20 percent reduction in the production of food waste due to the use of small plate sizes to serve guests. Despite the effective evidence, the magnitude of the nudging tool effect may differ depending on the mix of nudges applied.

Based on data from a survey of individuals in EU27 countries, Cecere et al. (2014) investigate whether social norms strongly influence people's behavior regarding waste reduction or intrinsic motivations, such as altruistic preferences. They reveal that, to reduce waste sources, individuals' preferences need not be limited to a recycling-based orientation. Again, the pattern of individual behavior toward cutting down waste is insensitive to peer pressure; however, it largely depends on altruistic attitudes. Oteng-Peprah et al. (2020) and Alhassan et al. (2020) support the assertion by Cecere et al. (2014), as they also posit that a crucial factor that drives an individual to exhibit pro-environmental behavior (like waste sorting behavior) is attitude. The use of social norms in shaping the behavior of individuals in society has yielded positive results in another context of studies.

In the context of tax compliance, an empirical study by Wenzel (2005) highlights that social norms influence individuals to comply with the payment of tax if one identifies with the group under consideration. This finding supports the fact that making social norms more specific to an individual group or situation is a particularly promising mechanism to address societal issues. We adopt this approach in the area of waste disposal to investigate whether the social norms approach employed in this study may play any role in affecting

the behavior of individuals in Bassano del Grappa. Alpizar & Gsottbauer (2015) perform a framed field experiment in Costa Rica relying on the system of forming a reputation for recycling practices by households. Heads of households in the urban cities were approached to decide on the hours within a framed threshold they would add to a public good fund described or framed as a contribution towards education and recycling workshops within the community. Experimenters could detach the relative impact of pride and shame on the choice to recycle by learning two different treatments based on whether the framed threshold is reached or not; each treatment group is assigned either a red or green flag noticeable to participants. At the end of this experiment, they discovered that the treatment group that reaches the threshold receives less contribution from participants, as opposed to more contribution in the treatment group that fails to hit the threshold. This further indicates that the impact of shame on the effort to recycle is much stronger than pride.

The Chandak (2010) includes a series of experiments discussed as follows: first, experimental research was undertaken to examine how framing techniques influenced decisions made by consumers about installing smart-grid technology in Denmark, Norway, and Switzerland, which shows that the framing of choices significantly affects the behavior of consumers. The experimenters suggest that, if possible, making sustainable choices the default stands to be a simpler and more effective approach to accomplishing sustainable objectives such as lowering the use of energy. Second, the programme reports an experiment conducted in Peru to encourage household recycling in response to the country's heightened solid waste challenges. The outcome of the experiment reveals that households that were given recycling bins were more likely to turn in recyclables. They argued that adding stickers to the bin for easy identification had no major effect, indicating that the provision of information and knowledge was less important in dealing with the menace.

However, the major challenge that led to non-compliance with the program was finding storage for the recyclable garbage, coupled with the inconvenience of occupying space in the homes. Having identified the root cause of non-compliance, environmentally friendly nudges were designed to curb and improve recycling. Third, in a similar context of waste disposal and recycling in the city of San Jose, California, the intervention of changing physical

characteristics such that residents were given small trash bins and bigger recycling bins led to a significant 50 percent decline in the trash service and an average of 6.3 percent rise in recycling every month.

It is therefore imperative to suggest that adopting consumer-focused and demand-oriented schemes in policy and governance architecture would be compelling enough. This ensures sustainable lifestyles and appropriate practices within the environment such that unsorted waste emission is reduced; efficient use of natural resources and improved welfare and human development are realized.

1.2.2 Waste Disposal Management

Given the daily escalation of total waste accumulation, pragmatic measures to enhance waste sorting and prevention practices among domestic users are crucial. According to Hoornweg et al. (2013), the total waste generated globally is projected to triple by 2100 as a result of industrialization, urbanization, and increased world population. The conventional theory of demand provides a framework upon which the demand for household utility services is modeled, which suggests that a commodity's demand is influenced by the consumer's income, prices of other related goods, and the commodity's own price (Marshall, 1890).

However, other studies show that the determinants of the demand for waste disposal services are not limited to the factors proposed by Marshall. The additional factors are age, geographical location, gender, level of education of the head of the household, household size, occupancy status, etc. (see e.g., Tadesse, 2009; Adzawla et al., 2019). In the past, people perceived the time dedicated to accurately segregating waste at source as unproductive. Nonetheless, Kinnaman & Fullerton (1999) model the choice of waste differentiation by households using a utility maximization problem where households are constrained to apportion their time between properly sorting waste generated and work. This establishes the positive utility that an individual derives from waste sorting because the environmental perils associated with mixed waste are mitigated. Additionally, the lack of a meticulous and viable legal framework to regulate and adequately enforce sanctions creates a lacuna in waste

management.

A recent study by Adzawla et al. (2019), using cross-sectional data from Ghana to assess the determinants of household solid waste disposal, corroborates the findings of Mamady (2016). The authors find that female-headed households mostly had their solid waste collected and disposed of at a public dump rather than disposing indiscriminately or burning it. The choice by these female-headed households may be dependent on their willingness to pay for the value placed on the use of environmental resources (Garrod & Willis, 1999).

Waste disposal methods are generally classified as either proper or improper (Frimpong, 2013). Proper waste management practices are crucial to minimize the adverse impact of waste on human health and the environment. When it comes to waste management, the costs associated with waste collection and disposal constitute a significant portion, approximately 80 percent, of the total costs (Un-Habitat, 2010). To address these concerns, the European Union (EU) has established Directive 2008/98/EC and Regulation 2014/955/EU, which advocate for the "polluter-pays" principle. These regulations hold waste producers accountable for appropriately managing waste. The EU has set specific targets to reduce food waste by 30 percent by 2025 and 50 percent by 2030, as well as promote the use of recycled materials (see EU revised Waste Framework Directive, 2018). Overall, it is crucial to address the challenges associated with separate waste collection and achieve significant reductions in waste production. Such efforts have the potential to mitigate the emission of greenhouse gases, save energy, and promote environmental sustainability (Nainggolan et al., 2019; Ranieri et al., 2018).

In the Veneto region of northern Italy, various municipalities have implemented two key waste management policies: a pricing scheme for waste disposal (such as flat fee versus PAYT) and an approach to waste collection (such as drop-off versus DtD). Bucciol et al. (2015) conducted a study in the district of Treviso (Italy), involving 95 municipalities, between 1999 and 2008 to examine the impact of integrating monetary and non-monetary incentive schemes on solid waste sorting. Their findings revealed that the PAYT pricing scheme led to a 17 percent increase in the ratio of sorted-to-total waste, thereby reinforcing

the effectiveness of the DtD waste collection system. In our experimental setting, the municipality of Bassano del Grappa in the Veneto region, the widely adopted waste management approach combines DtD collection with PAYT. This approach has proven to be effective in promoting waste segregation. However, challenges persist in achieving improved waste sorting quality. Therefore, this study aims to investigate the impact of integrating nudges in the form of text messages within the context of Bassano del Grappa's PAYT system. We seek to explore how these nudges can contribute to improved waste sorting practices and waste reduction in the municipality. In the next section, we present the experimental setting and design of our study.

1.3 Experimental Setting and Design

1.3.1 Experimental Setting

Bassano del Grappa is a municipality situated in the center of the Veneto region, positioned in the northeast of the Italian peninsula, and located on the border between Vicenza, Padua, and Treviso (see Figure 1.1). It has a total area of 47.06 square kilometers. As of 2020, the town recorded 42,527 total inhabitants, indicating a negative 0.58 percent variation compared to the previous year. The corresponding age distribution of the population shows that 6,546 residents fall between 0 and 17 years old, 25,268 residents can be found between 18 and 64 years old, and 10,713 residents are aged 65 years and above (UrbiStat, 2020)[1]. According to the last census by Istituto Nazionale di Statistica (Istat) in 2011, the residential buildings of the town are composed of 40 percent single houses, 30 percent two-member family apartments, 17 percent three- or four-member family apartments, 9 percent small condominiums with interior apartments accommodating between five and eight members, and large apartments account for the remaining 4 percent.

The total waste accumulation in the municipality rose from 20,501 to 21,216 tons between 2018 and 2019, respectively, amid declining total inhabitants. Similarly, the amount of unsorted municipal waste follows a rising trajectory as it soared from 4,438 to 4,728 tons at the end of 2018 and 2019, respectively (see ARPAV 2019)[2]. There are two main waste collection methods in Bassano, namely door-to-door and street collections. Indeed, the door-to-door collection combined with PAYT is predominant and active for both domestic and non-domestic users. Bassano consists of different provinces, each employing a specific waste collection method. In the municipal territory without scattered areas, the exclusive waste collection method employed for all waste fractions is door-to-door. However, in the historic center, street waste collection is only available to a limited extent. On the other hand, in hilly areas with scattered users, street collection is virtually the sole method employed for

[1] https://ugeo.urbistat.com/AdminStat/en/it/demografia/dati-sintesi/bassano-del-grappa/24012/4

[2] https://www.arpa.veneto.it/temiambientali/rifiuti/datirifiuti/banca_dati_ru.php

all waste fractions.

As pointed out earlier, we collaborate with a waste management company in Bassano del Grappa called Etra. Etra is a multi-utility public company contracted by the local government to deal primarily with waste-related services in 64 municipalities of the provinces of Padova and Vicenza, including Bassano del Grappa. The company is responsible for placing wheeled containers or bags with microchips at the doorstep of households or designated streets for garbage collection, and the emptying of containers is done at regular time intervals. Etra undertook a project called "LIFE ReThinkWaste" which spanned between 2019 and 2022 in Bassano del Grappa (see Etra website)[3]. The main goal of the project is to increase waste separation and reduce waste per capita, as well as cut the average household waste bill.

Firstly, a flyer was sent by Etra together with the authorities of Bassano del Grappa municipality to the citizens within collection area D. This engagement letter comprehensively describes and explains the objectives of the project. As part of this stage, citizens were invited to participate in the experiment by sending their mobile numbers to a platform that was provided for the project.

[3] https://rethinkwaste.eu/pilot-areas/



Figure 1.1: Bassano del Grappa's municipality location

1.3.2 Experiment Design and Intervention

In this study, we conduct a natural field experiment where the environment is one in which the subjects naturally undertake tasks and are oblivious to the fact that they are in an experiment. According to Harrison & List (2004), a field experiment, unlike a conventional lab experiment, has several strengths worth mentioning; first, as the natural settings of field experiments relate to real life, they generally yield results with higher ecological validity than laboratory experiments. Second, demand characteristics are less of an issue with field experiments than laboratory experiments in that subjects are unlikely to alter their natural behavior following their interpretation of the purpose of the study since they might be unaware that they are in a study.

It is also worth specifying some weaknesses of conducting a field experiment. First, the experiments may be vulnerable to potential problems such as sample bias if the participants are not randomly allocated to experimental conditions; thus, groups of participants are pre-set rather than randomly assigned. Second, the non-artificial environment of field experiments makes them extremely difficult to replicate, hence poor reliability, unlike conventional lab

experiments, where a recreation of exact conditions is possible.

Etra selected for the experiment an area of Bassano del Grappa named "D area". This pilot area consists of 8 neighborhoods totaling about 11,300 inhabitants with a corresponding 5,532 total users. In the D area, the territorial characteristics are similar to the remaining territories of Etra. It is a residential area with little presence of condominiums; door-to-door collection is an active method for the main fractions of waste, and a PAYT waste tariff is implemented. The total number of households that voluntarily participated and were provided with text messages in the experiment was 148. This experiment helps elicit the immediate and possible long-run net effect of nudges, particularly the provision of KAYT messages on household waste sorting behavior.

It is important to note that participation in the messaging program was voluntary. This self-selection process likely attracted households that were already more interested in waste management or more receptive to behavioral interventions. Consequently, our treatment group may not be fully representative of the general population in Area D, which could affect the external validity of our findings. Furthermore, the relatively small size of the treatment group limits the statistical power of our analysis, particularly for detecting differences between the two nudge types or for conducting more granular subgroup analyses. We address concerns regarding internal validity and pre-existing differences between groups in our estimation strategy (Section 1.4) and through robustness checks using propensity score matching (Table 1.A.2) in Appendix 1.A.

1.3.2.1 Experiment

A messaging system was designed where self-selected domestic users are assigned a unique code that enables recognition on the platform. Subsequently, the mobile numbers of the users are collated and used to communicate messages about personal behavior on waste accumulation, to give points, or to inform about various crucial issues such as proper waste differentiation rules and guidelines, achievement of the whole pilot area, meetings, etc. Households become aware of information regarding the weight of waste produced and the number of

unsorted waste bins used by a particular household in comparison with that of neighbors in the municipality.

Two separate treatment groups, namely Group 1 and Group 2, were randomly formed from the households that expressed interest in the experiment. Group 1 received real-time messages specifically related to the emptying of unsorted waste bins, providing information about their past and current waste sorting practices. On the other hand, Group 2 received messages about their waste sorting performance in the past relative to their nearby neighbors. For each household, all participating members were assigned to either Group 1 or Group 2. It is important to note that members within a particular group remained unaware of the message provided to the other group. This approach allowed for the independent assessment of the impact of the messages within each group, eliminating any potential cross-contamination of information.

However, other threats to internal validity require consideration. First, we cannot rule out spillover effects or information diffusion within the pilot area. Treated households might have discussed the messages or their waste-sorting efforts with neighbors in the control group, potentially diluting the measured treatment effect by also changing control group behavior. While the chat system was personal, the social nature of the intervention (e.g., references to neighborhood performance) could have facilitated such discussions. Second, while the messaging system was automated, we did not independently verify that every sent message was received and read by participants. Technical issues (e.g., wrong number, full inbox) or simple habituation could have led to non-compliance. If non-compliance was non-random (e.g., less engaged individuals ignored messages), it could bias our estimates. Our analysis follows the intention-to-treat principle, estimating the effect of being assigned to receive messages, which is the policy-relevant effect but may understate the effect on compliant households. These factors, alongside the imperfect comparability of the two message types, mean our results should be interpreted as the effect of deploying this messaging system in a real-world setting, with its inherent practical constraints.

With this design in place, we evaluate and gain insights into the effectiveness of the mes-

sages and their potential influence on the waste-sorting behavior of the participants. The findings of this research will provide valuable insights for waste management authorities in Bassano del Grappa, helping them tailor their operations towards implementing effective messaging strategies that promote waste sorting and reduce waste accumulation. The treatment messages were prepared in simple Italian to ensure better understanding and accurate feedback (see Appendix 1.A). We report below the English version of the messages provided to each group.

Group 1:

> *Hello, here is some new information for you.*
> *You emptied your bin X times in 2020; you have emptied it N times since the start of 2021.*
> *At the end of the year, do you think you can do better than last year?*

Group 2:

> *Hello, here is some new information for you.*
> *The Bassano families with the same number of members as yours emptied their bin X times on average in 2020.*
> *At the end of the year, do you think you can do better than them?*

Lastly, local shops were engaged in the project to reward users who actively participated till the end of the period. The reward was in the form of vouchers that participants could spend only in the shops that participated. The provision of vouchers served as a driving incentive for participants to commit their effort and time to complete the experiment. In addition to promoting their active participation, it also sought to address the problem of attrition bias. We aimed to reduce potential biases that might affect the reliability of our findings by raising participant satisfaction and decreasing the possibility of early withdrawal from the experiment. Furthermore, giving out vouchers was meant to build rapport with participants and secure their continuous participation in future experiments. It is, however,

important to highlight that, unfortunately, due to some miscommunication with the Etra technicians, the chat messages provided to the treated groups were not entirely comparable. Despite this issue hindering us from fully pursuing the initial objective, it is still essential to analyze the two messages, albeit with their non-perfect comparability, to gain valuable insights.[4]

1.3.3 Sample and Summary Statistics

We utilize the experimental data set to assess the impact of the nudging intervention on households' waste-sorting behavior. We consider all households living in Area D. In our analysis, domestic users whose waste collection service started in 2020 or later are excluded. Users who send their waste to a press container are also excluded. Finally, users whose service ended in 2021 or earlier are dropped from the analysis. The reduction in the final number of households is attributed mainly to the unavailable information on the number of emptying.

Due to the specific sample selection criteria, the final sample consists of 13,188 observations on 3,253 households that have been utilizing Etra's services annually from 2017 to 2021. Out of these households, 148 (accounting for 604 individual-time observations, or 4.6 percent) belong to the treatment group. Among the treated sample, 74 households are categorized in group 1, while 63 households are classified in group 2. In comparison with the entire area D, the treatment group is on average younger and lives in larger houses, and the household size is relatively larger (see Table 1.1).

Figure 1.2 plots the distribution of average bin emptying dedicated to unsorted waste in our sample, separately for the treatment and control groups. The distribution of the two

[4]Initially, our plan was to have two messages that were perfectly comparable to be provided during the experiment. For Group 2, during the planning stage, an additional sentence, "*You have provided the bins N times since the start of 2021*," was to be included in their message. The intention was to modify the reference category (i.e., self or neighbors) while still preserving the individual's performance in the current year. However, due to some communication issues with Etra, the implementation resulted in two messages that were not perfectly comparable being provided to the groups. We will further discuss this issue and its implications in the results section.

groups across the years is similar, although the average emptying in the treatment group is slightly above the control group. During the years under study, there was an initial increase in the overall average bin emptying in 2018. However, a subsequent downward trend is observed, particularly in 2021, with a significant drop in the average bin emptying. The observed decline in 2021 may be attributed to technological hitches. The operators encountered challenges in accurately tracking the number of bins emptied, resulting in their inability, at times, to identify some respondents and their respective groups. It is important to note that this problem is not isolated to specific individuals within a particular group but rather widespread. Therefore, it is reasonable to conclude that the issue is random and does not influence our overall results.

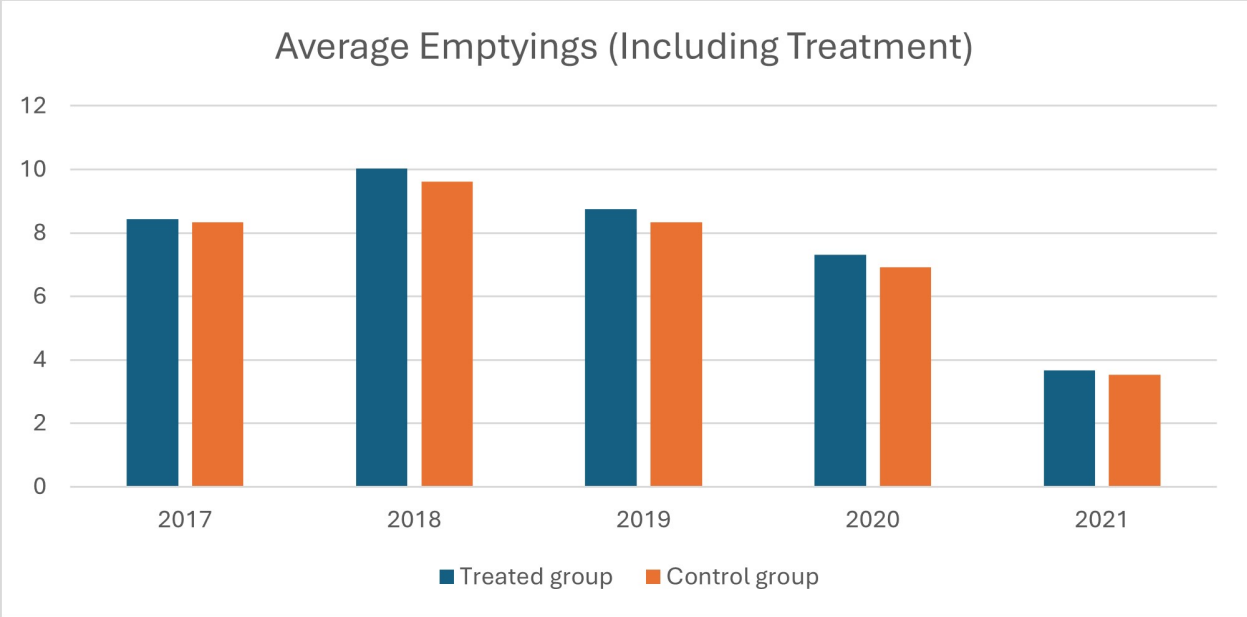


Figure 1.2: Distribution of average bin emptying in the treatment and control groups.

Table 1.1 presents summary statistics of the key variables used in our analysis and socio-demographic controls that have the potential to influence the outcome variable. Our outcome variable, *bin emptying*, measures the number of unsorted waste bins provided by households to waste collectors. In Bassano del Grappa, household waste bills consist of a fixed and a variable component. The fixed part depends on dwelling characteristics and is independent of actual use, whereas the variable part is proportional to the number and size of unsorted bins collected over the year. Our main outcome variable—the number of unsorted bins emptied

per household—therefore maps directly into the variable component of the PAYT bill. We do not observe household-level invoices in our data, so throughout the chapter we interpret our estimates as changes in unsorted waste generation, which are linearly related to changes in the variable share of the bill.

Table 1.1: Summary statistics of the experiment

Variable	Obs.	Mean	Std. Dev.	Min	Max
Bin emptying	13,188	6.689	5.944	1	53
Treated	13,188	0.046	0.209	0	1
Treated_2021	13,188	0.009	0.094	0	1
House surface	13,188	5.008	0.469	3.401	6.737
Household_1 member	13,188	0.226	0.418	0	1
Household_2 members	13,188	0.324	0.468	0	1
Household_3 members	13,188	0.196	0.397	0	1
Household_4 members	13,188	0.170	0.376	0	1
Fraction of females	13,188	0.535	0.287	0	1
Average age	13,188	51.875	19.265	18	105
Waste collection/weekly	13,188	0.002	0.049	0	1
Year_2021	13,188	0.185	0.388	0	1
Year_2020	13,188	0.221	0.415	0	1
Year_2019	13,188	0.214	0.410	0	1
Year_2018	13,188	0.198	0.399	0	1

The variable *Treated* is a dummy equal to 1 if the household took part in the experiment in 2021 and zero otherwise. On average, each household produces about 7 bins of unsorted waste. The percentage of users belonging to the treated group is 4.6 percent overall. Regarding the socio-demographic controls, the average age is 51 years. In fact, the individuals in the treated group are much younger than the control group by approximately 11 years. In terms of household size, the average distribution among users is as follows: 22.6 percent of users have a household size of 1 member, 32.4 percent have a household size of 2 members,

19.6 percent have a household size of 3 members, and 17.0 percent have a household size of 4 members.

The house surface is measured as the natural logarithm of the dwelling's floor area in square metres; hence, treated households on average tend to live in somewhat larger houses. The fraction of the respondents who are females is slightly higher (54 percent). Also, waste collection for unsorted bins is almost always on a biweekly schedule, which is the standard arrangement for residential users in Bassano. Only a very small minority of households (about 0.2 percent of observations) are served weekly, typically large or special-use buildings. We therefore treat biweekly collection as the reference frequency and regard weekly collection as an exceptional case. Several covariates differ significantly between the two groups. However, the standardized mean differences for these variables are generally modest in magnitude (see Table 1.A.1 in Appendix 1.A).

To assess the representativeness of the sample, key demographic characteristics were compared with the population for Italy and the Veneto region. The average household size in the sample is approximately 2.3–2.4 persons, which is very close to the Italian average of 2.2 persons (ISTAT)[5]. Similarly, females account for 53.5 percent of the sample compared with approximately 51.0 percent of the Italian population. The average age in the sample (51.9 years) is somewhat higher than the average age reported for Veneto (47.9 years), suggesting that the study population is slightly older than the regional population[6]. The main difference concerns household composition: single-person households account for 22.6 percent of the sample compared with approximately 37.1 percent nationally.

Overall, however, the demographic characteristics of the sample are broadly comparable to those observed in Italy and the Veneto region, supporting the external validity of the findings while acknowledging that the sample is drawn from a specific municipality and is not intended to be nationally representative. To further mitigate residual imbalance, in robustness checks, we implement Gaussian kernel matching based on pre-treatment covariates and re-estimate

[5]Available at https://www.istat.it/en/press-release/demographic-indicators-year-2025/

[6]https://www.statista.com/statistics/569187/average-age-of-the-population-in-italy-by-region/?srsltid=AfmBOoqcbT9GT0FQ_2S8SnX3QqoOi16knvT0nAjTbvVUCS42RgA5bYk4

the main specifications on the matched sample. The results remain qualitatively unchanged, suggesting that our conclusions are not driven by observable differences between treated and control areas.

1.4 Estimation and Results

In this section, we present the identification strategy utilized in this study. We conduct our analysis using a difference-in-differences approach to exploit the experimental data set. This helps to evaluate the net impact of the nudging intervention executed during the experiment and, by extension, examine whether there is persistence in the households' waste-sorting behavior post-treatment.

1.4.1 Estimation Strategy

We utilize a difference-in-differences (DiD) model in three alternative specifications to measure the impact of the nudging intervention on households' unsorted waste emptying. Specifically, we estimate the average impact by comparing changes in the number of emptyings for households who received the nudging messages in the treatment group and households in the control group before and during the intervention. Through the random assignment of self-selected users into control and treatment groups, it is implied that the groups may not be completely distinct, thereby creating a counterfactual scenario that enables the generation of reliable estimates for the intervention. The DiD estimator establishes the relationship between the outcome indicator (number of emptying) and the treatment (self and social comparison of waste sorting messages) as explicitly stated below:

$$Y_{it} = \alpha_0 + \alpha_1 D_i + \alpha_2 T_{it} + \alpha_3 (T_{it} * D_i) + \sum \alpha_i Z_{it} + \varepsilon_{it} \tag{1.1}$$

where Y_{it} denotes the number of emptying by household i at time t; D_i represents a binary indicator equal to 1 if the household is treated and 0 otherwise; T_{it} is a time dummy equal

to 1 if the year is 2021 and 0 otherwise; $T_{it} * D_i$ shows an interaction term between the time dummies and intervention; the vector Z_{it} includes possible control variables such as house surface, household size, average age, a fraction of females, and if weekly waste collection may potentially influence the number of emptying; and ε_{it} is a mean-zero disturbance term.

According to Wooldridge (2002), the DiD model controls for the unaccounted time-invariant indicators that are unobservable, including the differences between the control and treatment groups. The DiD identification strategy assumes parallel trends over time between the control and treatment groups. Because the administrative data follow the same households over time, the empirical analysis is based on a household-level panel observed annually before and during the KAYT intervention.

This panel structure allows us to assess the identifying assumptions underlying the difference-in-differences design. First, to examine the plausibility of the parallel-trends assumption, we restrict the sample to the pre-intervention period and estimate a model that interacts the treatment-group indicator with pre-treatment year indicators. The joint test of these interaction terms yields $F(3, 3095) = 1.02$ with a p-value of 0.382, indicating that treated and control households do not exhibit statistically different trends in unsorted-waste emptying before the intervention. Second, to assess potential anticipation effects, we test whether treatment status predicts pre-intervention changes in the outcome. The coefficient on the treatment indicator is negative (-0.709) but statistically insignificant ($p = 0.118$), suggesting that treated households were not already changing their waste-disposal behavior before the 2021 KAYT intervention. Together, these tests provide support for the identifying assumptions of the DiD framework and suggest that, in the absence of the intervention, treated and control households would have followed similar trends.

Regarding our benchmark analysis of the DiD approach, the average treatment parameter of interest is α_3, the coefficient on the interaction term between the time dummies and the intervention. Specifically, it measures the difference-in-differences net effect of the change in the number of emptyings that occurred in 2021 between the treated and the control group.

The OLS estimate of the coefficient α_3 is given below:

$$\hat{\alpha}_3 = \left(\bar{Y}_{T=1,D=1} - \bar{Y}_{T=0,D=1}\right) - \left(\bar{Y}_{T=1,D=0} - \bar{Y}_{T=0,D=0}\right) \tag{1.2}$$

where $\bar{Y}_{T=1,D=1}$ denotes the sample average of the treated group during the experiment. Similarly, $\bar{Y}_{T=0,D=1}$ represents the sample average before the experiment for the treated group. The remaining parameters follow. By this approach, we measure the net impact of the nudging intervention on the treatment group, devoid of any noise effect emanating from both group-specific differences (e.g., the treated group on average live in large houses) and common year effects (e.g., any changes in the waste collection system as a result of the Covid-19 pandemic).

In our second DiD specification, we consider a log transformation of the outcome variable y to help improve the model fit and to conveniently interpret the regression outcome. For example, the treatment would result in α_3 percent increase in y on average, holding all other things equal. Lastly, we exploit a negative binomial regression as the third specification in our analysis. Particularly, the negative binomial model is suitable for over-dispersed count data (Hilbe, 2011), as in our case. Indeed, the distribution of the outcome variable is concentrated around zero, and the average emptying is much lower than the variance. This approach generates a narrower confidence interval; hence, estimates are obtained with a limited margin of error and show robustness in the results. All three specifications aim to measure the overall impact of the nudging intervention on the number of bins emptying dedicated to unsorted waste.

For robustness checks, the same regression specifications are used to investigate which type of treatment plays a significant role in our study. Specifically, we measure the magnitude of impact each treatment type has on the number of emptying. In principle, we utilize the treatment according to the types, where type one (i.e., treated 1) is basically about self-comparison and type two (i.e., treated 2) is about comparison with neighbors, thus social comparison. For each treatment type, we employ the DID estimators to measure the average effect of the intervention by finding the difference between the control and treatment groups.

It is worth mentioning that we take into consideration the particular treatment message households received during the experiment in our analysis.

1.4.2 Impact of the Nudging Intervention on Waste Sorting

Table 1.2 shows the overall impact of the nudging intervention on households' waste-sorting behavior. We use the DiD identification strategy to ascertain the magnitude of the effect of the treatment on the number of bins emptied dedicated to unsorted waste (i.e., the outcome variable). In Column (1), an OLS regression is presented, using a level-dependent variable (i.e., bins emptying). Column (2) displays a similar regression with a log-transformed dependent variable, while Column (3) adopts a negative binomial approach. The number of bins emptying generally dropped in the year 2021 from 90.9 percent to 85.6 percent (Columns 2 and 3). Indeed, the drop in emptying is statistically significant at the 1 percent level. The treatment group, on average, reduces the unsorted waste bin emptying by 8.9 percent more than the control group (Column 2). Using a negative binomial approach for the analysis, we find that bin emptying dropped by 10.2 percent among the households that received the treatment messages (Column 3).

Regarding the net effect of the treatment (i.e., the provision of messages), we see a reduction in the number of emptying by 1.24 bins at a 5 percent level of significance. All things being equal, this indicates that each additional instance of communicating KAYT information through the Chat system has a tendency to influence households' intention to reduce unsorted waste bins by a factor of 1.24. Alternatively, the two other regression models with a log-dependent variable show that, concerning the net effect of the intervention, the unsorted waste bins decline substantially between 13.3 percent and 17.1 percent annually (Columns 2 and 3). The coefficients are statistically significant at the 5 percent level. This result is preserved after propensity score matching, with a reduction in unsorted waste bins by 8 percent annually (see Table 1.A.2 in Appendix 1.A).

Table 1.2: Overall treatment effect on households' waste sorting behavior.

	(1)	(2)	(3)
Dep. Variable	Emptyings	ln(Emptyings)	ln(Emptyings)
Method	OLS	OLS	Neg. binomial
T (the year 2021)	-4.540***	-0.909***	-0.856***
	(0.128)	(0.019)	(0.022)
D (treated)	-0.473	-0.089*	-0.102*
	(0.455)	(0.053)	(0.056)
T×D (diff-in-diff)	-1.241**	-0.133**	-0.171**
	(0.508)	(0.068)	(0.073)
House surface	1.113***	0.209***	0.166***
	(0.192)	(0.025)	(0.030)
Household_1 member	-4.523***	-0.725***	-0.679***
	(0.417)	(0.052)	(0.056)
Household_2 members	-3.054***	-0.400***	-0.405***
	(0.406)	(0.048)	(0.050)
Household_3 members	-2.436***	-0.250***	-0.290***
	(0.382)	(0.044)	(0.044)
Household_4 members	-0.815**	-0.072*	-0.095**
	(0.415)	(0.043)	(0.045)
Females (fraction in hh)	0.597**	0.122***	0.101*
	(0.29)	(0.04)	(0.05)
Average age	-0.014**	-0.002*	-0.001
	(0.01)	(0.00)	(0.00)
Waste collection/weekly	13.763***	1.112***	1.259***
	(5.014)	(0.327)	(0.322)
Year_2020	-1.413***	-0.216***	-0.199***
	(0.12)	(0.02)	(0.02)
Year_2019	-0.303***	-0.037***	-0.038***
	(0.11)	(0.01)	(0.01)
Year_2018	0.820***	0.099***	0.102***
	(0.09)	(0.01)	(0.01)
Constant	5.182***	1.086***	1.558***
	(1.02)	(0.14)	(0.16)
Observations	13,188	13,188	13,188
R squared	0.188	0.278	0.051

Note: Clustered standard errors at the household level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The reported R-squared in column 3 denotes the Pseudo-R squared value.

Moreover, the number of emptyings reduces by 4.52 if a household consists of only one member, with a corresponding 72.5 percent reduction in the bins emptying on average.

Also, we find that a four-member household contributes to a small but significant drop in bin emptying because the excluded category is 5+ inhabitants. Indeed, our results indicate an inverse relationship between household components and bin emptying. As the number of members in the household increases, we can see that the emptying of the bins reduces, but at a decreasing rate. On the contrary, females, on average, increase the unsorted waste bins by 12.2 percent more than males.

The coefficient on the weekly-collection indicator is large and positive across all specifications, reflecting substantially higher unsorted-waste emptying among households on a weekly schedule. However, weekly collection applies to only about 0.2 percent of households and typically concerns large or special-use units, making this subgroup both extremely small and atypical relative to standard residential users. Given the limited number of observations, a meaningful heterogeneity analysis by collection frequency is not feasible, as any subgroup estimates would be based on a very small and unrepresentative sample. Consequently, we do not pursue separate estimations by collection frequency and instead focus on the full sample. The estimated treatment effects should therefore be interpreted as primarily reflecting the behavior of households operating under the standard biweekly collection schedule used in Bassano del Grappa.

Overall, our findings indicate that the nudging intervention (i.e., provision of KAYT messages) did influence the observed households' behavior concerning the separate waste collection. We can appreciate how awareness creation through the provision of real-time information and education campaigns can be very instrumental in effecting positive change in households. Indeed, such a considerable net effect suggests that the use of nudges, particularly in this study, is more effective and must be encouraged since it is less expensive and easy to implement. Moreover, citizens feel extrinsically motivated to sufficiently collect sorted waste at the household level upon receiving exposure to the long-term environmental outcomes and benefits from their practices.

Table 1.3: Treatment effect by type on households' waste sorting behavior.

	(1)	(2)	(3)
Dep. Variable	Emptyings	ln(Emptyings)	ln(Emptyings)
Method	OLS	OLS	Neg. binomial
T (the year 2021)	-4.535***	-0.908***	-0.855***
	(0.128)	(0.019)	(0.022)
D1 (treated type 1)	-0.200	-0.067	-0.062
	(0.750)	(0.077)	(0.087)
D2 (treated type 2)	-0.831	-0.119	-0.157**
	(0.644)	(0.074)	(0.073)
T×D1 (diff-in-diff)	-1.599**	-0.164*	-0.226**
	(0.757)	(0.095)	(0.103)
T×D2 (diff-in-diff)	-1.005	-0.133	-0.191*
	(0.725)	(0.101)	(0.105)
House surface	1.113***	0.208***	0.166***
	(0.192)	(0.025)	(0.030)
Household_1 member	-4.538***	-0.724***	-0.680***
	(0.419)	(0.053)	(0.056)
Household_2 members	-3.063***	-0.397***	-0.404***
	(0.409)	(0.048)	(0.051)
Household_3 members	-2.479***	-0.253***	-0.294***
	(0.386)	(0.044)	(0.044)
Household_4 members	-0.820**	-0.07	-0.096**
	(0.418)	(0.043)	(0.045)
Females (fraction in hh)	0.601**	0.123***	0.101*
	(0.285)	(0.041)	(0.053)
Average age	-0.014**	-0.002*	-0.002
	(0.006)	(0.001)	(0.001)
Waste collection/weekly	15.459***	1.279***	1.349***
	(5.382)	(0.323)	(0.315)
Year_2020	-1.410***	-0.216***	-0.199***
	(0.118)	(0.016)	(0.016)
Year_2019	-0.297***	-0.036***	-0.037***
	(0.105)	(0.014)	(0.014)
Year_2018	0.831***	0.101***	0.103***
	(0.087)	(0.012)	(0.011)
Constant	5.225***	1.093***	1.567***
	(1.026)	(0.135)	(0.157)
R squared	0.189	0.280	0.051
Observations	13,147	13,147	13,147

Note: Clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The reported R-squared in column 3 denotes Pseudo-R squared value.

To complement the baseline results in Table 1.2, behavioural factors measured before the intervention provide further useful findings on the underlying drivers of waste-sorting

practices. Table 1.B.2 in Appendix 1.B shows that several behavioural factors are systematically correlated with households' unsorted-waste emptying even before any intervention takes place. In particular, stronger time preferences are consistently associated with more emptying across all specifications, while positive reciprocity also exhibits a positive and statistically significant association. Conversely, traits such as altruism, trust, conscientiousness, and emotional stability display negative correlations with the number of emptying, suggesting that more prosocial and emotionally stable households tend to generate less unsorted waste at baseline. Meanwhile, openness to experience shows a relatively robust positive relationship with emptying, indicating that households with greater receptiveness to new information or experiences may exhibit higher waste generation in the absence of targeted guidance. These behavioural patterns are correlational rather than causal, but they provide an important backdrop for the experimental findings by illustrating that pre-existing psychological dispositions help shape waste-sorting behaviour prior to the delivery of KAYT messages.

So far, we have evaluated the overall effect of the messages we provided to the individuals on their actual behavior about waste sorting. We, therefore, proceed to decompose the overall net effect into separate effects associated with the type of message each group receives (see Table 1.3). By this, we measure the impact of the intervention emanating from the use of self-comparison messages (i.e., treated type 1) compared with social comparison messages (i.e., treated type 2). As earlier pointed out in the experimental design, the two treatment messages are not perfectly comparable for the following reasons: On one hand, we have a different reference category that is either yourself as a household (group 1) or households with similar characteristics (group 2). On the other hand, there is an explicit mention of one's bin emptying performance in the current year in group 1, while, in group 2, the reference to the actual behavior of households in the current year is removed. Due to the nature of the second dimension, a comprehensive comparison between the two groups in our analysis is not feasible. Using the DiD approach, we carry out a regression with the output displayed in Table 1.3 to evaluate how the message in each group influences the actual behavior of households.

A simple back-of-the-envelope calculation helps illustrate the practical magnitude of the estimated effect. The preferred level specification indicates that the intervention reduced unsorted-waste emptying by approximately 1.24 bins per treated household per year. Applied to the 148 treated households, this implies roughly 184 fewer unsorted-waste emptyings annually. Because household-level waste bills and the exact monetary charge per unsorted-bin emptying are not observed in the data, this calculation should not be interpreted as a formal cost–benefit analysis. Nevertheless, it suggests that even a low-cost messaging intervention can generate meaningful operational benefits by reducing the number of unsorted-waste collections required.

Table 1.3 shows that the provision of type 1 messages reduces the number of emptying by 1.60 bins at a 5 percent level of significance, as against 1 bin by type 2 messages, but it is statistically insignificant. Furthermore, messages about self-performance over time contribute to about a 16.4 percent to 22.6 percent reduction in the number of emptying; however, it shows no statistically significant effect when households are compared with their neighbors (see Columns 2 and 3). For treatment 1, we consistently find a result at a lower significance level, whilst for treatment 2 we do not find any better significance. In addition, the coefficient estimates for treatment 2 are always lower than for treatment 1. Indeed, we can tell that only Group 1 messages (treatment 1) exert an effect on different behaviors. Two prevailing dimensions could be attributed to this outcome; that is, either the reference to yourself in the previous year rather than similar households or the explicit mention of your actual behavior in the current year. Unfortunately, we lack statistical evidence to determine which of the two dimensions is primarily influencing the results, as the two treatments differ in both dimensions simultaneously.

1.4.3 Post-Treatment Effect of the Nudges on Household Waste Sorting

In Table 1.4, we present the after-treatment effect of the nudging intervention on households' waste sorting behavior for the year 2022. We add to the sample data for the year 2022. The

Table 1.4: Overall post-treatment effect on households' waste sorting behavior

	(1)	(2)	(3)
Dep. Variable	Emptyings	ln(Emptyings)	ln(Emptyings)
Method	OLS	OLS	Neg. bin.
After (year 2022)	-3.919***	-0.726***	-0.693***
	(0.128)	(0.019)	(0.021)
T (year 2021)	-4.524***	-0.908***	-0.856***
	(0.127)	(0.019)	(0.022)
D (treated)	-0.294	-0.079	-0.093*
	(0.462)	(0.053)	(0.056)
T×D (diff-in-diff)	-1.225**	-0.133**	-0.171**
	(0.500)	(0.067)	(0.072)
After×D (diff-in-diff)	-1.791***	-0.214***	-0.273***
	(0.538)	(0.063)	(0.063)
House surface	1.078***	0.212***	0.177***
	(0.173)	(0.024)	(0.029)
Household_1 member	-4.088***	-0.690***	-0.655***
	(0.371)	(0.049)	(0.054)
Household_2 members	-2.791***	-0.393***	-0.401***
	(0.361)	(0.045)	(0.048)
Household_3 members	-2.184***	-0.238***	-0.282***
	(0.339)	(0.041)	(0.043)
Household_4 members	-0.738**	-0.069*	-0.094**
	(0.367)	(0.041)	(0.043)
Females (fraction in hh)	0.490*	0.106***	0.084*
	(0.257)	(0.039)	(0.050)
Average age	-0.010*	-0.001	-0.001
	(0.006)	(0.001)	(0.001)
Waste collection/weekly	12.129***	1.055***	1.223***
	(4.401)	(0.318)	(0.312)
Year_2020	-1.409***	-0.216***	-0.199***
	(0.118)	(0.016)	(0.016)
Year_2019	-0.301***	-0.037***	-0.038***
	(0.105)	(0.014)	(0.014)
Year_2018	0.820***	0.099***	0.102***
	(0.087)	(0.012)	(0.011)
Constant	4.995***	1.051***	1.488***
	(0.931)	(0.127)	(0.152)
R squared	0.202	0.287	0.056
Observations	15,788	15,788	15,788

Note: Clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The reported R-squared in column 3 denotes the Pseudo-R squared value.

post-treatment period, denoted by After (year 2022), interacts with the treatment indicator (treated) to ascertain the net effect on the interaction term. Indeed, we find the overall

effect at a 1 percent significance level that the number of bins emptying reduces by 1.80. We interpret this result as any unit of KAYT message given to households inducing their behavior to reduce the unsorted waste bins by 1.80. In the corresponding columns, we observe that an added unit of the nudge will contribute between 21.4 percent and 27.3 percent reduction in the unsorted waste bins.

Clearly, we could see that the effect of the KAYT messages observed in 2021 persists in 2022, with a rather more significant impact in 2022. Hence, it suggests that a regular provision of real-time KAYT messages has the potential to influence households' behavior to ensure accurate sorting is done and waste minimization is achieved. In addition, a t-test on the equality of coefficients on 2021 treatment (TxD) and 2022 treatment (AfterxD) gives p-values (0.053), (0.319), and (0.220), respectively, for columns (1), (2), and (3). The p-values indicate that the test fails to reject the null hypothesis and concludes that there is no significant difference in the post-treatment period.

In a further step, an attempt to establish which of the messages performs much better reveals that treatment message 1 reduces unsorted bins emptying between 29.6 percent and 35.8 percent at a 1 percent level of significance (see Table 1.A.3 in Appendix 1.A). In fact, this result also shows a substantial impact greater than what was observed in 2021 and further indicates that messages that include households' past and current waste sorting behavior could propel them to improve their sorting over time. Similarly, we observe that the post-treatment effect of message 2 shows about a 21 percent drop in bin emptying at a 5 percent significance level.

1.5 Conclusion

In collaboration with the waste management company Etra, we conducted a natural field experiment in the Bassano del Grappa municipality in Italy to investigate the impact of nudging on household-level unsorted waste. By providing different nudging messages through Etra's KAYT system to two treatment groups consisting of a total of 148 households, we

aimed to gain insights into the effectiveness of text message-based nudges in promoting proper waste sorting behavior.

Using a difference-in-differences method, our empirical analysis reveals a positive, significant overall effect of the nudging messages on households' bin emptying. This finding suggests that behavioral interventions, such as nudges, can serve as extrinsic motivators to bring about positive changes in individuals' waste disposal habits. The KAYT initiative, which updates users about relevant information on waste separation and waste prevention, serves as a basis to effectively influence households' behaviors. Furthermore, comparing the two treatment messages provided to households, we find that treatment 1 yields more significant changes in behavior than treatment 2. However, due to the lack of perfect comparability between the treatment messages, we cannot conclusively determine the primary factor driving these results. We can only speculate that referencing one's current performance in the current year plays a vital role, although further statistical evidence is needed.

Moreover, our study demonstrates that the treatment effect observed in 2021 persists even one year after the intervention, providing evidence of a potential long-term impact of the nudging intervention. However, additional research is required to ascertain whether the reference to oneself in the previous year or explicit mention of current behavior acts as the motivating factor behind these sustained effects.

Our findings also hold direct implications for waste management policy. The reduction in unsorted waste achieved through low-cost, automated messaging suggests that behavioral nudges can be a scalable and cost-effective complement to existing policies like PAYT. The intervention's primary cost lies in the initial setup of a messaging system, while the marginal cost of sending messages is negligible. Given the persistent effects observed one year post-intervention, such programs may not require continuous communication to sustain impact, enhancing their practical appeal. For municipalities, adopting similar nudge-based strategies could reduce the volume of waste requiring costly processing, ease operational burdens on collection services, and support broader environmental targets—all without significant ongoing investment.

While this study sheds light on the effectiveness of nudging interventions, it is essential to acknowledge its limitations. First, this was a field intervention with a treatment group of 148 households formed through voluntary sign-up. This self-selection process means participants were likely more environmentally conscious or amenable to feedback than the average resident, which limits the direct generalizability (external validity) of our effect sizes to the broader population. Second, the modest sample size, especially when split into two nudge conditions, also reduces statistical power and precision. While we employed matching techniques to improve comparability between the treatment and control groups, the possibility of unobserved confounding factors related to the decision to participate remains. Future studies should aim for larger, more representative samples, potentially using incentives or different recruitment strategies to mitigate self-selection bias. Furthermore, exploring the comparative analysis of the nudging intervention's effects across various municipalities in Veneto would be a valuable avenue for research. Third, as a field intervention set in a community, we had limited control over spillover effects and perfect compliance. The potential for treated households to influence their neighbors or for messages to go unread means our estimated effects might be conservative (i.e., if spillovers occurred) or might not reflect the full potential of the nudges (i.e., if compliance was imperfect). These aspects are common challenges in field studies and highlight the difference between efficacy under controlled conditions and effectiveness in practice. Future implementations could consider structured monitoring of message receipt and explore study designs to better account for social spillovers.

Beyond the environmental benefits, the intervention may also generate economically meaningful savings. According to information provided by the local waste-management authority, each additional unsorted-waste bin emptying costs approximately €5. Combining this figure with the estimated reduction of 1.24 emptyings per treated household implies a saving of about €6.20 per household annually. If comparable behavioral responses were achieved across the approximately 19,000 households in Bassano del Grappa, the resulting reduction in unsorted-waste collection could translate into savings of roughly €117,800 per year. Although this calculation is only illustrative and does not constitute a formal cost–benefit analysis, it highlights the potential for low-cost behavioral interventions to generate

both environmental and economic benefits.

In conclusion, our study highlights the positive impact of nudging interventions on household waste sorting and reduction. By leveraging behavioral insights, we can effectively influence individuals' waste disposal practices and contribute to sustainable waste management.

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1.A Appendix to Chapter 1

A) The original treatment messages in the Italian language are reported as follows.

Gruppo 1

Ciao, ecco delle nuove informazioni per te.

Hai conferito il bidone del secco X volte nel 2020; hai conferito il bidone del secco N volte dall'inizio del 2021.

A fine anno pensi di poter fare meglio dell'anno scorso?

Gruppo 2

Ciao, ecco delle nuove informazioni per te.

Le famiglie di Bassano conlo stesso numero di componenti della tua hanno conferito il bidone del secco mediamente X volte nel 2020.

A fine anno pensi di poter fare meglio di loro?

Table 1.A.1: Test of standardized mean differences

Variables	Diff before matching	Diff after Kernel matching (Gaussian)
House surface	0.078***	0.011
Household_1member	-0.126***	-0.041**
Household_2members	-0.105***	-0.036
Household_3members	0.060***	0.021
Household_4members	0.070***	0.042*
Females (fraction in hh)	-0.032***	-0.010
Average age	-10.863***	-3.983***
Waste collection/weekly	0.053***	0.053***
Observations	13,188	13,188

Note: The table reports the mean difference in the household socio-demographic characteristics between the treated and control groups. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.A.2: Difference-in-Difference estimation after kernel matching

Number of Obs.		Before	After	Total
	Control	10,260	1,561	11,821
	Treated	487	117	604
	Total	10,747	1,678	12,425
Outcome variable		Emptyings		
Before	Control	1.789		
	Treated	1.820		
	Diff (T-C)	0.032*** (0.016)		
After	Control	0.897		
	Treated	0.849		
	Diff (T-C)	-0.048 (0.036)		
DID				-0.079** (0.039)

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 1.A.3: Post-treatment effect by type on households' waste sorting behavior.

	(1)	(2)	(3)
Dep. Variable	Emptyings	ln(Emptyings)	ln(Emptyings)
Method	OLS	OLS	Neg. bin.
After (year 2022)	-3.917***	-0.725***	-0.693***
	(0.128)	(0.019)	(0.021)
T (year 2021)	-4.519***	-0.907***	-0.854***
	(0.127)	(0.019)	(0.022)
D1 (treated type 1)	-0.025	-0.059	-0.055
	(0.755)	(0.077)	(0.086)
D2 (treated type 2)	-0.665	-0.11	-0.148**
	(0.658)	(0.074)	(0.074)
After×D1 (diff-in-diff)	-2.308***	-0.296***	-0.358***
	(0.807)	(0.080)	(0.087)
T×D1 (diff-in-diff)	-1.563**	-0.163*	-0.225**
	(0.742)	(0.095)	(0.103)
After×D2 (diff-in-diff)	-1.237*	-0.158	-0.210**
	(0.746)	(0.104)	(0.096)
T×D2 (diff-in-diff)	-1.011	-0.134	-0.193*
	(0.722)	(0.101)	(0.106)
House surface	1.079***	0.211***	0.176***
	(0.174)	(0.024)	(0.029)
Household_1 member	-4.097***	-0.688***	-0.655***
	(0.373)	(0.049)	(0.054)
Household_2 members	-2.795***	-0.390***	-0.400***
	(0.364)	(0.045)	(0.048)
Household_3 members	-2.217***	-0.240***	-0.285***
	(0.343)	(0.042)	(0.043)
Household_4 members	-0.736**	-0.065	-0.094**
	(0.369)	(0.041)	(0.043)
Females (fraction in hh)	0.494*	0.107***	0.085*
	(0.258)	(0.039)	(0.050)
Average age	-0.011*	-0.001	-0.001
	(0.006)	(0.001)	(0.001)
Waste collection/weekly	13.718***	1.232***	1.323***
	(4.699)	(0.311)	(0.304)
Year_2020	-1.407***	-0.216***	-0.199***
	(0.118)	(0.016)	(0.016)
Year_2019	-0.296***	-0.036***	-0.037***
	(0.105)	(0.014)	(0.014)
Year_2018	0.830***	0.101***	0.102***
	(0.087)	(0.012)	(0.011)
Constant	5.024***	1.055***	1.494***
	(0.933)	(0.127)	(0.152)
R squared	0.204	0.288	0.057
Observations	15,738	15,738	15,738

Note: Clustered standard errors at household level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

B) Behavioral Factors Driving Household Waste Sorting

Given that the principal objective of this paper is to evaluate the effectiveness of the use of nudges on households' waste sorting through a field experiment, it is also important to appreciate how other factors may induce waste sorting in Bassano del Grappa. To this end, we investigate how key behavioral drivers such as preferences, reciprocity, and the Big Five personality traits of households correlate with unsorted waste emptying. In the quest to ascertain some findings, we administered a questionnaire before conducting the field experiment to help us obtain a data set about the households' attitudes to waste management in general.

Pre-Treatment Questionnaire

The questionnaire includes four broad sections. Specifically, households respond to a series of questions concerning beliefs, preferences, reciprocity, and personality to elicit general information about their actual behavior. It is worth mentioning that the questions were in no specific context that could be linked to households' observed waste-sorting behavior. Out of the 148 participants, 143 successfully completed the questionnaire, while 5 respondents provided partial answers.

We exploit the data set obtained from the respondents to evaluate the factors that drive households' waste-sorting behavior. It was developed in four broad sections to collect general information about the households' beliefs, preferences, reciprocity, and personality. In the first section, households were asked a series of questions about how they think separate waste collection and their readiness to adopt pro-environmental behaviors could help to mitigate climate change. The next section consists of three-item questions to elicit data about risk preferences, time preferences, and altruism of households. For each question, the respondents were asked to indicate how willing they are to act in the different situations on an 11-point Likert scale, which ranges between 0 for "completely unwilling to act" and 10 for "completely willing to act." The third section also had three sets of statements in relation to whether

people can be trusted and about positive and negative reciprocity. Similar to the second section, respondents indicated how well the statements represent them as individuals, with a measure of 0 indicating "it doesn't represent me at all" and 10 "it represents me perfectly."

The pre-treatment survey includes a short version of the Big Five personality inventory, a widely used psychological framework that summarizes individual differences across five broad and stable personality dimensions. The questionnaire adopts the ten-item inventory of Gosling et al. (2003), in which respondents evaluate how well specific pairs of traits describe their personality on a 7-point Likert scale ranging from 1 ("totally disagree") to 7 ("totally agree"). Each pair consists of two contrasting descriptors, allowing respondents to position themselves along the underlying continuum represented by each personality dimension.

The first dimension, Openness to Experience, reflects the extent to which individuals are imaginative, curious, and receptive to new ideas. Those scoring higher tend to enjoy exploring novel experiences and are often characterized by creativity and intellectual curiosity. Conscientiousness captures traits related to organization, persistence, and self-discipline. Highly conscientious individuals are typically reliable, responsible, and inclined toward orderly and goal-directed behaviour. Extraversion measures sociability, assertiveness, and the tendency to seek stimulation through interaction with others; individuals with higher extraversion scores are more outgoing, energetic, and comfortable in social settings. Agreeableness encompasses attributes such as cooperativeness, trust, and compassion. People scoring high on agreeableness are generally warm, considerate of others, and inclined toward prosocial behaviour. Finally, emotional stability, the inverse of neuroticism, reflects the degree to which individuals remain calm, resilient, and free from persistent negative emotions. Higher emotional stability is associated with lower tendencies toward anxiety, irritability, and emotional reactivity. These five dimensions provide a compact yet informative description of personality traits that may influence a wide range of behaviours, including environmental and household decision-making.

Sample and Summary Statistics

Table 1.B.1 presents descriptive and summary statistics of the key factors we explore, categorized into outcome and explanatory variables, and socio-demographic controls that may potentially influence the outcome variable. Our outcome variable, *bin emptying* measures the number of unsorted waste bins provided by households to waste collectors. The independent t-test indicates that all the individual variables are statistically significant at 1 percent. Regarding the explanatory variables, the average trust of households in our sample is 6. Households' preferences on average are higher than their level of reciprocity and personality traits. Concerning the socio-demographic controls, the average age in our sample is 41 and the fraction of female respondents is slightly above one half (51 percent). A small subgroup of respondents (4 percent) report weekly unsorted-waste collection rather than the standard biweekly schedule; these are mostly large or special-use households and are slightly over-represented in the questionnaire sample relative to the full administrative population, where only about 0.2 percent of observations correspond to weekly collection.

Estimation Strategy

We employ a multivariate regression model to explore whether the observed households' behavior (i.e., bin emptying) is driven by either their preferences, reciprocity, or personality dimensions. The ordinary least squares (linear) regression specification used is explicitly stated as follows:

$$y = \beta_0 + \beta_1 X + \beta_2 Y + \beta_3 Z + \beta_4 T + \epsilon$$

where y is the number of emptying dedicated to unsorted waste, X represents preferences, Y denotes reciprocity, Z includes the Big Five personality traits, and T includes control variables such as the log of house surface (square meters), household size, average age, a fraction of females, and whether weekly waste collection is done. β_0 is the intercept, β_i shows the coefficients of the independent variables, and the error term is denoted by ϵ.

Table 1.B.1: Summary statistics of the pre-treatment questionnaire

Variable	Obs.	Mean	Std. Dev.	Min	Max	t-test
Outcome variable						
Bin emptyings	342	8.225	7.176	1	47	0.000***
Explanatory variables						
Risk preference	342	7.260	1.967	1	10	0.000***
Time preference	342	8.249	1.588	3	10	0.000***
Altruism	342	7.936	1.886	2	10	0.000***
Positive reciprocity	342	8.532	1.825	1	10	0.000***
Negative reciprocity	342	2.459	2.398	0	9	0.000***
Trust	342	5.845	2.054	0	10	0.000***
Extraversion	342	3.760	1.233	1	7	0.000***
Agreeableness	342	5.652	0.944	3.5	7	0.000***
Conscientiousness	342	5.861	1.023	3.5	7	0.000***
Emotional stability	342	5.063	1.253	1.5	7	0.000***
Openness to experience	342	4.583	0.927	2.5	7	0.000***
Socio-demographic controls						
House surface	342	5.122	0.410	4.094	6.560	0.000***
Household_1 member	342	0.079	0.270	0	1	0.000***
Household_2 member	342	0.237	0.426	0	1	0.000***
Household_3 member	342	0.272	0.446	0	1	0.000***
Household_4 member	342	0.211	0.408	0	1	0.000***
Females (fraction in hh)	342	0.505	0.214	0	1	0.000***
Average age	342	41.496	16.417	18	79	0.000***
Waste collection/weekly	342	0.044	0.205	0	1	0.000***

Note: *** p<0.01, ** p<0.05, * p<0.1.

In the empirical analysis, the Big Five personality scores are standardized to have mean zero and unit variance before entering the regressions so that coefficients can be interpreted as the change in bin emptying associated with a one-standard-deviation difference in each trait. This transformation facilitates comparability across traits, which are measured on the same Likert scale but can differ in dispersion and response patterns, and ensures that the estimated coefficients reflect the effect of a one-standard-deviation change in each personality dimension. Standardization is common in economic literature using personality measures, particularly when traits enter jointly in behavioral equations. In some contexts, researchers further adjust Big Five scores for lifecycle effects, reflecting evidence that certain personality

traits follow predictable age-related patterns (e.g., Nyhus & Pons, 2005; Groves, 2005). In the present setting, the empirical strategy focuses on cross-sectional variation within a narrowly defined population, and the inclusion of age and demographic controls already absorbs much of the lifecycle-related heterogeneity. Standardizing the scores therefore provides a consistent and transparent way to incorporate personality traits into the analysis while maintaining comparability across traits and specifications.

Following the model above, four similar regression specifications are constructed to measure the association between the predictor variables and the number of emptying. In the first specification, we consider the immediate year before the experiment for the analysis. The rationale behind this consideration is to ascertain how the aforementioned behavioral factors may have had a bearing on households' tendency to empty more sorted waste or otherwise, particularly in the year 2020. For the second regression model, the average number of emptying across the years is determined and regressed on the independent variables for the year 2020. Thirdly, we estimate the third regression by incorporating all the years between 2017 and 2020. By this, we can find how the behavioral pattern of households in terms of waste sorting over time changes. Lastly, we consider the log-transformed dependent variable regressed on the explanatory variables.

Results

Table 1.B.2 presents the correlational analysis of households' bin emptying dedicated to unsorted waste and some behavior-induced factors. In the first column, bin emptying is regressed on the demographic variables for the year 2020. In the second column, we match the average bin emptying of the entire pre-treatment period with the explanatory variables in the year 2020. In the third column, we include all the pre-treatment periods for both the explanatory and dependent variables, which increases the sample observation size. The last column takes the log-transformed dependent variable regressed on the explanatory variables. In general, we find among the psychological variables that time preferences, positive reciprocity, and openness to experience have a strong positive correlation with the average

number of emptying. However, households that show more trust, are altruistic, conscientious, and emotionally stable exhibit the tendency to reduce unsorted waste bins over time. Moreover, it is worth mentioning that we speculate about the interpretations given to our predictor variables due to the lack of causal evidence to explain our results.

Regarding households' trust, we find that it negatively correlates with the number of emptying dedicated to unsorted waste at a 5 percent significance level. It has a significant and negative coefficient of 0.54 (Column 3). We interpret this result as a 0.54 decline in bin emptying is expected for each unit increase in the households' general trust level, holding all other explanatory variables constant. Indeed, it follows that households with higher levels of general trust tendencies, whether in public administrations or other people, are likely to be more compliant and exhibit socially desirable behaviors. This finding is consistent with general expectations and supports existing literature, such as Nguyen et al. (2015) and Kanbar (2006), who discussed that heightened levels of trust in individuals may influence their willingness to make greater financial commitments whenever they flout waste separation regulations, hence the keen participation in waste separation programs. We can therefore appreciate that the high waste sorting rates in Bassano del Grappa (78.3 percent in 2019) cannot entirely be attributed to the existing PAYT policy. Inference from our findings indicates that the enhanced levels of trust in households encourage them to be more compliant and pollute less.

Concerning altruism, we observe a negative correlation with the number of emptying dedicated to unsorted waste at a 10 percent level of significance, indicating that households that are unselfish and care more about the welfare of others have a greater intention to reduce unsorted waste bins to minimize environmental issues. The altruism coefficient of 0.82 is negative and statistically significant, showing that a 0.82 fall in bin emptying is likely for each unit increase in the households' altruistic concern, holding all other explanatory variables constant. Typically, people who exhibit altruistic environmental attitudes show greater concern about environmentally related problems such as extreme weather events, improper disposal of waste, climate change, etc. Implicitly, the individual considers that the social marginal benefit (i.e., altruistic concern) other people receive through proper

Table 1.B.2: Correlates of households' waste sorting behavior (Pre-treatment).

Dep. Variable	(1) Emptyings Yr. = 2020	(2) Avg. Emptyings Yr. = 2020	(3) Emptyings Yrs. $\leq$ 2020	(4) ln(Emptyings) Yrs. $\leq$ 2020
Risk preference	-0.429	-0.398	-0.436	-0.021
	(0.314)	(0.416)	(0.407)	(0.040)
Time preference	0.695*	1.314**	1.428***	0.162**
	(0.395)	(0.518)	(0.499)	(0.066)
Altruism	-0.237	-0.692	-0.820*	-0.104**
	(0.371)	(0.461)	(0.451)	(0.052)
Pos. reciprocity	0.179	0.569**	0.585**	0.041
	(0.193)	(0.266)	(0.237)	(0.034)
Neg. reciprocity	-0.000	-0.060	0.002	-0.004
	(0.165)	(0.218)	(0.208)	(0.026)
Trust	-0.237	-0.676**	-0.544**	-0.052*
	(0.183)	(0.273)	(0.260)	(0.031)
Extraversion	0.551	0.800	0.783	0.080
	(0.447)	(0.824)	(0.763)	(0.078)
Agreeableness	-0.022	-0.353	-0.222	-0.060
	(0.381)	(0.493)	(0.426)	(0.058)
Conscientiousness	-0.485	-0.981*	-0.949*	-0.073
	(0.406)	(0.520)	(0.489)	(0.054)
Emotional stability	-0.623	-0.675	-0.955*	-0.097
	(0.405)	(0.583)	(0.555)	(0.060)
Openness to experience	0.840**	1.174**	1.061*	0.070
	(0.415)	(0.549)	(0.594)	(0.061)
House surface	0.621	1.866	2.008	0.327
	(1.230)	(1.397)	(1.458)	(0.205)
Household_1 member	-4.243*	-4.676*	-4.710	-0.703*
	(2.438)	(2.755)	(2.978)	(0.368)
Household_2 member	-2.710	-4.948**	-5.061**	-0.588**
	(1.709)	(2.267)	(2.379)	(0.247)
Household_3 member	-3.538**	-3.998**	-4.276**	-0.412**
	(1.578)	(1.918)	(1.950)	(0.204)
Household_4 member	-0.699	-0.758	-1.112	-0.166
	(1.429)	(1.797)	(1.806)	(0.168)
Females (fraction in hh)	-3.713*	0.160	-0.640	0.026
	(1.981)	(2.051)	(2.054)	(0.269)
Average age	0.004	0.025	0.015	0.001
	(0.042)	(0.052)	(0.062)	(0.006)
Waste collection/ weekly	18.924***	13.529***	14.939***	0.986***
	(2.925)	(3.686)	(4.443)	(0.245)
Constant	5.733	-3.536	-4.005	0.009
	(6.241)	(7.870)	(7.846)	(1.129)
Observations	96	101	342	342
R-squared	0.693	0.529	0.428	0.321

Note: *** p<0.01, ** p<0.05, * p<0.1. Table 3 reports the OLS estimates of the correlational determinants of households' waste sorting before treatment (i.e., 2017-2020). Regression 1 focuses on explanatory and outcome variables only for the year 2020. Regression 2 also accounts for explanatory variables in 2020 matched with the average emptyings for the entire pre-treatment period. Regression 3 considers all the pre-treatment periods for both the explanatory and outcome variables. Column 4 takes the log-transformed dependent variable regressed on the explanatory variables. All standard errors reported in parentheses are clustered by household to account for serial correlation. Big Five personality traits are standardized.

waste sorting and less waste accumulation outweighs the private marginal cost incurred by him/her. Consequently, with the knowledge that general environmental issues pose a threat

to the welfare of others, we can understand that people with great altruistic environmental concerns would reduce the number of unsorted waste bins and also minimize total waste generation. This intuition supports our findings and previous literature, such as Arbués & Villanúa (2016) who posit that the key to what influences the recycling of batteries is households' level of environmental concern (see also, Bamberg & Möser, 2007; Miafodzyeva & Brandt, 2013).

Similarly, conscientiousness is negatively correlated with bin emptying, where the coefficient of 0.95 is negative and statistically significant at 10 percent. This implies that for each unit increase in the level of households' conscientiousness, we expect a 0.95 decline in bin emptying, holding all other explanatory variables constant. As discussed by John et al. (1999), people who portray a high level of conscientiousness are described by goal-driven behaviors that enable them to scrutinize self-actions thoroughly and comply with rules and norms. Hirsh (2010) also reiterates that people with an elevated level of conscientiousness adapt to socially and environmentally desirable behaviors and norms. Also, existing literature like Duckworth et al. (2012) points to the link between conscientiousness and wealth, where people with high conscientiousness are greatly endowed with wealth, hence a higher tendency to emit more carbon and other pollutants. In the same vein, we can appreciate the tendency for households in Bassano del Grappa to reduce the number of unsorted waste emptying, but at an increasing rate since the wealthier are likely to generate more waste.

Moreover, emotional stability exhibits a weak negative association with the number of emptying at a 10 percent level of significance. This suggests that high emotional stability (i.e., low neuroticism) propels environmentally desirable behaviors such as proper waste sorting and drastic minimization of waste production. Typically, emotionally resilient households can deal with stress; however, they have a strong aversion to behaviors and activities that attract economic sanctions such as payment of fines for one's refusal to sort waste. Meanwhile, openness to experience shows a relatively significant positive relationship with bin emptying, indicating that households with greater receptiveness to new information or experiences may exhibit higher waste generation in the absence of targeted guidance.

On the other hand, we find a strong positive correlation between time preferences and the number of emptying for unsorted waste. Table 1.B.2 shows that for each unit increase in the level of households' time preference, we expect a corresponding 1.43 increase in the bin emptying, holding all other explanatory variables constant (see column 3). This coefficient is statistically significant at 1 percent. A related concept, such as time discounting, establishes that immediate rewards attract greater value than future rewards. Connecting it to our study, we assert that households in Bassano who are more patient and willing to sacrifice something valuable today to have it in the future are likely to produce more unsorted waste. Certainly, households with this preference assign less value to the immediate environmental issues that emerge as a result of improper waste sorting and large waste accumulation; hence, the drive to increase the number of emptying for unsorted waste.

Similarly, positive reciprocity has a strong and positive coefficient of 0.59, which is statistically significant at 5 percent. We interpret this result as households with a tendency to return favors to people are likely to produce more unsorted waste. In fact, on average, the number of bins emptied increases by 0.59 for each unit increase in the tendency to positively reciprocate. Although a general question about the preference for reciprocity was asked, in a narrow sense, the intuition remains that people with positive reciprocity are expected to separate their household waste if they know that other households within the community also sort their waste. However, the result we find suggests that a higher level of cooperation due to a preference for reciprocity results in a lower commitment level in waste sorting and minimization, thus a greater intention to increase the number of emptying for unsorted waste.

The above-elaborated predictor variables in the regression model constitute the behavioral determinants that influence the number of emptying dedicated to unsorted waste at the household level. Clearly, other predictor variables presented in Table 1.B.2 show no statistical significance; hence, we remark that they cannot be considered drivers of household waste sorting.

CHAPTER 2.

Psychological and Environmental Shocks: Implications for Household Portfolio Decisions in the Aftermath of Disasters

2.1 Introduction

Natural and technological disasters have become increasingly frequent and severe worldwide, causing substantial economic and social disruptions for households, firms, and governments. In Europe, extreme weather events such as floods, storms, droughts, and heatwaves have intensified over the past decades, resulting in significant human and financial losses. Natural disasters cost EU member states an average of €12 billion annually between 1980 and 2020, affecting up to 50 million people[7]. According to the Intergovernmental Panel on Climate Change (IPCC, 2021), climate change is expected to further increase the frequency and intensity of extreme events, thereby exposing households to greater uncertainty and economic vulnerability. Beyond their immediate physical and economic consequences, disasters can have persistent effects on households' expectations, perceptions of uncertainty, and financial decision-making behavior.

A growing body of literature suggests that individuals' past experiences play an important role in shaping economic choices under uncertainty. Experience-based learning theories argue that individuals update their beliefs and preferences based on personally experienced events, particularly those associated with severe economic or psychological consequences (Malmendier & Nagel, 2011). Consequently, households exposed to disasters may become more cautious toward risky investments due to heightened perceptions of uncertainty and vulnerability. Empirical evidence supports this view. Bernile et al. (2017) show that expo-

[7]Source: European Commission, Directorate-General for European Civil Protection and Humanitarian Aid Operations (ECHO), *Overview of natural and man-made disaster risks the European Union may face – 2020 edition*, Publications Office, 2021, https://data.europa.eu/doi/10.2795/1521

sure to severe disasters leads individuals to adopt more conservative financial and corporate decisions, while Cassar et al. (2017) and P. Brown et al. (2018) find that adverse experiences influence risk preferences and investment behavior. Similarly, Takasaki (2018) documents that disaster experiences can shape long-term economic decisions through changes in subjective perceptions of risk.

Despite the growing interest in disaster experiences and economic behavior, relatively little attention has been devoted to how disaster exposure influences household portfolio allocation decisions, particularly in the European context. Existing studies have largely focused on insurance behavior, savings decisions, or general attitudes toward risk, with limited evidence on households' participation in risky asset markets and the proportion of financial wealth allocated to risky assets. Moreover, the literature provides limited evidence on whether the effects of disasters differ according to the frequency and timing of disaster exposure. A single disaster experience may influence financial behavior differently from repeated exposures, while recent disaster experiences may have different implications compared to disasters experienced many years earlier.

In addition, households may respond differently to disaster shocks depending on their personality characteristics. Personality traits influence how individuals process information, perceive uncertainty, and react to stressful events. The behavioral finance literature increasingly recognizes that stable personality traits are important determinants of financial decision-making and risk-taking behavior (Nosić & Weber, 2010; S. Brown & Taylor, 2014). In particular, conscientious individuals may respond to adverse events in a more disciplined and forward-looking manner, while neurotic individuals may be more emotionally sensitive to uncertainty and negative experiences. Therefore, personality traits may moderate the relationship between disaster exposure and risky financial decisions.

Against this background, this study addresses four main research questions. First, does disaster exposure affect households' participation in risky asset markets and the share of financial wealth invested in risky assets? Second, do repeated disaster experiences exert stronger effects on risky financial decisions compared to a single exposure? Third, does the

timing of disaster exposure matter for household portfolio allocation decisions? Finally, do personality traits moderate the relationship between disaster exposure and risky financial behavior?

To answer these questions, the study uses longitudinal household-level data from the Survey of Health, Ageing and Retirement in Europe (SHARE), combined with disaster information from the Emergency Events Database (EM-DAT). The analysis utilizes the full available SHARE panel covering the period from 2004 to 2019 across participating European countries. The analysis focuses on two dimensions of risky financial behavior: risky asset holding and risky asset share. Disaster exposure is measured using three alternative indicators: a binary disaster exposure measure, cumulative disaster exposure, and the timing of disaster exposure. The study further incorporates the Big Five personality traits to examine whether stable psychological characteristics condition households' responses to disaster shocks. Consistent with the psychology literature, personality traits are treated as relatively stable characteristics over the adult life cycle (Costa Jr & McCrae, 1992).

The empirical findings indicate that disaster exposure generally reduces households' participation in risky financial assets, with cumulative disaster experiences exerting stronger and more persistent effects than simple binary exposure measures. The results further show that long-term disaster exposure is associated with lower risky asset participation, suggesting that repeated or prolonged exposure to adverse events may increase financial caution among households. In addition, personality traits play an important moderating role. In particular, conscientiousness mitigates the negative effect of disaster exposure on risky asset participation, while neuroticism shows weaker evidence of amplifying the adverse effects of disaster experiences. These findings suggest that households' financial responses to disasters depend not only on the nature of disaster exposure but also on underlying psychological characteristics.

This study contributes to the literature in three important ways. First, it contributes to the literature on disaster exposure and household finance by examining how disaster experiences affect both the extensive margin of risky asset participation and the intensive margin

measured by risky asset share. Second, the study extends the experience-based learning literature by considering multiple dimensions of disaster exposure, including binary exposure, cumulative exposure, and the timing of exposure. This provides evidence on the dynamic nature of disaster experiences and financial decision-making. Third, the study contributes to the behavioral finance literature by examining whether personality traits moderate households' financial responses to disaster shocks.

The remainder of the chapter is organized as follows. Section 2.2 reviews related literature. Section 2.3 describes data and empirical methodology. Section 2.4 presents empirical results, while Section 2.5 concludes.

2.2 Literature Review

In this section, we provide a structured review of the relevant literature that relates to the topic of this paper. The literature review is divided into three subsections. First, we examine the existing research on the impact of past disaster occurrences on household financial decision-making, specifically focusing on risky asset holdings and equity shares. Second, we explore the relationship between personality traits and disaster experience. Third, we review prior studies on the relationship between personality traits and participation in risky asset investments.

2.2.1 Disaster Experience and Risky Asset Participation

Individuals' inclination to participate in the risky asset market, such as allocating a fraction of their wealth to buy stocks, bonds, mutual funds, or other unstable financial instruments, is very crucial when making financial decisions. Investors do not make financial decisions in a vacuum; thus, they consider several cognitive and non-cognitive factors that may potentially cause fluctuations in the financial market. In fact, the challenges associated with the willingness to engage in risky assets are not limited to demographic and socioeconomic

characteristics such as marital status, education, gender, health status, wealth, and total income (Atella et al., 2012; Betermier et al., 2012; Christiansen et al., 2010; Campbell, 2006), but other factors such as risk attitude (Barasinska et al., 2012), expectations of future risky asset market performance (Hurd et al., 2011; Malmendier & Nagel, 2011), cognitive abilities (Christelis et al., 2010), and personal experiences such as economic shocks, disease onset, natural hazards, crime, etc. may change people's behavior and preferences (Malmendier & Nagel, 2016; Fung & Carstensen, 2006; Weinstein, 1989).

Malmendier et al. (2017), posit that the experiences individuals accumulate throughout their lives significantly influence their investment choices. Specifically, there is evidence to suggest that individuals tend to give more weight to their own experiences of macroeconomic shocks when forming their beliefs and making decisions regarding investments. These findings underscore the importance of considering lifetime experiences as a crucial factor in understanding individuals' investment behaviors. Experiencing catastrophic events such as living through periods of economic downturns like the Great Depression or being exposed to high inflation can have a profound impact on people's expectations, which may then affect their willingness to invest in stocks. This insight, emphasized by Malmendier & Nagel (2016), suggests that these adverse experiences can influence economic actors' attitudes about stock holdings, potentially resulting in increased aversion to engaging in such financial investments.

Similarly, Malmendier & Nagel (2011) demonstrate a connection between individuals' past stock market experiences and their propensity to invest in future stocks, while Kaustia & Knüpfer (2008) propose a similar relationship for experiences with the initial public offering (IPO). Similarly, lingering investment slumps are prevalent in post-severe recessions (see Kozlowski et al., 2015). Regarding financial crisis-related experiences, Blanchard (2009) argues that the recent financial crisis has left lasting damage, which might impact both demand and supply for an extended period. This aligns with empirical evidence indicating that people's risk-taking behavior and long-term attitudes can be altered by their experiences with macroeconomic shocks (see Li & Liu, 2021). In our analysis, we explore investors' risk-taking in portfolio choice following experiences with environmental shocks across most European countries.

Another promising but so far unexplored strand of literature is on whether experiences with environmental disasters can also help to explain the limited participation puzzle in the risky asset market. Our main focus is to examine the impact of past experiences with natural and technological disasters on risky asset holdings and equity shares at the household level. Prior empirical studies investigated the relationship between natural disasters and risky asset participation. Bharath & Cho (2023) utilized data from the National Longitudinal Survey of Youth 1979 and the Federal Emergency Management Agency (FEMA) disaster database to investigate the impact of accumulated natural disaster experiences on households' decisions regarding portfolio choice. They find that households who have been affected by disasters tend to become less risk-tolerant and revise down their expectations of future stock market returns, hence less likely to engage in risky asset markets. The authors add that, interestingly, even after relocating to areas with lower disaster risks, households continue to make conservative portfolio choices, indicating a lasting influence of disaster experiences on risk preferences.

Moreover, Auh et al. (2022) investigate the impact of natural disasters due to climate change on municipal bond returns. The authors' findings reveal that uninsured bonds experience a slow decline in returns in the weeks after a disaster, averaging 0.31 percent. This decline translates to substantial investor losses of nearly $10 billion. Moreover, Gao et al. (2022) examined how strict climate change regulation increases labor income risk for households employed in high-emission industries, subsequently discouraging their willingness to take financial risks. The authors find that the execution of climate change action plans accounts for a 15 percent decrease in the proportion of risky assets held by households in high-emission industries. In addition, they identify a reduction in risky asset holdings following the implementation of strict EPA regulations. These findings are reinforced by the presence of climate change-related disasters. Following the works of Bharath & Cho (2023) and Fung & Carstensen (2006), we analyze a longitudinal dataset sourced from SHARE and EM-DAT that covers most European countries to examine how past natural and technological disaster experiences of older people exert influence on their willingness to engage in risky assets.

In conclusion, recent research indicates that individuals' engagement in risky assets may be significantly impacted by their experiences with disasters. Changes in socioeconomic and demographic factors, emotional reactions, and attitudes towards risk are just a few ways that the effects may show. The findings from this study in the European context can help financial institutions and policymakers to develop focused initiatives that support financial resilience and entice people to engage in risky assets even in the face of adversity.

2.2.2 Personality Traits and Disaster Experience

Past empirical studies have examined the relationship between personality traits and adverse life events. In this study, we consider the Big Five personality traits—conscientiousness, extraversion, neuroticism, openness to experience, and agreeableness—as fundamental characteristics that distinguish individuals in terms of behavior, emotional responses, and decision-making under uncertainty. These personality dimensions are particularly relevant in understanding how individuals perceive risk and respond to stressful experiences such as natural and technological disasters. According to Roberts & Mroczek (2008), personality traits represent relatively stable patterns of thoughts, emotions, and behaviors that differentiate individuals from one another over the life cycle.

Although personality traits are generally considered stable during adulthood, prior studies suggest that major adverse life events may influence how these traits are expressed or manifested in response to stressful experiences. Existing evidence on the relationship between disaster exposure and personality traits remains relatively limited and mixed. Milojev et al. (2014) examined the impact of the 2010/2011 Christchurch earthquakes on personality traits using longitudinal data from New Zealand residents affected and unaffected by the earthquakes. Their findings indicate that personality traits remained largely stable over the two years, although individuals exposed to the earthquakes exhibited a slight decline in emotional stability compared to unaffected individuals. Similarly, Damian et al. (2021) investigated the effect of hurricane exposure on personality development and found limited evidence that disaster exposure significantly altered personality trajectories over time.

Consistent with these findings, several studies document substantial stability in personality traits even after exposure to stressful life events. Forgeard et al. (2022) provide evidence that openness to experience generally remains stable following adversity, while Costa Jr et al. (2000) and Boals et al. (2015) report stability in neuroticism and conscientiousness across adverse circumstances. Specht et al. (2011) also emphasize that personality traits exhibit considerable rank-order stability over the life course despite major life events. Together, these findings suggest that although adverse experiences may influence short-term emotional responses, core personality characteristics tend to remain relatively persistent over adulthood.

Nevertheless, some studies suggest that traumatic events may still influence certain dimensions of personality. Löckenhoff et al. (2009) find that individuals who experienced extremely frightening life events exhibited higher levels of neuroticism and lower openness to values. Similarly, Boals et al. (2015), Bleidorn et al. (2018), Jeronimus et al. (2013), and Ogle et al. (2013) document that adverse life experiences may be associated with increases in neuroticism. DeYoung (2015) further argues that openness to experience reflects individuals' tendency toward cognitive exploration and receptiveness to new information, implying that stressful experiences may shape how individuals interpret and respond to uncertainty in their environment.

Overall, the literature suggests that while personality traits are generally stable over the adult life cycle, they may still play an important role in shaping how individuals perceive and respond to adverse experiences. This is particularly relevant in the context of household financial decision-making under uncertainty. Individuals with different personality characteristics may respond differently to disaster exposure depending on their ability to process risk, regulate emotions, and adapt to stressful situations. For example, conscientious individuals may respond to adverse shocks in a more disciplined and forward-looking manner, while highly neurotic individuals may be more emotionally sensitive to uncertainty and negative experiences. Consequently, personality traits may moderate the relationship between disaster exposure and households' participation in risky financial assets.

2.2.3 Personality Traits and Risky Asset Participation

Regarding the relationship between personality traits and risky asset participation, we review prior empirical research on all economic-related outcomes. Based on a survey on personality psychology and economics, Almlund et al. (2011) investigate the power of personality traits in predicting and influencing various aspects of life, including academic and economic success, health, and criminal activity. They argue that for many outcomes, personality measures are just as predictive as cognitive measures such as IQ and achievement tests, even after controlling for family background and cognition. A study conducted by Rustichini et al. (2016) demonstrates that for several life and economic outcomes, comprising credit score, heavy truck accidents, job persistence, smoking habit, and Body Mass Index (BMI), personality traits have a statistically significant predictive power that is comparable to or greater than economic preferences.

Turning to the influential role of personality traits in predicting portfolio choice decisions, Bucciol & Zarri (2017) investigate whether personality traits influence investors' portfolios using large survey data from the US Health and Retirement Study (HRS) spanning from 2006 to 2012. Their findings indicate that three personality traits, namely agreeableness, cynical hostility, and anxiety, have a significant negative correlation with the holding and amount of stock assets. Overall, they demonstrate that individuals' decisions regarding their investment portfolios are shaped by various stable traits and facets commonly explored in the field of personality psychology. Conlin et al. (2015) document that personality traits–and particularly their subscales–are important predictors of stock market participation. They emphasize that exploratory excitability, extravagance, sentimentality, and dependence in particular have significant effects.

S. Brown & Taylor (2014) focus on the link between personality traits at the individual level and within couples and unsecured debt and financial assets. They document that certain traits like extraversion typically show a relatively large correlation with household levels of debt and assets held. Specifically, extraversion in the individual sample shows a statistically significant positive association with debt, while there exists a relatively large

inverse correlation with assets held in the couples' sample. Motivated by this empirical evidence, we examine whether personality traits moderate the relationship between disaster exposure and households' participation in risky assets. Specifically, we investigate whether stable personality characteristics influence how households adjust their portfolio allocation decisions following disaster exposure.

2.3 Data Overview

In this study, we investigate how exposure to disasters influences households' risky investment decisions. Specifically, we examine whether disaster exposure affects households' participation in risky asset markets and the share of financial wealth allocated to risky assets. We further explore whether these effects vary according to the frequency and timing of disaster exposure and whether stable personality traits moderate households' financial responses to disaster-related shocks. To conduct the analysis, we compile geocoded data on natural and technological disasters, household investment portfolio decisions about risky asset holdings and shares, and Big Five personality traits.

The first data source used for this study is the Emergency Events Database (EM-DAT), a global dataset compiled from information provided by United Nations agencies, the United States Office of Foreign Disaster Assistance, national governments, the International Federation of Red Cross and Red Crescent Societies, non-governmental organizations, insurance companies, research institutes, and the media. EM-DAT provides core data on the occurrence and effects of more than 22,000 natural and technological disasters worldwide from 1900 to the present[8]. According to the Centre for Research on the Epidemiology of Disasters, a disaster is defined as "a situation or event that overwhelms local capacity, necessitating a request at the national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction, and human suffering." For a disaster to be included in EM-DAT, it must satisfy at least one of the following criteria: ten or more deaths, one hundred or more people affected, declaration of a state of emergency, or a call

[8]The EM-DAT data are available at https://www.emdat.be/.

for international assistance. Natural disasters include catastrophic events of meteorological, hydrological, geophysical, or climatological origin, such as earthquakes, floods, tsunamis, droughts, and storms. Technological disasters are classified into industrial, transport, and miscellaneous accidents, including road accidents, industrial pollution, factory fires, explosions, and chemical spills.

The Survey of Health, Ageing, and Retirement in Europe (SHARE), a cross-national longitudinal dataset with at least 140,000 participants coordinated by the Munich Center for the Economics of Aging (MEA), is the second major data source used in this study.[9] SHARE is based partly on the English Longitudinal Study of Ageing (ELSA) and the U.S. Health and Retirement Study (HRS). It covers the adult population aged 50 and above and their spouses, who can be any age. Since its inception in 2004, the survey has been carried out regularly, every two years, currently in about 27 countries across Europe, including Israel. Every question is uniform across all countries. The survey contains comprehensive information collected at the individual level, predominantly through face-to-face interviews on personality traits, cognitive skills, and socio-demographic characteristics, among others. However, a household may designate one person as the finance respondent who would respond to questions about assets and financial transactions on behalf of the whole household.

The analysis uses the available SHARE panel to examine how disaster exposure relates to household risky asset decisions over time. Personality traits are observed in selected SHARE waves and are incorporated into the analysis as stable individual characteristics after assessing their relative stability across waves. It is worth adding that SHARE also provides multiple imputations to reduce data loss arising from non-response. The imputation module for each SHARE wave includes five sets of data, each of which represents a different draw from the distribution of missing values. For example, if a participant fails to reveal his annual amount spent on food consumption, the imputation approach produces five estimates taking into consideration his other qualities, the amount spent on food intake, and the characteristics of other participants. For our analysis, we used the intermediate estimates generated by the imputation method.

[9]The SHARE data can be found at https://share-eric.eu/data/.

The Big Five Inventory-10 (BFI-10) measure utilized in the SHARE survey aligns with the full five-factor model (FFM) of personality, both in the overall SHARE sample and in most individual countries. It comprises 10 items, as per the approach outlined by Rammstedt & John (2007), and assesses the five broad personality dimensions, commonly referred to as the "Big Five," with two facets for each dimension. Within each pair of items representing a specific dimension, one item is formulated in a positive direction, while the other is formulated in a negative direction. Participants rated their agreement with 10 questions on a five-point Likert-type scale, ranging from 1 (fully disagree) to 5 (fully agree), reflecting their true personality (refer to Table 2.A.2 in Appendix 2.A for the complete questions). Each variable was computed as the mean of the respective pair of items (one item was reverse-coded). The two facets for each trait encompass openness to experience (e.g., few interests, imagination), conscientiousness (e.g., lazy, thorough), extraversion (e.g., reserved, outgoing), agreeableness (e.g., generally trusting, find fault with others), and neuroticism (e.g., relaxed, nervous). According to SHARE data, the reliability of the two facets within each trait showed slight variation, as indicated by the Spearman-Brown coefficients: openness to experience (0.45), conscientiousness (0.50), extraversion (0.53), agreeableness (0.39), and neuroticism (0.67). Figure 2.1 displays the regional pattern of the Big Five personality traits across European countries. It is evident that the score of the conscientiousness trait is noticeably high, while the neuroticism trait appears to be the lowest, with average scores among the four regions. This suggests that most individual households across countries in Europe feel that they are more thoughtful and disciplined and exhibit the ability to regulate impulse control to engage in goal-directed behaviors.

We matched the compiled dataset from both EM-DAT and SHARE in terms of the date and location of the events and interviews. Concerning the date, we consider the start year and month, while for location, we use the first-level nomenclature of territorial units for statistics (NUTS 1) to manually match the two datasets. As sample restrictions, we focus on household members aged between 50 and 100 years and all participants whose years of education are 25 or less, and to control for country fixed effects, we use Austria and

Germany as reference categories.[10] The analysis utilizes the full available SHARE panel spanning the period from 2004 to 2019, thereby allowing households to be followed over multiple survey waves. It is worth noting that our dataset has a panel structure, although the panel dimension is small. A repeated cross-sectional dataset is suitable since our main objective is to examine how households' economic decisions change after the occurrence of disasters and whether changes in personality also contribute to the decision, isolated from time disturbances. In the quest to perform cross-sectional analysis and, by extension, correct the serial correlation across observations, we use standard errors clustered at the household level.

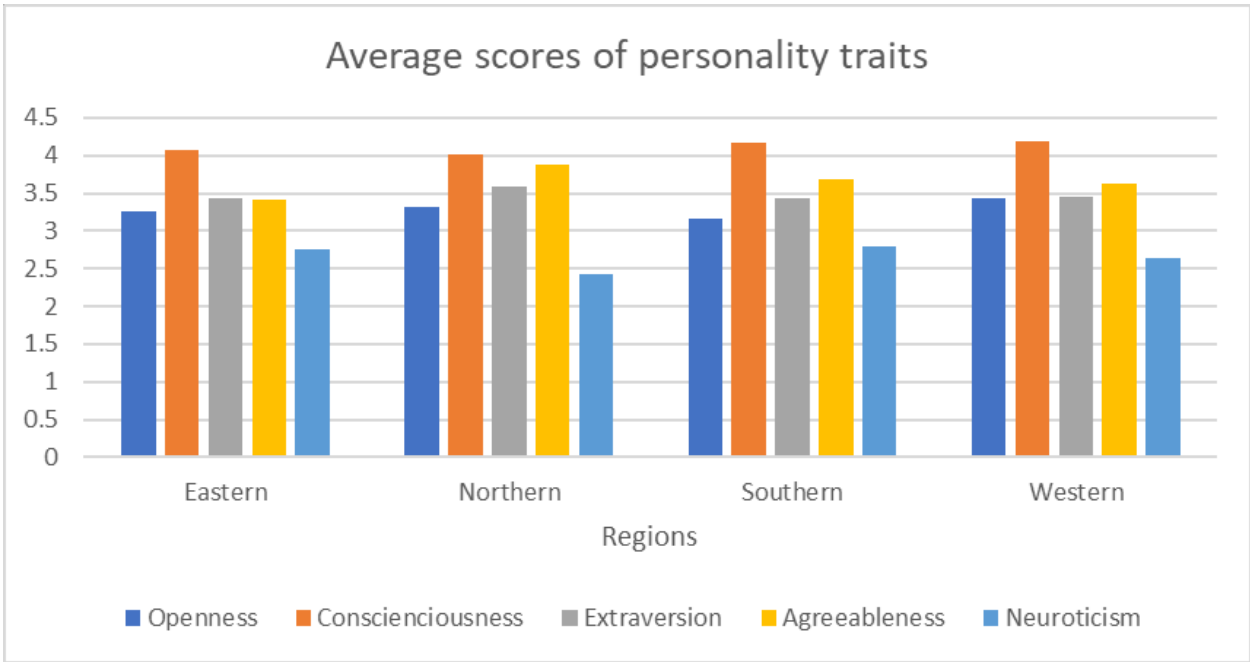


Figure 2.1: Distribution of the Big Five Personality Traits by Region

Figure 2.2 depicts the average frequency of disaster occurrence in the countries we analyze. The distribution shows that there is a considerable variation in disaster occurrences across countries. In our sample, the frequency of disasters ranges from 0.13 in Germany and France to 0.67 in Slovakia. In general, countries in the Eastern and Southern regions of Europe are

[10] Among the countries, Austria and Germany have the least cumulative frequency of past disaster occurrences. The countries included as controls for our analysis are Sweden, the Netherlands, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Israel, the Czech Republic, Poland, Luxembourg, Hungary, Portugal, Slovenia, Estonia, Croatia, Lithuania, Bulgaria, Cyprus, Finland, Latvia, Malta, Romania, and Slovakia.

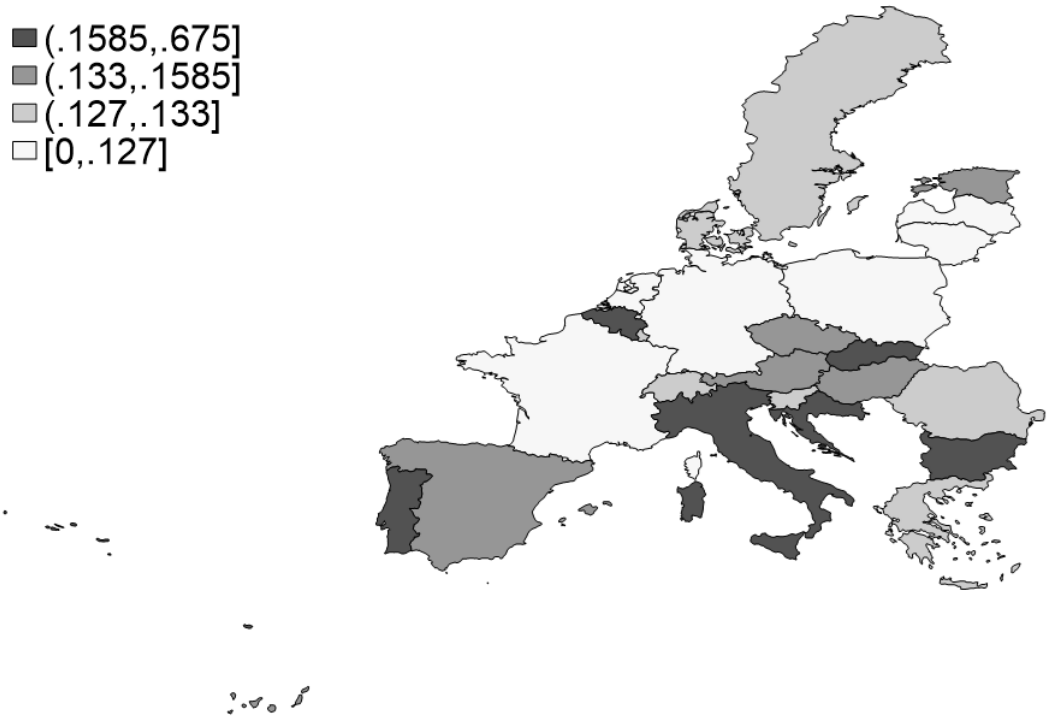


Figure 2.2: Distribution of average disaster occurrences.

more prone to disaster occurrence compared to the Northern and Western regions, which are relatively more disaster-resistant. Moreover, the length of disaster occurrence in the Southern part of Europe appears to be relatively high compared to the Northern part, where disasters last for a shorter period. A few plausible causes for the observed regional variations in disaster occurrence may be attributed to natural hazards, disaster preparedness, and socioeconomic conditions in various regions. Thus, it is revealing that disaster management ought to be prioritized in locations with a higher incidence of disasters.

Figure 2.3 illustrates the spatial distribution of risky asset holdings across SHARE countries (excluding Israel). The data reveal significant heterogeneity, with proportions ranging from a mere 0.8 percent of households holding risky assets in Romania to a substantial 64 percent in Sweden. Notably, the share of financial portfolios invested in risky assets displays a strong correlation with the prevalence of risky asset holdings. Western and Northern European countries show notably higher proportions of risky asset holdings compared to their Southern and Eastern counterparts. This variation could be related to several factors, including differences in the development of the financial sector and the impact of frequent

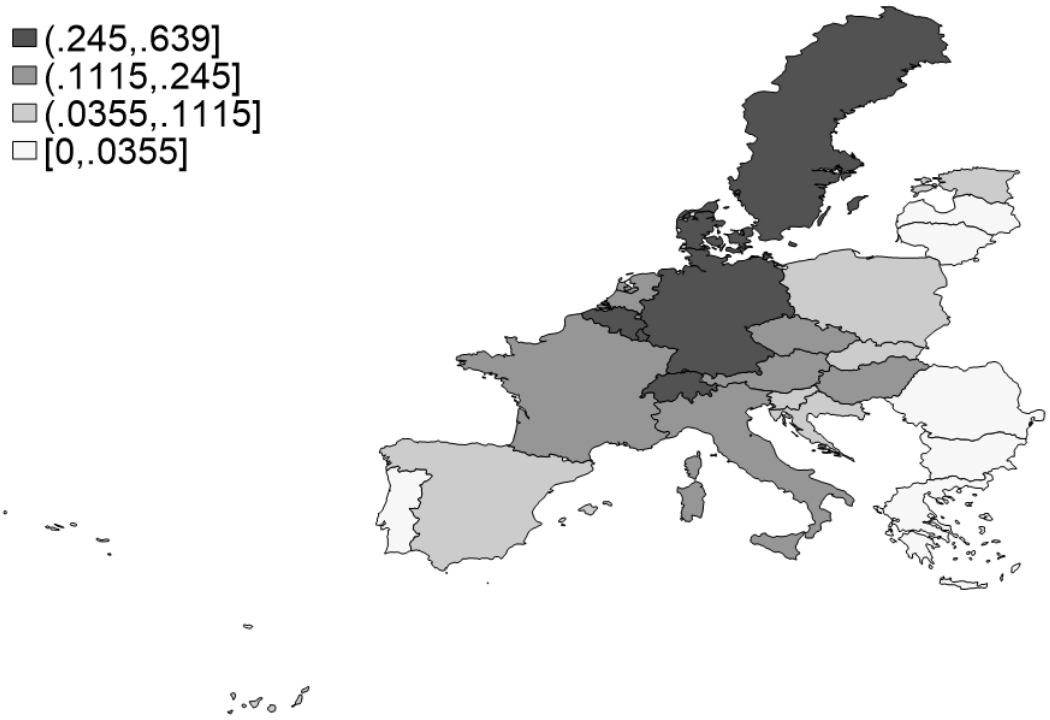


Figure 2.3: Distribution of risky asset participation.

disaster occurrences leading to changes in personality traits and risk attitudes, among other potential reasons. It is, therefore, crucial for policymakers to expand financial inclusion and education initiatives. Financial institutions could encourage households, particularly in Romania, to employ risk-appropriate asset allocation through programs that aim to advance financial literacy and widen access to investment opportunities. Moreover, countries with greater proportions of people holding risky assets, like Sweden (64 percent), may need to make sure the environment is favorable for investments. To retain investor confidence and draw in more risk-taking investors, policymakers should concentrate on upholding stable financial markets, open regulations, and investor protection.

Table 2.1 presents the summary statistics for the key variables used in the analysis, categorized into dependent variables, personality traits, and explanatory variables. The mean values of each variable in two sub-samples for households exposed to disasters and those without disaster exposure are compared in Table 2.1. In addition, the table reports the results of a statistical t-test on the equality of the averages in the two sub-samples, as shown in the last column. This straightforward analysis shows systematic differences among

most of the variables under the experience of past disaster. This variation could simply be the result of comparing two sub-samples of households each time, each with different attributes. This possible issue is addressed in Section 2.4's analysis, which also examines, among other things, the relationship between disaster experiences and personality traits while controlling for the observable characteristics of the household.

Table 2.1: Summary statistics

	Full sample		Disaster exposure	No exposure	
Variables	Mean	Std. dev.	Mean	Mean	Test
Dependent variables					
Risky asset holding	0.281	0.449	0.3	0.271	-8.438***
Risky asset share	0.137	0.276	0.145	0.133	-6.095***
Personality traits					
Openness to experience	3.313	0.964	3.3	3.319	3.212***
Conscientiousness	4.104	0.794	4.116	4.097	-3.857***
Extraversion	3.496	0.935	3.497	3.496	-0.15
Agreeableness	3.712	0.808	3.683	3.726	8.467***
Neuroticism	2.602	1.009	2.63	2.589	-6.650***
Explanatory variables					
Disaster experience (dummy)	0.328	0.469	1	0	.
Cumulative disaster experience (count)	1.086	1.077	1.849	0.714	-195.672***
Age	69.025	9.308	68.418	69.321	15.669***
Age2	4851.133	1320.723	4765.217	4893.009	15.623***
Gender	0.429	0.495	0.438	0.424	-4.672***
Household size	1.962	0.958	1.99	1.948	-6.933***
Ifchild	0.918	0.275	0.914	0.92	3.501***
Married	0.608	0.488	0.623	0.601	-7.362***
University	0.161	0.367	0.167	0.158	-3.943***
Income	1190.296	1.05E+05	39.439	1794.216	2.143**
Observations	74,298	74,298	26,300	47,998	

Note: Monetary values are in thousand euros and PPP-adjusted. The last column reports the t-test on the equality of the mean between households that have disaster exposure and those without disaster exposure. The alternative hypothesis indicates that the means are different. *** p<0.01, ** p<0.05, * p<0.1

Our dependent variables include risky asset holdings and shares. For this study, we measure risky asset share as a fraction of households' total net financial wealth invested in stocks, bonds, and mutual funds. Clearly, this measure is subject to monetary amounts and may potentially suffer from two main drawbacks because the investments are recorded at the time of the interview. The first potential issue that may arise, according to Calvet et al. (2009), is that households may not modify their investment portfolio regularly; hence, we

may attribute the observed changes in asset shares to the volatility in the financial market, particularly for stock prices (i.e., changes in the exchange rate or financial market easily influence the number of stock holdings). The second drawback relates to a measurement error that emanates from the fact that households may be oblivious to the actual amount of their investment and its allocations across different portfolios. However, risky asset holding, which is a binary indicator for whether households hold risky assets or otherwise, does not suffer from the aforementioned issues; hence, we direct much attention to this outcome variable in our analysis.

The summary statistics indicate that approximately 28.1 percent of households participate in risky asset markets, while the average risky asset share is 13.7 percent. Households exposed to disasters exhibit higher risky asset participation and risky asset shares on average compared to households without disaster exposure. Specifically, the mean risky asset participation for disaster-exposed households is 30 percent, compared to 27.1 percent for non-exposed households. Similarly, disaster-exposed households report a higher average risky asset share of 14.5 percent relative to 13.3 percent among households without disaster exposure. The mean differences between the two groups are statistically significant at the 1 percent level.

Turning to the Big Five personality traits, conscientiousness records the highest average score among the Big Five personality dimensions, with a mean value of 4.1, while neuroticism exhibits the lowest average score of 2.6. The results further show statistically significant differences in several personality traits between households exposed to disasters and those without disaster exposure. Disaster-exposed households exhibit slightly lower levels of openness to experience and agreeableness but higher levels of conscientiousness and neuroticism. In contrast, no statistically significant difference is observed for extraversion between the two groups.

The summary statistics also reveal notable differences in demographic and socioeconomic characteristics across disaster exposure groups. Approximately 32.8 percent of households in the sample experienced at least one disaster event during the study period. The aver-

age cumulative disaster exposure is 1.086 disaster events, while disaster-exposed households report substantially higher cumulative exposure than non-exposed households. Disaster-exposed households also tend to be relatively younger on average, with lower average age and age-squared values compared to households without disaster exposure.

In terms of household characteristics, disaster-exposed households are slightly more likely to be male, married, university-educated, and living in larger households. The results further indicate that households exposed to disasters are more likely to have children in the household. Income levels also differ across groups, with statistically significant differences observed between disaster-exposed and non-exposed households. This suggests that the consequences associated with disaster experience may impede attainment of university education. It is expected that individuals with a university education are well-informed about the evolution of the financial market and could diversify their investment portfolios to reduce losses. In addition, households with disaster experience have relatively lower income than households without disaster experience. Overall, the summary statistics suggest meaningful differences in financial behavior, personality traits, and socioeconomic characteristics between households exposed to disasters and those without disaster exposure, highlighting the importance of controlling for these factors in the empirical analysis.

2.3.1 Model Specifications

To examine how disaster exposure influences households' risky financial behavior, this study uses household-level data across all the waves from the SHARE database. The empirical framework is motivated by the household finance literature, which emphasizes that adverse experiences and uncertainty may influence financial risk-taking behavior and portfolio allocation decisions (Malmendier & Nagel, 2011; Guiso et al., 2018; Bernile et al., 2017). In particular, exposure to disasters may alter households' perceptions of risk and future uncertainty, thereby affecting participation in risky asset markets and the proportion of wealth invested in risky financial assets.

The analysis focuses on two dimensions of risky financial behavior. The first dependent

variable is risky asset holding, which captures the extensive margin of participation by indicating whether a household holds risky financial assets. The second dependent variable is risky asset share, which measures the proportion of household financial wealth allocated to risky assets and captures the intensive margin of financial risk-taking. Examining both outcomes provides a more comprehensive understanding of how disaster exposure influences household portfolio decisions.

Following previous studies examining the determinants of household risky asset participation (Guiso & Paiella, 2008; Bucciol & Zarri, 2017; S. Brown & Taylor, 2014), we estimate the following baseline specification:

$$Y_{it} = \alpha_0 + \alpha_1 Disaster_{it} + \beta X_{it} + \delta_i + \lambda_t + \varepsilon_{it} \tag{2.1}$$

where Y_{it} represents either risky asset holdings or risky asset share for the household i in wave t. $Disaster_{it}$ denotes disaster exposure. X_{it} is a vector of household-level control variables, including age, age squared, gender, household size, presence of children in the household, marital status, university education, and household income. δ_i represents country fixed effects, while λ_t captures wave fixed effects to account for macroeconomic and survey-period shocks common across households. The error term is represented by ε_{it}, and standard errors are clustered at the household level to account for serial correlation within households over time.

To comprehensively capture disaster exposure, the study employs two alternative measures in the baseline analysis. First, we use a binary disaster exposure indicator ($After_event$) equal to one if the household experienced at least one disaster event and zero otherwise. This measure captures the general effect of disaster experience on household financial behavior. Second, we employ a cumulative disaster exposure variable ($Disaster_count$), which measures the total number of disaster experiences accumulated by the household over time. This specification allows us to examine whether repeated disaster exposure generates stronger behavioral responses than a single disaster experience. The cumulative exposure approach is consistent with the experience-based learning literature, which argues that repeated ad-

verse experiences may exert persistent effects on economic expectations and risk perceptions (Malmendier & Nagel, 2011; Kuchler & Zafar, 2019).

Beyond the direct effect of disaster exposure, this study further examines whether personality traits moderate households' financial responses to disaster-related shocks. The moderation framework is motivated by the psychology and behavioral finance literature, which suggests that stable personality characteristics shape individuals' attitudes toward uncertainty, emotional regulation, and financial decision-making (Costa Jr & McCrae, 1992; Cobb-Clark & Schurer, 2012; Nosić & Weber, 2010). Specifically, conscientious individuals may respond to adverse shocks more cautiously and strategically, while highly neurotic individuals may exhibit stronger emotional reactions to uncertainty.

To evaluate the moderating role of personality traits, we augment Equation (1) with interaction terms between disaster exposure and the Big Five personality traits as follows:

$$Y_{it} = \alpha_0 + \alpha_1 Disaster_{it} + \alpha_2 Personality_i + \alpha_3 (Disaster_{it} * Personality_i) + \beta X_{it} + \delta_i + \lambda_t + \varepsilon_{it} \quad (2.2)$$

where $Personality_i$ represents the standardized Big Five personality traits, including openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. The coefficient on the interaction term, α_3, captures whether the effect of disaster exposure varies according to household personality characteristics. A statistically significant interaction coefficient indicates that personality traits condition households' financial responses to disaster exposure.

Consistent with the psychology literature, personality traits are treated as relatively stable individual characteristics over adulthood (Roberts & Mroczek, 2008; Specht et al., 2011). Correlation analysis across SHARE waves further supports the relative stability of the personality measures used in this study (see Table 2.A.1 in Appendix 2.A). To facilitate interpretation and comparability across traits, all personality variables are standardized before the estimation.

To further examine whether the effect of disaster exposure differs depending on the timing of exposure, we conduct a heterogeneous-effects analysis based on the number of years since the most recent disaster event. Specifically, disaster exposure is categorized into short-term exposure (0–2 years), medium-term exposure (3–5 years), and long-term exposure (6 or more years). This specification allows us to assess whether households respond differently to recent versus more distant disaster experiences.

The timing-based heterogeneous specification is estimated as follows:

$$Y_{it} = \alpha_0 + \alpha_1 D_{it}^{0-2} + \alpha_2 D_{it}^{3-5} + \alpha_3 D_{it}^{6+} + \alpha_1 Disaster_{it} + \beta X_{it} + \delta_i + \lambda_t + \varepsilon_{it} \tag{2.3}$$

where D_{it}^{0-2}, D_{it}^{3-5}, and D_{it}^{6+} represent indicators for disaster exposure occurring within 0–2 years, 3–5 years, and 6 or more years prior to the survey period, respectively. Households without prior disaster exposure serve as the reference group. This approach is consistent with studies emphasizing the persistence and salience of past adverse experiences in shaping economic behavior (Bernile et al., 2017; Malmendier & Nagel, 2011).

Finally, to assess whether personality traits moderate the timing effects of disaster exposure, we estimate interaction models between personality traits and the timing categories of disaster exposure. This allows us to examine whether personality characteristics influence households' short-run and long-run financial responses differently following disaster experiences. It is also worth mentioning that one of the limitations of the estimator is that the dependent variable has to be binary. As a robustness check, we replicate the benchmark analysis for the share of risky assets using a fractional response probit model (see Papke & Wooldridge, 1996) with standard errors robust to heteroskedasticity and a probit model for the probability of holding risky assets. We also enrich the benchmark specification by introducing the different types of disasters and additional covariates about the nature of disaster occurrence.

2.4 Results and Discussion

Our analyses begin in subsection 2.4.1 by investigating the relationship between risky asset decisions and disaster exposure. In subsection 2.4.2, we analyze the role of personality traits and the moderating effect of disaster exposure. Lastly, in subsection 2.4.3, we examine the timing heterogeneity in disaster exposure and risky financial decisions.

2.4.1 Direct Effects of Disaster Exposure on Risky Asset Decision

Table 2.2 presents the baseline estimates of the relationship between disaster exposure and household risky asset decisions. The analysis considers two measures of disaster exposure: a binary indicator for whether a household has experienced a disaster and a cumulative measure capturing the number of disaster experiences. The results are reported separately for two dependent variables: risky asset holding, which captures the extensive margin of participation in risky asset markets, and risky asset share, which captures the intensive margin of portfolio allocation.

The estimates show that the binary disaster exposure variable is negative across both risky asset holding and risky asset share, but the coefficients are small and statistically insignificant. For risky asset holding, the estimated coefficient is approximately -0.004, while for risky asset share, the coefficient is approximately -0.002. These results suggest that simply distinguishing households based on whether they have ever experienced a disaster may not be sufficient to capture meaningful differences in risky financial behavior. This finding is important because it indicates that the effect of disaster exposure may not operate through a simple treated-versus-untreated distinction. Instead, the behavioral consequences of disaster experience may depend on the intensity, frequency, or timing of exposure.

Table 2.2: Benchmark Analysis

Dependent variables	Risky Asset Holding			Risky Asset Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster experience	-0.004	-0.004		-0.002	-0.002	
	(0.003)	(0.003)		(0.002)	(0.002)	
Cum. disaster experience			-0.001			-0.002
			(0.002)			(0.002)
Openness to experience		0.013***	0.013***		0.007***	0.007***
		(0.002)	(0.002)		(0.002)	(0.002)
Conscientiousness		-0.009***	-0.009***		-0.006***	-0.006***
		(0.003)	(0.003)		(0.002)	(0.002)
Extraversion		-0.003	-0.003		-0.003**	-0.003**
		(0.002)	(0.002)		(0.002)	(0.002)
Agreeableness		-0.004	-0.004		-0.001	-0.001
		(0.003)	(0.003)		(0.002)	(0.002)
Neuroticism		-0.009***	-0.009***		-0.004***	-0.004***
		(0.002)	(0.002)		(0.001)	(0.001)
Age	0.021***	0.021***	0.021***	0.023***	0.023***	0.023***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	0.023***	0.020***	0.020***	0.008***	0.007**	0.007**
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Household size	-0.010***	-0.009***	-0.009***	-0.006***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Ifchild	-0.050***	-0.049***	-0.049***	-0.035***	-0.034***	-0.034***
	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
Married	0.068***	0.070***	0.070***	0.031***	0.032***	0.032***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
University	0.115***	0.108***	0.108***	0.059***	0.055***	0.055***
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Income	0.037***	0.036***	0.036***	0.017***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.743***	-0.695***	-0.699***	-0.850***	-0.823***	-0.829***
	(0.094)	(0.096)	(0.096)	(0.058)	(0.059)	(0.059)
Observations	74,298	74,298	74,298	74,298	74,298	74,298
R-squared	0.209	0.210	0.210	0.134	0.135	0.135
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES

Note: The table reports the probability of holding risky assets (Columns 1-3), and the share of risky assets (Columns 3-4). Clustered standard errors at household level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

This result is consistent with the broader experience-based learning literature, which argues that individuals' economic behavior is shaped not merely by whether they have ex-

perienced a shock, but by the nature and intensity of that experience. Malmendier & Nagel (2011) show that individuals who lived through severe macroeconomic shocks, such as the Great Depression, are less likely to participate in stock markets later in life. However, their framework emphasizes cumulative and lived experience rather than a simple binary event indicator. Similarly, Kuchler & Zafar (2019) show that personal experiences influence beliefs about aggregate outcomes, suggesting that repeated or salient experiences may shape expectations more strongly than one-time exposure. Therefore, the weak effect of the binary disaster indicator does not necessarily imply that disasters are irrelevant for financial behavior. Rather, it suggests that the binary measure may be too coarse to capture the underlying behavioral channel.

The cumulative disaster exposure variable provides a more informative measure of disaster experience. In Table 2.2, the coefficient on cumulative disaster exposure is negative for both risky asset holding and risky asset share, although it is not statistically significant in the baseline specification. The direction of the coefficient is nevertheless consistent with the expectation that repeated exposure to disasters may reduce households' willingness to hold risky financial assets. This aligns with studies showing that adverse experiences can generate more conservative financial behavior by increasing perceived background risk and lowering expected returns from risky investments (Malmendier & Nagel, 2011; Bernile et al., 2017; Bharath & Cho, 2023).

The distinction between the binary and cumulative measures is central to the interpretation of the results. The binary measure captures whether a household has ever experienced a disaster, while the cumulative measure captures the frequency of exposure. From a behavioral perspective, repeated exposure may be more likely to influence financial decision-making because it can reinforce perceptions of vulnerability, uncertainty, and future risk. This argument is consistent with Bernile et al. (2017), who show that the intensity of early-life disaster experience matters for later risk-taking behavior. It also relates to Bharath & Cho (2023), who find that accumulated natural disaster experiences reduce household stock market participation and risk tolerance. In this sense, Table 2.2 provides an important baseline by showing that average disaster exposure effects are modest but that the direction of the

cumulative exposure effect is consistent with experience-based learning.

The results also reveal strong and consistent effects of standard household characteristics. Age has a positive and statistically significant coefficient, while age squared is negative and significant. This indicates a nonlinear relationship between age and risky asset participation: older households are more likely to hold risky assets up to a certain point, after which the effect declines. This pattern is consistent with household finance models suggesting that portfolio allocation varies over the life cycle as individuals adjust savings, investment horizons, and risk-bearing capacity (Campbell, 2006; Guiso & Paiella, 2008). Gender is positive and statistically significant, indicating that male respondents are more likely to hold risky assets and allocate a higher share of wealth to risky assets. This finding aligns with prior evidence that men tend to participate more in risky financial markets than women, partly due to differences in risk tolerance and financial confidence (Barasinska et al., 2012).

Household size and the presence of children are negatively associated with risky asset decisions. This suggests that households with greater family responsibilities may be more financially cautious, possibly because dependents increase background risk and liquidity needs. This is consistent with the broader household finance literature, which emphasizes that income risk, family structure, and precautionary motives can shape portfolio allocation (Campbell, 2006; Guiso & Paiella, 2008). In contrast, being married, having a university education, and higher income are positively and significantly associated with risky asset holding and risky asset share. These findings are expected. Education may improve financial literacy and reduce participation costs in risky asset markets, while higher income relaxes liquidity constraints and increases households' ability to bear financial risk (Christelis et al., 2010; Van Rooij et al., 2011).

Overall, the baseline results suggest that the average effect of disaster exposure on risky financial behavior is relatively modest when measured using a simple binary indicator. However, the consistently negative coefficients associated with cumulative disaster exposure provide evidence that repeated disaster experiences may gradually discourage participation in risky financial markets and reduce households' willingness to allocate wealth toward risky

assets. These findings support the experience-based learning framework, which emphasizes that repeated exposure to adverse events can shape economic expectations and financial decision-making over time. More importantly, the limited average effects observed in the baseline models suggest that households may respond heterogeneously to disaster exposure depending on underlying psychological characteristics, thereby motivating the moderation analysis.

2.4.2 Personality Traits and the Moderating Effect of Disaster Exposure

Table 2.3 examines whether personality traits shape households' risky financial behavior and whether they moderate the relationship between disaster exposure and risky asset decisions. The results are presented for both risky asset holding and risky asset share. Columns (1) and (3) focus on the interaction between the binary disaster exposure variable and the Big Five traits, while columns (2) and (4) examine the interaction between cumulative disaster exposure and the Big Five traits.

The direct effects of personality traits show that openness to experience is positively and significantly associated with both risky asset holding and risky asset share. In columns (1) and (3), a one standard deviation increase in openness is associated with a 1.2 percentage point increase in the probability of holding risky assets and a 0.7 percentage point increase in risky asset share. This finding is consistent with the behavioral interpretation of openness as a trait associated with curiosity, willingness to explore new opportunities, and greater receptiveness to financial innovation. It also aligns with previous studies showing that openness is positively related to risky financial participation and stockholding behavior (S. Brown & Taylor, 2014; Bucciol & Zarri, 2017).

Table 2.3: Moderation Analysis

Dependent variables	Risky Asset Holding		Risky Asset Share	
	(1)	(2)	(3)	(4)
Disaster experience	-0.0003		0.0002	
	(0.003)		(0.002)	
Cum. disaster experience		-0.006**		-0.004***
		(0.002)		(0.001)
Openness to experience	0.012***	0.009***	0.007***	0.006***
	(0.002)	(0.003)	(0.002)	(0.002)
Conscientiousness	-0.010***	-0.014***	-0.006***	-0.010***
	(0.003)	(0.003)	(0.002)	(0.002)
Extraversion	-0.001	-0.003	-0.002	-0.002
	(0.003)	(0.003)	(0.002)	(0.002)
Agreeableness	-0.003	0.000	-0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.002)
Neuroticism	-0.008***	-0.005	-0.003**	-0.002
	(0.003)	(0.003)	(0.002)	(0.002)
Disaster*Open	0.000		-0.002	
	(0.003)		(0.002)	
Disaster*Consc	0.006*		0.005**	
	(0.004)		(0.002)	
Disaster*Extra	-0.005		-0.003	
	(0.004)		(0.002)	
Disaster*Agree	0.000		0.001	
	(0.004)		(0.002)	
Disaster*Neuro	-0.002		-0.002	
	(0.004)		(0.002)	
Cum. disaster*Open		0.002		0.000
		(0.002)		(0.001)
Cum. disaster*Consc		0.006***		0.005***
		(0.002)		(0.001)
Cum. disaster*Extra		0.000		-0.000
		(0.002)		(0.001)
Cum. disaster*Agree		-0.002		-0.001
		(0.002)		(0.001)
Cum. disaster*Neuro		-0.004*		-0.002
		(0.002)		(0.001)
Constant	-0.735***	-0.754***	-0.837***	-0.851***
	(0.095)	(0.095)	(0.058)	(0.058)
Observations	74,298	74,298	74,298	74,298
R-squared	0.207	0.207	0.134	0.134
Controls	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES

Note: Clustered standard errors at household level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Conscientiousness is negatively and significantly associated with risky asset participation and risky asset share in the direct-effect specifications. This suggests that, on average, more

conscientious households are less likely to hold risky assets and allocate a smaller share of their financial wealth to risky investments. This may reflect greater caution, discipline, and preference for financial security among conscientious individuals. However, as shown by the interaction terms, the role of conscientiousness changes once disaster exposure is considered jointly with personality. This distinction is important: conscientiousness may reduce general risk-taking, but it also appears to help households respond more resiliently when exposed to disaster shocks.

Neuroticism is also negatively and significantly associated with both risky asset holding and risky asset share. This result is consistent with the idea that neurotic individuals are more sensitive to uncertainty, emotional distress, and perceived downside risk. Since risky financial assets involve volatility and uncertainty, higher neuroticism may discourage participation in risky asset markets. This finding is consistent with the behavioral finance literature linking emotional instability and risk perception to more cautious financial decisions (Nosić & Weber, 2010; S. Brown & Taylor, 2014).

Extraversion and agreeableness are generally not statistically significant in Table 2.3. This suggests that, after controlling for household characteristics, disaster exposure, and other personality dimensions, these traits do not play a strong direct role in explaining risky asset participation or risky asset share in this sample.

Turning to the moderation results, the interaction between binary disaster exposure and conscientiousness is positive and statistically significant for both risky asset holding and risky asset share. This indicates that conscientiousness weakens the negative effect of disaster exposure on risky financial decisions. In other words, although conscientious households may generally be more cautious investors, they are less likely to reduce risky asset participation after experiencing a disaster. This supports the interpretation that conscientiousness acts as a stabilizing trait in the presence of shocks.

The moderation effect is even clearer for cumulative disaster exposure. The interaction between cumulative disaster exposure and conscientiousness is positive and statistically significant at the 1 percent level for both outcomes. This means that repeated disaster exposure

has a less negative effect among households with higher conscientiousness. Put differently, conscientiousness appears to mitigate the adverse financial response to repeated disaster experiences. This is consistent with the view that conscientious individuals are more disciplined, organized, and forward-looking, allowing them to maintain investment plans even when exposed to adverse events (Costa Jr & McCrae, 1992; Cobb-Clark & Schurer, 2012).

There is also weak evidence that neuroticism amplifies the adverse effect of cumulative disaster exposure. The interaction between cumulative disaster exposure and neuroticism is negative and statistically significant at the 10 percent level for risky asset holding, although it is not significant for risky asset share. This suggests that repeated disaster exposure may discourage risky asset participation more strongly among more neurotic households. However, because this effect is only weakly significant and does not hold across both outcome variables, it should be interpreted as suggestive rather than conclusive.

The remaining interaction terms involving openness, extraversion, and agreeableness are not statistically significant. This suggests that while openness matters directly for risky financial behavior, it does not significantly alter the effect of disaster exposure. Similarly, extraversion and agreeableness do not appear to condition household responses to disaster shocks. Moreover, the likelihood to hold risky assets and portfolio share increases for older people, individuals who are married, with a university education, have a high income, and lower for people with children[11].

Overall, Table 2.3 shows that personality traits matter in two ways. First, openness increases risky financial participation, while conscientiousness and neuroticism are associated with lower participation and lower risky asset shares. Second, and more importantly for the moderation analysis, conscientiousness consistently mitigates the negative effect of disaster exposure, especially cumulative exposure. This suggests that households' responses to disaster shocks are not uniform: stable personality traits shape how individuals process and

[11]We performed some heterogeneity tasks to see if the impact of the disasters affected men more than women, and if the level of education plays a role in explaining the effects of natural disasters on people's behavior. It turns out that the impact of the disasters on risky asset participation does not differ significantly between men and women in our sampled data. Similarly, the education level shows no significant heterogeneity effect with regard to households' portfolio decisions.

respond to repeated adverse experiences.

2.4.3 Timing Heterogeneity in Disaster Exposure and Risky Financial Decisions

Table 2.4 examines whether the effect of disaster exposure varies according to the timing of exposure. Specifically, disaster experiences are categorized into short-term exposure (0–2 years), medium-term exposure (3–5 years), and long-term exposure (6 or more years) since the most recent disaster event. This specification allows the analysis to distinguish between immediate and persistent behavioral responses to disasters and provides additional insight into the dynamic nature of household financial decision-making following adverse events.

The results show that short-term disaster exposure, defined as exposure occurring within the previous 0–2 years, is negatively associated with risky asset holding and risky asset share, although the coefficients are statistically insignificant in the baseline timing specifications. The negative sign nevertheless suggests that households may initially respond to recent disasters by becoming more financially cautious and reducing participation in risky financial markets. This pattern is consistent with behavioral theories emphasizing that recent adverse experiences increase uncertainty perceptions and heighten precautionary motives (Malmendier & Nagel, 2011). However, the absence of strong statistical significance indicates that the immediate behavioral response to disaster exposure may vary substantially across households.

Similarly, medium-term disaster exposure, measured as disasters occurring within 3–5 years, does not exhibit statistically significant effects on risky financial decisions. The coefficients remain relatively small across both risky asset holding and risky asset share. This finding suggests that the behavioral effect of disasters may not persist uniformly during the intermediate period following exposure. One possible explanation is that households gradually adapt to disaster-related uncertainty over time, thereby weakening the initial behavioral response. Another possibility is that the economic and psychological consequences of disas-

ters evolve differently across households depending on financial resilience, recovery capacity, and institutional support systems.

Table 2.4: Heterogeneous Effect of Disaster Exposure

Dependent variables	Risky Asset Holding			Risky Asset Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster exp. (0-2 yrs)	-0.003	-0.003	-0.003	-0.002	-0.002	-0.001
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Disaster exp. (3-5 yrs)	-0.006	-0.006	0.013	-0.000	-0.000	0.005
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Disaster exp. (6+ yrs)	-0.060**	-0.060**	-0.062**	-0.015	-0.015	-0.016
	(0.025)	(0.025)	(0.025)	(0.017)	(0.017)	(0.017)
Openness to experience		0.013***	0.012***		0.007***	0.006***
		(0.002)	(0.002)		(0.002)	(0.001)
Conscientiousness		-0.009***	-0.009***		-0.006***	-0.006***
		(0.003)	(0.002)		(0.002)	(0.002)
Extraversion		-0.003	-0.003		-0.003**	-0.003**
		(0.002)	(0.002)		(0.002)	(0.001)
Agreeableness		-0.004	-0.003		-0.001	-0.000
		(0.003)	(0.002)		(0.002)	(0.001)
Neuroticism		-0.009***	-0.009***		-0.004***	-0.004***
		(0.002)	(0.002)		(0.001)	(0.001)
Disaster exp. (0-2 yrs)*Consc			0.008**			0.006**
			(0.004)			(0.002)
Disaster exp. (3-5 yrs)*Consc			-0.005			0.002
			(0.006)			(0.004)
Disaster exp. (6+ yrs)*Consc			0.025			0.006
			(0.026)			(0.017)
Constant	-0.740***	-0.692***	-0.730***	-0.850***	-0.822***	-0.836***
	(0.094)	(0.096)	(0.095)	(0.058)	(0.059)	(0.058)
Observations	74,298	74,298	74,298	74,298	74,298	74,298
R-squared	0.209	0.210	0.207	0.134	0.135	0.133
Controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES

Note: Clustered standard errors at the household level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

In contrast, long-term disaster exposure, defined as disaster experiences occurring six or more years earlier, exhibits a negative and statistically significant effect on risky asset holding. The coefficient on long-term disaster exposure is approximately -0.060 and remains statistically significant across specifications. This finding suggests that households exposed to disasters in the distant past are significantly less likely to participate in risky asset markets

compared to households without prior disaster exposure. The persistence of this negative effect provides evidence that disaster experiences may generate long-lasting changes in economic expectations and financial behavior.

The long-term effect is particularly important because it supports the experience-based learning framework proposed by Malmendier & Nagel (2011), which argues that adverse experiences can shape economic beliefs and risk perceptions over extended periods. Rather than disappearing quickly, disaster experiences may remain psychologically salient and continue to influence household financial decisions long after the event itself has occurred. The findings also align with Bernile et al. (2017), who show that exposure to severe disasters can generate persistent changes in risk-taking behavior. In the context of household finance, repeated recollection of adverse events may reinforce perceptions of background risk and future vulnerability, thereby discouraging participation in risky financial markets.

Interestingly, the long-term disaster exposure effect is statistically significant for risky asset holding but not for risky asset share. This distinction suggests that disasters primarily influence households' decision to participate in risky asset markets rather than the proportion of wealth allocated to risky assets conditional on participation. In other words, disaster experiences may discourage entry into risky financial markets, but among households already participating, the allocation of risky assets may be less sensitive to past disaster experiences. This distinction between the extensive and intensive margins is consistent with the household finance literature, which emphasizes that the determinants of market participation may differ from those affecting portfolio allocation conditional on participation (Campbell, 2006; Guiso & Paiella, 2008).

Table 2.4 further examines whether conscientiousness moderates the timing effects of disaster exposure. The interaction between conscientiousness and short-term disaster exposure is positive and statistically significant for both risky asset holding and risky asset share. The coefficient is approximately 0.008 for risky asset holding and 0.006 for risky asset share. These findings indicate that conscientious individuals are less likely to reduce risky financial participation immediately following disaster exposure. In other words, conscientiousness

mitigates the short-run adverse effect of disasters on risky financial decisions.

This result is consistent with psychological theories describing conscientious individuals as disciplined, organized, and future-oriented (Costa Jr & McCrae, 1992). Such individuals may be more capable of maintaining long-term financial strategies despite temporary uncertainty generated by disaster events. Rather than reacting emotionally to recent shocks, conscientious households may evaluate investment decisions more systematically and maintain participation in risky financial markets even after experiencing adverse events. Consequently, conscientiousness appears to provide a form of behavioral resilience against short-term disaster-related uncertainty.

In contrast, the interaction terms involving medium-term and long-term disaster exposure are statistically insignificant. This suggests that the moderating role of conscientiousness is strongest immediately following disaster exposure and weakens over time. One possible explanation is that conscientious individuals are particularly effective at coping with short-run uncertainty and emotional responses following disasters, but over longer periods the direct influence of disaster experiences may dominate personality-related behavioral differences. Alternatively, households may gradually adjust to disaster-related uncertainty over time regardless of personality characteristics.

The direct effects of personality traits reported in Table 2.4 remain broadly consistent with the earlier interaction models. Openness to experience continues to exhibit a positive and statistically significant relationship with risky financial behavior, while conscientiousness and neuroticism remain negatively associated with risky asset participation. Extraversion also has a negative effect on risky asset decisions. These findings reinforce the broader conclusion that personality traits play an important role in shaping household financial behavior under uncertainty.

Overall, the timing analysis reveals that the behavioral consequences of disaster exposure are dynamic rather than uniform over time. While recent disaster exposure produces relatively weak average effects, long-term disaster exposure significantly reduces risky asset participation, suggesting that disaster experiences may have persistent consequences for

household financial behavior. The interaction results further demonstrate that conscientiousness mitigates the adverse short-run effects of disaster exposure, highlighting the importance of psychological resilience in financial decision-making under uncertainty. Together, these findings suggest that both the timing of disaster exposure and stable personality characteristics are important for understanding how households adjust risky financial behavior following adverse events.

2.5 Conclusion

This chapter examines the relationship between disaster exposure and household risky financial behavior using longitudinal data from the Survey of Health, Ageing and Retirement in Europe (SHARE) combined with disaster information from the Emergency Events Database (EM-DAT). Drawing on insights from the experience-based learning and behavioral finance literature, the chapter investigated whether disaster experiences influence households' participation in risky asset markets and the proportion of financial wealth invested in risky assets. Furthermore, the chapter examines whether personality traits moderate these relationships and whether the effects of disaster exposure vary according to the timing of exposure.

The baseline results indicate that a simple binary measure of disaster exposure has a limited effect on risky financial decisions. However, cumulative disaster exposure is consistently associated with lower risky asset participation and lower risky asset shares, suggesting that repeated exposure to adverse events may gradually increase financial caution among households. These findings support the experience-based learning framework, which argues that repeated experiences shape economic expectations and risk perceptions over time (Malmendier & Nagel, 2011). The results imply that the frequency of disaster exposure is more relevant for household financial behavior than a single disaster experience.

The chapter also demonstrates that personality traits play an important role in shaping household financial behavior and explaining heterogeneity in responses to disaster exposure. The results show that openness to experience is positively associated with risky asset

participation and risky asset share, while conscientiousness and neuroticism are negatively associated with risky financial risk-taking. More importantly, the interaction analysis reveals that conscientiousness significantly moderates the effect of disaster exposure on risky financial decisions. Although more conscientious households generally exhibit lower levels of risky financial participation, they are less likely to reduce risky asset holdings following disaster exposure, suggesting that disciplined and forward-looking individuals are better able to maintain long-term investment strategies in the face of adverse shocks. There is also weaker evidence that neuroticism amplifies the adverse effect of repeated disaster exposure on risky asset participation.

The timing analysis further reveals that the effects of disaster exposure are not uniform over time. While recent disaster exposure is not associated with statistically significant changes in risky financial behavior, long-term disaster exposure significantly reduces risky asset participation. This finding suggests that the influence of disaster experiences may persist well beyond the immediate aftermath of the event. The results therefore provide additional support for the experience-based learning literature by showing that disaster experiences can have long-lasting consequences for household financial decision-making. Moreover, the moderating role of conscientiousness is strongest in the short run, indicating that personality traits may be particularly important in shaping immediate behavioral responses to adverse events.

Overall, the findings highlight the importance of considering both disaster experiences and individual psychological characteristics when examining household financial behavior under uncertainty. The results suggest that households do not respond uniformly to disaster-related shocks and that stable personality traits play a crucial role in determining the extent to which disaster experiences influence financial decision-making. These findings contribute to the growing literature on household finance, behavioral economics, and disaster risk by demonstrating that the relationship between disaster exposure and risky financial behavior depends not only on the occurrence of adverse events but also on how individuals perceive and respond to those experiences.

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2.A Appendix to Chapter 2

Table 2.A.1: Correlates of household personality traits

	(1)	(2)	(3)	(4)	(5)
Variables	O	C	E	A	N
Disaster exposure	0.028**	0.007	-0.003	0.021*	0.037***
	(0.013)	(0.011)	(0.013)	(0.011)	(0.014)
Age	0.018***	0.010*	0.001	-0.013**	0.002
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
(Age)^2	-0.000***	-0.000*	-0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.095***	-0.102***	-0.064***	-0.069***	-0.246***
	(0.010)	(0.008)	(0.009)	(0.008)	(0.010)
Household size	-0.031***	0.017***	0.000	0.008	0.004
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Ifchild	-0.016	0.092***	0.137***	0.048**	-0.034
	(0.025)	(0.023)	(0.026)	(0.022)	(0.027)
Married	0.027**	0.085***	0.045***	-0.044***	0.060***
	(0.012)	(0.010)	(0.012)	(0.010)	(0.012)
University	0.390***	-0.048***	-0.051***	0.010	-0.086***
	(0.013)	(0.011)	(0.013)	(0.011)	(0.014)
Income	-0.002*	0.001	0.005***	0.005***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	3.140***	3.673***	3.441***	3.910***	2.604***
	(0.235)	(0.201)	(0.231)	(0.202)	(0.245)
Country FE	YES	YES	YES	YES	YES
Observations	40,247	40,372	40,331	40,374	40,405
R-squared	0.082	0.037	0.059	0.087	0.094

Note: The table reports the correlation between the Big Five personality traits and the explanatory variables. The acronyms are defined as O=openness to experience, C=conscientiousness, E=extraversion, A=agreeableness, N=neuroticism. Income is transformed using the inverse hyperbolic sine function, which behaves like the natural log for large values. It is defined at zero, allowing all income observations to be retained. Clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.2: BF1-10 Items

Personality Trait	Question
Openness to experience	I see myself as someone who has few artistic interests.
	I see myself as someone who has an active imagination.
Conscientiousness	I see myself as someone who tends to be lazy.
	I see myself as someone who does a thorough job.
Extraversion	I see myself as someone who is reserved.
	I see myself as someone who is outgoing and sociable.
Agreeableness	I see myself as someone who is generally trusting.
	I see myself as someone who tends to find fault with others.
Neuroticism	I see myself as someone who is relaxed and handles stress well.
	I see myself as someone who gets nervous easily.

Source: SHARE Wave 7 First Results Book.

Note: Within each pair of questions representing a specific dimension, one question is formulated in a positive direction, while the other is formulated in a negative direction. Participants rated their agreement with the 10 questions on a five-point Likert-type scale, ranging from 1 (fully disagree) to 5 (fully agree), reflecting their true personality. Each personality trait was computed as the mean of the respective pair of items (one item was reverse-coded).

CHAPTER 3.

Job Lock and Life Satisfaction among Older US Workers

3.1 Introduction

The prevailing dynamics of the US labour market have contributed partly to the phenomenon of job lock, which has attracted more attention recently, especially in the context of the aging workforce. Job lock has multiple meanings in the US, but this study follows Fisher, Ryan, et al. (2016) and describes it as a condition where workers aged 50 years and above get stuck in their jobs due to financial and health insurance needs, although they would wish to retire or quit altogether. This phenomenon is evident in the US because of how the health insurance system is structured, coupled with changes linked to social security and retirement plans.

Currently, the minimum age for any American worker to qualify for full social security retirement benefits stands at 67 years or even until 70 years, although 62 years is the earliest age at which one is eligible for a pension. Older workers who postpone social security claims until they qualify for all of their benefits earn larger monthly payouts relative to their counterparts who choose to receive payouts at 62 years (i.e., the benefit is about 30 percent lower)[12]. Most older workers are motivated by financial incentives to stay in the workforce beyond the earliest eligible age at which they can retire. In the US, the high cost of private health insurance also deters workers with access to employer-sponsored health insurance from retiring early until they reach 65 years to be eligible for Medicare. These two principal factors have compelled late adult workers to continue working in their jobs longer than they would want.

In this paper, we conjecture that among older workers, job lock has a negative correlation with general life satisfaction. Life satisfaction, a central concept in our analysis, has

[12] https://www.ssa.gov/benefits/retirement/planner/agereduction.html

been the focus of an extensive body of research spanning economics, psychology, and social sciences. We provide a detailed discussion of the aforementioned notion in Section 3.2 of this chapter. While existing literature has tended to focus on younger workers who report being job-locked—often due to employer-sponsored health insurance that discourages job changes—we provide a fresh, broader perspective on work, aging, and retirement by examining the subjective well-being of older workers who may experience job lock alongside personal constraints.

The link between job lock, perceived control, and well-being is conceptually grounded in self-determination theory (SDT), which posits that autonomy—the need to feel in control of one's own actions—is a fundamental psychological need essential for well-being (Ryan & Deci, 2000). When this need is hindered by external constraints, such as feeling locked in a job, it can lead to reduced motivation and lower life satisfaction. We further integrate the locus of control construct (Rotter, 1966), distinguishing between individuals with an internal locus (who believe they can influence outcomes) and those with an external locus (who feel outcomes are determined by external forces). Job lock represents a situational external constraint that threatens autonomy. We hypothesize that individuals with stronger internal control beliefs (higher mastery, lower perceived constraints) will be better equipped to cope with this constraint, thereby moderating its negative impact on well-being. This conceptual integration allows us to move beyond a descriptive association to test a psychological buffering mechanism: control beliefs as a protective resource against the experience of job lock.

To this aim, we add to the body of empirical research by exploring the following questions: (i) What is the correlation between workers' perception of job lock and overall life satisfaction? (ii) How does job lock influence the domain-specific measures of life satisfaction? (iii) Does the relationship between perceived job lock and life satisfaction get moderated by control beliefs such as perceived mastery and constraints on personal control?

Our paper presents the following key contributions: First, while an extensive empirical literature has examined general life satisfaction, there is relatively scant research on domain-

specific measures of life satisfaction (B. M. Van Praag et al., 2003; B. M. S. Van Praag et al., 2010; Bardo & Yamashita, 2014; Diener et al., 2018). This study is important because of its inclusion of both the general index and a number of domain-specific life satisfaction metrics. It has been found in previous studies that a mix of economic, social, and personal factors influence subjective well-being; however, not much is currently known about the life satisfaction of adult workers who continue to work into later life, especially past the age at which one is first eligible for social security retirement benefits to fulfill their financial and health insurance needs.

In fact, none of the previous studies employ panel data as extensive as we do. Hence, this study contributes to the area of research by simultaneously examining overall and distinct aspects of life satisfaction in relation to job lock reports among older workers. Second, prior studies have concentrated on the association between various job attributes and job satisfaction, including job stress, working conditions, employment contracts, and salaries (Card et al., 2012). Less focus has been placed on how job lock influences job satisfaction and how these two factors combine to affect life satisfaction. This study takes into account these dimensions to extend the traditional factors influencing job satisfaction in the existing literature. Third, we contribute to the expanding research in economics and psychology examining the role of personality traits (particularly the "Big Five" model introduced in Chapter 2) and other psychological variables in economically relevant domains by elucidating how individuals' subjective resources (perceived mastery and constraint on personal control) serve as a mechanism through which job lock influences life satisfaction. By integrating concepts from self-determination theory and locus of control, this study contributes to behavioral labor economics by examining not only whether job lock matters, but also for whom it matters most. We test the hypothesis that psychological resources, specifically, perceived mastery and constraints serve as crucial moderators, potentially buffering the well-being costs of structural constraints.

To conduct our analysis, we employ an extensive panel dataset from seven waves (2008–2020) of the Health and Retirement Study, typical of the 50+ population in the United States. The survey offers detailed information on present subjective well-being levels (inclusive of

both overall and domain-specific measures of life satisfaction), job lock, personality traits, control beliefs, and other relevant socio-demographic controls that allow us to respond to our empirical research questions.

The key findings from this study are summarized as follows: we find that older workers who perceive themselves to be in a state of job lock report lower levels of overall life satisfaction. Specifically, the negative correlation is stronger among individuals who actually need both health insurance and income from work (i.e., combined necessity lock), compared to those needing either health insurance or income (i.e., economic necessity lock). Next, we show that job lock substantially reduces satisfaction across the different domains of life, with the largest negative impact on financial and leisure satisfaction, especially when both health insurance and financial needs are combined. Moreover, our moderation analysis reveals that control beliefs (and particularly constraints on personal control) moderate the relationship between job lock and overall life satisfaction.

The rest of the paper is organized as follows. The pertinent streams of literature are selectively reviewed in Section 3.2. Section 3.3 shows the data and variables we employ to discuss this topic. Section 3.5 summarizes our main analysis results, and Section 3.6 concludes. Several robustness checks of the analysis are provided in Appendix 3.A.

3.2 Literature Review

Our paper speaks to three distinct strands of literature. First, we are close to the vast line of inquiry in economics and psychology that sheds light on the determinants of individual well-being, both via single subjective well-being measures as well as through a domain-based approach to life satisfaction. Second, this study connects to the labour economics literature dealing with the determinants of individuals' job satisfaction. Third, we are also close to the growing economics and psychology literature examining the role of personality traits (and, in particular, the so-called "Big Five" model) and other psychological variables in economically relevant domains.

Over the past few decades, there has been considerable development in the literature on life satisfaction and its determinants. Broad concepts of subjective well-being (SWB) have facilitated a more nuanced understanding of both general and domain-specific satisfaction. According to Diener et al. (2018), SWB encompasses individuals' emotional reactions to ongoing life with regard to negative and positive emotions, as well as reflective cognitive assessments of their own lives. The construct of life satisfaction relates to a cognitive assessment of the quality of life of people based on personal standards (Pavot & Diener, 2008), while the happiness measure is the emotive component (Strobel et al., 2011). In particular, an extensive body of research has come to generally accept the validity of self-reported measures of SWB, including life satisfaction, as reliable indicators of well-being (B. M. Van Praag et al., 2003; Tella & MacCulloch, 2006; Metcalfe et al., 2011) as well as domain-specific measures of life satisfaction (Krueger & Schkade, 2008; Schimmack et al., 2010). Bartels (2015), in his paper, he emphasizes that researchers have increasingly become interested in examining the determinants of subjective well-being across various scientific disciplines, such as psychology, economics, and medicine. According to recent meta-analyses and reviews in the literature, a variety of factors, such as those in the sociodemographic, health-related, social, and psychological domains, influence life satisfaction (Bühler et al., 2021; Cheng et al., 2022; Diener et al., 2018).

However, prior studies on life satisfaction correlates suggest that significant factors differ based on sample characteristics, particularly when comparing general and clinical populations. For example, an online study with over 25,000 respondents in the United States indicated that, among general population samples, job satisfaction is one of the strongest predictors of life satisfaction (Gillespie et al., 2015). Park et al. (2019), drew from a representative annual survey of Japanese respondents, documenting a significant correlation between life satisfaction and household income. Similarly, among randomly selected and nationally representative samples, household financial satisfaction was found to be one of the strongest predictors of life satisfaction in an extensive analysis of data from 1 million people in 150 countries (Joshanloo & Jovanović, 2021). Using a clinical sample, however, two recent pieces of Korean research (Lee et al., 2020; Kim et al., 2022) revealed that leisure

satisfaction among employees with sensory impairments and physical disabilities is the most significant predictor of life satisfaction.

With regard to employment status, A. E. Clark & Oswald (1994) find that unemployment is significantly and negatively associated with well-being using UK data on mental distress (see also Blanchflower & Oswald, 2004). The observed impact is very large and statistically significant across different model specifications. Furthermore, the authors show that people who have been jobless for a long period experience less distress compared to their counterparts who have just lost their jobs. Fisher, Chaffee, & Sonnega (2016) document several factors that influence late adult workers' decisions to retire or keep working beyond pensionable age. Several economic studies suggest that two possible sources of prolonged retirement (i.e., job lock) are financial and health insurance needs. Using extensive panel data on Germany, Bonsang & Klein (2012) demonstrate that involuntary retirement has a slight positive impact on life satisfaction, but voluntary retirement has a negative impact.

Based on two independent samples from different waves of the HRS data, Fisher, Ryan, et al. (2016) investigate the relationship between job lock, workers' job attitudes, and well-being. The authors emphasized that job lock might result in extended employment beyond the traditional retirement age, which generally lowers job satisfaction and general well-being. These results highlight the need to understand job lock as a driving factor affecting the timing of retirement and the quality of life in later years. Specifically, they find that job lock due to financial constraints was significantly linked to reduced life satisfaction, while the results for job lock brought on by employer-provided health insurance varied across the two samples (see also Gruber & Madrian, 2002, how health insurance relates to labor supply and job mobility to influence overall well-being). Since the focus of this paper is to analyze how reported job lock among late adult workers is associated with their current life satisfaction through control beliefs, Fisher, Ryan, et al. (2016) is the work that is closest to ours.

Our study also speaks to the plethora of labour economics literature examining the factors that influence individuals' job satisfaction. According to Warr (2007), overall job satisfaction is the degree to which an individual is satisfied with his or her job as a whole. Workers' job

satisfaction has a crucial role in influencing both job performance (Kumar, 2022; Warr, 2007) and life satisfaction (Judge & Watanabe, 1993), as dissatisfied workers are less productive and more likely to quit their jobs. Promotional opportunities, remuneration, workload, training, supervisory relationships, work-life balance, and performance appraisal satisfaction are among the environmental variables that have been identified as drivers of job satisfaction (Ellickson & Logsdon, 2002). However, the significance of these variables may differ based on the particular organization, industry, and job attributes. Due to the combined effects of higher job security and higher intrinsic motivation for work, smaller firms, permanent contracts, and employment among other job attributes in the public sector are frequently associated with higher levels of job satisfaction (Ghinetti, 2007; Vladisavljević et al., 2017).

Card et al. (2012) demonstrate that information about peers' pay at work influences workers' level of job satisfaction. They show, specifically, that workers who are below-median earners for their salary unit and occupation report lower salary and job satisfaction. As they highlight, prior work documented systematic relationships between relative income and job satisfaction (A. E. Clark & Oswald, 1996) and happiness (Luttmer, 2005). By analyzing survey data from a large sample of British workers, A. Clark et al. (1996) provide compelling evidence of a U-shaped link between job satisfaction and age. Gazioglu & Tansel (2006) confirms the finding of A. Clark et al. (1996). The authors highlight in addition that although married status among individual characteristics is often linked to greater levels of job satisfaction, they found that married individuals reported lower job satisfaction than their unmarried counterparts among employees in the UK. Moreover, there is a mixed relationship between job satisfaction and educational attainment, with some studies finding a negative influence of education. This has been attributed by some researchers (e.g. A. E. Clark & Oswald, 1996) to the increased work expectations placed by highly educated individuals in the workplace. According to Perugini & Vladisavljević (2019), women generally report higher levels of job satisfaction despite being paid less than men and dealing with harsher working conditions, lower promotion opportunities, and discrimination at work.

Psychological literature attests to the fact that job-related well-being indicators typically have predictable antecedents. For instance, research by Totterdell et al. (2006) demonstrates

that low job-related well-being is a result of high work demands, as shown by control on depression and anxiety indicators. Good emotional and mental health among employees is correlated with high job satisfaction (Bozeman & Gaughan, 2011; Hirschfeld, 2000). After controlling for individual and household characteristics such as income, the relationship between working hours and job satisfaction is non-linear: satisfaction increases with the number of hours worked but starts to decrease when the number of hours becomes burdensome and excessive (Dolan et al., 2008; Meier & Stutzer, 2008).

In a cross-national context, Sousa-Poza & Sousa-Poza (2000) examined the factors that influence job satisfaction using data on work orientations from the International Social Survey Program. It has been discovered that nations with high work-role outputs, such as having an interesting job and positive management relations, generally have high job satisfaction rankings (also refer to Asuyama, 2021, who posits that a person's interest in their work improves learning, task performance, job satisfaction, and discourages them from quitting). Pagán (2013) uses data from the Survey of Health, Ageing, and Retirement in Europe to examine the job satisfaction levels of older workers between 50–64 years with and without disabilities. The author demonstrates how the overall job satisfaction expressed by limited disabled workers is significantly influenced by their levels of satisfaction with physical effort, support in harsher conditions, and acknowledgement of their labor. According to Fisher, Ryan, et al. (2016), a certain group of older workers continues to work due to job satisfaction derived from social support, higher levels of autonomy, lower job demands, and other factors rather than financial or other economic (employer-provided health insurance) reasons.

Lastly, our paper relates to the economics and psychology literature on non-cognitive traits such as the Big Five personality traits and their relevance in economics studies. Personality traits have been explained in psychology as "the relatively enduring patterns of thoughts, feelings, and behaviours that reflect the tendency to respond in certain ways under certain circumstances" (Roberts, 2009; p.140), and they constitute the "natural counterparts" of economic preferences (Jagelka, 2024). Over time, there has been widespread acceptance of the adoption of the comprehensive "Big Five" model: this taxonomy encompasses a wide range of personality attributes and, at the broadest level of abstraction, posits the existence

of five basic or primary non-cognitive traits–openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. These traits are to some extent largely invariant across age groups and cultural backgrounds (Costa & McCrae, 1992).

This model was developed to represent as much of the variability in personality as possible by taking into account only a limited number of trait dimensions (Soto & Jackson, 2013) and, in recent years, it has been progressively employed also in economics and finance by virtue of its predictive power (Heckman et al., 2019). Openness to experience is the tendency to be receptive to new aesthetic, cultural, or intellectual experiences. Conscientiousness is the inclination to be well-organized, hardworking, and responsible. Extraversion is an orientation of one's interests and energies towards the outer world of people and things, and it is defined by sociability and positive affect. Agreeableness is a trait linked to interpersonal orientation: agreeable people are extremely group-oriented and frequently behave in a cooperative, unselfish manner. Neuroticism is a persistent degree of emotional instability and proneness to psychological distress: neurotic individuals are often impulsive and are likely to interpret ordinary situations as threats rather than challenges (Keyes et al., 2002; Almlund et al., 2011; Bucciol & Zarri, 2017, 2021; Pruysers et al., 2019). Furthermore, a comprehensive body of literature in psychology (also known as the "happy personality" line of inquiry) found significant associations between "Big Five" traits and subjective well-being (Keyes et al., 2002; Stephan et al., 2020; Busseri & Erb, 2024). More importantly, research shows that control beliefs can be characterized in two distinct dimensions (Lachman & Weaver, 1998): while mastery beliefs represent positive perceptions of being in control, perceived constraints demonstrate a sense of helplessness or perceptions of personal constraints. So far, there are consistent findings of mastery beliefs as a positive resource across the adult lifespan, whereas perceived constraints have been related to negative effects (Kunzmann et al., 2002).

3.3 Data Overview

We source data from the Health and Retirement Study (HRS) to perform our empirical analysis. The HRS is a large nationally representative longitudinal survey conducted biennially

by the University of Michigan to learn more about the retirement and health status, as well as various socioeconomic, life history, and psychological factors of the US adult population aged 50 years and above. Since 2004, a psychosocial and lifestyle module has been included in the survey using a self-administered questionnaire, which is left behind with respondents upon completion of an in-person core interview to collect data about participants' evaluations of their subjective well-being, life circumstances, and lifestyle. Hitherto, the psychosocial module covers six main areas, namely subjective well-being, personality traits, self-related beliefs, work-related beliefs, lifestyle and experience of stress, and quality of social ties. This module is administered on a rotational basis, with randomly chosen half of the sample completing it every four years to minimize the burden of collecting surveys. This means that half of the sample that completed the self-administered questionnaire in 2006, for instance, were reinterviewed in 2010; the other half of the sample responded to the lifestyle questions in the subsequent wave.

For the purpose of this study, we make use of data from the first four aforementioned substantive areas contained in the psychosocial module. Our analysis is focused on a subgroup of respondents who are currently working and uses datasets between the 2008 and 2020 waves of the HRS. This is because prior waves do not contain data on job lock, a key variable of interest for our study. We excluded all observations with at least one missing value in our explanatory variables to ensure precise and reliable estimates. Given the focus of our study group and restrictions, our main estimation sample includes 2,304 households, representing a total of 4,090 individual observations. Despite having a longitudinal survey design, our data's panel dimension is small. Since the sample of individuals who respond to the "participant lifestyle" questionnaire rotates every two years, we do, in fact, have an average of 1.8 observations for each household. This does not allow us to exploit model specifications suitable for panel data. Hence, to account for the likelihood of within-observation correlation pertaining to the same household, we treat our dataset as though it were purely cross-sectional and use standard errors clustered at the household level for all the analyses.

3.3.1 Measures of Key Variables

Following the psychosocial module of the HRS data, our key variables can be grouped into four categories, namely, Life satisfaction, job-related variables, control beliefs, and personality traits, in addition to socio-demographic controls. To facilitate comparison and interpretability of coefficients across different scales and to reduce multicollinearity in models containing interaction terms, all continuous explanatory variables, including personality traits, control beliefs, income, and wealth measures, were standardized to have a mean of 0 and a standard deviation of 1 before inclusion in the regression models (see e.g., Schielzeth, 2010). Dummy variables (e.g., gender, marital status) were left in their original form.

Life satisfaction: As our outcome measure, we evaluate the subjective well-being of respondents through an aggregate index of overall life satisfaction together with six domain-specific measures covering how respondents are satisfied with their health, finances, family, leisure, city, and house. With regard to overall life satisfaction, an index is generated by averaging the scores across five distinct items ranging from "*In most ways, my life is close to ideal*" to "*If I could live my life again, I would change almost nothing*". In this study, the internal consistency reliability of the set of items assessed by Cronbach's alpha is a = 0.90. This high value indicates that the five items are highly correlated with each other, hence very high reliability. As for the domain-specific measures, a single question is asked specifically about how satisfied respondents are with respect to the six important domains of life mentioned above. These measures are ordinal variables rated on a five-point Likert scale ranging from 1 to 5, where lower values (higher values) correspond to lower levels of satisfaction (higher satisfaction).

Job-related variables: Job lock is the main regressor of interest, and it relates to the reasons behind participants' decision to continue working. The purpose of the job lock measure is to identify individuals who work just because it is necessary for them to earn money or obtain health insurance coverage. Originally, individuals respond to two items of job lock as follows: "*Right now, would you like to leave work altogether but plan to keep working because you need the money*? (Yes/No) and "*Right now, would you like to leave*

work altogether but plan to keep working because you need health insurance? (Yes/No). In a slightly different fashion, we assess job lock by creating two dummy variables, such as *economic_necessity lock* equal to 1 to refer to individuals who are still working because they need to obtain either money or health insurance; otherwise, no lock *combined_necessity lock* is coded 1 to also refer to individuals who keep working because they need to make money and be covered by health insurance at the same time; otherwise, no lock. Job satisfaction is assessed based on a single item, such as "*All things considered, I am satisfied with my job*". Respondents report their agreement or otherwise with the statement on a four-point Likert scale ranging from 1=strongly disagree to 4=strongly agree.

Control beliefs: Using the scales created by Lachman & Weaver (1998) and Pearlin & Schooler (1978), we generate two common indexes of control beliefs measuring *perceived mastery* and *perceived constraints on personal control*. Five items are used to evaluate each index. Mastery beliefs and perceived constraints are assessed based on agreement with statements such as "*I can do just about anything I really set my mind to*" and "*I often feel helpless in dealing with the problems of life*" respectively. Respondents are required to use a 6-point response scale on a range from 1 (strongly disagree) to 6 (strongly agree) to indicate, for each item, their agreement with the statements. The internal consistency of the items measuring perceived mastery is a = 0.91, and the constraints on personal control are a = 0.86 in this study. Both values show that the items in the scale are strongly correlated with each other, demonstrating high reliability. Additionally, three single-item measures of domain-specific control belief for finances, social life, and health obtained directly from Lachman & Weaver (1998) are controlled for in this study. Using an 11-point scale ranging from "no control at all" (0) to "very much control" (10), each of the following questions: "*how would you rate the amount of control you have over your health these days?*"; "*how would you rate the amount of control you have over your social life these days?*"; and "*how would you rate the amount of control you have over your financial situation these days?* " is used to assess each of the three measures.

Personality traits: The Midlife Development Inventory (MIDI) personality scale developed by Lachman & Weaver (1997) is used to evaluate the "Big Five" personality traits.

The 26-item scale, designed specifically to measure personality in midlife, asks respondents to self-rate on a four-point scale whether each item, which is an adjective associated with a particular personality dimension, represents them. The Big Five traits include openness, conscientiousness, extraversion, agreeableness, and neuroticism, with each trait consisting of at least four possible sets of adjectives. Except for a few negatively worded items, we reverse-scored every item and averaged the scores for the items within each trait's sub-facets to produce the five broad personality scales. Higher values on all scales suggest stronger validation of the trait dimension. In this study, internal consistency for openness (a = 0.79), conscientiousness (a = 0.68), extraversion (a = 0.76), agreeableness (a = 0.80), and neuroticism (a = 0.72) shows that the items in the scale are moderately correlated with each other, suggesting acceptable reliability for our analysis.

The Midlife Development Inventory (MIDI) personality scale (Lachman & Weaver, 1997) is used in this chapter to assess the Big Five personality traits. This differs from the Big Five Inventory-10 (BFI-10) used in Chapter 2 (Rammstedt & John, 2007). While both scales are derived from the same five-factor model and are widely validated, they differ in length, item format, and psychometric properties. The MIDI includes 26 adjective-based items rated on a 4-point scale, offering broader coverage of each trait domain and higher reliability (α = 0.68–0.80 in our sample). In contrast, the BFI-10 uses 10 short statements rated on a 5-point scale and is designed for brevity, with lower but acceptable reliability in population surveys (Rammstedt & John, 2007). The choice of scale in each chapter was determined by data availability: SHARE (Chapter 2) administers the BFI-10, while HRS (Chapter 3) uses the MIDI. Despite these differences, both instruments validly capture the same underlying constructs (Gosling et al., 2003; Soto & John, 2017), and in our analyses, all trait scores are standardized to ensure comparability within each study.

Socio-demographic controls: Based on self-assessed responses, we take into account a number of control variables that prior studies have linked to life satisfaction and may have an impact on an individual's decision to continue working. For demographic controls, we account for age, a continuous variable; female, a dummy measure for gender coded 1 or 0 otherwise; non-white, a dummy measure for race coded 1 if a respondent is not Caucasian;

immigrate, a dichotomous measure of nationality coded 1 if a respondent has immigrated from another country; and health, a dummy variable equal to 1 if the self-rated health status of the respondent is very good. Some social control variables include married, a dummy coded variable equal to 1 if a respondent is married or living with a partner; college, which is a dichotomous variable coded 1 if a respondent has attained a college degree; and home ownership, which is a dummy measure coded 1 if individuals own a house. Moreover, total household income, financial and real wealth reported in thousands of US dollars, and demonstrating the economic status of respondents are accounted for in this study.

Table 3.1 presents summary statistics on all key variables and analysis of the descriptive comparison for the sub-samples of U.S. workers aged at least 50 years who report being job-locked due to money and health insurance needs and those who do not, as shown in the last three columns. The overall life satisfaction score on a 1 to 5 scale is 3.96 on average, with a median of 4, along with a statistically significant difference between respondents who report job lock and those who do not. At the domain level, respondents tend to be more satisfied with their cities, followed by housing, than they are with their health and finances. We can attribute this evidence partly to the fact that the study participants are older and may be experiencing deteriorating health conditions and have less personal savings because they may have expended so much on family, coupled with the inclusion of a period of recent economic and financial crisis in our sample under study. Interestingly, we learn that the proportion of workers with reports of job lock due to both money and health insurance needs is about 45 percent, with about 24 percent referring to those who report job lock due to either money or health insurance. Additionally, job satisfaction on average is approximately 3.47, with a median of 4 on a 5-point response scale. Respondents are more likely to be agreeable, conscientious, and less neurotic. The inclusion of the Big Five personality traits as controls in our study is consistent with existing literature that has shown the link between subjective well-being and personality (see, e.g., Stephan et al., 2020; Busseri & Erb, 2024). We also learn that the respondents tend to have a perception of more mastery beliefs, less personal constraints, and relatively strong control over social life, health, or finances. Furthermore, the socio-demographic controls show that the average respondent is about 64 years old,

Table 3.1: Summary statistics

Variables	Full sample N	Mean	Median	Std. Dev.	No job lock N=1,262 Mean	Job lock N=2,828 Mean	T-test
Life satisfaction *(scale 1-5)*							
Life satisfaction (overall)	4,090	3.96	4	0.878	4.28	3.82	15.75***
Satisfaction with housing	4,072	4.08	4	0.884	4.33	3.97	12.07***
Satisfaction with city	4,073	4.10	4	0.859	4.3	4.01	9.92***
Satisfaction with leisure	4,068	3.85	4	0.865	4.15	3.72	14.96***
Satisfaction with family	4,064	3.98	4	0.906	4.2	3.88	10.5***
Satisfaction with finances	4,069	3.39	3	1.061	4	3.12	26.54***
Satisfaction with health	4,073	3.58	4	0.892	3.83	3.47	12.34***
Job related variables							
Economic_necessity lock *(d)*	4,090	0.24	0	0.429	0	0.35	-26.13***
Combined_necessity lock *(d)*	4,090	0.45	0	0.497	0	0.65	-48.28***
Job satisfaction *(scale 1-4)*	4,018	3.47	4	0.704	3.69	3.37	13.61***
Control beliefs							
Mastery *(scale 1-6)*	4,090	4.97	5.2	0.974	5.15	4.89	7.75***
Personal constraints *(scale 1-6)*	4,090	1.85	1.4	0.984	1.55	1.98	-13.17***
Control over health *(scale 0-10)*	4,090	7.72	8	1.904	7.97	7.61	5.55***
Control over social life *(scale 0-10)*	4,090	8.25	9	1.891	8.58	8.1	7.63***
Control over finances *(scale 0-10)*	4,090	7.55	8	2.102	8.21	7.25	13.73***
Personality traits *(scale 1-4)*							
Openness	4,090	3.04	3	0.522	3.14	2.99	8.67***
Conscientiousness	4,090	3.48	3.6	0.421	3.53	3.46	5.29***
Extraversion	4,090	3.25	3.4	0.538	3.32	3.21	5.73***
Agreeableness	4,090	3.55	3.6	0.467	3.57	3.54	2.04**
Neuroticism	4,090	1.94	2	0.593	1.81	2	-9.48***
Socio-demographics							
Age	4,090	63.80	63	6.864	66.52	62.58	17.58***
Female *(d)*	4,090	0.57	1	0.495	0.51	0.6	-5.24***
Non-white *(d)*	4,090	0.14	0	0.352	0.08	0.17	-8.14***
Immigrate *(d)*	4,090	0.08	0	0.265	0.05	0.09	-4.47***
Married *(d)*	4,090	0.71	1	0.454	0.78	0.68	6.42***
Good health *(d)*	4,090	0.59	1	0.491	0.7	0.55	9.38***
College *(d)*	4,090	0.18	0	0.388	0.29	0.14	11.6***
Home ownership *(d)*	4,090	0.87	1	0.335	0.93	0.84	7.92***
Income *(thousand USD)*	4,090	121.53	87.48	148.771	152.93	107.51	9.11***
Financial wealth *(thousand USD)*	4,090	185.01	21.214	1,573.154	368.52	103.13	5***
Real wealth *(thousand USD)*	4,090	409.52	180.78	916.739	670.42	293.1	12.38***

Note: N denotes the number of individual observations, (d) represents a dummy. "No job lock" refers to the group of individuals who do not report feelings of job lock whereas "job lock" is the sample proportion with the feeling of job lock. All monetary values are adjusted for inflation. The last column reports the t-test on the equality of the mean between participants who report a feeling of job lock and those who do not. The alternative hypothesis indicates that the means are different. ***p<0.01, **p<0.05, *p<0.1.

female, White, non-immigrant, married, in good health, has not attained a college degree, owns a house, and has household financial wealth and income of about 185 and 121 thousand USD.

About the mean statistics of the sub-samples of job lock and no job lock as reported in

the last three columns, we learn that the level of life satisfaction reported by those without feelings of job lock is relatively higher, suggesting a significant detrimental impact of job lock on subjective well-being in general. Similarly, individuals in the job lock group tend to consistently report lower satisfaction on average across all the specific domains of life satisfaction. For example, respondents in the group experiencing job lock are relatively less satisfied with their financial resources compared to the group without job lock, indicating that financial strain and lower quality of life influence older adults to keep working although they would like to leave work altogether. Individuals reporting job lock often show to be less open, agreeable, extraverted, conscientious, and more neurotic compared to their counterparts without job lock. Moreover, stronger control beliefs are prevalent among people without job lock, particularly mastery and control over finances, health, and social life. This suggests that a better sense of control beliefs may serve as a cushion against the adverse impact of job lock on life satisfaction. There are also notable differences between the two groups regarding the sociodemographic characteristics and job-related variables. The next section aims to present the results of the analyses and shed light on the relationship between job lock and life satisfaction while controlling for several observable factors.

3.4 Estimation Strategy

The objective of this chapter is to examine the relationship between job lock and life satisfaction among older workers in the United States. Since both overall life satisfaction and the domain-specific satisfaction measures are reported using ordered response categories, the empirical analysis employs ordered probit models. Ordered response models are widely used in the subjective well-being literature because they explicitly account for the ordinal nature of satisfaction outcomes and avoid imposing the assumption that the distance between adjacent response categories is equal (A. E. Clark & Oswald, 1994; Winkelmann & Winkelmann, 1998). Although previous studies have shown that treating subjective well-being measures as cardinal often yields similar conclusions (Ferrer-i-Carbonell & Frijters, 2004), ordered probit models remain the preferred approach when the dependent variable is inherently ordinal.

The ordered probit model assumes the existence of an underlying latent level of life satisfaction that cannot be directly observed. Let i denote individuals and t denote survey waves. The latent life satisfaction equation is specified as:

$$LS_{it}^{*} = \alpha + \beta_1 Joblock_{it} + \gamma X_{it}' + \delta_\tau + \lambda_t + \varepsilon_{it} \tag{3.1}$$

where LS_{it}^{*} is the latent (unobserved) life satisfaction of individual i in wave t; X_{it} represents the vector of control variables; δ_τ and λ_t denote the region and survey-wave fixed effects, respectively, and ε_{it} is the error term. The vector X_{it} includes demographic, socioeconomic, employment, health, and psychological characteristics that may influence both job lock and subjective well-being. Specifically, the analysis controls for age, gender, marital status, educational attainment, household income, employment characteristics, health status, personality traits, and measures of control beliefs. Including these controls helps reduce omitted-variable bias arising from observable factors that may jointly influence job lock and life satisfaction. The primary coefficient of interest is β_1, which captures the relationship between job lock and the latent propensity to report higher life satisfaction. A negative coefficient indicates that greater job lock is associated with lower subjective well-being.

To investigate whether job lock affects different dimensions of well-being, separate ordered probit models are estimated for each domain-specific satisfaction outcome. Let k denote a specific domain of satisfaction, including health, finances, family relationships, leisure activities, housing, and neighborhood satisfaction. The domain-specific specification is:

$$LS_{kit}^{*} = \alpha_k + \beta_{1k} Joblock_{it} + \gamma_k X_{it}' + \delta_\tau + \lambda_t + \varepsilon_{kit} \tag{3.2}$$

where LS_{kit}^{*} represents the latent level of satisfaction in domain k for individual i in survey wave t. Estimating separate models allows the analysis to identify whether job lock affects some dimensions of well-being more strongly than others.

We further examine whether control beliefs moderate the relationship between job lock and life satisfaction. Research suggests that individuals with stronger perceptions of personal control are better able to cope with adverse circumstances and therefore may be less

negatively affected by employment constraints (Lachman & Weaver, 1998; Mirowsky & Ross, 2007). To test this hypothesis, interaction terms between job lock and control beliefs are included in the empirical model:

$$LS_{it}^{*} = \beta_0 + \beta_1 Joblock_{it} + \beta_2 Beliefs_{it} + \beta_3 (Joblock_{it} * Beliefs_{it}) + \gamma X_{it}' + \delta_\tau + \lambda_t + \varepsilon_{it} \quad (3.3)$$

where $Beliefs_{it}$ represents either perceived mastery or perceived constraints. The interaction coefficient β_3 captures whether the association between job lock and life satisfaction varies according to an individual's level of perceived control. A positive interaction between job lock and mastery would suggest that mastery mitigates the negative consequences of job lock, whereas a negative interaction between job lock and perceived constraints would indicate that constraints amplify the adverse effects of job lock on well-being.

Because coefficients from ordered probit models reflect changes in an unobserved latent index rather than direct changes in probabilities, average marginal effects are computed to facilitate interpretation (Filippini et al., 2018). Marginal effects show how changes in job lock alter the probability of reporting each satisfaction category and therefore provide a more intuitive measure of the substantive importance of the estimated effects. All specifications include region fixed effects and survey-wave fixed effects to account for unobserved geographic and temporal heterogeneity. Standard errors are clustered at the household level to account for within-household dependence arising from repeated observations over time and shared household characteristics (Colin Cameron & Miller, 2015). This approach provides consistent inference in the presence of correlated error terms within households.

Overall, this empirical strategy allows for an examination of the direct association between job lock and subjective well-being while also identifying the specific dimensions of life satisfaction most affected by job lock and assessing whether perceptions of personal control moderate these relationships.

3.5 Regression Results

There are three subsections in this section, and each one is set out to evaluate a research question. Subsection 3.5.1 begins the analysis by examining the relationship between workers' perception of job lock and overall life satisfaction. In subsection 3.5.2, we discuss how job lock influences the domain-specific measures of life satisfaction. Finally, subsection 3.5.3 investigates whether the association between job lock and life satisfaction is moderated by control beliefs such as perceived mastery and constraints on personal control.

We present Tables 3.2–3.4 as our main regression output, reporting estimates from ordered probit models with household-clustered standard errors. Our analysis also accounts for time and region-fixed effects in all specifications by using dummy variables to identify the specific wave and region of the respondents to capture potential regional disparities and unobserved temporal events. For comparison, all non-dummy independent variables are standardized to take values in the 0-1 range.

To ensure the robustness and economic interpretability of our findings, we perform several supplementary analyses presented in the Appendix. Table 3.A.1 reports average marginal effects to facilitate the economic interpretation of our ordered probit estimates. Table 3.A.2 replicates the baseline analysis using OLS for comparability. Table 3.A.3 examines job satisfaction as both a predictor of life satisfaction and an outcome of job lock, suggesting that job satisfaction may partially influence the association between job lock and well-being.

To address concerns that self-reported measures of job lock and life satisfaction may be influenced by common psychological dispositions—particularly control beliefs—we conduct a residual-based analysis in Table 3.A.4. Here, we regress job lock and life satisfaction on the control belief variables and use the residuals from these regressions as cleaned measures. This approach isolates variation in job lock and life satisfaction that is orthogonal to control beliefs, thereby reducing potential confounding from latent psychological factors. The results remain consistent with our main findings, strengthening confidence in the robustness of the job lock–life satisfaction relationship. Tables 3.A.5–3.A.7 further explore domain-specific

moderation and objective correlates of job lock, including socioeconomic and health insurance characteristics, confirming the persistence of our core results across alternative specifications and measures.

As highlighted in Bucciol & Zarri (2020), Bond & Lang (2019) recently criticized the conventional approach to analyzing subjective measures of well-being. The authors argue that the standard methods, which mostly rely on mean statistics, are flawed because they consider the variables as cardinal even when they are actually ordinal. This does not allow an accurate comparison of two groups of survey participants unless strong and unrealistic conditions on the distribution are fulfilled due to the arbitrary nature of the distance between two values, which does not convey any meaningful information. Indeed, one may consider increasing transformations of the measure of subjective well-being while maintaining the original ranking and still obtain contrasting conclusions compared to methods that assume cardinality. This issue also applies to the life satisfaction measures in this study since they depend on discrete ordinal scales.

A solution to this problem is to use median rankings instead of mean rankings. The median, unlike the mean, preserves the ordinal ranking of subjective well-being data since it is equivariant to monotonic transformations (see Chen et al., 2019). The authors also suggest that ordered probit and logit regressions are the most suitable models for analyzing discrete ordinal variables because of the fact that the median is identical to the mean in the case of a symmetric distribution. They therefore propose the use of these models and proceed to interpret the regression output as median rankings rather than mean rankings. We acknowledge the perspective of Chen et al. (2019) and conduct our analysis using cross-sectional ordered probit regressions instead of standard OLS. In the subsequent sections, we choose to adhere to the standard practice of commenting only on coefficients that are statistically significant at the 5 percent level or higher.

3.5.1 Overall Life Satisfaction and Perception of Job Lock

In Table 3.2, we present coefficient estimates for five separate models using a cross-sectional ordered probit regression in our benchmark analysis. Life satisfaction, in general, is the dependent variable rated on a five-point Likert scale ranging discretely from 1 to 5, to indicate that lower values (higher values) correspond to lower levels of satisfaction (higher satisfaction). The aim is to examine the relationship between workers' perception of job lock and their life satisfaction in general while controlling for other key explanatory variables.

We initially regress the overall life satisfaction index on the socio-demographic characteristics as reported in Column 1. In Column 2, we introduce two job-related stressors: economic_necessity lock— refers to respondents who are still working because they need to obtain either money or health insurance, and combined_necessity lock— identifies individuals who keep working because they need to make money and be covered by health insurance at the same time, although they would wish to retire. Columns 3 and 4 add to the specification the Big Five personality traits and control beliefs variables, respectively, to observe the relation of these psychological characteristics to our key variables. Lastly, Column 5 is the baseline model, simultaneously including the full set of variables of interest and all the controls.

We learn from Column 1 that individuals who are older, immigrants, married, in good health, have attained a college degree, own a home, and are wealthy tend to have higher median life satisfaction. In terms of marginal effects, being in good health increases the probability of reporting the highest life satisfaction by 14.6 percent, while home ownership adds 5.1 percent—demonstrating the substantial economic magnitude of these factors (see Table 3.A.1 in the appendix). This finding aligns with existing literature (see Blanchflower & Oswald, 2004; Bucciol & Zarri, 2020). As we add the other new variables, almost all the coefficients of the control variables change in size, and a number of them either decrease or lose significance in this horse race. Surprisingly, being a female is the only variable that does not significantly predict life satisfaction among older US workers across all models. This finding somewhat contrasts with some previous literature that reports higher subjective well-

being among women in general population samples (e.g., Blanchflower & Oswald, 2004). However, it aligns with past studies that show that once socio-demographic controls and psychological traits are accounted for, gender effects often diminish or disappear (Fisher, Ryan, et al., 2016; Joshanloo & Jovanović, 2021). This underscores that in the context of job lock and late-career employment, gender may not independently shape overall life satisfaction beyond its association with other measured covariates.

Regarding job-related stressors, we show that both economic_necessity lock and combined_necessity lock are negatively and significantly associated with overall life satisfaction across the last four models (i.e., columns 2-5). The average marginal effects reported in Table 3.A.1 reveal that experiencing economic necessity lock reduces the probability of highest life satisfaction by 11.8 percent in Model 2, while combined necessity lock reduces it by 14.2 percent. These effects remain economically meaningful in the full model, at 7.1 and 8.3 percent, respectively, even after controlling for psychological traits. Specifically, we learn that older workers who are locked in jobs because of both money and health insurance needs (i.e., combined_necessity lock) have relatively lower median satisfaction compared to individuals who report being job locked due to either money or health insurance needs (i.e., economic_necessity lock). The 1.2 percent larger marginal effect for combined lock (8.3 percent vs. 7.1 percent in Model 5) suggests that the psychological burden of dual dependency is not merely additive but represents a distinct, more severe form of constraint. This evidence corroborates prior studies that demonstrate that being stuck at work and falling into a state of job lock because of employer-covered health insurance causes a feeling of helplessness and consequently reduces the general subjective well-being (see e.g., Gruber & Madrian, 2004).

Table 3.2: Benchmark analysis

Life satisfaction (Overall)	(1)	(2)	(3)	(4)	(5)
Economic_necessity lock		-0.376***	-0.323***	-0.252***	-0.246***
		(0.051)	(0.051)	(0.052)	(0.052)
Combined_necessity lock		-0.453***	-0.389***	-0.289***	-0.289***
		(0.051)	(0.051)	(0.051)	(0.051)
Mastery				0.184***	0.149***
				(0.027)	(0.027)
Personal constraints				-0.226***	-0.165***
				(0.027)	(0.027)
Control over health				-0.005	-0.024
				(0.027)	(0.027)
Control over social life				0.124***	0.100***
				(0.027)	(0.027)
Control over finances				0.176***	0.158***
				(0.027)	(0.027)
Openness			-0.045		-0.060**
			(0.028)		(0.027)
Conscientiousness			0.109***		0.065***
			(0.025)		(0.025)
Extraversion			0.208***		0.139***
			(0.027)		(0.028)
Agreeableness			0.005		0.000
			(0.025)		(0.025)
Neuroticism			-0.254***		-0.160***
			(0.023)		(0.024)
Age/10	0.113***	0.044	0.002	0.076**	0.042
	(0.031)	(0.032)	(0.032)	(0.032)	(0.032)
Female	0.045	0.043	0.025	0.064	0.050
	(0.044)	(0.044)	(0.045)	(0.044)	(0.046)
Non-white	0.028	0.046	-0.080	-0.146**	-0.181***
	(0.061)	(0.061)	(0.063)	(0.066)	(0.066)
Immigrate	0.244***	0.276***	0.331***	0.348***	0.362***
	(0.080)	(0.080)	(0.082)	(0.084)	(0.083)
Married	0.233***	0.211***	0.228***	0.309***	0.295***
	(0.048)	(0.047)	(0.047)	(0.048)	(0.047)
Good health	0.455***	0.432***	0.270***	0.266***	0.215***
	(0.041)	(0.041)	(0.042)	(0.042)	(0.043)
College	0.135**	0.086	0.156**	0.139**	0.184***
	(0.061)	(0.061)	(0.061)	(0.061)	(0.062)
Ln(income)	0.071**	0.062**	0.034	0.009	0.006
	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)
Home ownership	0.160**	0.167**	0.168**	0.152**	0.155**
	(0.069)	(0.068)	(0.068)	(0.071)	(0.070)

Life satisfaction (Overall)	(1)	(2)	(3)	(4)	(5)
Ln(fin. wealth)	0.098***	0.067***	0.065***	0.048**	0.049**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Ln(real wealth)	0.088***	0.070**	0.076**	0.027	0.039
	(0.032)	(0.031)	(0.032)	(0.032)	(0.032)
Threshold 1	-1.784***	-2.097***	-2.244***	-2.265***	-2.330***
	(0.136)	(0.138)	(0.137)	(0.144)	(0.144)
Threshold 2	-1.025***	-1.335***	-1.456***	-1.444***	-1.504***
	(0.127)	(0.128)	(0.125)	(0.128)	(0.127)
Threshold 3	0.041	-0.255**	-0.319***	-0.267**	-0.312**
	(0.125)	(0.126)	(0.121)	(0.123)	(0.123)
Threshold 4	1.305***	1.030***	1.055***	1.140***	1.125***
	(0.127)	(0.127)	(0.123)	(0.125)	(0.125)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Log-likelihood	-4,791.894	-4,728.995	-4,517.326	-4,431.553	-4,368.429
Observations	4,090	4,090	4,090	4,090	4,090

Note: The table reports factors that drive overall life satisfaction among workers; All non-dummy explanatory variables are standardized (mean = 0, SD = 1). Coefficients represent changes in the latent satisfaction propensity associated with a one-standard-deviation increase in the predictor. Coefficients are from cross-sectional ordered probit regressions; Standard errors are clustered at the household level and reported in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Turning to the five personality traits reported in Column 3, we find that two traits exhibit a significantly positive correlation with life satisfaction, and one shows a significantly negative association with life satisfaction. The marginal effects quantify these relationships: a one-standard-deviation increase in extraversion increases the probability of highest life satisfaction by 6.2 percent, while the same increase in neuroticism decreases it by 7.5 percent—effects comparable in magnitude to many demographic factors. The negative relationship suggests that older workers who possess more neuroticism and openness traits could be more prone to the detrimental consequences of job lock. However, older workers who score high in extraversion and conscientiousness traits might be more resistant to the adverse effects of job lock. These findings are generally in line with prior studies on the relationship between personality traits and subjective well-being (see e.g., Hayes & Joseph, 2003; Bucciol & Zarri, 2020).

Moreover, variables such as mastery and perceived control over finance and social life

relate positively with life satisfaction, suggesting that older workers who perceive a greater sense of control and feel they can do just anything they set their mind to do tend to have higher median life satisfaction and are more suited to cope with limitations imposed by a perception of job lock. The marginal effects reveal that mastery beliefs increase the probability of highest satisfaction by 4.3 percent, while perceived control over finances adds 4.6 percent—highlighting the protective role of financial autonomy specifically.

Conversely, individuals who perceive having more personal constraints, that is, often feel helpless in dealing with the problems of life, are more likely to have lower median life satisfaction and consider it more challenging to deal with the constraints imposed by job lock. Personal constraints show a substantial negative marginal effect (-4.8 percentage points), nearly as large as the positive effect of mastery beliefs, underscoring the symmetric importance of avoiding helplessness as cultivating competence. The robustness of these associations is further supported by the ordinary least squares (OLS) analysis, which yields qualitatively similar results (see Table 3.A.2), confirming that the findings are not sensitive to the choice of estimator. Moreover, to address potential confounding from shared psychological dispositions, we residualized both job lock and life satisfaction on control belief variables. The persistent negative relationship between residualized measures (Table 3.A.4) suggests that the job lock effect is not merely an artifact of correlated psychological traits.

Indeed, the average marginal effects reported in Appendix Table 3.A.2 provide crucial economic context to the statistical relationships shown in Table 3.2. Several patterns emerge: First, job lock effects are economically substantial—combined necessity lock reduces the probability of highest life satisfaction by 8.3 percent, an effect size comparable to being unmarried (8.5 percent) or having poor health (-6.2 percent). Second, psychological factors show meaningful magnitudes: neuroticism's effect (-4.6 percent) is larger than that of income (2.2 percent per log unit) or financial wealth (1.4 percent per log unit), highlighting the economic relevance of personality in well-being models. Third, the attenuation of job lock coefficients from models 2 to 5 (from 14.2 to 8.3 percent for combined lock) suggests that approximately 42 percent of job lock's total effect operates through correlated psychological channels—personality traits and control beliefs—while the remainder represents a direct

effect.

3.5.2 Job Lock and Domain-Specific Life Satisfaction

Previous studies on life satisfaction determinants have primarily focused on general life satisfaction; however, it should be noted that these determinants may differ in various domains of life satisfaction. We therefore set out to examine how job lock influences the different domain-specific measures of life satisfaction to add to our previous analysis on overall life satisfaction. Table 3.3 uses six domain-specific measures of life satisfaction, namely satisfaction with housing, city, leisure, family, finances, and health, as dependent variables to replicate the baseline specification (i.e., column 5) of Table 3.2. We employ ordered probit regression for this analysis also since the domain-specific life satisfaction variables are ordinal on a 5-point Likert scale.

Table 3.3: Domain-specific life satisfaction

Life satisfaction	(1) Housing	(2) City	(3) Leisure	(4) Family	(5) Finances	(6) Health
Economic_necessity lock	-0.165***	-0.149***	-0.273***	-0.177***	-0.567***	-0.197***
	(0.052)	(0.053)	(0.052)	(0.053)	(0.053)	(0.048)
Combined_necessity lock	-0.171***	-0.112**	-0.300***	-0.082	-0.647***	-0.237***
	(0.052)	(0.052)	(0.049)	(0.051)	(0.052)	(0.049)
Mastery	0.056**	0.013	0.084***	0.058**	0.055**	0.061**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.026)
Personal constraints	-0.056**	-0.066**	-0.110***	-0.153***	-0.050*	-0.003
	(0.028)	(0.027)	(0.030)	(0.028)	(0.028)	(0.029)
Control over health	0.019	0.010	-0.033	-0.100***	-0.105***	0.355***
	(0.028)	(0.028)	(0.029)	(0.028)	(0.029)	(0.032)
Control over social life	0.045	0.101***	0.255***	0.246***	-0.074***	0.011
	(0.028)	(0.028)	(0.030)	(0.029)	(0.028)	(0.029)
Control over finances	0.145***	0.112***	0.121***	0.172***	0.602***	0.123***
	(0.029)	(0.028)	(0.029)	(0.028)	(0.031)	(0.028)
Openness	-0.047*	-0.059**	-0.052*	-0.082***	-0.022	-0.071***
	(0.028)	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)
Conscientiousness	0.140***	0.053**	0.058**	0.047*	0.058**	0.034
	(0.025)	(0.026)	(0.026)	(0.025)	(0.026)	(0.025)
Extraversion	0.104***	0.118***	0.228***	0.104***	0.074***	0.159***
	(0.028)	(0.030)	(0.028)	(0.028)	(0.027)	(0.028)
Agreeableness	0.036	0.095***	0.036	0.095***	-0.015	-0.024
	(0.026)	(0.027)	(0.026)	(0.026)	(0.024)	(0.025)
Neuroticism	-0.076***	-0.071***	-0.200***	-0.188***	-0.115***	-0.177***
	(0.024)	(0.023)	(0.024)	(0.024)	(0.023)	(0.024)
Age/10	0.122***	0.155***	0.126***	0.147***	0.033	0.037
	(0.033)	(0.032)	(0.031)	(0.034)	(0.033)	(0.032)
Female	-0.060	0.043	-0.061	-0.089*	0.011	-0.054
	(0.048)	(0.047)	(0.046)	(0.046)	(0.045)	(0.046)
Non-white	-0.246***	-0.243***	-0.126*	-0.091	-0.081	0.022
	(0.065)	(0.065)	(0.065)	(0.068)	(0.068)	(0.071)
Immigrate	0.263***	0.175**	0.185**	0.287***	0.246***	0.204**
	(0.083)	(0.080)	(0.085)	(0.085)	(0.086)	(0.080)
Married	0.075	-0.067	0.121**	0.426***	0.235***	0.074
	(0.052)	(0.051)	(0.049)	(0.051)	(0.049)	(0.048)
Good health	0.163***	0.047	0.188***	0.134***	0.229***	1.067***
	(0.043)	(0.041)	(0.042)	(0.042)	(0.042)	(0.047)
College	-0.002	-0.016	-0.054	-0.043	0.059	-0.048
	(0.061)	(0.062)	(0.057)	(0.058)	(0.058)	(0.057)
Ln(income)	0.017	0.019	-0.005	0.019	0.079**	-0.015
	(0.028)	(0.027)	(0.027)	(0.030)	(0.036)	(0.032)

Life satisfaction	(1) Housing	(2) City	(3) Leisure	(4) Family	(5) Finances	(6) Health
Home ownership	0.138*	-0.034	0.010	0.098	0.003	0.099
	(0.071)	(0.069)	(0.073)	(0.074)	(0.070)	(0.073)
Ln(fin. wealth)	0.073***	0.062**	0.029	-0.045*	0.255***	0.036
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)
Ln(real wealth)	0.146***	0.147***	0.081**	0.020	0.132***	-0.006
	(0.030)	(0.030)	(0.032)	(0.033)	(0.031)	(0.032)
Threshold 1	-2.745***	-3.006***	-3.265***	-2.588***	-2.368***	-2.426***
	(0.151)	(0.160)	(0.162)	(0.153)	(0.133)	(0.152)
Threshold 2	-2.049***	-2.210***	-2.144***	-1.770***	-1.362***	-1.303***
	(0.142)	(0.147)	(0.138)	(0.147)	(0.127)	(0.135)
Threshold 3	-0.919***	-1.171***	-0.596***	-0.599***	0.002	0.315**
	(0.137)	(0.143)	(0.132)	(0.144)	(0.128)	(0.131)
Threshold 4	0.295**	0.069	0.771***	0.718***	1.276***	1.956***
	(0.137)	(0.142)	(0.134)	(0.145)	(0.130)	(0.135)
Year FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Log-likelihood	-4483.718	-4506.506	-4294.580	-4471.165	-4744.659	-4165.041
Observations	4,072	4,073	4,068	4,064	4,069	4,073

Note: Coefficients are from cross-sectional ordered probit regressions; All non-dummy explanatory variables are standardized (mean = 0, SD = 1). Coefficients represent changes in the latent satisfaction propensity associated with a one-standard-deviation increase in the predictor. Standard errors are clustered at the household level and reported in parentheses; Average marginal effects table for the domain specific analysis is not presented for brevity. ***p<0.01, **p<0.05, *p<0.

The regression output in Table 3.3 shows a consistently negative association of job lock in almost all the domains of life satisfaction. Particularly, both economic_necessity lock and combined_necessity lock correlate significantly and negatively with the domain-specific measures of life satisfaction. Of the six domains, we learn that the correlation of combined_necessity lock is more pronounced among satisfaction with housing, leisure, finances, and health, with an unexpectedly no significant association with family satisfaction, while the effect of economic_necessity lock is stronger in both city and family satisfaction. This prevalent negative effect across multiple life domains underscores that job lock is not merely a work-related stressor but permeates broader life evaluation, consistent with spillover theories of work-life balance (Judge & Watanabe, 1993) and the holistic impact of perceived entrapment on well-being (Fisher, Ryan, et al., 2016).

Overall, we observe substantial negative effects of job lock across life domains. The largest ordered probit coefficients appear for financial and leisure satisfactions, followed by health satisfaction. Average marginal effects indicate that combined job lock reduces the probability of highest financial satisfaction (i.e., a value of 5) by approximately 11.8 percent, leisure satisfaction by 7.8 percent, and health satisfaction by 4.2 percent. This finding is intuitive and aligns with the domain-congruence hypothesis in well-being research, where stressors show the strongest effects in directly related life domains (Schimmack et al., 2010). Financial and health-related job lock directly threaten economic security and healthcare access, thereby exerting the largest toll on satisfaction in these areas. It is worth adding that many late adult workers report a perception of job lock as a result of insufficient savings towards their retirement or the need to hold onto health insurance provided by their employers. This makes them reluctant to switch to higher–paying jobs because of the fear of self-funding the health insurance, especially when they have underlying conditions that may require expensive health care in the future. This mechanism is well-documented in health economics and labor studies, where employer-sponsored health insurance creates a significant insurance-based job lock that reduces mobility and exacerbates financial anxiety, particularly among older adults with chronic conditions (Gruber & Madrian, 2004). Since older workers who are locked up in their jobs do so out of necessity, they experience psychological and physical stress due to prioritizing their job security above their well-being, which is detrimental to their health.

Extraversion and Neuroticism are the personality traits that have a stable association with each domain of life satisfaction, although their coefficients differ in size. In general, we find that each trait has at least two significant correlations with the domains of life satisfaction. This pattern reinforces the trait-consistency perspective in personality psychology, where broad dispositions like extraversion and neuroticism exert pervasive influences across multiple life domains (Costa & McCrae, 1992; Steel et al., 2008). A strong positive correlation exists between extraversion and satisfaction with leisure, health, and the city, implying that individuals who are sociable and outgoing tend to gain more happiness from non-working hours, the place where they live, as well as maintaining good health status. However, neuroticism relates negatively to all the domains of life satisfaction, and it suggests that individuals

who score high in neuroticism are more likely to see the median satisfaction in various areas of their lives reduced.

With respect to control beliefs, both mastery and personal constraints have at least four strong associations with the domains of life satisfaction. Mastery belief shows a positive and significant relationship, most notably with leisure satisfaction, while perceived personal constraints correlate negatively and significantly, most especially with family satisfaction. These results extend Lachman & Weaver's (1998) model of control beliefs by demonstrating their domain-specific relevance. We also learn that perceived control over finances has a consistent positive association with life satisfaction across all the domains, suggesting that people with financial autonomy get happier in most facets of their lives. These domain-specific patterns hold across alternative model specifications, including those using residualized measures to control for psychological confounds (Table 3.A.4). Additionally, job satisfaction is examined as a separate outcome of job lock in Table 3.A.3, revealing that job lock significantly reduces job satisfaction—a finding consistent with the broader literature on work-related well-being (Fisher, Ryan, et al., 2016).

3.5.3 Moderation Analysis: Control Beliefs as Moderators

In this subsection, we examine how control beliefs, especially mastery and personal constraints, moderate the relationship between job lock and overall as well as domain-specific life satisfaction outcomes using two-way interactions. As reported in Tables 3.2 and 3.3, which established that both job lock and perceived control independently affect life satisfaction, we now use a continuous measure of job lock ranging from 0 to 2, where 0 denotes no job lock, 1 denotes lock due to either economic or health reasons, and 2 represents combined necessity lock to capture the intensity of employment constraints. This allows us to explore whether the effect of increasing job lock intensity is buffered or amplified by individuals' beliefs about their personal control.

As reported in Table 3.4, job lock has a strong negative main effect on overall life satisfaction across several domains, particularly housing, leisure, finances, and health satisfaction.

Table 3.4: Moderation analysis

Life satisfaction	(1) Overall	(2) Housing	(3) City	(4) Leisure	(5) Family	(6) Finances	(7) Health
Job lock	-0.106***	-0.054**	-0.039	-0.116***	-0.016	-0.282***	-0.098***
	(0.026)	(0.027)	(0.027)	(0.026)	(0.026)	(0.027)	(0.026)
Mastery	0.140***	0.121***	0.040	0.145***	0.111***	0.082**	0.063*
	(0.043)	(0.034)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Personal constraints	-0.330***	-0.142***	-0.105**	-0.194***	-0.201***	-0.155***	-0.078*
	(0.047)	(0.044)	(0.044)	(0.045)	(0.042)	(0.041)	(0.042)
Job lock*Mastery	0.006	-0.056**	-0.023	-0.053**	-0.045*	-0.023	-0.002
	(0.029)	(0.025)	(0.024)	(0.025)	(0.025)	(0.026)	(0.027)
Job lock*Personal cons.	0.126***	0.064**	0.029	0.062**	0.034	0.079***	0.057*
	(0.029)	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)	(0.029)
Control over health	-0.022	0.019	0.009	-0.033	-0.100***	-0.105***	0.356***
	(0.027)	(0.028)	(0.028)	(0.029)	(0.028)	(0.029)	(0.031)
Control over social life	0.097***	0.045	0.099***	0.254***	0.245***	-0.078***	0.010
	(0.027)	(0.028)	(0.029)	(0.030)	(0.029)	(0.029)	(0.029)
Control over finances	0.169***	0.152***	0.117***	0.130***	0.179***	0.612***	0.129***
	(0.027)	(0.029)	(0.028)	(0.029)	(0.028)	(0.031)	(0.028)
Openness	-0.060**	-0.046*	-0.059**	-0.052*	-0.083***	-0.023	-0.071***
	(0.027)	(0.028)	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)
Conscientiousness	0.065***	0.138***	0.053**	0.057**	0.047*	0.058**	0.034
	(0.025)	(0.025)	(0.026)	(0.026)	(0.025)	(0.026)	(0.025)
Extraversion	0.138***	0.102***	0.117***	0.226***	0.102***	0.073***	0.158***
	(0.028)	(0.027)	(0.030)	(0.028)	(0.028)	(0.027)	(0.028)
Agreeableness	0.002	0.038	0.095***	0.038	0.096***	-0.014	-0.023
	(0.025)	(0.026)	(0.027)	(0.026)	(0.026)	(0.024)	(0.025)
Neuroticism	-0.161***	-0.077***	-0.071***	-0.201***	-0.189***	-0.117***	-0.177***
	(0.024)	(0.024)	(0.023)	(0.024)	(0.023)	(0.023)	(0.024)
Socio-demographic	YES	YES	YES	YES	YES	YES	YES
Threshold 1	-2.227***	-2.661***	-2.939***	-3.152***	-2.489***	-2.203***	-2.362***
	(0.141)	(0.150)	(0.159)	(0.162)	(0.153)	(0.131)	(0.152)
Threshold 2	-1.403***	-1.963***	-2.145***	-2.035***	-1.672***	-1.202***	-1.240***
	(0.125)	(0.141)	(0.146)	(0.138)	(0.147)	(0.126)	(0.134)
Threshold 3	-0.212*	-0.834***	-1.107***	-0.493***	-0.504***	0.157	0.378***
	(0.121)	(0.136)	(0.141)	(0.132)	(0.144)	(0.126)	(0.130)
Threshold 4	1.230***	0.382***	0.132	0.877***	0.812***	1.426***	2.020***
	(0.123)	(0.135)	(0.140)	(0.133)	(0.145)	(0.128)	(0.134)
Year FE	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-4358.858	-4477.144	-4507.429	-4291.231	-4472.770	-4755.949	-4164.118
Observations	4,090	4,072	4,073	4,068	4,064	4,069	4,073

Note: Coefficients are from cross-sectional ordered probit regressions; Job lock is measured as a continuous variable ranging from 0 (no job lock) to 2 (both economic and health necessity). All non-dummy explanatory variables are standardized (mean = 0, SD = 1). Coefficients represent changes in the latent satisfaction propensity associated with a one-standard-deviation increase in the predictor. Standard errors are clustered at the household level and reported in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Regarding moderation effects, we observe that the interaction between job lock and mastery is not statistically significant for overall life satisfaction, suggesting that a broad sense

of personal efficacy does not meaningfully mitigate the negative effects of job lock at the general level. However, significant negative interaction terms are found for housing and leisure satisfaction, indicating that individuals with high mastery beliefs may experience greater frustration from job lock in these domains—likely because their perceived ability to influence life circumstances clashes with constraints imposed by continued, necessity-driven employment.

On the other hand, the interaction between job lock and personal constraints is positive and statistically significant for overall life satisfaction, as well as in the domains of housing, leisure, finances, and health. This suggests that the negative consequences of job lock are less pronounced among individuals who already perceive low control over life circumstances. One possible interpretation is that such individuals may have lower expectations or have adapted psychologically to external constraints and thus experience less dissatisfaction when job lock occurs.

Our moderation analysis moves beyond documenting a negative association to shed light on how psychological resources can alter the impact of structural constraints. Drawing from the conservation of resources theory (Hobfoll, 1989), we view perceived mastery and constraints as key personal resources. Contrary to a simple buffering view, the interaction terms indicate that the negative relationship between job lock and life satisfaction is weaker among individuals with high perceived constraints, while higher mastery does not attenuate this relationship and is even associated with a stronger negative effect of job lock in the housing and leisure domains. This pattern is only partly consistent with the stress-buffering hypothesis in health psychology, according to which psychological resources do not eliminate stressors but alter one's appraisal of and capacity to cope with them (Cohen & Wills, 1985). Rather, it suggests that the appraisal of job lock depends on individuals' expectations: those who expect to be in control of their lives experience an additional constraint as more costly, whereas those who already perceive limited control may have adapted to constrained circumstances.

These results position our study at the intersection of behavioral labor economics and

occupational health psychology, highlighting that the economic cost of job lock is not uniform but depends critically on individual differences in perceived control.

We acknowledge that our analysis may be subject to simultaneity, as job lock and life satisfaction are both subjective measures that may be influenced by common unobserved factors. For example, individuals with low overall well-being may be more likely to perceive themselves as job-locked, while experiencing job lock may, in turn, lower their reported life satisfaction. To explore this issue, we estimated a two-step model where job satisfaction is first modeled as a function of job lock and other covariates, and then life satisfaction is regressed on the predicted job satisfaction. This approach is intended to isolate the indirect pathway from job lock to life satisfaction through job satisfaction. However, we note that using job lock as an instrument for job satisfaction may raise concerns regarding instrument validity, as job lock may exert a direct effect on life satisfaction that violates the exclusion restriction. As such, we do not report these results in the main text, though they are available upon request. We emphasize that caution is warranted in interpreting relationships causally, and we encourage future research using longitudinal data and more objective measures to further address these concerns.

Our findings underscore that job lock is not merely an individual psychological experience but is fundamentally shaped by institutional structures. In the U.S. context, the link between employment and health insurance (before Medicare eligibility at 65) and the structure of Social Security benefits create powerful financial disincentives to retire earlier. Policy reforms that decouple health insurance from employment—such as lowering the Medicare eligibility age or creating a public option—could directly reduce health-insurance-driven job lock. Similarly, enhancing pension portability and promoting phased retirement programs would grant older workers greater autonomy over their retirement timing. While our analysis focuses on the United States, the psychological mechanism—perceived constraints eroding well-being—is likely universal. However, the institutional drivers vary. In countries with universal healthcare (e.g., Canada, the UK), health insurance is less likely to cause job lock, but pension eligibility ages and means-tested benefits may play a stronger role. In nations with flexible retirement schemes (e.g., Nordic countries), the prevalence of job lock may be

lower. Future comparative research could test whether our findings hold in different welfare regimes, offering insights for tailoring policies to national contexts.

3.6 Conclusion

Subjective well-being literature has progressed largely over the past few decades, but how the perception of job lock among adult workers in the US influences their general life satisfaction is less explored. We contribute to the literature by examining the relationship between workers' perception of job lock and overall life satisfaction, how job lock influences the domain-specific measures of life satisfaction, and whether the association between job lock and life satisfaction is moderated by control beliefs such as perceived mastery and constraints on personal control. We use data from HRS, which comprehensively covers measures of subjective well-being, job-related variables, personality traits, control beliefs, and socio-demographic characteristics.

Our analysis shows that the overall life satisfaction of adult workers declines after experiencing a perceived job lock; particularly, the negative effect associated with job lock due to both financial and health insurance needs on life satisfaction is more pronounced. Based on our assessment of life satisfaction across different domain-specific measures, we find that job lock induced by both health insurance and income turns out to be largely correlated with financial and leisure satisfaction. Also, we document that constraints on personal control significantly moderate the negative impact of job lock on general life satisfaction, such that the negative association is weaker among workers who already perceive greater constraints. These results are corroborated by a series of robustness checks detailed in the Appendix, including analyses using alternative estimators, residualized measures to isolate psychological confounding, and objective indicators of socioeconomic and insurance constraints. Collectively, these checks reinforce the validity of the conclusion that job lock meaningfully undermines well-being among older U.S. workers, highlighting the need for policies that address both financial security and health coverage in later working life. Our study demonstrates that the negative impact of job lock on life satisfaction is conditioned by

psychological factors. This finding advances the literature by moving from a purely economic model of constraints to a behaviorally-informed model that incorporates perceived control as a moderator. For policymakers, this implies that interventions aimed at reducing job lock should pay particular attention to workers who expect a high degree of control over their lives, for whom being locked in a job appears especially costly.

Our findings should be considered in light of some limitations. First, we acknowledge that our analysis may suffer from simultaneity since all the psycho-social measures in the data are subjective. Second, single-item measures were used to evaluate domain-specific measures of life satisfaction and the job lock index as provided in the HRS. This might have reduced the validity and reliability of the results. The treatment of job lock as a dummy variable, in that respondents answered yes or no to indicate whether they perceive it to be job locked or not based on their income and health needs, might have also reduced the variation in the variable compared to evaluating the construct as a continuous variable. Third, the panel dimension of our data is somewhat small, so we are unable to exploit panel estimation models to infer causality from our analysis. Finally, we acknowledge that the generalizability of our findings to workers living in countries other than the US remains challenging, as outside the US (and particularly in countries with government-funded healthcare) may well perceive job lock differently. Future research should consider extending the waves of the HRS data to obtain a large panel dimension to capture long-term trends and effects of job lock on life satisfaction. Another point for future studies is to analyze the gender disparities associated with job lock to uncover how job lock affects women and men differently in terms of subjective well-being.

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3.A Appendix to Chapter 3

Table 3.A.1: Average Marginal Effects

Life satisfaction (Overall)	(1)	(2)	(3)	(4)	(5)
Economic_necessity lock		-0.118***	-0.096***	-0.074***	-0.071***
		(0.016)	(0.015)	(0.015)	(0.015)
Combined_necessity lock		-0.142***	-0.116***	-0.085***	-0.083***
		(0.016)	(0.015)	(0.015)	(0.015)
Mastery				0.054***	0.043***
				(0.008)	(0.008)
Personal constraints				-0.066***	-0.048***
				(0.008)	(0.008)
Control over health				-0.001	-0.007
				(0.008)	(0.008)
Control over social life				0.036***	0.029***
				(0.008)	(0.008)
Control over finances				0.052***	0.046***
				(0.008)	(0.008)
Openness to experience			-0.013		-0.017**
			(0.008)		(0.008)
Conscientiousness			0.032***		0.019***
			(0.007)		(0.007)
Extraversion			0.062***		0.040***
			(0.008)		(0.008)
Agreeableness			0.001		0.000
			(0.007)		(0.007)
Neuroticism			-0.075***		-0.046***
			(0.007)		(0.007)
Age/10	0.036***	0.014	0.001	0.022**	0.012
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Female	0.015	0.014	0.007	0.019	0.015
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Non-white	0.009	0.014	-0.024	-0.043**	-0.052***
	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
Immigrate	0.078***	0.086***	0.098***	0.102***	0.104***
	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)
Married	0.075***	0.066***	0.068***	0.091***	0.085***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
Good health	0.146***	0.135***	0.080***	0.078***	0.062***
	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
College	0.043**	0.027	0.046**	0.041**	0.053***
	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)
Ln(income)	0.023**	0.019**	0.010	0.003	0.002
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Home ownership	0.051**	0.052**	0.050**	0.045**	0.045**
	(0.022)	(0.021)	(0.020)	(0.021)	(0.020)
Ln(fin. wealth)	0.031***	0.021***	0.019***	0.014**	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Ln(real wealth)	0.028***	0.022**	0.022**	0.008	0.011
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Observations	4090	4090	4090	4090	4090

Note: This table reports average marginal effects (AMEs) from ordered probit models. AMEs represent the change in the probability of reporting life satisfaction = 5 associated with a one-standard-deviation increase in standardized variables or a change from 0 to 1 for dummy variables. ***p<0.01, **p<0.05, *p<0.1.

Table 3.A.2: Effect of Job lock on life satisfaction

Life satisfaction (Overall)	(1)	(2)	(3)	(4)	(5)
Economic_necessity lock		-0.262***	-0.210***	-0.154***	-0.147***
		(0.036)	(0.034)	(0.034)	(0.034)
Combined_necessity lock		-0.323***	-0.260***	-0.181***	-0.179***
		(0.037)	(0.034)	(0.034)	(0.034)
Mastery				0.125***	0.101***
				(0.019)	(0.019)
Personal constraints				-0.165***	-0.124***
				(0.020)	(0.020)
Control over health				-0.005	-0.018
				(0.020)	(0.019)
Control over social life				0.089***	0.072***
				(0.020)	(0.020)
Control over finances				0.120***	0.106***
				(0.020)	(0.020)
Openness			-0.031		-0.042**
			(0.020)		(0.019)
Conscientiousness			0.072***		0.038**
			(0.018)		(0.017)
Extraversion			0.146***		0.093***
			(0.020)		(0.019)
Agreeableness			-0.004		-0.007
			(0.018)		(0.017)
Neuroticism			-0.181***		-0.108***
			(0.017)		(0.017)
Age/10	0.082***	0.033	0.003	0.053**	0.031
	(0.022)	(0.022)	(0.021)	(0.021)	(0.020)
Female	0.036	0.034	0.027	0.044	0.041
	(0.033)	(0.032)	(0.032)	(0.030)	(0.031)
Non-white	0.027	0.041	-0.047	-0.090*	-0.111**
	(0.048)	(0.048)	(0.046)	(0.047)	(0.046)
Immigrate	0.181***	0.202***	0.226***	0.234***	0.238***
	(0.060)	(0.059)	(0.057)	(0.057)	(0.055)
Married	0.178***	0.158***	0.162***	0.214***	0.202***
	(0.038)	(0.037)	(0.034)	(0.034)	(0.033)
Good health	0.344***	0.323***	0.191***	0.182***	0.145***
	(0.031)	(0.031)	(0.030)	(0.029)	(0.030)
College	0.085**	0.049	0.095**	0.081**	0.112***
	(0.043)	(0.043)	(0.041)	(0.039)	(0.039)
Ln(income)	0.056**	0.049**	0.027	0.008	0.006
	(0.022)	(0.022)	(0.021)	(0.021)	(0.020)
Home ownership	0.135**	0.140**	0.130**	0.117**	0.115**
	(0.056)	(0.055)	(0.052)	(0.052)	(0.051)

Life satisfaction (Overall)	(1)	(2)	(3)	(4)	(5)
Ln(fin. wealth)	0.070***	0.047***	0.042**	0.030*	0.030*
	(0.018)	(0.017)	(0.017)	(0.016)	(0.016)
Ln(real wealth)	0.072***	0.058**	0.060**	0.023	0.031
	(0.026)	(0.025)	(0.024)	(0.024)	(0.023)
Constant	3.417***	3.623***	3.650***	3.615***	3.638***
	(0.096)	(0.094)	(0.086)	(0.084)	(0.083)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	4,090	4,090	4,090	4,090	4,090
R-squared	0.122	0.143	0.225	0.261	0.282

Note: This table is a robustness check replicating the baseline analysis using OLS regressions ; Standard errors are clustered by household and reported in parentheses;***p<0.01, **p<0.05, *p<0.1.

Table 3.A.3: Role of Job Satisfaction

Variables	(1) Life satisfaction	(2) Life satisfaction	(3) Job satisfaction
Economic_necessity lock	-0.246***	-0.219***	-0.313***
	(0.052)	(0.053)	(0.058)
Combined_necessity lock	-0.289***	-0.252***	-0.426***
	(0.051)	(0.052)	(0.057)
Job satisfaction		0.242***	
		(0.029)	
Controls	YES	YES	YES
Year FE	YES	YES	YES
Region FE	YES	YES	YES
Log likelihood	-4368.43	-4248.05	-3397.83
Observations	4,090	4,018	4,018

Note: ***p<0.01, **p<0.05, *p<0.1.

Table 3.A.4: Baseline models with residual job lock measures

Life satisfaction (Overall)	(1)	(2)	(3)	(4)	(5)
Economic_necessity lock_residual		-0.119***	-0.118***	-0.154***	-0.147***
		(0.037)	(0.035)	(0.034)	(0.034)
Combined_necessity lock_residual		-0.128***	-0.135***	-0.181***	-0.179***
		(0.038)	(0.035)	(0.034)	(0.034)
Mastery				0.126***	0.102***
				(0.019)	(0.019)
Personal constraints				-0.179***	-0.137***
				(0.020)	(0.020)
Control over health				-0.009	-0.021
				(0.020)	(0.020)
Control over social life				0.088***	0.071***
				(0.020)	(0.020)
Control over finances				0.135***	0.121***
				(0.020)	(0.020)
Openness			-0.027		-0.042**
			(0.020)		(0.019)
Conscientiousness			0.073***		0.038**
			(0.018)		(0.017)
Extraversion			0.150***		0.093***
			(0.020)		(0.019)
Agreeableness			-0.004		-0.007
			(0.018)		(0.017)
Neuroticism			-0.189***		-0.108***
			(0.017)		(0.017)
Age/10	0.082***	0.064***	0.022	0.053**	0.031
	(0.022)	(0.023)	(0.021)	(0.021)	(0.020)
Female	0.036	0.035	0.028	0.044	0.041
	(0.033)	(0.033)	(0.032)	(0.030)	(0.031)
Non-white	0.027	0.037	-0.052	-0.090*	-0.111**
	(0.048)	(0.048)	(0.046)	(0.047)	(0.046)
Immigrate	0.181***	0.186***	0.217***	0.234***	0.238***
	(0.060)	(0.060)	(0.057)	(0.057)	(0.055)
Married	0.178***	0.167***	0.168***	0.214***	0.202***
	(0.038)	(0.037)	(0.035)	(0.034)	(0.033)
Good health	0.344***	0.341***	0.200***	0.182***	0.145***
	(0.031)	(0.031)	(0.030)	(0.029)	(0.030)
College	0.085**	0.070	0.109***	0.081**	0.112***
	(0.043)	(0.044)	(0.041)	(0.039)	(0.039)
Ln(income)	0.056**	0.055**	0.031	0.008	0.006
	(0.022)	(0.022)	(0.021)	(0.021)	(0.020)
Home ownership	0.135**	0.138**	0.129**	0.117**	0.115**
	(0.056)	(0.056)	(0.053)	(0.052)	(0.051)

Life satisfaction (Overall)	(1)	(2)	(3)	(4)	(5)
Ln(fin. wealth)	0.070***	0.062***	0.053***	0.030*	0.030*
	(0.018)	(0.018)	(0.017)	(0.016)	(0.016)
Ln(real wealth)	0.072***	0.068***	0.067***	0.023	0.031
	(0.026)	(0.026)	(0.024)	(0.024)	(0.023)
Constant	3.417***	3.413***	3.480***	3.495***	3.520***
	(0.096)	(0.095)	(0.084)	(0.083)	(0.081)
Year FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Observations	4,090	4,090	4,090	4,090	4,090
R-squared	0.122	0.126	0.215	0.261	0.282

Note: This table replicates the baseline analysis using residualized job lock variables to account for variation explained by observable characteristics. The approach helps isolate the component of job lock not driven by demographic or economic factors. The table reports coefficients from OLS regressions; Standard errors are clustered by household and reported in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Table 3.A.5: Moderating role of domain-specific control beliefs

Life satisfaction	(1) Housing	(2) City	(3) Leisure	(4) Family	(5) Finances	(6) Health
Job lock	-0.069***	-0.048*	-0.136***	-0.021	-0.301***	-0.109***
	(0.026)	(0.026)	(0.025)	(0.026)	(0.026)	(0.025)
Mastery	0.055**	0.013	0.084***	0.059**	0.055**	0.061**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.026)
Personal constraints	-0.064**	-0.069**	-0.117***	-0.159***	-0.062**	-0.008
	(0.028)	(0.027)	(0.030)	(0.028)	(0.028)	(0.029)
Control over health	0.041	0.009	-0.035	-0.052	-0.119***	0.382***
	(0.048)	(0.050)	(0.047)	(0.046)	(0.046)	(0.052)
Control over social life	0.080	0.106*	0.269***	0.302***	-0.083*	-0.002
	(0.050)	(0.056)	(0.048)	(0.050)	(0.049)	(0.048)
Control over finances	0.242***	0.152***	0.211***	0.177***	0.776***	0.167***
	(0.054)	(0.052)	(0.049)	(0.049)	(0.054)	(0.048)
Job lock*health control	-0.019	0.000	0.000	-0.040	0.009	-0.022
	(0.032)	(0.032)	(0.033)	(0.032)	(0.033)	(0.034)
Job lock*soc. life control	-0.028	-0.006	-0.013	-0.045	0.004	0.009
	(0.032)	(0.035)	(0.031)	(0.032)	(0.031)	(0.031)
Job lock*financial control	-0.071**	-0.027	-0.066**	0.000	-0.130***	-0.031
	(0.034)	(0.033)	(0.032)	(0.032)	(0.034)	(0.033)
neuroticism	-0.046*	-0.060**	-0.053*	-0.083***	-0.024	-0.071***
	(0.028)	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)
Conscientiousness	0.135***	0.053**	0.056**	0.046*	0.054**	0.033
	(0.025)	(0.026)	(0.026)	(0.025)	(0.027)	(0.025)
Extraversion	0.101***	0.117***	0.225***	0.102***	0.071***	0.158***
	(0.027)	(0.030)	(0.028)	(0.028)	(0.027)	(0.028)
Agreeableness	0.036	0.094***	0.036	0.093***	-0.015	-0.024
	(0.026)	(0.027)	(0.026)	(0.026)	(0.024)	(0.025)
Neuroticism	-0.077***	-0.072***	-0.201***	-0.189***	-0.118***	-0.177***
	(0.024)	(0.023)	(0.024)	(0.024)	(0.023)	(0.024)
Socio-demographic	YES	YES	YES	YES	YES	YES
Threshold 1	-2.662***	-2.948***	-3.168***	-2.496***	-2.195***	-2.369***
	(0.150)	(0.159)	(0.162)	(0.153)	(0.132)	(0.152)
Threshold 2	-1.967***	-2.154***	-2.052***	-1.678***	-1.197***	-1.248***
	(0.141)	(0.146)	(0.138)	(0.148)	(0.126)	(0.134)
Threshold 3	-0.837***	-1.116***	-0.509***	-0.509***	0.160	0.368***
	(0.136)	(0.142)	(0.132)	(0.145)	(0.127)	(0.130)
Threshold 4	0.379***	0.122	0.859***	0.807***	1.436***	2.010***
	(0.135)	(0.141)	(0.133)	(0.146)	(0.130)	(0.135)
Year FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Log-likelihood	-4477.934	-4508.264	-4294.914	-4472.216	-4750.679	-4165.469
Observations	4,072	4,073	4,068	4,064	4,069	4,073

Note: Coefficients are from cross-sectional ordered probit regressions; Job lock is measured as a continuous variable ranging from 0 (no job lock) to 2 (both economic and health necessity). Standard errors are clustered by household and reported in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Table 3.A.6: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)
(1) Job lock	1.000				
(2) <138% FPL	0.095	1.000			
	(0.000)				
(3) 138% - 200% FPL	0.037	-0.188	1.000		
	(0.015)	(0.000)			
(4) 200% - 400% FPL	0.036	-0.330	-0.241	1.000	
	(0.018)	(0.000)	(0.000)		
(5) >400% FPL	-0.126	-0.395	-0.288	-0.507	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	

Note: The table reports categories of household total income based on the Federal Poverty Level (FPL) and examine their correlation with job lock.

Table 3.A.7: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Job lock	1.000							
(2) Employer ins (d)	0.442	1.000						
	(0.000)							
(3) Spouse employer ins (d)	0.106	0.167	1.000					
	(0.002)	(0.000)						
(4) Number private ins	0.094	0.068	0.098	1.000				
	(0.000)	(0.000)	(0.000)					
(5) Other insurance (d)	-0.122	-0.015	-0.009	-0.142	1.000			
	(0.000)	(0.161)	(0.638)	(0.000)				
(6) Public ins (d)	-0.351	-0.335	-0.481	-0.311	0.048	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(7) Age social security (d)	-0.287	-0.224	-0.404	-0.184	0.038	0.660	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(8) Age Medicare (d)	-0.334	-0.277	-0.446	-0.256	0.039	0.883	0.735	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Note: The table presents the correlation between declaring to be job locked and several health insurance-related characteristics of the adult workers.

Conclusion

This dissertation has explored the interplay between behavioral influences, external shocks, and personal constraints in shaping individual and household decision-making across three distinct but thematically linked domains: environmental sustainability, financial risk-taking, and labor market experiences. Although each chapter addresses a unique context, together they provide a cohesive narrative about the importance of psychological, informational, and situational factors in economic and social behaviors.

The first study demonstrates that behavioral interventions, specifically personalized text message nudges, can effectively improve household waste sorting behavior. The use of self-comparison messages significantly reduced unsorted waste disposal and, notably, produced sustained behavioral change even one year after the intervention. This finding highlights the potential of low-cost, scalable behavioral tools to complement traditional policy measures in promoting environmental sustainability. Moreover, it underscores the importance of framing and personalization in designing interventions aimed at shifting everyday practices toward more socially desirable outcomes.

The second study shifts the focus to financial behavior, illustrating that external environmental shocks—namely, natural and technological disasters—have lasting effects on household portfolio choices. While a single disaster experience shows no effect, repeated exposure reduces both the likelihood of participating in risky asset markets and the proportion of wealth allocated to risky assets, and exposure that occurred six or more years earlier continues to depress risky asset participation. Furthermore, personality traits condition these responses: conscientiousness mitigates the adverse effect of disaster exposure, while there is weaker evidence that neuroticism amplifies it. This chapter enriches the understanding of how adverse life events influence financial decision-making, emphasizing that psychological characteristics play a critical role alongside traditional economic determinants such as income and education.

The third study investigates the consequences of job lock among older American workers

and its impact on life satisfaction. Workers who feel constrained to continue employment due to financial needs or health insurance dependency report significantly lower overall and domain-specific life satisfaction, particularly regarding their finances and leisure. Importantly, individual differences in perceived control beliefs moderate this relationship: the decline in well-being associated with job lock is smaller among workers who already perceive greater constraints on their personal control, consistent with adaptation to constrained circumstances. These results contribute to the growing literature on the aging workforce and subjective well-being by showing that the well-being cost of labor market constraints depends on how much control individuals expect to have over their lives.

Across all three chapters, a common thread emerges: individual behavior is not determined solely by rational calculation or market incentives but is also deeply influenced by information framing, past experiences, emotional states, and perceived autonomy. Behavioral interventions such as nudges can successfully promote sustainable practices when designed with sensitivity to individual motivations. Traumatic experiences can shape financial risk preferences long after the immediate event has passed. Constraints perceived in the workplace can significantly affect overall happiness, with perceived control shaping how strongly these effects are felt.

From a policy perspective, these findings suggest that effective interventions—whether aimed at improving environmental outcomes, enhancing financial resilience, or supporting worker well-being—must recognize and incorporate behavioral and psychological dimensions. Governments, municipalities, and organizations should not only focus on structural reforms but also consider how individuals process information, respond to shocks, and exercise control over their circumstances. Tailoring interventions to leverage psychological strengths, mitigate vulnerabilities, and support autonomy can lead to more robust and lasting impacts.

Future research could further expand on the connections identified in this dissertation by exploring, for example, how cumulative experiences across different domains such as disaster exposure combined with financial insecurity interact to shape long-term behavioral patterns. Additionally, experimental approaches could be extended to test multi-faceted interventions

that simultaneously target information provision, emotional resilience, and perceived agency.

In conclusion, this dissertation emphasizes the profound value of a behavioral lens in economic research. Understanding not only what individuals choose but also how and why they make those choices is crucial for designing interventions that are both effective and humane. Whether in sorting waste, managing wealth, or navigating later-life employment, people's choices are the product of a rich interplay between environment, experience, and psychology—a reality that must be acknowledged in both academic inquiry and practical policymaking.