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The financial uncertainty of climate-related assets: A factor stochastic volatility approach☆

Graziano Moramarco[1]

Department of Economics, University of Verona, Via Cantarane 24, 37129 Verona, Italy

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ABSTRACT

We measure common financial uncertainty across climate-relevant assets and study its relationship with the market volatility of green and brown firms. Using a factor stochastic volatility model, we first construct an econometric measure of aggregate uncertainty for assets involved in the climate transition, then we decompose total uncertainty to extract "uncertainty factors", defined as components that reflect common uncertainty shocks across different asset classes. We investigate the empirical relationship of these factors with the option-implied volatility of stocks. One factor emerges as a robust predictor of the excess volatility of brown stocks relative to green ones, especially for longer option maturities. Further analysis suggests that this factor captures the financial-uncertainty dimension of the climate and energy transition.

1. Introduction

Climate change is projected to have a sizeable impact on a wide range of asset markets. Some markets, such as those for agricultural commodities, are directly affected by worsening climate conditions and extreme weather events (e.g., De Winne and Peersman, 2021), and many more are involved in the transition towards a low-carbon economy. In particular, since substantial divestment from carbon-intensive technologies is required to reach sustainability goals, assets related to fossil fuels are likely to become less attractive for investors, and new investment projects by oil and gas companies may become less financially viable (e.g., van Benthem et al., 2022).[2] Indeed, the transition is expected to make many of these assets "stranded", thereby depressing their market value (e.g., Ansar et al., 2013). Conversely, assets related to clean technologies and renewable energy sources, such as green stocks and bonds (i.e., financial instruments used to finance environmentally sustainable investment projects) or industrial metals (intensively used by clean energy technologies) are set to experience growing demand and increasing market prices (Flammer, 2021; Ardia et al., 2023; Boer et al., 2021; World Bank, 2020). Overall, the green transition may represent a tectonic shift for energy markets. As of 2022, over 80% of global primary energy was still coming from fossil fuels (Energy Institute, 2023). The transition is also starting to reshape the global financial system. Krueger et al. (2020) document that most institutional investors now consider climate risks in their investment decisions. A rapidly growing literature is investigating how climate-related risks are

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E-mail address: graziano.moramarco@univr.it.

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2 For example, in February 2024, "Barclays, Britain's biggest lender to the oil and gas industry, told Reuters it will stop direct financing of new oil and gas fields and restrict lending more broadly to energy companies expanding fossil fuel production" (Reuters, February 9, 2024, "Barclays to adopt fresh curbs on oil and gas financing", https://www.reuters.com/world/uk/barclays-adopt-fresh-curbs-oil-gas-financing-2024-02-09/).

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priced in financial markets (see, e.g., Campiglio et al., 2023; Giglio et al., 2021; Venturini, 2022; Eren et al., 2022) and included in risk management practices (Breitenstein et al., 2021).

The radical transformation of economic and financial systems induced by climate change comes with remarkable uncertainty along many dimensions, e.g., about the introduction of new climate policies and technological innovations, the size of economic damages due to climate change, or consumers' response to growing climate concerns. Some risks related to the climate can be directly measured, but radical uncertainty is also an important issue that inevitably impacts financial markets (Barnett et al., 2020). In particular, climate-related uncertainty can translate into greater financial market volatility: uncertainty about future cash flows impairs the possibility of correctly pricing financial instruments, making them more sensitive to the arrival of new information and therefore prone to considerable volatility (Ansar et al., 2013). Such climate-induced financial uncertainty may become an additional drag on economic activity, on top of the most direct effects of global warming. As shown by a recent literature (e.g., Ludvigson et al., 2021; Caggiano and Castelnuovo, 2023), uncertainty about financial markets is *per se* a source of output fluctuations.

In this paper, we study common financial uncertainty across climate-related assets. The main contribution of the paper is twofold. First, we construct an econometric measure of financial uncertainty for these assets. Following the seminal work by Jurado et al. (2015), we consider a definition of uncertainty as the conditional volatility of purely unforecastable components, and use a model featuring stochastic volatility, which allows us to capture uncertainty (second-moment) shocks distinct from expectations (first-moment) shocks. However, we modify the Jurado et al. (2015) approach in an important way, by considering *multivariate* stochastic volatility. This allows us to estimate not only time-varying volatilities but also time-varying covariances of shocks across assets. More importantly, by considering a factor structure in the multivariate stochastic volatility model, we are able to decompose total uncertainty into components that depend on common uncertainty shocks across assets ("uncertainty factors") and a residual component that reflects idiosyncratic uncertainty shocks, hitting individual asset classes and affecting other assets only indirectly, through the interconnections of global markets. Then, we focus on the common factors of uncertainty, as they are more likely to be linked to global climate issues than the idiosyncratic components. The second contribution of the paper consists in isolating an uncertainty component that is strongly associated with the difference in market volatility between "brown" and "green" firms, classified using their carbon emission intensities. In particular, we study the empirical relationship of our uncertainty factors with the option-implied volatility of stocks, and find that one factor is a robust predictor of the excess volatility of brown firms relative to green ones, especially for longer option maturities. This property is not found when we simply consider aggregate financial uncertainty. The factor in question is substantially correlated with indices of climate concerns and shows high loadings in commodity markets (agricultural, energy and industrial metals). Further analysis confirms that it captures a component of financial uncertainty strongly linked to the climate and energy transition, and appears to be mainly driven by shocks related to climate concerns, rather than by general financial uncertainty or commodity market events. Overall, the results suggest that this factor may be particularly able to capture climate-related financial uncertainty.

The paper contributes to a growing literature on climate-related uncertainty and its impact on financial markets. Some recent contributions in this field focus on financial volatility related to the energy transition. Campos-Martins and Hendry (2024) measure a common volatility component in oil and gas companies using a GARCH model. Fuchs et al. (2024) measure the option-implied volatility of the emission allowances in the European Emissions Trading System, as a proxy for carbon price uncertainty. Compared to these papers, we aim to provide a broader measure of financial uncertainty, covering a wider variety of climate-related assets, and we construct an econometric measure of uncertainty rather than just using market volatility, as recommended by the literature stemming from Jurado et al. (2015). A different stream of related research is concerned with constructing news-based indicators of climate policy uncertainty, such as Gavriilidis (2021), or climate concerns, such as Ardia et al. (2023). Other papers focus on the market impact of climate uncertainty. Barnett et al. (2020) develop a decision theory framework to address how climate uncertainty affects asset prices. Nam (2021) investigates the effects of uncertainty about a major climate phenomenon (El Niño-Southern Oscillation, or ENSO) on global commodity markets. Ilhan et al. (2021) show that climate policy uncertainty is priced in option markets. Specifically, they document that the cost of option protection against downside tail risk is larger for more carbon-intensive firms. To some extent, we complement that work by showing that a broad-based measure of climate-related financial uncertainty, not specifically focusing on climate policy, is able to account for observed patterns of option-implied volatilities. Regarding the more general literature on financial uncertainty, Ludvigson et al. (2021) show that uncertainty about financial markets is a likely source of output fluctuations. Caggiano and Castelnuovo (2023) study global financial uncertainty through a dynamic factor model with global, regional, and country-specific uncertainty factors. They find that global financial uncertainty has substantially contributed to world output contraction during the Great Recession, and is strongly correlated with the VIX index of U.S. option-implied stock market volatility. Our paper also relates to the broader literature on measuring economic uncertainty (see, e.g., Bloom, 2014, for a review). As already mentioned, our econometric approach for measuring uncertainty builds on the methodology by Jurado et al. (2015), based on stochastic volatility, but augments it by considering factor stochastic volatility. Other works using factor stochastic volatility to model economic uncertainty include Crespo Cuaresma et al. (2020) and Huber (2016).

The rest of the paper is organized as follows. Section 2 presents the data. Section 3 illustrates the econometric framework used to measure uncertainty and uncertainty factors. In Section 4, we provide our empirical measures of uncertainty and factors, and estimate their relationships with the option-implied volatility of green and brown firms. The section also explores the economic interpretation of the factor empirically related to the brown-green volatility differential, and provides several robustness checks. Section 5 concludes.

2. Data

Our empirical analysis of uncertainty is conducted using data on weekly returns for a variety of asset classes over the period from October 1, 2010 to June 30, 2023. While in principle a vast majority of real and financial assets may be affected by climate change to some extent, we want to focus on asset categories for which climate change arguably represents the main, or one of the main, sources of risk and valuation. The goal is to reduce noise and to achieve sharper identification of uncertainty components that are truly related to climate issues. We consider seven composite indices of climate-sensitive asset classes, aggregating a large number of underlying assets. Specifically, we use indices for green-economy stocks, green bonds, energy commodities (fossil fuels), agricultural commodities, industrial metals, power exchange markets and traded carbon emissions. In more detail:

1. ***Green-economy stocks***. To measure the returns of green-economy stocks, we use the NASDAQ OMX Green Economy Index. This is a global index designed to track "the performance of companies across the spectrum of industries most closely associated with the economic model around sustainable development through every economic sector".[3] The top sectors (weighted by market capitalization) are: industrials (27% of the index), consumer discretionary goods (25%), utilities (14%), technology (9%), and basic materials (6%). The index is composed of 330 companies worldwide (148 based in the U.S., 90 in Europe, 57 in Asia, and 35 in other countries).[4]
2. ***Green bonds***. To track the global green bond market, we use the S&P Green Bond Index. The index measures the performance of globally issued, green-labeled bonds, weighted by market value. The index includes only those bonds whose proceeds are used to finance environmentally friendly projects. It is composed of several sub-indices: the S&P Green Bond Select Index, which measures the capped market-value weighted performance of globally issued, green-labeled bonds; the S&P U.S. Municipal Green Bond Index, which measures the market-value weighted performance of U.S. green-labeled municipal bonds; and the S&P Green Bond U.S. Dollar Select Index, which measures the capped market-value weighted performance of U.S. dollar-denominated green-labeled bonds.[5]
3. ***Energy commodities (fossil fuels)***. To track the returns of the "brown" energy sector, we use the S&P GSCI Energy Total Return Index, which is a basket of fossil fuels: WTI Crude Oil (21.83% weight in the overall S&P GSCI index in 2023), Brent Crude Oil (19.94%), Gasoil (5.76%), Natural Gas (4.72%), Heating Oil (4.62%), RBOB Gasoline (4.60%).[6] The index is highly correlated with composite indices of stocks in the energy sector (such as, for example, the S&P Global 1200 Energy index) and can be regarded as a general proxy for brown assets.
4. ***Agricultural commodities***. For the agricultural commodity market, we use the Bloomberg Agriculture Subindex. Formerly known as Dow Jones-UBS Agriculture Subindex, this is a subindex of the composite Bloomberg Commodity Index. It is composed of futures contracts on coffee, corn, cotton, soybeans, soybean oil, soybean meal, sugar and wheat.
5. ***Industrial metals***. For industrial metals, we use the London Metal Exchange Index (LMEX), which is a benchmark index tracking the prices of six major metals on the LME: aluminum (with a weight of 42.8% in the index), copper (31.2%), lead (8.2%), nickel (2.0%), tin (1.0%), zinc (14.8%). These metals play a vital role in the transition to a low-carbon economy, as recently highlighted by the literature (e.g., Boer et al., 2021; World Bank, 2020).
6. ***Electricity***. To track international power markets, we calculate the average return across three global electricity price benchmarks: the Amsterdam Power Exchange (APX) index, the European Energy Exchange (EEX) Phelix Base Index, and the PJM Base Rate for the United States.[7]
7. ***Traded carbon emissions***. To proxy for the global price of carbon, we use the price of the emission allowances in the European Union Emissions Trading System (EU ETS). Set up in 2005, the EU ETS was the first large greenhouse gas emissions trading system in the world, and provides a relatively long time series of the carbon price. Also, it is still the most developed and by far the largest in terms of revenues (ICAP, 2023; World Bank, 2023). By comparison, China's national ETS, which is now the largest in terms of emissions covered, only began operating in 2021.

All data on price indices are collected from Refinitiv Datastream, except for the EU ETS data, which are from the International Carbon Action Partnership (ICAP). The sample start date is constrained by data availability, in particular for the green stock index.

To study the empirical relationship between our uncertainty measures and the expected financial market volatility of green and brown firms over both short-term and long-term horizons, we collect data on 1-month and 2-year option-implied volatility for the individual stocks composing the S&P 500 stock market index. These data are from Refinitiv. Data on 1-month options are available

[3] See indexes.nasdaqomx.com/docs/methodology_QGREEN.pdf (accessed October 2023).

[4] More information is provided at indexes.nasdaqomx.com/Index/Overview/QGREEN (accessed October 2023). We have also considered two alternative indices of green stocks, the S&P Global Fossil Fuel Free index and the MSCI Carbon Leaders index. However, these indices are only available for a shorter period compared to the NASDAQ OMX Green Economy Index. Moreover, they are almost identical to general stock market indices (for both, the correlation of returns with the MSCI World index and the S&P Global 1200 is above 0.99), while the NASDAQ OMX is slightly more differentiated (correlation of about 0.93), which suggests it may better capture specificities of green sectors. In any case, the main results are robust to using alternative stock indices.

[5] Methodological details are available at spglobal.com/spdji/en/indices/esg/sp-green-bond-index (accessed October 2023). We have also considered two alternative indices, the Bloomberg Green Bond Index and the ICE BofA Green Bond Index. However, these indices are available only for shorter time periods and are highly correlated with the S&P Green Bond Index.

[6] Methodological details are provided at spglobal.com/spdji/en/documents/methodologies/methodology-sp-gsci.pdf (accessed October 2023).

[7] PJM Interconnection is the largest regional transmission organization in the United States and operates the largest competitive wholesale electricity market (see, e.g., Ott, 2017).

for 475 stocks included in the S&P 500, while data on 2-year options (the longest maturity provided) are available for 384 stocks. For each company, we also collect annual data from Refinitiv on the ratio of total CO_2 equivalent emissions to revenues, over the period 2010–2022. We use this ratio to classify firms into green and brown, as explained in more detail in Section 4. Finally, data sources for control variables are indicated in Section 4.

3. Econometric framework

This section presents the econometric approach used to measure uncertainty and its common factors across climate-related assets. Section 3.1 introduces the model and Section 3.2 explains how it is used to construct uncertainty measures.

3.1. A model with factor stochastic volatility

Let $\mathbf{y}_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$ be the vector of returns on the $n = 7$ different asset classes at time t. We start by considering a vector autoregressive (VAR) model for $\mathbf{y}_t$:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1 \mathbf{y}_{t-1} + \cdots + \mathbf{A}_p \mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\mathbf{c}$ is a vector of constants, $\mathbf{A}_1, \dots, \mathbf{A}_p$ are $n \times n$ matrices of coefficients, and $\boldsymbol{\varepsilon}_t$ is a vector of innovation terms. The innovations $\boldsymbol{\varepsilon}_t$ follow a factor stochastic volatility (FSV) process (Kastner et al., 2017; Hosszejni and Kastner, 2021). Specifically, we have:

$$\boldsymbol{\varepsilon}_t = \boldsymbol{\Lambda} \mathbf{f}_t + \boldsymbol{\nu}_t \tag{2}$$

where $\mathbf{f}_t$ is an r-dimensional column vector of latent factors, $\boldsymbol{\Lambda}$ is an $n \times r$ matrix of factor loadings, and $\boldsymbol{\nu}_t$ is an n-dimensional column vector of idiosyncratic errors, independent of the factors. Factors $\mathbf{f}_t$ and idiosyncratic errors $\boldsymbol{\nu}_t$ are characterized by time-varying variance–covariance matrices $\widetilde{\boldsymbol{\Sigma}}_t$ and $\bar{\boldsymbol{\Sigma}}_t$, respectively. In particular, $\mathbf{f}_t | \widetilde{\boldsymbol{\Sigma}}_t \sim \mathcal{N}_r(\mathbf{0}, \widetilde{\boldsymbol{\Sigma}}_t)$ and $\boldsymbol{\nu}_t | \bar{\boldsymbol{\Sigma}}_t \sim \mathcal{N}_n(\mathbf{0}, \bar{\boldsymbol{\Sigma}}_t)$. Accordingly, $\boldsymbol{\varepsilon}_t | \widetilde{\boldsymbol{\Sigma}}_t, \bar{\boldsymbol{\Sigma}}_t \sim \mathcal{N}_n(\mathbf{0}, \boldsymbol{\Sigma}_t)$, where:

$$\boldsymbol{\Sigma}_t = \boldsymbol{\Lambda} \widetilde{\boldsymbol{\Sigma}}_t \boldsymbol{\Lambda}' + \bar{\boldsymbol{\Sigma}}_t \tag{3}$$

The term $\boldsymbol{\Lambda} \widetilde{\boldsymbol{\Sigma}}_t \boldsymbol{\Lambda}'$ represents the common component of the time-varying variance–covariance matrix of $\boldsymbol{\varepsilon}_t$, and $\bar{\boldsymbol{\Sigma}}_t$ is the idiosyncratic component.[8] The matrices $\widetilde{\boldsymbol{\Sigma}}_t$ and $\bar{\boldsymbol{\Sigma}}_t$ are both diagonal, with diagonal elements representing independent stochastic volatility processes, i.e.:

$$\widetilde{\boldsymbol{\Sigma}}_t = \operatorname{diag}(\exp(\widetilde{h}_{1,t}), \dots, \exp(\widetilde{h}_{r,t})) \tag{4}$$

$$\bar{\boldsymbol{\Sigma}}_t = \operatorname{diag}(\exp(\bar{h}_{1,t}), \dots, \exp(\bar{h}_{n,t})) \tag{5}$$

$$\widetilde{h}_{k,t} \sim \mathcal{N}(\widetilde{\mu}_k + \widetilde{\phi}_k(\widetilde{h}_{k,t-1} - \widetilde{\mu}_k), \widetilde{\sigma}_k^2) \tag{6}$$

$$\bar{h}_{i,t} \sim \mathcal{N}(\bar{\mu}_i + \bar{\phi}_i(\bar{h}_{i,t-1} - \bar{\mu}_i), \bar{\sigma}_i^2) \tag{7}$$

where $\widetilde{\mu}_k, \widetilde{\phi}_k, \widetilde{\sigma}_k, \bar{\mu}_i, \bar{\phi}_i, \bar{\sigma}_i$ are parameters, for $k = 1, \dots, r$ and $i = 1, \dots, n$. The scale of the factors is identified by fixing the level of their log-variance to zero, i.e., $\widetilde{\mu}_k = 0$ for any k (Hosszejni and Kastner, 2021).

Let $\boldsymbol{\Sigma}_t^{(F)} = \boldsymbol{\Lambda} \widetilde{\boldsymbol{\Sigma}}_t \boldsymbol{\Lambda}'$ and $\boldsymbol{\Sigma}_t^{(I)} = \bar{\boldsymbol{\Sigma}}_t$ (where F stands for factors and I for idiosyncratic components). Then, from (3), we can decompose the variance–covariance matrix of innovations as $\boldsymbol{\Sigma}_t = \boldsymbol{\Sigma}_t^{(F)} + \boldsymbol{\Sigma}_t^{(I)}$. Finally, let $\boldsymbol{\Sigma}_{k,t}^{(F)}$ denote the component of $\boldsymbol{\Sigma}_t$ specifically associated with the kth factor, for $k = 1, \dots, r$, i.e.:

$$\boldsymbol{\Sigma}_{k,t}^{(F)} = \lambda_k \exp(\widetilde{h}_{k,t}) \lambda_k' \tag{8}$$

where λ_k is the n-dimensional column vector corresponding to the kth column of $\boldsymbol{\Lambda}$, i.e., containing the loadings of all variables with respect to the kth factor. Hence, we have that $\boldsymbol{\Sigma}_t^{(F)} = \sum_{k=1}^{r} \boldsymbol{\Sigma}_{k,t}^{(F)}$.

As commonly done in factor analysis, we standardize the variables in $\mathbf{y}_t$ before estimating (cf. Jurado et al., 2015). This prevents more volatile assets from unduly dominating in factor construction.

Stochastic volatility models are particularly suited to measuring uncertainty because they allow shocks to volatility itself, i.e., shocks to the second moment of the return distribution, to be distinguished from shocks to expected returns, i.e., shocks to the first moment (Jurado et al., 2015). By contrast, in GARCH-type models, volatility is a deterministic function of past returns, so uncertainty does not evolve through an independent shock process. This distinction appears especially relevant in the context of the climate transition, because climate-related uncertainty is inherently latent and forward-looking. Unexpected developments regarding climate/energy policy or physical climate risks may alter the uncertainty surrounding future cash flows and asset valuations even when their immediate effects on returns are modest. Moreover, climate risks are systemic and affect several climate-sensitive asset classes simultaneously. Unlike simpler volatility models, the factor stochastic volatility specification allows us to isolate these *common uncertainty shocks* and to distinguish them from idiosyncratic volatility fluctuations affecting individual markets.

[8] Note that the assumption of conditional normality, while facilitating the estimation of the FSV model, still allows for a non-normal (e.g., fat-tailed) marginal distribution of $\boldsymbol{\varepsilon}_t$ (e.g., Kastner et al., 2017).

Our modeling approach is similar to the seminal approach by Jurado et al. (2015). However, unlike Jurado et al. (2015), who estimate a factor-augmented VAR where innovations follow univariate stochastic volatility processes, we assume that errors follow a factor stochastic volatility process (Kastner et al., 2017). By relying on this approach, we model not just individual time-varying volatilities, but the entire time-varying covariance matrix of shocks, and we assume that the co-volatility dynamics is driven by a small number of latent factors. This allows us to isolate common sources of uncertainty such as the climate and energy transition. Broad uncertainty measures, such as the VIX or the index of Jurado et al. (2015), are designed to capture aggregate uncertainty, not these latent driving factors of uncertainty. From a practical point of view, the factor specification allows for parsimony in the estimation of the time-varying covariance matrix $\boldsymbol{\Sigma}_t$, greatly reducing the number of parameters to be estimated. Multivariate factor stochastic volatility models are increasingly being used to study macroeconomic and financial uncertainty (e.g., Crespo Cuaresma et al., 2020; Huber, 2016). Similarly to Jurado et al. (2015), we estimate the stochastic volatility model on VAR residuals using Bayesian methods. Specifically, estimation of the FSV model is performed using an efficient Markov chain Monte Carlo (MCMC) method recently developed by Hosszejni and Kastner (2021), based on Kastner et al. (2017).

3.2. Measuring uncertainty and factors of uncertainty

Next, we use our model to construct an econometric measure of uncertainty. To this aim, it is convenient to consider the companion form of the VAR, i.e.:

$$\mathbf{Y}_t = \mathbf{C} + \boldsymbol{\Phi}\mathbf{Y}_{t-1} + \mathbf{E}_t \tag{9}$$

where

$$\mathbf{Y}_t = \begin{bmatrix} \mathbf{y}_t \\ \mathbf{y}_{t-1} \\ \vdots \\ \mathbf{y}_{t-p+1} \end{bmatrix}, \quad \mathbf{C} = \begin{bmatrix} \mathbf{c} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}, \quad \boldsymbol{\Phi} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_2 & \dots & \mathbf{A}_{p-1} & \mathbf{A}_p \\ \mathbf{I}_n & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_n & \dots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{I}_n & \mathbf{0} \end{bmatrix}, \quad \mathbf{E}_t = \begin{bmatrix} \boldsymbol{\varepsilon}_t \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix} \tag{10}$$

Defining the $np \times np$ matrix $\mathbf{S}_t = \mathbb{E}(\mathbf{E}_t\mathbf{E}_t' | \widetilde{\boldsymbol{\Sigma}}_t, \bar{\boldsymbol{\Sigma}}_t)$, where $\mathbb{E}$ is the expectation operator, i.e.,

$$\mathbf{S}_t = \begin{bmatrix} \boldsymbol{\Sigma}_t & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix} \tag{11}$$

then, the variance of the h-step-ahead forecast errors from the companion-form VAR, denoted as $\boldsymbol{\Omega}_{t+h} \equiv \mathrm{Var}(\mathbf{Y}_{t+h}|\mathcal{I}_t)$, where $\mathcal{I}_t$ is the information set available at time t, is given by:

$$\boldsymbol{\Omega}_{t+h} = \boldsymbol{\Phi}\boldsymbol{\Omega}_{t+h-1}\boldsymbol{\Phi}' + \mathbb{E}_t(\mathbf{S}_{t+h}) \tag{12}$$

where $\mathbb{E}_t(\mathbf{S}_{t+h}) = \mathbb{E}(\mathbf{S}_{t+h} | \widetilde{\boldsymbol{\Sigma}}_t, \bar{\boldsymbol{\Sigma}}_t)$ and with $\boldsymbol{\Omega}_t = \mathbf{0}$. The expected value of $\mathbf{S}_{t+h}$ is calculated based on Eqs. (4)–(7). Note that, being in companion form, $\boldsymbol{\Omega}_{t+h}$ has size $np \times np$. Accordingly, the forecast error variance–covariance matrix for $\mathbf{y}_{t+h}$ is:

$$\mathbf{U}_{t+h} = \mathbf{J}\boldsymbol{\Omega}_{t+h}\mathbf{J}' \tag{13}$$

where $\mathbf{J}$ is an $n \times np$ selection matrix that extracts the $n \times n$ upper-left block from $\boldsymbol{\Omega}_{t+h}$, i.e., $\mathbf{J} = [\mathbf{I}_n, \mathbf{0}_{n\times(p-1)n}]$, where $\mathbf{I}_n$ is an identity matrix. The ith variable-specific uncertainty $u_{i,t+h}$ is given by the square root of the ith diagonal element of $\mathbf{U}_{t+h}$:

$$u_{i,t+h} = \sqrt{[\mathbf{U}_{t+h}]_{ii}} \tag{14}$$

Like Jurado et al. (2015), we take the cross-sectional average of $u_{i,t+h}$ as an *aggregate measure of uncertainty*, which we denote with u_{t+h} (without the i subscript).

Next, we exploit our factor stochastic volatility specification to decompose total uncertainty into two types of components: one that reflects uncertainty shocks that are common across asset classes, and another that reflects idiosyncratic uncertainty shocks hitting individual asset classes and generating indirect dynamic effects on the rest of the system through asset market interconnections. Specifically, we decompose $\mathbf{U}_{t+h}$ as:

$$\mathbf{U}_{t+h} = \mathbf{U}^{(F)}_{t+h} + \mathbf{U}^{(I)}_{t+h} \tag{15}$$

where $\mathbf{U}^{(F)}_{t+h}$ and $\mathbf{U}^{(I)}_{t+h}$ are calculated in the same way as $\mathbf{U}_{t+h}$, but using $\boldsymbol{\Sigma}^{(F)}_t$ and $\boldsymbol{\Sigma}^{(I)}_t$, respectively, instead of $\boldsymbol{\Sigma}_t$ in (11). In particular, the component of forecast error variance specifically associated with the kth factor, denoted as $\mathbf{U}^{(F)}_{k,t+h}$, for $k = 1, \dots, r$, is calculated analogously to $\mathbf{U}_{t+h}$, replacing $\boldsymbol{\Sigma}_t$ with $\boldsymbol{\Sigma}^{(F)}_{k,t}$ in (11). Accordingly, $\mathbf{U}^{(F)}_{t+h} = \sum_{k=1}^{r} \mathbf{U}^{(F)}_{k,t+h}$. We denote with $u^{(F)}_{i,k,t+h}$ the counterpart of the individual uncertainty measure $u_{i,t+h}$ calculated using $\mathbf{U}^{(F)}_{k,t+h}$ instead of $\mathbf{U}_{t+h}$. We denote the cross-sectional average of $u^{(F)}_{i,k,t+h}$ as $u^{(F)}_{k,t+h}$, and we refer to it as the kth *uncertainty factor*.

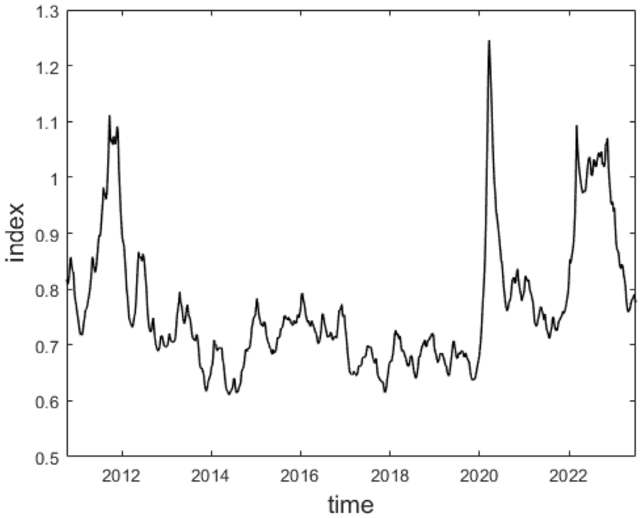


Fig. 1. Financial uncertainty of climate-related assets.
Notes: The figure plots our measure of aggregate financial uncertainty of climate-related asset classes. The data are weekly and span the period from October 8, 2010 to June 30, 2023.

4. Results

4.1. Index of financial uncertainty and uncertainty factors

We construct our uncertainty measure at the weekly frequency from October 8, 2010 to June 30, 2023. We consider a forecast horizon h of one month (4 weeks), in line with the most popular proxy of uncertainty in financial markets, the VIX index, which is constructed as the 1-month (30-day) option-implied volatility of the S&P 500 index. However, very similar time profiles of uncertainty are obtained if we consider different horizons.[9] As mentioned above, the FSV model is estimated using Bayesian methods (Kastner et al., 2017; Hosszejni and Kastner, 2021).[10] To select the number of uncertainty factors to consider, we rely on a scree plot based on the eigenvalues of the cross-product of loadings (see Hosszejni and Kastner, 2021), which suggests two factors, i.e., $r = 2$. These common uncertainty factors account for about 20% of total forecast error variance (squared uncertainty) at the weekly frequency. This is in line with the average correlation of weekly returns across assets, which is around 17% over the period considered. In particular, the first factor accounts for about 12% of total variance and the second for 7%. We estimate the VAR model with 1 lag, as suggested by the Bayesian information criterion. In what follows, recalling the notation from Section 3.2 and fixing the forecast horizon at $h = 4$, we index uncertainty by the forecast origin t. Accordingly, we denote our aggregate measure of uncertainty at time t by u_t and our two uncertainty factors by $u_{1,t}^{(F)}$ and $u_{2,t}^{(F)}$, respectively.

Fig. 1 displays our aggregate measure of financial uncertainty of climate-sensitive assets. The index shows a first large increase in late 2011, in line with a generalized increase in financial volatility in that period, due to the Euro crisis and the aftermath of the Global Financial Crisis. Then, the index shows a short-lived spike after the outbreak of the COVID-19 pandemic (early 2020) and persistently high levels in 2022. Note that, since the VAR-FSV approach is applied to standardized variables, the uncertainty measure has no direct interpretation in terms of percent volatility of returns, but its scale can be interpreted as number of standard deviations. Fig. 2 shows the two uncertainty factors. We order the factors based on the fraction of total uncertainty they account for. The first factor (dotted blue line) shows a time profile which is very similar to that of total uncertainty from Fig. 1. The second factor (solid green line) increases in late 2015 and early 2016, i.e., around the Paris Agreement, and then shows an upward trend from 2017. Unlike total uncertainty and the first factor, it shows only a moderate increase during the COVID-19 period, and a much larger spike in early 2022, following the outbreak of the Russia–Ukraine war. Also, it does not share the large late-2011 spike of total uncertainty and the first factor. To allow for an initial interpretation of the estimated factors, in Table 1 we report the factor loadings for each asset class (with 90% credible intervals in brackets), i.e., the estimate of matrix $\boldsymbol{\Lambda}$. Factor 1 is strongly associated with financial instruments (green stocks and bonds), but also with industrial metals. Factor 2 has high loadings in commodity markets, in particular on energy commodities, but also has a large loading on green stocks. Overall, the first factor appears to capture uncertainty components that are more financial in nature, while the second factor captures components of uncertainty with a larger impact on commodities. Factor 2 also shows a higher loading than factor 1 in electricity markets, while the two factors have similar loadings on carbon price.

[9] For instance, the correlation of the uncertainty measures calculated for $h = 4$ (1 month) and $h = 52$ (one year) is 0.92, approximately.

[10] Bayesian estimation of the FSV model is performed through the R package `factorstochvol`, developed by Hosszejni and Kastner (2021), using the default priors.

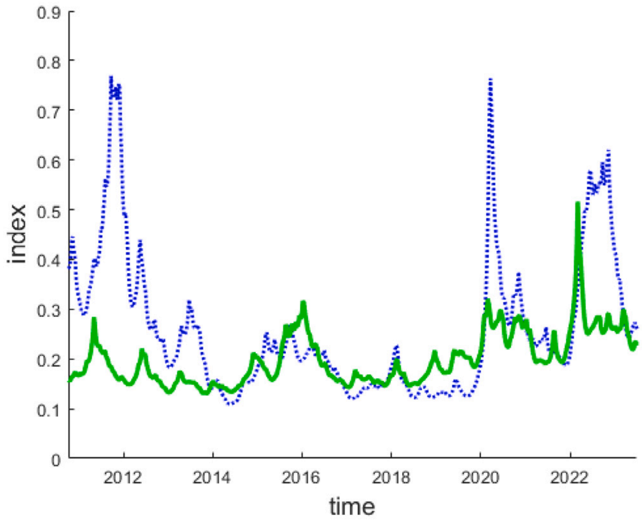


Fig. 2. Uncertainty factors.
Notes: The figure plots the two estimated uncertainty factors, i.e., components of financial uncertainty that are determined by common shocks across climate-related asset classes. The dotted blue line represents the first factor, $u_{1,t}^{(F)}$. The solid green line represents the second factor, $u_{2,t}^{(F)}$. The data are weekly and span the period from October 8, 2010 to June 30, 2023.

Table 1
Loadings of uncertainty factors.

	factor 1	factor 2
Green stocks	0.404	0.227
	[0.234 0.586]	[0.020 0.372]
Green bonds	0.512	−0.003
	[0.315 0.706]	[−0.106 0.193]
Energy commodities	0.147	0.417
	[0.000 0.250]	[0.277 0.558]
Agricultural commodities	0.119	0.243
	[0.000 0.214]	[0.147 0.366]
Industrial metals	0.359	0.294
	[0.157 0.521]	[0.179 0.496]
Electricity	0.002	0.058
	[−0.006 0.018]	[0.016 0.098]
Carbon price (ETS)	0.120	0.095
	[0.053 0.202]	[0.000 0.176]

Notes: The table reports the estimates (posterior means) of the loadings of the two uncertainty factors on the different asset classes, along with the 5th and 95th percentiles (in brackets).

4.2. Uncertainty factors and the volatility of green and brown firms

Next, we estimate a panel model to study the empirical relationship between the uncertainty factors and the financial-market volatility of green and brown firms. We consider stocks included in the S&P 500 index, for which option markets are very liquid. To classify firms as "green" or "brown", we use the ratio of total CO_2 equivalent emissions (CO_2e) over revenues. The literature provides mixed evidence on which measures of corporate emissions are priced by financial markets. For instance, Bolton and Kacperczyk (2021, 2023) find that carbon emission intensity is not priced, while the total level of emissions and their year-by-year change command a risk premium, a result later on challenged by Zhang (2025) after accounting for adequate publication lags in firm emissions data. In this context, however, we do not aim to test the pricing of emissions per se. Rather, we use emission intensity to proxy for firms' heterogeneous exposure to climate-related uncertainty, which is the object of our analysis. Specifically, for each firm we calculate the average ratio over the period 2010–2022 (or the shorter period available), then we calculate the median ratio across firms, and lastly we classify as green those firms having their ratio below the median, and brown those above the median. As our dependent variable, we consider either the 1-month or the 2-year option-implied volatility, in order to assess both short-term

Table 2
Uncertainty factors and option-implied volatility of stocks.

	1M vol. (1)	2Y vol. (2)	1M vol. (3)	2Y vol. (4)
$u_1^{(F)}$	0.314***	0.258***	0.318***	0.253***
	(0.012)	(0.032)	(0.011)	(0.026)
$u_2^{(F)}$	0.394***	0.082***	0.357***	−0.010
	(0.030)	(0.029)	(0.027)	(0.038)
$brown \times u_1^{(F)}$	−0.047**	−0.045	−0.042**	−0.029
	(0.019)	(0.035)	(0.019)	(0.031)
$brown \times u_2^{(F)}$	0.209***	0.265***	0.224***	0.325***
	(0.058)	(0.080)	(0.058)	(0.076)
$brown$	−0.029**	−0.044**		
	(0.012)	(0.018)		
$const$	0.122***	0.218***		
	(0.008)	(0.011)		
firm FE			x	x
obs.	251,063	195,066	251,063	195,066
N	475	384	475	384
R^2	0.119	0.028	0.139	0.029

Notes: The table reports the estimates of panel regressions (with standard errors in parentheses) for 1-month and 2-year option-implied volatilities of stocks composing the S&P 500 index. $u_1^{(F)}$ and $u_2^{(F)}$ are the uncertainty factors estimated across climate-related assets, *brown* is a dummy that takes value 1 for "brown" stocks and 0 for "green" stocks, using a classification based on the ratio of CO_2 equivalent emissions to firm revenues. The data are weekly. Robust standard errors are clustered at the firm level. For fixed effects (FE) estimates, the R^2 reported is the "within" R^2. Significance levels: *** 1%, ** 5%, * 10%.

and long-term effects of uncertainty factors on expected market volatility. On the one hand, climate-related uncertainty is expected to be especially associated with long-term volatility (see, e.g., Bansal et al., 2016). On the other hand, short-term options adjust faster to changes in uncertainty, given their higher liquidity, and are more affected by tail events (Ilhan et al., 2021). For each stock, we consider the average volatility between put and call options. Option data are available from the week ending on May 23, 2008, but the estimation sample starts on October 8, 2010 due to availability issues of data used to measure uncertainty (see Section 2). The sample start period is in line with that considered in the related paper by Ilhan et al. (2021). More generally, it appears that climate-related issues have been given special importance by financial markets only in recent years (see, e.g., Eren et al., 2022).

We start by estimating the following panel model:

$$vol_{it} = const + \alpha brown_i + \beta_1 u_{1,t}^{(F)} + \beta_2 u_{2,t}^{(F)} + \beta_3(brown_i \times u_{1,t}^{(F)}) + \beta_4(brown_i \times u_{2,t}^{(F)}) + \epsilon_{it} \tag{16}$$

where vol_{it} indicates the option-implied volatility of firm i at time (week) t, $brown_i$ is a dummy variable taking value 1 if the firm is classified as brown based on the CO_2e/revenues ratio and 0 otherwise, $u_{1,t}^{(F)}$ and $u_{2,t}^{(F)}$ are the first and second uncertainty factors, respectively, $const$ denotes the constant, $\alpha, \beta_1, \dots, \beta_4$ are coefficients, and ϵ_{it} is an error term.[11] We also report estimates including firm fixed effects, in order to control for all sorts of individual stock characteristics (of course, in this case the *brown* dummy is omitted because of perfect collinearity with firm fixed effects). The regressors of greatest interest are the interaction terms $brown_i \times u_{1,t}^{(F)}$ and $brown_i \times u_{2,t}^{(F)}$. Their coefficients capture the differential effects of uncertainty on brown relative to green firms. Thus, they are especially likely to reflect climate-related concerns. For all panel regressions throughout the paper, we report standard errors clustered at the firm level, which are robust to heteroskedasticity and within-firm autocorrelation of errors.

Table 2 reports the estimation results. Columns (1)-(2) report results using the specification (16) for 1-month and 2-year volatility, respectively, while columns (3)-(4) include firm fixed effects. As the table shows, an increase in $u_{2,t}^{(F)}$ is generally associated with larger changes in the volatility of brown firms compared to green firms: the coefficient on the interaction term $brown \times u_2^{(F)}$ is always positive and strongly significant. In the case of 1-month option-implied volatility, higher values of the factor are associated with increases in the volatility of both green and brown firms, as the coefficient on non-interacted $u_{2,t}^{(F)}$ is also positive and significant. In the case of 2-year volatility, the sign of the effect of $u_{2,t}^{(F)}$ is more ambiguous, but the coefficient on the interaction term $brown \times u_2^{(F)}$ remains positive and strongly significant, indicating again an increase in the excess volatility of brown firms relative to green firms. To get a sense of the magnitude of the estimated effects, consider that a 0.1 increase in $u_{2,t}^{(F)}$ (a value which is close to the overall standard deviation of u, around 0.12) is associated with an increase of $0.1 \times 0.224 = 0.0224$, i.e., 2.24 percentage points in the differential between the 1-month volatility of brown firms and that of green firms, and with an increase of $0.1 \times 0.325 = 0.0325$, i.e., 3.25 percentage points in the differential between 2-year volatilities.[12] Conversely, $u_{1,t}^{(F)}$ is actually associated with slightly larger changes in the volatility of green stocks, although only for 1-month volatility. This result may be at least in part explained by the

[11] We exclude the aggregate uncertainty measure u_t because of its high collinearity with factor $u_{1,t}^{(F)}$ and because we are focusing on the effects of uncertainty factors.

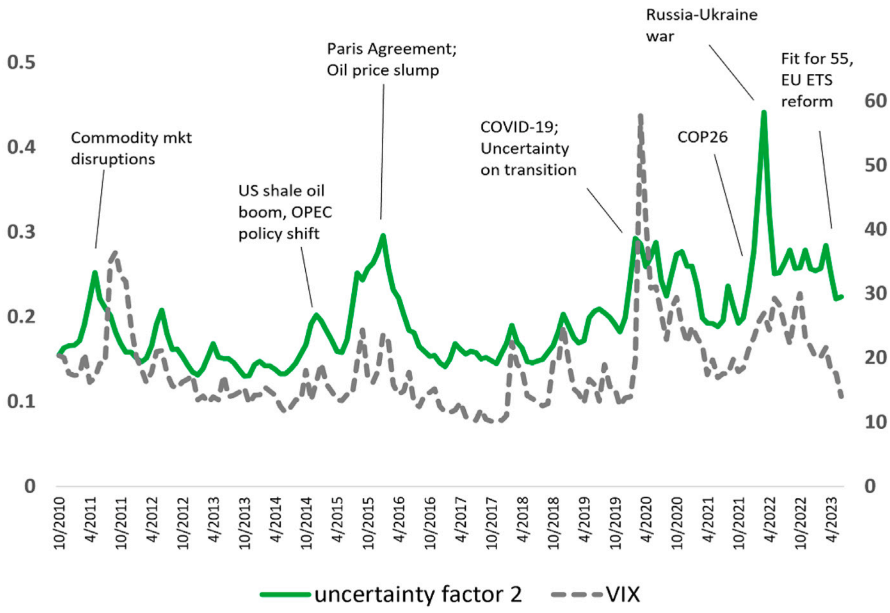


Fig. 3. Uncertainty factor $u_2^{(F)}$, VIX, and major climate/energy events.
Notes: The figure compares our uncertainty factor $u_{2,t}^{(F)}$ (left axis) with the VIX (right axis) at the monthly frequency from October 2010 to June 2023.

fact that this factor captures a general financial-market component of uncertainty (highly correlated with the VIX, as shown below), which is strongly associated with negative business-cycle phases, which could actually slow down the energy transition or at least overshadow climate concerns. Results from Table 2 are robust to the exclusion of the post-COVID-19 period.

In the Appendix, we consider an alternative regression in which uncertainty factors are interacted directly with the time-varying (log) CO_2e/revenues ratio, instead of the *brown* dummy. The main finding is confirmed: the interaction of $u_{2,t}^{(F)}$ with the measure of carbon intensity has a positive and significant effect on volatility.

To further explore the behavior of volatility and why the brown-green difference may matter, in the Appendix we also provide the results of a heterogeneity analysis conducted on the cross-section of firms, relating option-implied volatility to firm-level measures of carbon exposure and stranded-asset risk (capital intensity and investment irreversibility) derived from balance-sheet data.

4.3. On the economic interpretation of the uncertainty factor $u_2^{(F)}$

In this subsection, we expand on the economic interpretation of the uncertainty factor $u_{2,t}^{(F)}$, which has been shown to be empirically associated with the brown-green volatility differential. In particular, we provide further evidence that the factor captures a specific type of financial uncertainty that is closely linked to climate and energy-transition issues, and is especially driven by climate-related shocks.

We start by comparing the factor with overall financial market volatility, measured by the VIX, in Fig. 3, highlighting major events associated with climate and energy issues. While the two measures exhibit some notable co-movement, reflecting the fact that both capture financial uncertainty by construction, the figure allows us to detect some major differences between them. First, unlike the VIX, the factor $u_{2,t}^{(F)}$ exhibits an upward trend, especially after 2017, which is consistent with increasing attention to climate and energy-transition issues (see Fig. A.1 in the Appendix). Furthermore, while the VIX mainly spikes during episodes of generalized financial stress such as the COVID-19 pandemic and the Euro crisis of 2011-12, the factor exhibits more pronounced increases around events specifically related to climate policy, such as the Paris Agreement of December 2015, or episodes of energy market restructuring, such as the one triggered by the Russia–Ukraine war or the 2014 disruption in the oil market, which was driven by structural supply factors (booming U.S. shale oil production and shifting OPEC policies). All this suggests that the factor may capture financial uncertainty especially associated with shifts in expectations and capital reallocation during the low-carbon transition, rather than a general type of market volatility.

[12] The result that the effect of $brown \times u_2^{(F)}$ is stronger for long-maturity options could be consistent with long-run risk pricing (Bansal and Yaron, 2004). In particular, the long-run risk model with temperatures by Bansal et al. (2016) provides a theoretical framework in which climate change risk affects the valuations of long-lived assets. In that model, the combination of (i) individuals' preference for early resolution of uncertainty and (ii) the long-run nature of climate change determines a negative effect on asset valuations, which, in our context, is likely to be more strongly captured by long-maturity options.

Table 3
Correlations among uncertainty measures, climate-related indices, and energy/commodity variables.

	u	$u_1^{(F)}$	$u_2^{(F)}$	vix	$mccc$	cpu	ccr_1	ccr_2	ccr_3	ccr_4	ovx	$emvc$	eui
u	1.00												
$u_1^{(F)}$	0.93	1.00											
$u_2^{(F)}$	0.62	0.42	1.00										
vix	0.84	0.76	0.58	1.00									
$mccc$	0.13	−0.05	0.47	0.09	1.00								
cpu	0.31	0.14	0.44	0.32	0.62	1.00							
ccr_1	0.24	0.09	0.38	0.14	0.65	0.65	1.00						
ccr_2	0.16	0.17	0.08	0.07	0.29	0.16	0.24	1.00					
ccr_3	0.25	0.19	0.32	0.20	0.50	0.43	0.59	0.60	1.00				
ccr_4	0.35	0.28	0.44	0.21	0.51	0.39	0.50	0.06	0.33	1.00			
ovx	0.64	0.50	0.59	0.75	0.15	0.33	0.12	0.06	0.13	0.16	1.00		
$emvc$	0.49	0.38	0.49	0.74	0.03	0.18	0.03	−0.05	0.01	0.03	0.63	1.00	
eui	0.04	−0.12	0.25	0.03	0.09	0.04	−0.04	−0.07	−0.07	0.03	0.41	0.11	1.00

Notes: The table reports correlation coefficients between our aggregate uncertainty measure (u), the uncertainty factors ($u_1^{(F)}$, $u_2^{(F)}$), overall financial volatility (VIX), climate-related news-based indices (MCCC, CPU, CCR measures), and energy/commodity uncertainty measures (OVX, EMVC, EUI). The correlations are calculated on monthly data over the period October 2010–April 2023.

We then move on to show that the second uncertainty factor is more correlated than other uncertainty components with climate and energy-transition issues. Specifically, we compare our index of financial uncertainty (u) and the two uncertainty factors ($u_1^{(F)}$ and $u_2^{(F)}$) with widely used measures of climate concerns/risks, constructed through textual analysis of news, and with several energy and commodity-related uncertainty measures. The climate-news indices are: the Media Climate Change Concerns (MCCC) index developed by Ardia et al. (2023); the Climate Policy Uncertainty (CPU) index proposed by Gavriilidis (2021); and the Climate Change Risk (CCR) measures proposed by Faccini et al. (2023), which decompose climate-related news into four thematic dimensions: U.S. climate policy (CCR_1), international climate summits (CCR_2), global warming (CCR_3), and natural disasters (CCR_4). The energy-related uncertainty measures are: the OVX index, i.e., the CBOE Crude Oil Volatility Index, which measures the option-implied volatility of oil prices; the energy-related uncertainty index (EUI) developed by Dang et al. (2023), which captures policy-related uncertainty specifically associated with energy markets and regulation; the Equity Market Volatility tracker for Commodity Markets (EMVC), developed by Baker et al. (2026), which measures newspaper-based volatility related to commodity markets.[13] Table 3 reports the correlations, also including the VIX as a benchmark. The uncertainty factor $u_1^{(F)}$ is very highly correlated with aggregate uncertainty u (the correlation coefficient is 0.93) and both are highly correlated with the VIX, while $u_2^{(F)}$ shows a lower correlation with overall financial uncertainty. Instead, factor $u_2^{(F)}$ is the most correlated with indices related to climate issues. In particular, it is more correlated than both aggregate uncertainty (u and VIX) and $u_1^{(F)}$ with the MCCC, CPU, CCR_1, CCR_3, and CCR_4 indices. It is also more correlated with the EUI. Overall, the results are suggestive of a specific empirical relationship between the uncertainty factor $u_2^{(F)}$ and climate-related issues.

Next, we conduct a more formal econometric analysis showing that the factor is related to climate and energy-transition issues, and is especially driven by climate-related shocks. This analysis proceeds in two steps. In the first step, we select the best predictors of our uncertainty factor among those included in Table 3, showing that the factor combines financial uncertainty with climate and energy uncertainty. Specifically, we start from a regression of $u_{2,t}^{(F)}$ on all ten external indicators reported in Table 3, then we iteratively remove the least significant variables one at a time (backward stepwise regression), and we end up focusing on the 5 indicators that remain significant at the 10% level: OVX, MCCC, VIX, CCR_4 (Natural disasters), and EMVC.[14] We report the final regression in Table 4. In this regression, we use the variables in logs so that the coefficients can be interpreted as elasticities and easily compared with one another. The results strengthen the idea that the second factor does not simply reflect overall financial uncertainty: although the VIX enters significantly in the regression, its explanatory contribution is quantitatively limited as climate-related and energy-related variables are included. In particular, the largest elasticities are associated with the OVX and MCCC.

In the second step of this analysis, we take the uncertainty factor and the predictors selected in the first step, and we estimate a monthly vector autoregressive (VAR) model for these variables (again in logs, but the results are very similar for levels).[15] Then, we use the VAR estimates to calculate the forecast error variance decomposition (FEVD) over a 12-month horizon, decomposing the total variability of our factor into the contributions provided by different variables. More specifically, we rely on the Generalized FEVD (GFEVD) first introduced by Pesaran and Shin (1998), to avoid any discretionary structural assumptions such as variable ordering.

[13] The CPU and EUI indices are only available at the monthly frequency. Also, the MCCC is available at the daily and at the monthly frequency, with the monthly index not simply corresponding to the monthly average of the daily index. Thus, in our comparison, we consider the monthly frequency, and take monthly averages of those indicators which are available at the weekly frequency, including our uncertainty measures.

[14] The same selected set is obtained using forward stepwise selection. Very similar results are obtained using LASSO.

[15] Based on the Akaike information criterion, we estimate a VAR(2).

Table 4
Selected predictors of uncertainty factor $u_2^{(F)}$.

Dependent:	$\log(u_2^{(F)})$
$\log(ovx)$	0.274***
	(0.049)
$\log(mccc)$	0.196***
	(0.035)
$\log(vix)$	0.169***
	(0.063)
$\log(ccr_4)$	0.027***
	(0.010)
$\log(emvc)$	0.095*
	(0.049)
obs.	153
adj. R^2	0.69

Notes: The table reports the results of a monthly regression of the uncertainty factor $u_2^{(F)}$ on selected predictors, based on a stepwise variable selection procedure with a significance threshold of 10%. All variables are in logs, so the coefficients can be interpreted as elasticities and directly compared. The sample is October 2010–June 2023. Standard errors are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

Table 5
Forecast error variance decomposition of $u_2^{(F)}$ (12-month horizon).

Variable	Contribution (%)
$u_2^{(F)}$	58.79
$mccc$	18.50
ccr_4	17.05
ovx	3.45
vix	1.85
$emvc$	0.36

Notes: The table reports the results of generalized forecast error variance decomposition (GFEVD) based on a monthly VAR(2) model for the reported variables (in logs). The sample is December 2010–June 2023.

The GFEVD is reported in Table 5. The results provide two main insights. First, the variability of the factor appears to be driven much more by innovations to climate-related variables than by innovations to energy-related variables or general financial volatility. In particular, the two climate concern indicators, MCCC and CCR_4, explain a sizeable fraction (36%, jointly) of the forecast error variance of the factor, whereas the VIX and the commodity-market volatility measures OVX and EMVC contribute only marginally (specifically, the contribution is 1.85% in the case of VIX, 3.45% for OVX, and 0.36% for EMVC). Second, the fact that 59% of the variance of $u_{2,t}^{(F)}$ depends on its own shocks corroborates the idea that this uncertainty measure is not simply a replication of the existing ones.

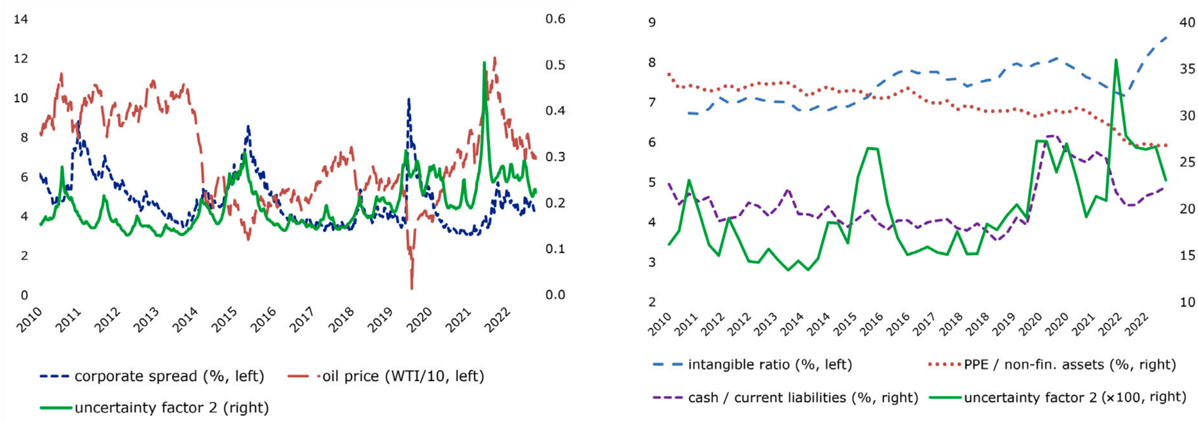
Overall, these results suggest that the factor represents a component of financial uncertainty strongly related to the climate and energy transition.

Having found evidence that this factor may be transition-related, it is now interesting to compare it with proxies for stranded-asset risk, fossil fuel market developments, and aggregate financial conditions.

Fig. 4(a) compares the uncertainty factor with a corporate credit spread (the ICE BofA US High Yield Index Option-Adjusted Spread) and the crude oil price (WTI).[16] The plot shows that movements in the factor appear to be associated both with changes in financial conditions, as measured by the risk premium (corporate credit spread), and with swings in fossil fuel markets. In particular, tighter financing conditions and higher instability of oil prices (which may also be seen as a proxy for uncertainty on the future profitability of carbon-intensive activities) both seem to contribute to upward movements in the uncertainty factor.

Fig. 4(b) instead helps connect the factor to trends in firms' aggregate balance sheets, in particular regarding investment irreversibility and stranded-asset concerns, as well as cash-flow risk. The upward trend in the factor coincides with a declining share of tangible, more illiquid capital, as measured by the ratio of Property, Plant and Equipment (PPE) to total non-financial assets of the U.S. corporate sector. This ratio can be interpreted as a proxy for exposure to irreversible physical capital. Symmetrically, the trend is associated with a growing role of intangible assets, as captured by the ratio of intangible to total assets. This pattern is consistent with the idea that the transition toward a low-carbon economy reduces the attractiveness of long-lived carbon-intensive capital and increases the risk that existing physical assets may become stranded. The figure also shows that higher realizations of

[16] The data for these variables have been retrieved from the FRED database. The primary sources are Ice Data Indices LLC and the U.S. Energy Information Administration.



(a) Factor vs. credit spread and oil price

(b) Factor vs. firms' aggregate balance sheet

Fig. 4. Linking factor $u_2^{(F)}$ to risk premia, fossil fuel markets, and stranded-asset risk.
Notes: Panel (a) compares the uncertainty factor $u_2^{(F)}$ with the U.S. high-yield corporate credit spread (ICE BofA US High Yield Index Option-Adjusted Spread) and crude oil price (WTI). Panel (b) compares $u_2^{(F)}$ with firms' aggregate balance-sheet variables for the U.S. corporate sector, namely: the ratio of Property, Plant and Equipment (PPE) to total non-financial assets; the ratio of intangible to total assets; and the ratio of cash to current liabilities in the manufacturing sector. The series in panel (a) are reported at the weekly frequency. The series in panel (b) are quarterly, with $u_2^{(F)}$ averaged within each quarter.

the factor tend to be associated with higher values of firms' liquidity buffers, as measured by the ratio of cash to current liabilities in the manufacturing sector. This is consistent with firms responding to heightened uncertainty and more volatile expected cash flows by postponing irreversible investment decisions and increasing precautionary liquidity holdings.[17]

To summarize, the evidence provided supports interpreting the uncertainty factor $u_2^{(F)}$ as a broad, market-based measure of financial uncertainty that is closely tied to the climate and energy transition. At the same time, some caution is warranted about what the factor is not. It should not be taken as a direct measure of climate uncertainty or uncertainty about technological/regulatory dimensions of the transition: it is a factor extracted from asset returns, and its climate-related interpretation rests on correlational and predictive evidence rather than on structural identification of climate-related shocks. Nor is it purely climate-driven, as a substantial share of its variation is unexplained by climate-related indicators, and it partly co-moves with energy markets and aggregate financial conditions. Accordingly, the factor is best viewed as capturing the financial-uncertainty dimension of the climate and energy transition, i.e., uncertainty about valuations and capital reallocation in climate-sensitive asset markets.

4.4. Robustness analysis

In this section, we first show that the main empirical results from Table 2 are robust to the inclusion of control variables related to climate concerns, energy/commodity uncertainty, and aggregate financial conditions. We focus primarily on the indicators reported in Table 3, together with a measure of risk aversion and a novel measure of commodity-market uncertainty obtained using our VAR-FSV approach. In the Appendix, we also consider three additional indicators: the Climate Attention Index (CAI) developed by Arteaga-Garavito et al. (2025); the Carbon VIX proposed by Fuchs et al. (2024), i.e., the option-derived volatility of the EU ETS emission allowances, which is used as a proxy for carbon price uncertainty; and the oil price uncertainty index by Abiad and Qureshi (2023). These measures are only available over much shorter time spans (see Fig. A.1), so we exclude them from our main analysis in order to preserve our baseline estimation sample. Fig. A.1 in the Appendix plots all measures.

Finally, in Section 4.4.4, we show that the general effect of $u_{2,t}^{(F)}$ on volatility has increased after the Paris Agreement, and its differential effect on brown relative to green firms has remained stable at the 2-year maturity.

4.4.1. Controlling for climate-related indices

We check whether the estimated effects associated with $u_{2,t}^{(F)}$ in Table 2 are robust to the inclusion of indices of climate uncertainty and climate concerns. Table 6 reports the results obtained when MCCC, CPU, and the four CCR factors are added to the basic specification (16), both on their own and interacted with the *brown* dummy.

[17] The data sources for aggregate balance sheet variables are the U.S. Census Bureau's Quarterly Financial Report and Refinitiv.

Table 6
Controlling for climate-related indices.

	1M vol. (1)	2Y vol. (2)
$u_1^{(F)}$	0.336***	0.234***
	(0.011)	(0.018)
$u_2^{(F)}$	0.354***	−0.036
	(0.019)	(0.057)
$brown \times u_1^{(F)}$	−0.039**	−0.015
	(0.018)	(0.023)
$brown \times u_2^{(F)}$	0.206***	0.306***
	(0.049)	(0.089)
$mccc$	−0.002	−0.020***
	(0.003)	(0.006)
cpu	0.026***	0.012***
	(0.002)	(0.002)
ccr_1	−0.017***	−0.002
	(0.002)	(0.002)
ccr_2	−0.023***	−0.013***
	(0.003)	(0.002)
ccr_3	0.020***	0.021***
	(0.003)	(0.005)
ccr_4	−0.031***	0.013
	(0.001)	(0.015)
$brown \times mccc$	0.006	0.008
	(0.005)	(0.008)
$brown \times cpu$	0.008**	0.003
	(0.003)	(0.004)
$brown \times ccr_1$	−0.014**	0.002
	(0.006)	(0.005)
$brown \times ccr_2$	−0.010	−0.007
	(0.006)	(0.006)
$brown \times ccr_3$	0.010	0.012
	(0.007)	(0.009)
$brown \times ccr_4$	−0.001	−0.015
	(0.003)	(0.015)
firm FE	x	x
obs.	57,186	44,416
within R^2	0.187	0.049

Notes: The table reports the estimates of panel regressions (with cluster-robust standard errors in parentheses) for 1-month and 2-year option-implied volatilities of stocks composing the S&P 500 index. The regressors are the uncertainty factors $u_1^{(F)}$ and $u_2^{(F)}$ and climate-related news-based indices (MCCC, CPU, CCR measures). To facilitate reading of the results, CPU has been divided by 100. The regressions are estimated on monthly data. The sample goes from October 2010 to April 2023. Significance levels: *** 1%, ** 5%, * 10%.

As Table 6 shows, the positive coefficient of the interaction between $u_{2,t}^{(F)}$ and the *brown* dummy remains strongly significant and almost unaffected in its size. The CPU index shows qualitatively similar effects, increasing volatility especially for brown stocks, but only for 1-month volatility. Conversely, the MCCC index shows no significant differential effect between brown and green firms. All this suggests that $u_{2,t}^{(F)}$ may provide a more relevant measure of climate-related uncertainty for option markets.

In the Appendix, we provide additional results on robustness to climate-related indicators. First, we report results obtained when controlling for an additional measure, namely the CAI. Since this variable is only available from October 2014 (so its inclusion in Table 6 would entail a loss of 4 years of sample), we choose to consider it separately from the main regressions. Interestingly, the result using CAI suggests that our main finding is especially robust for long-maturity options, which is consistent with the long-run nature of climate risks (see also footnote 12). Second, we provide regression results obtained using shocks in climate indicators instead of their levels.[18] The main results are confirmed. More details are provided in the Appendix.

4.4.2. *Controlling for overall market volatility and time-varying risk aversion*

To make sure our previous results do not simply capture the effects of generalized financial-market volatility, we control for the VIX, i.e., the option-implied volatility of the S&P 500 index. As an index-wide measure, the VIX captures common movements in expected volatility across firms.

[18] The previous literature has used both the levels and the innovations of climate change risk measures to conduct asset pricing analysis, depending on the specific research question (see Faccini et al., 2023, for a discussion of this issue).

Table 7
Controlling for aggregate volatility and time-varying risk aversion.

	1M vol. (1)	2Y vol. (2)
$u_1^{(F)}$	0.037***	0.194***
	(0.011)	(0.034)
$u_2^{(F)}$	0.019	−0.114***
	(0.025)	(0.034)
$brown \times u_1^{(F)}$	−0.088***	−0.057
	(0.024)	(0.041)
$brown \times u_2^{(F)}$	0.171***	0.295***
	(0.045)	(0.080)
vix	0.760***	0.318***
	(0.021)	(0.018)
bex	0.021***	−0.013***
	(0.002)	(0.004)
$brown \times vix$	0.100	0.068
	(0.064)	(0.052)
$brown \times bex$	0.006	0.003
	(0.004)	(0.005)
firm FE	x	x
obs.	241,545	187,662
within R^2	0.234	0.031

Notes: The table reports the estimates of panel regressions (with cluster-robust standard errors in parentheses) for 1-month and 2-year option-implied volatilities of stocks composing the S&P 500 index. vix is the VIX index of stock market volatility and bex is the index of time-varying risk aversion by Bekaert et al. (2022). See the previous tables for the definition of the other variables. The VIX has been divided by 100 to facilitate reading of the results. The data are weekly and the estimation sample goes from October 8, 2010 to June 30, 2023. Significance levels: *** 1%, ** 5%, * 10%.

Option-implied volatility is a risk-neutral forward measure of volatility. For this reason, its changes may partly reflect time variation in investors' risk aversion. To control for this effect, we also include as a regressor the index of time-varying risk aversion recently developed by Bekaert et al. (2022), based on a dynamic no-arbitrage asset pricing model. This measure reflects the utility function of a representative agent in a generalized habit-like model with preference shocks, and is estimated through an instrumental-variable approach using a set of observed financial variables (earnings yield, credit and term spreads, equity and corporate bond realized variances, and equity risk-neutral variance).

Table 7 shows the results. Again, our uncertainty factor $u_{2,t}^{(F)}$ remains significantly associated with the excess volatility of brown relative to green stocks, whereas the effects of both the VIX and time-varying risk aversion do not differ between brown and green stocks.

4.4.3. Controlling for commodity and energy market uncertainty measures

As highlighted by Table 1, the uncertainty factor $u_{2,t}^{(F)}$ is strongly associated with commodity markets. This raises the concern that its differentiated effect on the market volatility of brown vs. green stocks may simply capture relationships between commodity markets and stocks classified as brown (e.g., oil companies).

In this section, we check that the effect of the second uncertainty factor is not simply driven by commodity market events. We consider several indicators of energy/commodity market uncertainty as controls. First, we construct a measure of commodity market uncertainty ($ucomm$), applying the same econometric methodology as before on data at the single-commodity level provided by the World Bank (so-called "Pink Sheet" data). The dataset starts in 1960M1, but data on coal prices are only available from 1970M1. We calculate aggregate commodity uncertainty using monthly returns on 31 commodities over the period from 1970M2 to 2023M6 (the uncertainty series starts in 1970M3, as the first observation is lost due to the VAR lag).[19] In addition, we include the time series of OVX, the EMVC index and the EUI introduced in Section 4.3. Again, we consider the monthly frequency, as $ucomm$ and eui are only available at this frequency.

Fig. 5 shows our measure of commodity market uncertainty. Over the period 2010–2023, the measure shows similar properties compared to the uncertainty factor $u_2^{(F)}$ displayed in Fig. 2. In particular, the series shows an upward trend after 2010 and a higher peak in 2022 compared to the COVID-19 period. The correlation of commodity uncertainty with factor $u_2^{(F)}$ over this sub-period is around 0.74. At the same time, Fig. 5 allows us to put these recent dynamics into a broader perspective. In particular, commodity market uncertainty exhibits major increases following the Oil Crisis of 1973-74 and during the Great Recession period (2008–2009).

[19] See worldbank.org/en/research/commodity-markets. The 31 commodities are: crude oil (global average), natural gas, coal (Australian), cocoa, coffee (average of arabica and robusta), tea, coconut oil, groundnut oil, palm oil, soybeans, soybean oil, soybean meal, maize, rice (Thai 5%), wheat (US HRW), sugar, banana (US), orange, beef, chicken, timber, tobacco, cotton, rubber, aluminum, iron ore, copper, lead, tin, nickel, zinc.

Table 8
Controlling for commodity and energy market uncertainty measures.

	1M vol. (1)	2Y vol. (2)
$u_1^{(F)}$	0.203***	0.221***
	(0.012)	(0.028)
$u_2^{(F)}$	−0.028	−0.108***
	(0.021)	(0.036)
$brown \times u_1^{(F)}$	−0.085***	−0.069**
	(0.022)	(0.035)
$brown \times u_2^{(F)}$	0.113***	0.137*
	(0.039)	(0.071)
$ucomm$	0.092***	0.096***
	(0.020)	(0.022)
ovx	0.129***	0.025***
	(0.008)	(0.007)
$emvc$	0.709***	0.089***
	(0.021)	(0.025)
eui	−0.021***	−0.013***
	(0.003)	(0.002)
$brown \times ucomm$	0.043	0.161***
	(0.035)	(0.060)
$brown \times ovx$	0.075***	0.043
	(0.016)	(0.027)
$brown \times emvc$	−0.000	−0.001
	(0.038)	(0.036)
$brown \times eui$	−0.007	0.001
	(0.005)	(0.006)
firm FE	x	x
obs.	58,126	45,176
within R^2	0.227	0.049

Notes: The table reports the estimates of panel regressions (with cluster-robust standard errors in parentheses) for 1-month and 2-year option-implied volatilities of stocks composing the S&P 500 index. *ucomm* is our stochastic volatility-based measure of commodity market uncertainty, *ovx* is the CBOE Crude Oil Volatility Index, *emvc* is the equity market volatility tracker for commodity markets by Baker et al. (2026), and *eui* is the energy-related uncertainty index by Dang et al. (2023). The *ovx* and *emvc* indices have been divided by 100 to facilitate reading of the results. The data are monthly. The sample goes from October 2010 to June 2023. Significance levels: *** 1%, ** 5%, * 10%.

Table 8 reports the results of our regression augmented with commodity market controls. For each commodity market variable, we include both the level and the interaction with the *brown* dummy, in order to account for differentiated effects on brown and green stocks. Importantly, the table shows that the interaction between our uncertainty factor $u_2^{(F)}$ and the *brown* dummy remains positive and statistically significant for both 1-month and 2-year volatilities. Combined with the findings from previous sections, these results suggest that factor $u_2^{(F)}$ incorporates information that is climate-related but not just overlapping with commodity market uncertainty (whose sources include, e.g., geopolitical events and aggregate demand-side uncertainty, along with climate/weather conditions).

In the Appendix, we provide additional results using as controls the news-based index of oil price uncertainty (OPU) constructed by Abiad and Qureshi (2023) and the Carbon VIX (Fuchs et al., 2024). The OPU series is only available until December 2019, while the Carbon VIX is only available from September 2013 to December 2022.

4.4.4. Parameter stability analysis

Next, we assess the stability of the parameters of interest over time. To this aim, we choose the date on which the Paris Agreement was adopted (12 December 2015) as a relevant break date, and define a sample-split dummy, *post_paris*, taking value 1 after the Agreement and 0 before. Then, we augment the baseline regression with the post-Paris dummy, its interaction with the brown indicator, and interaction terms allowing the effects of the uncertainty factors to change after the Agreement.

Table 9 reports the estimates of this regression. The coefficient on the $post\_paris \times u_2^{(F)}$ interaction is positive and significant for both 1-month and 2-year volatility, suggesting a broader role of climate-related components of uncertainty in firms' volatility in the post-Paris period. The three-way interaction term $post\_paris \times brown \times u_2^{(F)}$ is non-significant for 2-year volatility, indicating that the differential effect of $u_2^{(F)}$ on brown relative to green firms has remained fairly stable after the Paris Agreement at longer option maturities. For 1-month volatility, instead, the three-way interaction is negative and significant. Thus, at shorter horizons, the factor appears to have increased its impact on green stocks' volatility after Paris, while the differential effect on brown firms has weakened, that is, the sensitivities of green and brown stocks have tended to converge.

The finding that the effect on the brown-green differential remains strong and stable at longer maturities is consistent with the inherently long-run nature of climate-related risks.

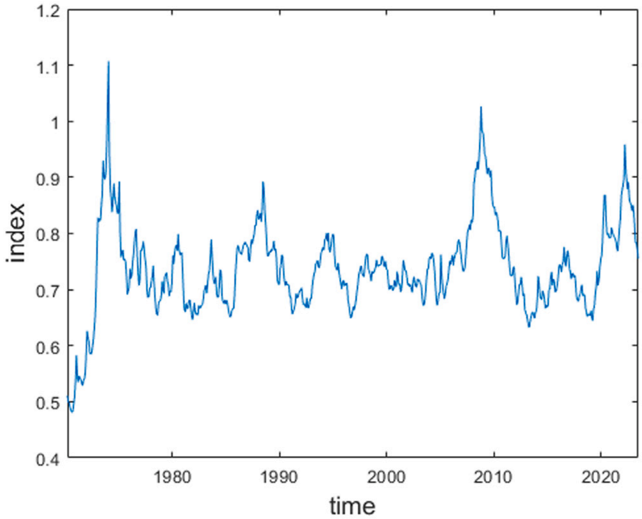


Fig. 5. Commodity market uncertainty.
Notes: The figure shows the measure of commodity market uncertainty obtained by applying our multivariate stochastic volatility model to monthly returns on 31 commodities provided by the World Bank ''Pink Sheet'' dataset. The time series is monthly and spans the period 1970M3-2023M6.

Table 9
Changes in effects after the Paris Agreement.

	1M vol. (1)	2Y vol. (2)
$u_1^{(F)}$	0.308***	0.258***
	(0.017)	(0.016)
$u_2^{(F)}$	0.083***	−0.245***
	(0.025)	(0.024)
$brown \times u_1^{(F)}$	−0.061***	−0.031
	(0.023)	(0.021)
$brown \times u_2^{(F)}$	0.290***	0.204***
	(0.051)	(0.041)
$post\_paris$	−0.024***	−0.041***
	(0.008)	(0.009)
$post\_paris \times u_1^{(F)}$	0.061***	−0.007
	(0.021)	(0.058)
$post\_paris \times u_2^{(F)}$	0.177***	0.271***
	(0.032)	(0.098)
$post\_paris \times brown$	0.048***	−0.003
	(0.016)	(0.022)
$post\_paris \times brown \times u_1^{(F)}$	0.096***	0.032
	(0.030)	(0.065)
$post\_paris \times brown \times u_2^{(F)}$	−0.279***	0.050
	(0.067)	(0.134)
firm FE	x	x
obs.	251,063	195,066
within R^2	0.150	0.030

Notes: The table reports the estimates of panel regressions (with cluster-robust standard errors in parentheses) for 1-month and 2-year option-implied volatilities of stocks. $post\_paris$ is a dummy equal to one after the adoption of the Paris Agreement (12 December 2015). Significance levels: *** 1%, ** 5%, * 10%.

5. Conclusions

In this paper, we have studied the financial uncertainty of asset classes that are particularly involved in the climate transition, focusing on those components of uncertainty that originate from common shocks and are therefore more likely to incorporate information on overarching climate issues.

Using an econometric approach based on a factor stochastic volatility model, we have measured the time-varying uncertainty of these climate-related assets and, more importantly, we have been able to estimate "uncertainty factors", i.e., components stemming from common uncertainty shocks. The analysis has singled out one factor that captures the financial-uncertainty dimension of the climate and energy transition. We have shown that the difference in option-implied volatility between brown and green firms appears strongly associated with this transition-related factor, the empirical relationship being robust to the inclusion of a wide variety of controls. Also, this uncertainty factor is characterized by a relatively high correlation with indices of climate concerns and by high loadings in commodity markets (energy, agricultural, industrial metals), which are generally sensitive to both transition and physical climate risks.

Our measure of uncertainty is inherently global, as it is estimated from asset data with worldwide coverage, including global green equity and bond indices, commodity markets, electricity markets, and carbon markets. Therefore, the uncertainty factors themselves are not just tied to the U.S. economy. The analysis of option-implied volatility, however, relies on U.S. firms because the U.S. offers the deepest and most liquid option markets, especially at long maturities. Extending the analysis to other economies represents an interesting direction for future research, although data limitations regarding options and firms' emissions disclosures may pose challenges.

Declaration of competing interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Additional tables and figures

In this appendix, we include tables and figures providing additional details, robustness checks and extensions to our main results.

Fig. A.1 shows the time series of our uncertainty measures as well as measures of climate news-based indices and energy/commodity uncertainty considered in our analysis.

Table A.1 reports the results of the baseline regression for stocks' option-implied volatility, replacing the *brown* dummy with the (log) CO_2e-to-revenues ratio ($lco2e$). As the table shows, the interaction of the second uncertainty factor $u_2^{(F)}$ with this measure of carbon intensity has a positive and significant coefficient in both regressions for 1-month and 2-year volatilities, corroborating the baseline results from Table 2. To get a sense of the magnitude of the effects in this case, it is useful to consider an example. In particular, consider two firms for which the difference in emissions corresponds approximately to the interquartile range (IQR) of emissions intensity. The 25th percentile of $lco2e$ in our sample is about 2.5 (log of tonnes per million $), and the 75th percentile is 5.3, so the IQR is 2.8. The estimated coefficient of 0.091 on the interaction term $lco2e \times u_2^{(F)}$ implies that, all else being equal, the effect of the uncertainty factor $u_2^{(F)}$ on volatility will be higher by about $2.8 \times 0.091 = 0.25$ for the more carbon-intensive firm, relative to the less carbon-intensive one. This value is very similar to the brown-green differential effect in Table 2, that is, to the coefficient on the interaction term $brown \times u_2^{(F)}$. Thus, the alternative results in Table A.1 are broadly in line with the baseline results.

Table A.2 is the counterpart of Table 6 in which shocks to climate-related indices are used in place of their levels. In line with the related literature (e.g., Faccini et al., 2023; Engle et al., 2020), we estimate the shock series as the residuals from autoregressive (AR) models of order 1 for the variables in levels. Shocks are computed at each index's native frequency and then aggregated to the monthly frequency in the same way as the corresponding levels: for MCCC and CPU, which are monthly indices, they are residuals from AR(1) regressions on the monthly series; for the CCR measures and CAI, which are available at higher frequency and enter the regressions as within-month averages, they are within-month averages of residuals from weekly AR(1) regressions. The results on the relationship between option-implied volatility and our uncertainty factors remain unaffected.

Tables A.3–A.5 report the results of the regressions controlling for the Climate Attention Index (CAI) by Arteaga-Garavito et al. (2025), the Carbon VIX (Fuchs et al., 2024), and the oil price uncertainty (OPU) index by Abiad and Qureshi (2023), respectively. Again, our main results continue to hold, particularly for 2-year volatility.

Finally, Table A.6 reports the results of a firm-level heterogeneity analysis conducted among the constituents of the S&P 500 index, relating option-implied volatility to firm-level carbon exposure, capital intensity and investment irreversibility, and thus to stranded-asset risk. In particular, we regress firm-level implied volatility on (i) the firm's environmental score (the "E" from the ESG score), as a proxy for carbon exposure, (ii) the firm's ratio of capital expenditure (CapEx) to revenues, which is a measure of capital intensity, and (iii) the firm's ratio of balance-sheet item Property, Plant, and Equipment (PPE) to total assets, which measures the reliance on tangible, illiquid assets and serves as a proxy for investment irreversibility. The data source for these variables is Refinitiv. Variables (ii) and (iii) can help capture exposure to "stranded-asset risk". As Table A.6 shows, volatility appears to be negatively and significantly related to the environmental score of the firm, and positively and significantly related to the CapEx-to-revenues ratio. These results go in the direction of suggesting a relationship between volatility and exposure to transition risks, which provides an empirical rationale for our main result linking brown-green volatility differences to climate-related uncertainty components.

Data availability

The author does not have permission to share data.

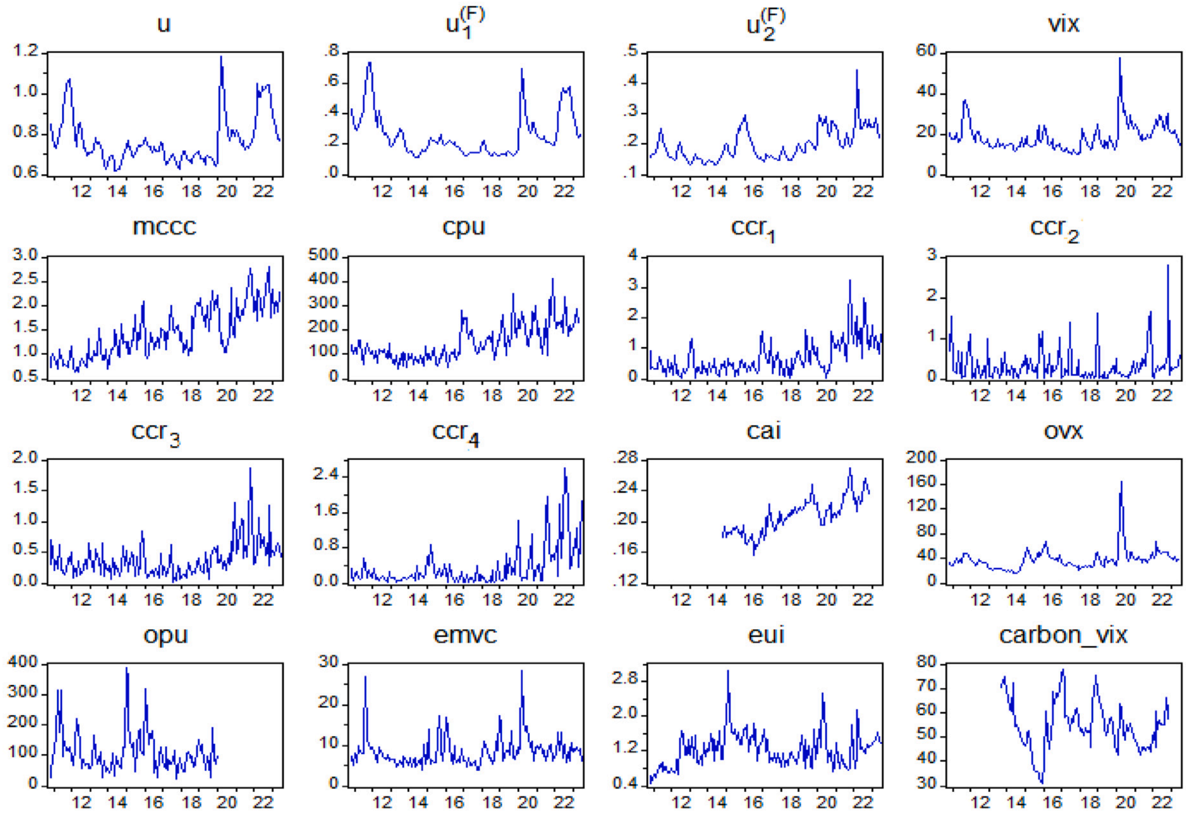


Fig. A.1. Measures of uncertainty, climate concerns, and energy/commodity uncertainty.
Notes: All indicators are reported at the monthly frequency, to facilitate comparisons. Please refer to Section 4 for a description of the variables.

Table A.1
Regressions using log CO_2e emissions/revenues.

	1M vol. (1)	2Y vol. (2)
$u_1^{(F)}$	0.379***	0.266***
	(0.029)	(0.043)
$u_2^{(F)}$	0.364***	−0.109
	(0.069)	(0.079)
$lco2e$	−0.011*	−0.010**
	(0.006)	(0.005)
$lco2e \times u_1^{(F)}$	−0.013*	−0.007
	(0.008)	(0.009)
$lco2e \times u_2^{(F)}$	0.091***	0.091***
	(0.021)	(0.019)
firm FE	x	x
obs.	164,848	130,880
within R^2	0.161	0.041

Notes: The table reports the estimates of panel regressions for 1-month and 2-year option-implied volatilities of stocks. $u_1^{(F)}$ and $u_2^{(F)}$ denote our uncertainty factors, and $lco2e$ denotes log carbon intensity (CO_2e/revenues). The regressions are estimated at the weekly frequency over the period from Oct. 8, 2010 to Dec. 24, 2021. The $lco2e$ variable is annual and is held constant within each year. Cluster-robust standard errors are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

Table A.2
Controlling for climate indices, using shocks instead of levels.

	1M vol. (1)	2Y vol. (2)
$u_1^{(F)}$	0.318***	0.251***
	(0.012)	(0.023)
$u_2^{(F)}$	0.417***	−0.059
	(0.024)	(0.068)
$brown \times u_1^{(F)}$	−0.047**	−0.026
	(0.019)	(0.027)
$brown \times u_2^{(F)}$	0.244***	0.336***
	(0.056)	(0.090)
$mccc$	−0.012***	−0.000
	(0.001)	(0.001)
cpu	0.014***	0.002
	(0.001)	(0.002)
ccr_1	−0.005**	0.000
	(0.002)	(0.002)
ccr_2	−0.008**	−0.015***
	(0.003)	(0.003)
ccr_3	0.021***	0.017**
	(0.004)	(0.008)
ccr_4	−0.038***	0.017
	(0.002)	(0.021)
$brown \times mccc$	0.004	−0.002
	(0.004)	(0.002)
$brown \times cpu$	0.005***	0.001
	(0.001)	(0.002)
$brown \times ccr_1$	−0.011*	0.007
	(0.006)	(0.006)
$brown \times ccr_2$	−0.011	−0.007
	(0.006)	(0.006)
$brown \times ccr_3$	0.013	0.017
	(0.008)	(0.012)
$brown \times ccr_4$	0.002	−0.019
	(0.004)	(0.023)
firm FE	x	x
obs.	57,186	44,416
within R^2	0.173	0.047

Notes: The table reports the estimates of panel regressions (with cluster-robust standard errors in parentheses) for 1-month and 2-year option-implied volatilities of stocks composing the S&P 500 index. The regressors are the uncertainty factors $u_1^{(F)}$ and $u_2^{(F)}$, and the shocks (innovations) to climate-related news-based indices MCCC, CPU, and CCR. The shocks to MCCC and CPU are residuals from AR(1) regressions on the monthly indices; those to the CCR measures are residuals from weekly AR(1) regressions averaged within each month. The regressions are estimated on monthly data. The sample goes from October 2010 to April 2023. Significance levels: *** 1%, ** 5%, * 10%.

Table A.3
Controlling for CAI.

	Levels of CAI		*Shocks of CAI*	
	1M vol. (1)	2Y vol. (2)	1M vol. (3)	2Y vol. (4)
$u_1^{(F)}$	0.374***	0.241***	0.373***	0.243***
	(0.014)	(0.052)	(0.014)	(0.050)
$u_2^{(F)}$	0.293***	0.030	0.284***	0.032
	(0.022)	(0.089)	(0.022)	(0.089)
$brown \times u_1^{(F)}$	0.034	0.010	0.032	0.012
	(0.023)	(0.059)	(0.023)	(0.057)
$brown \times u_2^{(F)}$	0.067	0.264**	0.060	0.261**
	(0.052)	(0.121)	(0.052)	(0.122)
cai	−0.185***	0.224***	−0.650***	0.773***
	(0.048)	(0.048)	(0.120)	(0.217)
$brown \times cai$	−0.129	−0.022	−0.279	−0.228
	(0.095)	(0.106)	(0.241)	(0.334)
firm FE	x	x	x	x
obs.	39,529	30,906	39,174	30,635
within R^2	0.164	0.038	0.163	0.037

Notes: The table reports the estimates of panel regressions for 1-month and 2-year option-implied volatilities of stocks. cai denotes the Climate Attention Index (CAI) by Arteaga-Garavito et al. (2025). Columns (1)–(2) include the cai in levels, while columns (3)–(4) include its shocks or innovations, calculated as residuals from an AR(1) regression. The regressions are estimated at the monthly frequency over the period from October 2014 to December 2022. Cluster-robust standard errors are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

Table A.4
Controlling for Carbon VIX.

	1M vol. (1)	2Y vol. (2)
$u_1^{(F)}$	0.339***	0.236***
	(0.014)	(0.048)
$u_2^{(F)}$	0.402***	0.059
	(0.022)	(0.086)
$brown \times u_1^{(F)}$	0.033	0.012
	(0.023)	(0.056)
$brown \times u_2^{(F)}$	0.095*	0.288**
	(0.054)	(0.120)
$carbon\_vix$	0.139***	0.054***
	(0.006)	(0.010)
$brown \times carbon\_vix$	−0.016*	0.011
	(0.009)	(0.020)
firm FE	x	x
obs.	189,169	147,475
within R^2	0.155	0.025

Notes: The table reports the estimates of panel regressions for 1-month and 2-year option-implied volatilities of stocks. $carbon\_vix$ denotes the Carbon VIX proposed by Fuchs et al. (2024), i.e., a measure of carbon market volatility. The Carbon VIX has been divided by 100 to facilitate reading of the results. The regressions are estimated at the weekly frequency over the period from September 2013 to December 2022. Cluster-robust standard errors are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

Table A.5
Controlling for oil price uncertainty.

	1M vol. (1)	2Y vol. (2)
$u_1^{(F)}$	0.269***	0.253***
	(0.016)	(0.016)
$u_2^{(F)}$	0.270***	−0.060***
	(0.024)	(0.021)
$brown \times u_1^{(F)}$	−0.085***	−0.055***
	(0.024)	(0.021)
$brown \times u_2^{(F)}$	0.305***	0.210***
	(0.061)	(0.048)
opu	−0.002	−0.004***
	(0.001)	(0.001)
$brown \times opu$	−0.001	0.002
	(0.002)	(0.001)
firm FE	x	x
obs.	40,034	30,810
within R^2	0.128	0.113

Notes: The table reports the estimates of panel regressions for 1-month and 2-year option-implied volatilities of stocks. opu is the news-based index of oil price uncertainty by Abiad and Qureshi (2023), divided by 100 to facilitate reading of the results. The regressions are estimated at the monthly frequency over the period from October 2010 to December 2019. Cluster-robust standard errors are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

Table A.6
Firm-level heterogeneity analysis.

	1M vol. (1)	2Y vol. (2)
e_esg	−0.052**	−0.066***
	(0.022)	(0.024)
$capex\_rev$	0.086*	0.125*
	(0.051)	(0.065)
ppe_assets	−0.003	−0.033
	(0.027)	(0.031)
time FE	x	x
obs.	77,252	60,303
adj. R^2	0.248	0.032

Notes: The table reports panel regressions of 1-month and 2-year option-implied volatilities on firm characteristics, namely the Environmental score (the E from ESG) (e_esg), the CapEx-to-revenues ratio ($capex\_rev$), and the ratio of Property, Plant and Equipment to total assets (ppe_assets). The regressions are estimated at the weekly frequency over the period from Jan. 1, 2010 to Aug. 4, 2023. The dependent variables are observed weekly, while the explanatory variables are annual and are held constant within each year. Cluster-robust standard errors are reported in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

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