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UNCERTAIN CLIMATE POLICY AS A SOURCE OF MACRO-FINANCIAL SHOCKS: EVIDENCE FROM CARBON FUTURES VOLATILITY

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Uncertain Climate Policy as a Source of Macro-Financial Shocks: Evidence from Carbon Futures Volatility*

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Abstract

We study forward-looking climate policy uncertainty through a macro-finance lens, focusing on the transmission of climate uncertainty shocks to aggregate and sectoral dynamics. Using monthly U.S. data from 2014 to 2025, we estimate a Bayesian Proxy-SVAR identified with an external instrument derived from the realized volatility of the ICE U.S. Carbon Futures Index, a market directly exposed to climate regulation. This proxy isolates the unexpected and forward- looking component of climate-policy uncertainty. We find that climate uncertainty shocks tighten financial conditions, raise market volatility and financial stress, and reduce output, prices, and stock market valuations, triggering an accommodative monetary policy response. At the sectoral level, we document heterogeneity along two complementary dimensions. A broad green–brown decomposition shows that transition risk-exposed (brown) sectors experience deeper and more persistent contractions, whereas less exposed (green) sectors recover faster. We then perform a full sector-by-sector disaggregation of industrial production and valuation responses and match each sector to its EPA supply-chain emission intensity. This granular mapping reveals a systematic relationship between carbon intensity and the severity of climate uncertainty-induced contractions: higher-emission industries exhibit larger and more persistent real and financial declines. Overall, forward-looking climate-policy uncertainty acts as a financial amplifier, propagating primarily through volatility and valuation channels and reinforcing the asymmetric dynamics of the low-carbon transition.

Keywords: Climate Policy Uncertainty, Financial Transmission Mechanism, Bayesian Proxy-SVAR, Green vs Brown Sectors, Realized Volatility.

JEL Codes: E32, E44, Q54, G12.

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1 Introduction

The accelerating effects of climate change pose mounting risks to global macroeconomic and financial stability by altering production technologies, asset valuations, and the distribution of future economic outcomes (see Battiston et al. (2021)). Governments around the world have adopted increasingly ambitious environmental targets, yet the future path and credibility of climate policy remain highly uncertain (see Rogelj et al. (2023)). In the United States, these uncertainties have intensified during recent political transitions (e.g., presidential elections), most notably around the beginning and the end of the two non-consecutive Trump's presidential mandates, which have marked a sharp reversal in federal U.S. climate policy (see Besher et al. (2025)). Ambiguity over the timing, scope, and persistence of climate policy has created what is now referred to as climate (policy) uncertainty —a type of risk that can delay investments, raise financing costs to private firms and the public sector alike, and ultimately amplify macroeconomic instability and the financial stress resulting from shocks to climate uncertainty (Barnett et al., 2020).

Measuring climate transition uncertainty, however, poses a major empirical challenge, as uncertainty about future policy paths and their consequences is inherently latent and not directly observable.. Existing approaches rely primarily on narrative and textual methods that capture policy-related uncertainty as reflected in media coverage. Gavriilidis (2021) and Känzig et al. (2025) construct news-based indices of climate uncertainty using textual analysis of major U.S. newspapers, building on the methodology of Baker et al. (2016). Their indices identify articles simultaneously referencing uncertainty, climate issues, and government policy, thus capturing fluctuations in the salience and intensity of the climate change and policy debates over time.

Although the economic transition towards net-zero emissions is expected to entail short-term adjustment costs, unpredictable or inconsistent policy signals may generate even greater losses by undermining confidence and distorting the allocation of resources. A growing literature shows that climate *policy* uncertainty has measurable macroeconomic and financial effects. In particular, Känzig et al. (2025) demonstrates that climate uncertainty shocks have recessionary impacts, acting as supply-side disturbances that reduce output and investment through higher production costs and delayed adjustment in the real economy. Similar evidence is found in Palikhe et al. (2024), who develop an index of environmental policy uncertainty and use a VAR framework to show that higher uncertainty lowers firm-level investment in industries sensitive to environmental policies. Likewise, Noailly et al. (2022) construct a broader environmental policy uncertainty index using machine learning techniques and find that higher environmental policy uncertainty reduces low-carbon investment and venture-capital funding.

Based on a similar textual approach, Basaglia et al. (2025) analyze the firm-level implications of climate policy uncertainty. They document that heightened climate uncertainty leads to lower capital expenditures, innovation, and R&D spending—especially among carbon-intensive (brown) firms—and increases stock-market volatility. These results are consistent with the theoretical argument that predictable and credible climate policies can reduce transition costs and support long-term growth (Fried et al., 2021). Besides these macroeconomic and microeconomic perspectives, an growing literature has emphasized the financial transmission mechanisms for climate and transition risks, showing how they affect the pricing of financial assets, the cost of capital of firms, and portfolio allocation across sectors through the volatility and discount rate channels (e.g., Bolton and Kacperczyk, 2021a; Pástor et al., 2022; Ardia et al., 2023).

To our knowledge, most of the existing measures of climatic uncertainty are backward-looking in the sense that they rely on textual or narrative sources (such as newspapers articles) that capture the intensity of policy debates *after the fact*. While such indicators are valuable for historical quantification, they often fail to capture forward-looking revisions in expectations—that is, the real-time re-assessment perfomed by financial market actors that determine how policy uncertainty is priced and transmitted to the economy. Therefore there may substantial value in pursuing an empirical analysis of the economic impact of measures capturing the financial market assessment of climate uncertainty shocks. For instance, consider a situation in which credible information about a potential tightening of climate regulation becomes available to market participants, but the probability of enactment remains unclear. In such cases, financial markets may immediately re-price assets exposed to transition risk, leading to sharp adjustments in derivatives-implied volatility or risk premia, even in the absence of contemporaneous price movements. Text-based uncertainty measures, by contrast, may respond only once the episode is explicitly framed in the media using uncertainty-related language, potentially with a delay and conditional on editorial emphasis.[1] In fact, our work is closely related in spirit to recent studies on market-implied measures of climate uncertainty, such as the Carbon VIX developed for the

[1]Event-study evidence indicates that climate-policy news can be priced very quickly in traded assets. Using event studies on sectoral ETF data, Antoniuk and Leirvik (2024) find broadly positive cumulative abnormal returns around the adoption of the Paris Agreement, while the November 2016 U.S. presidential election is associated with a sharp negative repricing, with post-event cumulative returns below -2.5% across all sectors. By contrast, consistent with measurement differences across textual constructions, Gavriilidis (2021) reports that CPU reacted over all of early 2016 to the Agreement, which is consistent with the fact that their CPU index correlates only 0.41 with the Wall Street Journal climate-change news index of Engle et al. (2020).

EU Emissions Trading System, which captures carbon-price volatility (Hensel et al., 2024).

We contribute to the literature by providing a market-based, forward-looking measure of climate transition uncertainty and by analyzing its macro-financial and sectoral effects on the U.S. economy. We construct an external instrument derived from the realized volatility of the ICE (Intercontinental Exchange) U.S. Carbon Futures Index—a financial market directly exposed to developments in emission-allowance regulation. This index tracks the futures prices of carbon allowance contracts and represents a market-based measure of expected carbon prices and, by extension, of climate policy stringency and volatility. Therefore it provides a market-based, forward-looking proxy for climate (policy) shocks.

To isolate the unpredictable component of volatility, we remove its autoregressive structure and retain the innovation term, which captures unanticipated shifts in investors' perceptions of climate-policy risk. The resulting realized volatility innovation captures real-time revisions in policy expectations, offering a clean, high-frequency proxy for exogenous climate uncertainty shocks embedded in financial markets. We use this instrument to identify a monthly Bayesian Proxy-SVAR over the period 2014–2025, in which the VIX, the implied volatility index, serves as the financial variable through which climate transition uncertainty shocks are transmitted. This setup allows us to trace how climate uncertainty interacts with broader market volatility and propagates through the financial transmission channel to affect real activity and asset valuations.

In addition to the aggregate analysis, we contribute a novel sectoral dimension that has not been explored in the prior literature. We study heterogeneity in the transmission of climate uncertainty shocks along two complementary layers of disaggregation. First, we construct a broad green–brown decomposition to document differences between transition-risk-exposed and transition-resilient industries. Second, we move to a full sector-by-sector analysis of both industrial production (using the the complete set of NAICS-based industry groups in the Federal Reserve G.17 IP series) and sectoral valuation dynamics (using the Fama–French 49 Industry Portfolios). A key advantage of this granular structure is that it permits a systematic mapping between each sector and its EPA supply-chain emission intensity. Through this linkage, we can directly assess whether the severity of the sectoral responses to climate transition uncertainty shocks varies with the underlying carbon intensity of economic activity. This is an aspect that, to our knowledge, has not been quantitatively examined in previous studies of climate-policy uncertainty.

Our results show that an unanticipated increase in carbon-futures implied climate uncertainty tightens financial conditions—raising aggregate equity implied volatility—while reducing industrial production, the goods price level, and stock market valuations, in fact triggering an accommodative monetary policy response. The decline in asset valuations, measured by the price–dividend ratio, is particularly persistent. This is consistent with a sustained re-pricing of climate risks. Our findings are robust to alternative model specifications, including different lag structures, prior settings, and the selection of alternative macro-financial aggregates; our key empirical findings also hold under both Local Projections (LP) and Bayesian Local Projections (BLP) frameworks.

When we extend our analysis to a sectoral dimension by investigating how different sectors are affected by carbon-futures implied uncertainty shocks, we uncover a clear green–brown asymmetry. Climate transition uncertainty shocks lower aggregate activity but their effects are unevenly distributed: carbon-intensive (brown) sectors such as oil, gas, and utilities experience deeper and more persistent contractions, while low-emission and technology-intensive (green) sectors display greater resilience and faster recovery. In a financial perspective, the price–dividend ratio falls for all sectors immediately after the shock but rebounds and overshoots in the case of green industries, indicating a reallocation of investors' wealth toward transition-resilient assets.

Moving beyond this broad decomposition, a full sector-by-sector analysis shows that these asymmetries become even sharper. Once we examine individual industries, we find a clear gradient: sectors characterized by higher carbon intensity exhibit systematically larger declines in both output and valuations, whereas lower-emission sectors experience milder effects. This granular evidence extends the green–brown findings, demonstrating that the severity of climate uncertainty-induced adjustments increases monotonically with emission intensity.

Overall, this evidence supports the interpretation of carbon futures implied climate transition uncertainty as a distinct and market-based form of uncertainty that links policy ambiguity to macro-financial volatility. Our results highlight the importance of transparent and credible climate policy in reducing transition costs, stabilizing financial markets, and supporting the efficient allocation of capital toward low-carbon activities.

The remainder of the paper is structured as follows. Section 2 introduces the carbon futures realized variance-based climate uncertainty instrument, detailing its construction and validation. Section 3 presents the data and methodology. Section 4 reports the aggregate macro-financial results discussing their robustness across specifications, which occurs in Section 5. Section 6 explores sectoral heterogeneity at two complementary levels: a broad green–brown decomposition and a granular sector-by-sector analysis of real and financial responses, including their mapping to EPA emission intensities. Section 7 concludes.

2 Backward-Looking vs. Forward-Looking Uncertainty

A key motivation of this paper is that, by using carbon futures-implied measures, it focuses on a *forward-looking* measure of climate uncertainty, as opposed to the more conventional *backward-looking* approaches commonly used in the literature. Backward-looking indicators—such as narrative indices or measures based on textual analysis, capture the frequency or intensity of policy-related discussions after uncertainty has (at least partially) materialized (see the discussion in Baker et al. (2016)). While these methods are useful to historical measurement, they primarily reflect the *observed* component of uncertainty rather than agents' expectations; therefore their use in defining a shock assumes their persistence. Moreover, news-based indicators often record policy events or narratives that markets have already anticipated and priced in, thus failing to capture genuine revisions in uncertainty, i.e., they offer potentially noisy measures of true shocks.[2]

In contrast, the realized volatility innovations extracted from carbon futures prices provide a distinctly forward-looking proxy. Because allowance prices incorporate new information about the expected trajectory, credibility, and timing of climate policies, their high-frequency volatility captures investors' real-time re-pricing of policy risk. This perspective aligns with the recent proxy-SVAR literature on monetary policy, which has emphasized the real-time behavior of financial markets and the use of external instruments to capture exogenous policy shocks in the presence of communication, forward-guidance, and information effects (see, e.g., Gertler and Karadi (2015), Nakamura and Steinsson (2018), Miranda-Agrippino and Ricco (2021)).

Therefore our approach also differs from recent contributions that identify carbon futures-implied uncertainty through narrative or textual analyses, such as Gavriilidis (2021), Ardia et al. (2023), and Känzig et al. (2025), as they rely on low-frequency policy announcements or media-based indicators. By contrast, our realized volatility uncertainty proxy captures high-frequency, market-based revisions in expectations about climate regulation, providing a cleaner identification of the *anticipated* and indeed forward-looking component of climate uncertainty. This makes our measure complementary to textual and event-based indices, while particularly suited to assessing how financial markets internalize and transmit climate-policy uncertainty, besides studying their impact on real macroeconomic aggregates.

[2] Cascaldi-Garcia et al. (2023) show the effects and interpretation of uncertainty heavily depend on the measure's construction (e.g., news-based vs. market-based). They remark that news-based indices capture a portion of uncertainty but also admit the existence of identification issues and that not all measures map cleanly to expectation revisions because they may lack a distinctive forward-looking nature.

A Market-Based Proxy for Climate Policy Uncertainty

The realized volatility estimator derived from carbon futures prices is the core instrument of our empirical identification strategy. This estimator is *non-parametric, consistent under mild assumptions, and robust to model misspecification*, providing an ex-post measure of total return variation that efficiently aggregates high-frequency information from market prices (Andersen et al., 2001).

To implement this approach, we use data from the ICE U.S. Carbon Futures Index, which focuses specifically on U.S. carbon markets and aggregates futures prices from the two major regional cap-and-trade systems: the Western Climate Initiative (California and Québec) and the Regional Greenhouse Gas Initiative (northeastern and mid-Atlantic states).[3]

In the United States, carbon futures markets are organized around cap-and-trade programs that regulate greenhouse gas emissions at the state and regional level. Under these schemes, regulators set an upper limit on total emissions and issue a fixed number of allowances, each granting the right to emit one metric ton of CO2-equivalent. Firms that emit less than their allocation can sell their surplus allowances, while those exceeding their limits must buy additional permits to comply with regulation. This creates a secondary market in which prices are determined by the interaction of demand (driven by firms' expected emissions, energy demand, and technological efficiency and supply, determined by the regulatory cap, allowance auctions, and policy adjustments. The Western Climate Initiative, and the Regional Greenhouse Gas Initiative, constitute the backbone of U.S. carbon compliance markets. Futures contracts on the allowances issued in these regions are actively traded on the Intercontinental Exchange (ICE), where they prove useful to both compliance entities and financial investors. Compliance participants (the regulated emitters) use futures to hedge against the risk of higher carbon prices in the face of their demand of flexibility to adjust their inventories if their emissions forecast were to change, while speculators and institutional investors provide liquidity and express views on the future path of policy and energy markets. As a result, futures prices embed the collective expectations of market participants regarding policy stringency, regulatory credibility, and the cost of compliance. Because these expectations are continuously updated as new political or regulatory information arrives, volatility in carbon futures prices provides a direct and high-frequency measure of how markets reassess climate-policy risk in real time. This feature makes ICE carbon futures an ideal foundation for our market-based proxy of Climate Policy Uncertainty.

[3] These contracts are standardized, fully collateralized, and cleared, which lowers counterparty risk and creates a transparent price discovery process.

Let P_t denote the daily closing price of the ICE carbon futures contract. Daily log-returns are computed as $r_t \equiv \log P_t - \log P_{t-1}$, and monthly realized volatility as

$$RV_m = \sqrt{\frac{30}{n_m}\sum_{t=1}^{n_m} r_t^2},$$

where n_m is the number of trading days in month m, and the factor 30 adjusts for unequal trading days during a month. Figure 1 plots the standardized realized volatility measure for the ICE U.S. Carbon Futures Index. Visibly, the resulting time series displays pronounced spikes corresponding to episodes of elevated uncertainty about the credibility and the timing of U.S. climate policy.

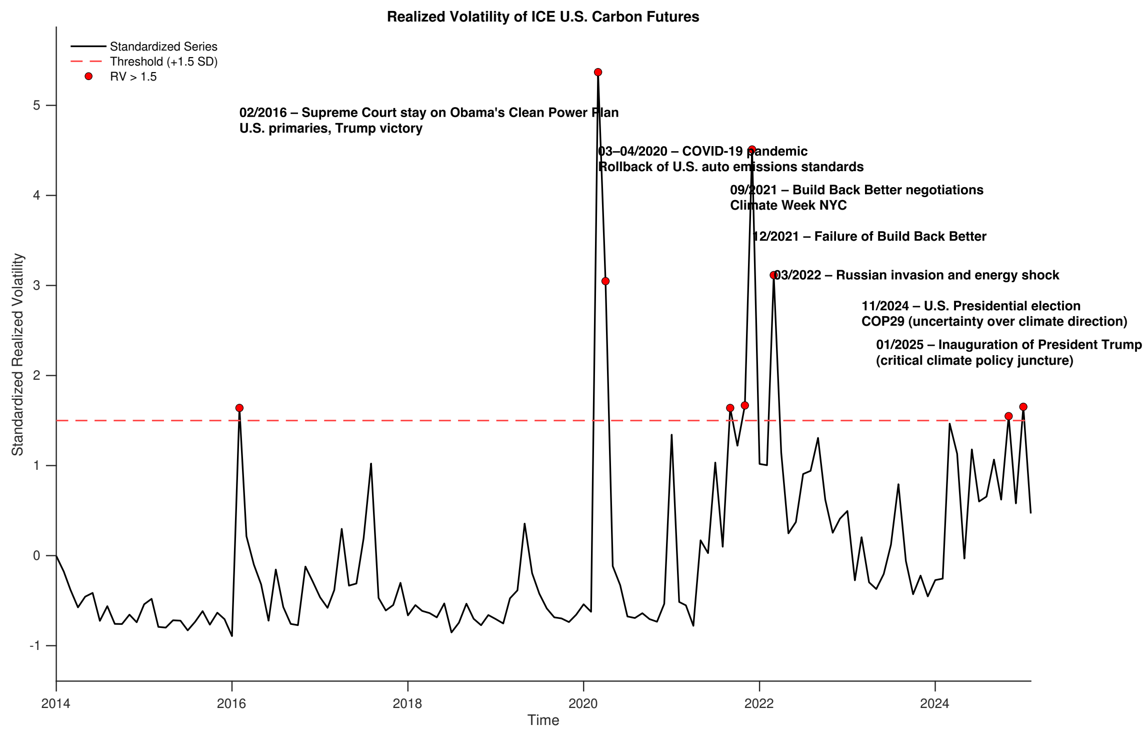

Figure 1
Realized Volatility of ICE U.S. Carbon Futures.
Standardized realized volatility of the ICE U.S. Carbon Futures Index (2014–2025). Red dots indicate volatility spikes exceeding 1.5 standard deviations, corresponding to major climate-policy events.

The spike of 2016, for instance, followed the U.S. Supreme Court's suspension of the Clean Power Plan and coincided with the presidential election campaign, when the prospect of a Trump administration created significant uncertainty over the future course of U.S. climate policy. The 2020 episode overlapped with the COVID-19 outbreak and the rollback of vehicle emissions standards, both of which weakened perceptions of regulatory commitment to decarbonization. The fluctuations in carbon futures price realized volatility observed in 2021–22 reflect the turbulence surrounding the Build Back Better negotiations and the geopolitical shock of the Russian invasion of Ukraine, events that together heightened doubts about the pace and credibility of the energy transition.[4] Finally, the final spikes in late 2024 and early 2025 coincide with renewed political uncertainty linked to the U.S. presidential election, the COP29 negotiations, and the return of Donald Trump to the presidency. These are all developments that are likely to have intensified investors' concerns about the continuity of climate policy commitments. Financial markets appear to have reacted to these events through increased volatility andwidespread portfolio re-shuffling, which is consistent with on-going reassessment of policy credibility by market participants (see Monasterolo et al. (2019)).

In addition, following Miranda-Agrippino and Ricco (2021) and a broader finance literature which documents a degree of persistence in realized-volatility dynamics reflecting the slow adjustment of expectations to the arrival of new information, we extract the innovation component of realized volatility to construct an exogenous instrument to identify climate uncertainty shocks. Specifically, we remove the autoregressive portion of the series, isolating its true surprise element, consistent with the gradual assimilation of information by market participants, an established feature of imperfect-information environments (see Coibion and Gorodnichenko (2015)). To model this predictable component, we examine the stochastic properties of realized volatility by fitting alternative ARMA(p,q) specifications and selecting from them using the Bayesian and Hannan–Quinn information criteria. Both criteria select a parsimonious AR(1) representation:

$$RV_t = \alpha + \beta RV_{t-1} + \varepsilon_t.$$

This model is estimated over the full sample for carbon futures prices, January 2014 - February 2025. The residuals ε_t represent the realized-volatility innovations, that is, the unexpected component capturing real-time revisions in market expectations about climate policy, which provides an exogenous source of variation to support structural identification.

The choice of the ICE U.S. Carbon Futures as our benchmark instrument also reflects its superior first-stage performance relative to alternative carbon-market-based surprises that could

[4]The Build Back Better Act was a major climate-oriented policy proposal designed to expand clean-energy investment through large federal tax credits and support for low-carbon technologies. Its repeated legislative breakdowns in 2021–22 created substantial uncertainty about the future strength of U.S. climate policy, generating volatility in expectations about long-run decarbonization incentives.

be used for identification, as documented in Table 1. All alternative proxies are based on futures contracts traded on ICE and sourced from Bloomberg, and belong to the ICE Carbon Futures Index Family, covering the Western Climate Initiative (California–Québec), the Regional Greenhouse Gas Initiative (U.S. Northeast), their U.S. aggregation, and their global aggregation.[5] Moreover, all candidate proxies are constructed using the same realized-volatility methodology and correspond to innovations extracted from an autoregressive process of order one, selected according to standard information criteria, as in the case of the ICE U.S. index.

Instrument	Market coverage	First-stage F-statistic
ICE U.S. Carbon Futures (US aggregate)	WCI + RGGI	18.25
ICE California (WCI)	CA + QC	16.10
ICE RGGI	U.S. Northeast	1.33
Global Carbon Futures Index	International markets	3.41

Table 1: First-stage relevance of alternative carbon-market-based instruments.
The table reports first-stage F-statistics from the projection of reduced-form VAR residuals on alternative carbon-market-based instruments. The proxied variable is the VIX. The BVAR includes VIX, IP, PCE, PD ratio, and FFR. Sample: February 2014–January 2025.

Beyond its conceptual appeal, the ICE U.S. Carbon Futures Index provides the strongest first-stage relevance for aggregate financial volatility among the alternative proxies considered, reflecting its broader market coverage and tighter link to U.S. financial conditions. Its first-stage F-statistic is comfortably above the conventional threshold of 10 typically recommended in the literature (Stock and Watson, 2018; Känzig et al., 2025), whereas proxies based on more regional or global carbon markets display substantially weaker relevance for the U.S. financial channel.

To further assess the empirical plausibility of our proxy, we examine its pairwise correlation with alternative measures of uncertainty (Table 2).

The strongest correlation with RV/climate uncertainty shocks occurs in the case of RVUS (0.85), as the innovation is derived from the same realized-volatility series. This likely reflects the mechanical link between the two measures: the autoregressive filtering may remove the persistent component of volatility, while the remaining innovation captures the policy-related uncertainty behind unexpected movements in the carbon futures market. The correlation of RV/climate uncertainty shocks with the textual CPU index (0.27) is moderate, suggesting that our market-based proxy may capture a component of climate-policy uncertainty that is related to, but distinct from, the narrative-based measure derived from textual analysis. Finally, the

[5]Further details on the ICE Carbon Futures Index Family are available at `https://www.ice.com/fixed-income-data-services/index-solutions/commodity-indices/carbon-futures`.

Variables	RV/Climate uncertainty shocks	RVUS	CPU Index	VIX
RV/Climate uncertainty shocks	1.000	0.849	0.273	0.306
RVUS	0.849	1.000	0.413	0.445
CPU Index	0.273	0.413	1.000	0.280
VIX	0.306	0.445	0.280	1.000

Table 2: Correlation matrix between uncertainty indicators.
Correlation matrix is estimated with reference to the sample period February 2014–January 2025. The matrix concerns correlations between realized-volatility innovations (RV/climate uncertainty shocks), the realized volatility of ICE U.S. Carbon Futures (RVUS), the textual Climate Policy Uncertainty (CPU) index of Gavriilidis (2021), and the VIX implied-volatility index.

correlation with the VIX (0.31) provides evidence of a financial transmission channel linking climate-policy uncertainty to broader market volatility. This connection indicates that carbon-market shocks are internalized by investors and transmitted to aggregate financial conditions through standard volatility channels. The moderate size of this correlation is consistent with a climate-specific source of risk that interacts with, but does not merely replicate, general financial uncertainty.

Overall, these correlations support the interpretation of the realized-volatility innovation as a meaningful proxy for climate-policy uncertainty. It shows sufficient association with existing uncertainty indicators to ensure empirical relevance, while remaining distinct enough to avoid its redundancy. This balance between overlap and specificity reinforces the suitability of RV/climate uncertainty shocks as an external instrument for identifying exogenous climate policy uncertainty shocks in a Bayesian Proxy-SVAR framework

3 Data and Methodology

3.1 Data

Our empirical analysis relies on a monthly dataset combining standard U.S. macro-financial indicators with a market-based measure of climate policy uncertainty. The sample spans the period February 2014 - January 2025. The data include variables capturing financial conditions, real activity, besides our high-frequency proxy for climate-related financial uncertainty.

The CBOE Volatility Index (VIX) is included in the analysis as the benchmark measure of aggregate financial uncertainty. Widely regarded as the "fear gauge" of the U.S. equity markets, it reflects investors' expectations of near-term volatility implied by S&P 500 options. Following the large literature on uncertainty and macro-financial dynamics (Bloom, 2009; Baker et al., 2016), the VIX serves as a reference measure of market-based uncertainty that allows us to assess how climate-related shocks interact with broader financial volatility.

Our proxy for climate policy uncertainty is based on the realized volatility of the ICE U.S. Carbon Futures Index, obtained from Bloomberg. The macroeconomic variables are sourced from FRED database: the VIX, the Industrial Production (IP) index, the Personal Consumption Expenditure (PCE) price index, and the Federal Funds Rate (FFR). The S&P 500 price–dividend ratio (PD) is from Robert Shiller's dataset.[6] We focus on the price–dividend ratio rather than the S&P 500 index itself, as it provides a valuation-based measure that filters out short-term price fluctuations and better captures investors' expectations about future cash flows and discount rates.[7] This approach aligns with the extensive literature showing that valuation ratios summarize investors' long-horizon expectations and are informative about long-run risks, long-run growth uncertainty, and discount-rate variation, see Philips (1999).[8]

3.2 Bayesian Proxy-SVAR Framework

We estimate a Bayesian Structural VAR(p) model identified through an external instrument. Let y_t denote an $n \times 1$ vector of de-meaned, endogenous variables following the reduced-form representation

$$y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + u_t, \qquad u_t \sim \mathcal{N}(0, \Sigma_u),$$

and the corresponding structural form

$$A_0 y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t, \qquad E[\varepsilon_t \varepsilon_t'] = I_n,$$

where $u_t = A_0^{-1}\varepsilon_t$ and A_0^{-1} maps structural shocks into reduced-form innovations.

Identification of the structural shock of interest, denoted ε_t^k, follows the proxy BVAR approach of Stock and Watson (2018) and Mertens and Ravn (2013). The method exploits an external

[6] Shiller's data are available at https://shillerdata.com/.

[7] The price–dividend ratio is a standard forward-looking valuation measure in asset pricing. In a standard log-linear Campbell- Shiller decomposition (see Campbell and Shiller (1988)), the PD ratio encodes expectations of future dividend growth and discount rates, whereas index prices alone commingle these components with short-term noise. Because climate-related uncertainty affects both expected long-run cash flows (via growth prospects, damages, stranded-asset risk, (see Campbell and Shiller (1998) and Giglio et al. (2021)) and discount rates (via risk and ambiguity premia), PD movements provide a cleaner lens through which to study how climate-related shocks transmit to valuations.

[8] Further details on the dataset are provided in Appendix A.

instrument z_t that satisfies the following relevance and orthogonality conditions:

$$E[\varepsilon_t^k z_t] \neq 0,$$
$$E[\varepsilon_t^j z_t] = 0 \quad \forall j \neq k.$$

The first condition (relevance) ensures that z_t is correlated with the targeted structural innovation, while the second (exogeneity) requires independence from all other contemporaneous shocks. Together, these conditions allow the covariance between the VAR residuals and the proxy to isolate the structural disturbance of interest, because they imply that the reduced-form shock most strongly associated with z_t must coincide with ϵ_t^k and hence can be recovered without imposing further structural restrictions.

The BVAR is estimated following Miranda-Agrippino and Ricco (2021) and using standard Normal–Inverse Wishart priors; the priors' tightness is set as in Giannone et al. (2015). Posterior inference is performed via Gibbs sampling, allowing full propagation of parameter and identification uncertainty to the posterior distribution of the structural parameters. As explained earlier, the model includes VIX, IP, PCE, PD, and FFR. All variables enter the VAR in natural logarithms except for FFR. Given the relatively short time span of investigated sample, the lag order is set to $p = 6$, allowing the model to capture short-run propagation without an excessive loss of degrees of freedom. The use of six lags in a monthly VAR is not unusual (see, for example, Ludvigson et al. (2021), Caggiano et al. (2021), Cascaldi-Garcia and Galvao (2021)).

Given posterior draws of (B, Σ_u), identification proceeds by projecting the reduced-form innovations u_t onto the external instrument $z_t = \varepsilon_t^{RV}$, which corresponds to the innovation in the realized volatility of ICE carbon futures log-price changes. This step recovers the contemporaneous impact vector associated with the structural shock, from which the posterior distributions of A_0^{-1} is then derived. The relevance of the instrument arises from the fact that carbon allowance markets incorporate new information about the expected trajectory of climate regulation at high frequency, making realized volatility a direct proxy for financial uncertainty related to climate-policy news. In practice, we assess the empirical strength of this effect through the first-stage F-statistic from the projection of the reduced-form residuals on the realized-volatility instrument.

Our F-statistic test equals 18.25, confirming that the realized volatility innovation provides a sufficiently strong and relevant instrument for identification. Finally, the exogeneity condition is also plausible, as daily fluctuations in carbon futures are primarily driven by discrete policy announcements and regulatory developments rather than by contemporaneous macroeconomic shocks.

4 Main Results

Figure 2 reports the impulse responses of all endogenous variables in the VAR to a climate transition uncertainty shock normalized to raise the VIX by one standard deviation, corresponding to an increase of 30.65 percent. IRFs are reported in percentage points.

To facilitate the interpretation of the dynamic responses shown in Figure 2, Table 3 reports a concise quantitative summary of their main features, including impact effects, peak responses, and the horizon over which each response remains statistically significant.

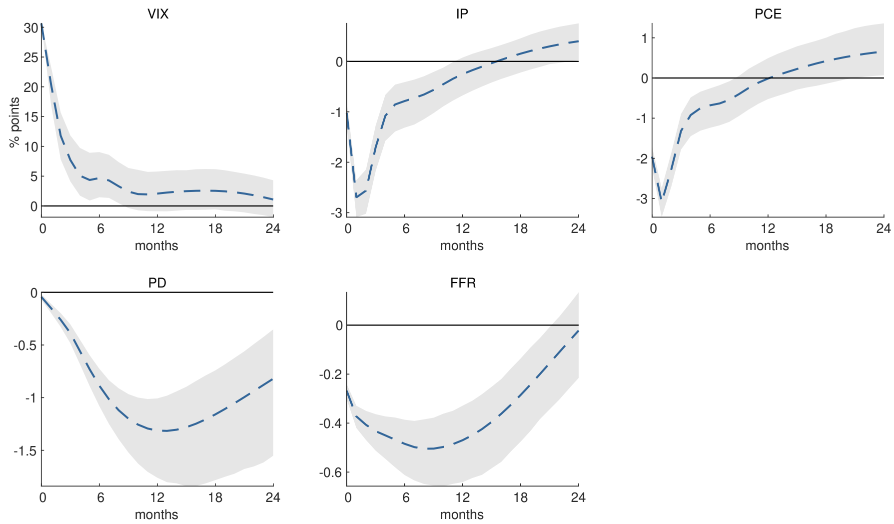

Figure 2
The Effects of Climate Policy Uncertainty Shocks

Impulse responses to the identified climate transition uncertainty shock for all endogenous VAR variables (VIX, IP, PCE, PD ratio, and FFR). The shock is identified using the realized volatility innovation from ICE carbon futures log-price changes as the external instrument. Shaded areas denote 68% posterior credible intervals. IRFs are reported in percentage points. Sample: February 2014–January 2025.

Variable	Impact	Peak Response	Persistence (Month)
VIX	30.65	30.65	8
IP	-1.02	-2.70	11
PCE	-1.95	-3.08	9
PD	-0.05	-1.31	24
FFR	-0.27	-0.50	22

Table 3: Quantitative Summary of Aggregate Impulse Responses to Climate Policy Uncertainty Shocks.
The table reports impact and peak impulse responses corresponding to a Climate Policy Uncertainty Shock. Peak responses are defined as the maximum absolute response. The last column reports the final horizon at which the response remains statistically significant at 68%. IRFs are reported in percentage points. Sample: February 2014–January 2025.

Overall, the results show that an unanticipated increase in climate-related financial uncertainty generates macro-financial effects comparable to those typically associated with tightening uncertainty shocks. The VIX rises sharply on impact and remains elevated in the short and medium run, confirming the activation of a strong financial volatility channel. At the same time, real activity and asset valuations decline in the months following the shock. Industrial production contracts significantly, falling by about 1 percent on impact and reaching a trough of approximately -2.7 percentage points after two to three months. The decline is persistent, with industrial production remaining below baseline for roughly one year before gradually recovering. Consumer prices also display a negative response. The PCE price index falls by nearly 2 percentage points on impact and reaches a maximum decline of about -3.08 percentage points within the first few months after the shock, before slowly reverting toward baseline. This pattern is consistent with short-run demand effects dominating following an increase in climate-related uncertainty. Asset valuations respond strongly and persistently. The price-dividend ratio declines steadily over time, reaching a maximum contraction of about -1.31 percentage points after roughly one year, and remains substantially below its pre-shock level throughout the two-year horizon. This persistence points to a prolonged adjustment in market valuations, consistent with sustained increases in discount rates and risk premia. Monetary policy reacts accommodatively. The federal funds rate declines on impact by about 27 basis points and continues to fall gradually, reaching a maximum reduction of approximately 50 basis points, before slowly converging back toward baseline. This response suggests a systematic accommodative monetary policy reaction to the weaker macroeconomic and financial conditions induced by heightened climate uncertainty.

The negative price reaction suggests that our proxy effectively isolates the *second-moment* component of policy uncertainty rather than the *first-moment* policy shock itself. Indeed, the existing literature generally finds that climate-policy shocks that raise carbon prices are inflationary, as tighter environmental regulation increases firms' production costs, constrains energy supply, and generates cost-push pressures. Within the EU Emissions Trading System, both Känzig (2023) and Hensel et al. (2024) show that carbon price policy shocks are inflationary and contractionary, as higher allowance prices raise firms' marginal costs and depress output, confirming the supply-side nature of these disturbances. Our measure, however, captures fluctuations in the volatility of the rate of change of futures prices rather than in their levels. Hence, while changes in the carbon price reflect *policy actions* or expectations of regulatory tightening, movements in volatility reflect *uncertainty* surrounding the timing, credibility, and intensity of such actions.

Interestingly, the responses of financial variables—such as the price–dividend ratio, and the policy rate—are considerably more persistent than those of real variables like industrial production and consumer prices, with statistically significant effects extending up to roughly 22 months for the policy rate, and the entire horizon for asset valuations, compared to about 9–11 months for output and prices (Table 3). This pattern is consistent with a financial transmission mechanism through which climate-policy uncertainty primarily operates via risk re-assessment, asset re-pricing, and adjustments in financial conditions, thereby amplifying macro-financial fluctuations and inducing a sustained easing in policy rates.

5 Robustness Checks

5.1 Alternative Model Specifications

In this section, we assess the robustness of our baseline findings to alternative model specifications and sample definitions. The purpose of these exercises is to assess whether the dynamic responses to carbon futures–implied uncertainty shocks are sensitive to alternative modeling assumptions and estimation choices.

We complement the BVAR approach with an alternative estimation framework based on local projections, following Ramey (2016). She argues that LPs allow the estimation of impulse responses directly at each horizon, reducing sensitivity to potential misspecifications in the VAR dynamics. Third, we implement a Bayesian LP approach following Miranda-Agrippino and Ricco (2021) who have proposed to regularize horizon-specific LP coefficients by centering their prior around the iterated coefficients from the baseline BVAR, thereby combining the efficiency of

VAR estimation with the robustness of LP methods. The prior tightness is estimated at each horizon within a hierarchical Bayesian framework, allowing the data to determine the optimal degree of shrinkage.[9]

Our findings from the first robustness exercise consisting of the adoption of alternative lag lengths. The outcomes from the alternative model specifications, including the LP and BLP estimations, are shown in Figure 3. Across these exercises, the dynamic responses display remarkably similar magnitudes and persistence vs. those shown in our section on main empirical results, confirming that the estimated effects of carbon futures-implied uncertainty shocks are not driven by model-specific assumptions.

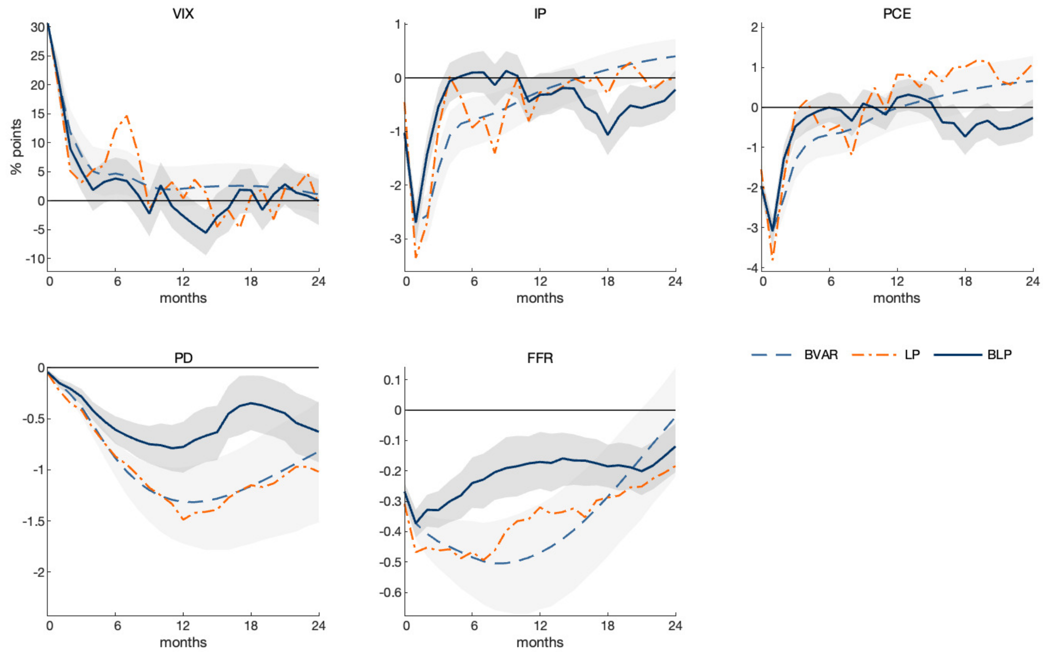

Figure 3
BVAR vs LP or Bayesian LP: Robustness to Different Model Specifications.
Impulse responses to the identified climate uncertainty shock for all endogenous variables (VIX, IP, PCE, PD ratio, and FFR). The shock is identified using the realized-volatility innovation from ICE carbon futures as the external instrument. Shaded areas denote 68% posterior credible intervals.IRFs are reported in percentage points. Sample: February 2014–January 2025.

We have also verified that the results are robust to alternative lag-length choices (see Appendix B). In addition, the findings remain unchanged when varying prior hyperparameters and shrinkage settings in the BVAR specification; full results are available upon request.

[9]For the BLP the pre-sample period, running from February 2014 to February 2018.

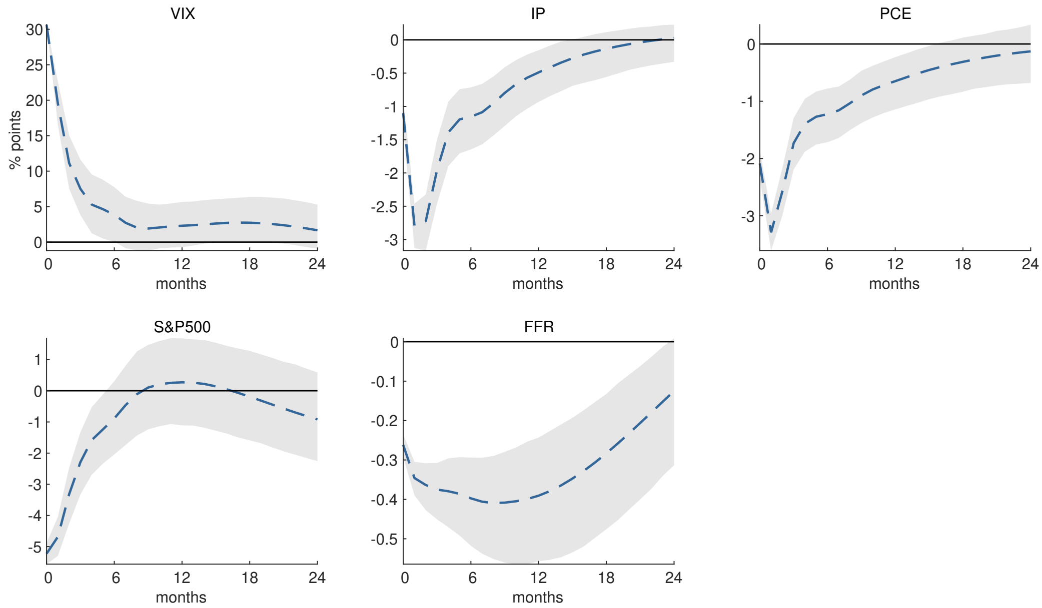

Figure 4
Alternative Aggregate: S&P 500 Index.
Impulse response functions to the identified climate uncertainty shock when the S&P 500 index replaces the price–dividend ratio in the Bayesian Proxy-SVAR. The specification includes VIX, industrial production, PCE, S&P 500, and the federal funds rate. Shaded areas denote 68% posterior credible intervals. IRFs are reported in percentage points. Sample: February 2014–January 2025.

5.2 Alternative Variables: S&P 500 and Unemployment

To further assess the robustness of our findings, we re-estimate the BVAR using alternative aggregate variables that capture the same macro-financial phenomena, yet through different indicators. Specifically, we first replace the log-price–dividend ratio with the S&P 500 log-index; we also substitute industrial production with the US unemployment rate.[10] Figure 4 shows the results obtained when the S&P 500 index replaces the price–dividend ratio in the VAR specification. The overall pattern of responses remains nearly identical to the baseline: the VIX rises immediately, while the S&P 500 index declines on impact, reflecting a tightening of financial conditions. The magnitude of these responses is very similar to those obtained with the price–dividend ratio in Figure 2; however, the negative effect on the market valuation index turns out to be somewhat less persistent.

Figure 5 shows that replacing industrial production with the unemployment rate does not alter the recessionary dynamics illustratd earlier. Following a climate transition uncertainty shock, the unemployment rate rises persistently, mirroring the contraction in output observed

[10]The S&P 500 index is obtained from Robert Shiller's website, while the US unemployment rate is sourced from the FRED database.

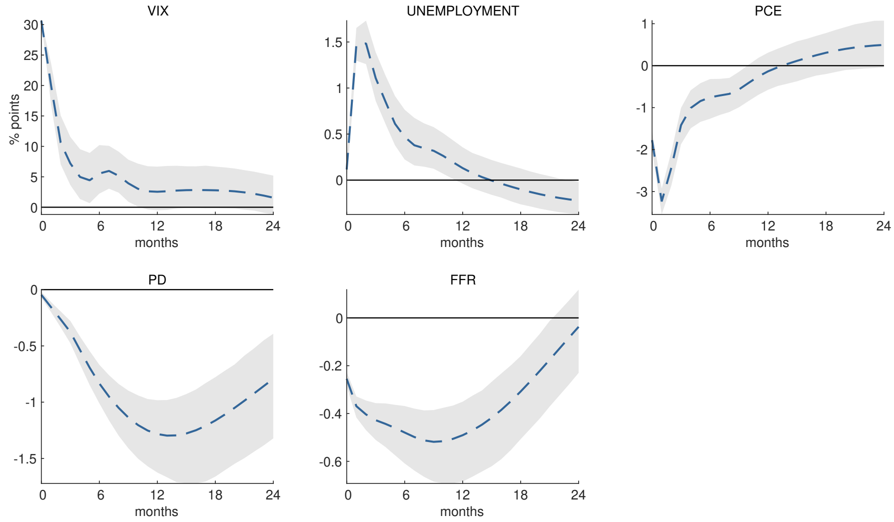

Figure 5
Alternative Aggregate: Unemployment Rate.

Impulse response functions to the identified climate uncertainty shock when the unemployment rate replaces industrial production in the Bayesian Proxy-SVAR. The specification includes VIX, unemployment rate, PCE, price–dividend ratio, and the federal funds rate. Shaded areas denote 68% posterior credible intervals. IRFs are reported in percentage points. Sample: February 2014–January 2025.

in the baseline set of results. The similarity of the responses across specifications reinforces the robustness of our findings and indicates that the transmission mechanism of climate uncertainty shocks is stable across different indicators of real/financial activity.

6 Analysis of the Heterogeneity in Green vs. Brown Sectoral Responses

6.1 Sectoral Heterogeneity: Green vs. Brown Industries

To investigate how climate uncertainty shocks propagate throughout the economy, we construct broad *green* and *brown* aggregates for both real activity (industrial production) and asset valuations (price–dividend ratio). This sectoral perspective is crucial because the transition to a low-carbon economy entails an uneven redistribution of risks and investment opportunities across industries. While climate-related policies may penalize carbon-intensive activities through tighter regulations or higher abatement costs, they can simultaneously benefit green and technology-oriented sectors by stimulating innovation and investment in sustainable production. In our macro-finance sectoral setting, we define as *brown* the sectors that are fossil-fuel-based, to include the energy supply industries (e.g., utilities, oil and gas extraction, and petroleum refining) that are directly exposed to transition and regulatory risks. Conversely, the *green* sectors comprise low emission and transition enabling manufacturing activities, such as electrical equipment and electronic components, which provide the technological backbone for electrification, energy efficiency, and renewable integration.

6.1.1 Sectoral Industrial Production Analysis

We use the sectoral industrial production indices made available by the Federal Reserve's G.17 data repository and based on the North American Industry Classification System (NAICS) classification.[11] We construct two broad aggregates reflecting industries' exposure to climate-transition risk: *brown* (carbon-intensive) and *green* (low-emission or transition-enabling) sectors. The brown sectors–*Utilities*, *Oil and Gas Extraction*, and *Petroleum and Coal Products*–represent the core of the fossil-fuel value chain. They exhibit high direct greenhouse gas emissions, rely heavily on carbon-based energy inputs, and are most exposed to policy shocks such as carbon pricing and emission standards. This grouping is consistent with the literature which identifies fossil energy production, utilities, and energy-intensive manufacturing as the most vulnerable to climate policy risk (Battiston et al., 2017; Bolton and Kacperczyk, 2021a; Känzig et al., 2025). In contrast, *Computers and Electronic Products* and *Electrical Equipment, Appliances, and Components* are categorized as green sectors. These industries exhibit low operational emissions and act as key transition enablers by providing essential inputs for electrification, renewable-energy systems, and energy-efficiency technologies, such as semiconductors, sensors, electric motors, and power-conversion components. This grouping is consistent with the literature, which identifies technology-intensive and innovation-driven manufacturing sectors as central to the low-carbon transition and as beneficiaries of climate-related and policy support (Vona et al., 2018; Alessi et al., 2023; Zhang et al., 2024). In practice, we construct the green and brown industrial production indices as simple (equal-weighted) averages of the NAICS industrial production series included in each group. This aggregation provides the data useful to esstimate a summary measure of the average responses of high- vs. low-emission sectors to climate uncertainty shocks

[11] NAICS is the standardized taxonomy used by U.S., Canadian, and Mexican statistical agencies to categorize all establishments into economically meaningful and mutually exclusive industries. NAICS replaced the older Standard Industrial Classification (SIC) codes by grouping firms according to similarity in production processes rather than end products. This has yielded a more consistent mapping between technological input structure and measured output. In the context of the G.17 release, NAICS codes determine the aggregation used to construct the industrial production series: establishment-level output is first assigned to detailed 4–6-digit NAICS industries, then aggregated hierarchically into higher-level sectors.

while preserving comparability with the aggregate VAR specification.

We therefore extend our baseline analysis by re-estimating the BVAR to include sectoral activity data. The vector of endogenous variables now comprises the VIX, the aggregate IP, PCE, PD, FFR, and the two sectoral, overall IP indices for the green and brown industries, respectively. Apart from this sectoral IP extension, the model is estimated using the same data, sample period, priors, and identification strategy as in the baseline specification. In fact, the impulse response functions of the aggregate variables, VIX, IP, PCE, PD, and FFR, are generally unchanged vs. those obtained in the main model.[12]

As shown in Figure 6, industrial production in the brown sectors experiences a deeper and more persistent contraction relative to the green sectors, with a peak decline of around 2.21% compared to 1.18% for green industries. This asymmetric reaction reflects the greater exposure of carbon-intensive industries to transition risk, consistent with standard theoretical predictions by which high emissions or technologically inflexible production face disproportionately larger valuation losses when the probability of future carbon regulation increases. This occurs because firms with higher emissions intensities bear greater adjustment costs—through stranded assets, higher future compliance expenditures, or accelerated depreciation of brown capital—which amplifies their sensitivity to shocks in policy stringency or expectations about decarbonization pathways (Dietz et al. (2016); Lemoine and Traeger (2016); Barnett et al. (2020); Engle et al. (2020); Van der Ploeg and Rezai (2020); Bolton and Kacperczyk (2021b)).[13]

6.1.2 Sectoral Price–Dividend Ratios Analysis

After documenting these asymmetric responses in real activity, we next examine whether climate-policy uncertainty affects financial valuations across sectors. To this end, we construct sectoral PD ratios from the Fama–French 49 Industry portfolios.[14] The classification mirrors the one used for industrial production: brown industries include *Oil (Petroleum and Natural Gas)*, *Utilities (Electric and Gas)*, and *Coal*, while the green industries include *Chips (Electronic Components)* and *Electrical Equipment*. Each sectoral PD ratio is computed using the previous twelve months of implied dividends (annualized);[15] and series are aggregated up at sectoral level as equally-

[12]Detailed results and IRF plots are available from the authors upon request.

[13]Equilibrium frameworks demonstrate that carbon-intensive sectors load more heavily on the transition component of climate risk because investors require compensation for holding assets whose cash flows depend on regulatory and technological trajectories that are both uncertain and downward-skewed for polluting industries (see Pástor et al. (2022); Giglio et al. (2021).

[14]Stock prices and dividends are sourced from French's website.

[15]Only in the case of coal, the window is extended to the previous 36 months due to the limited number of firms in the portfolio and the frequent occurrence of zero dividend distributions over a shorter, 12-month sample.

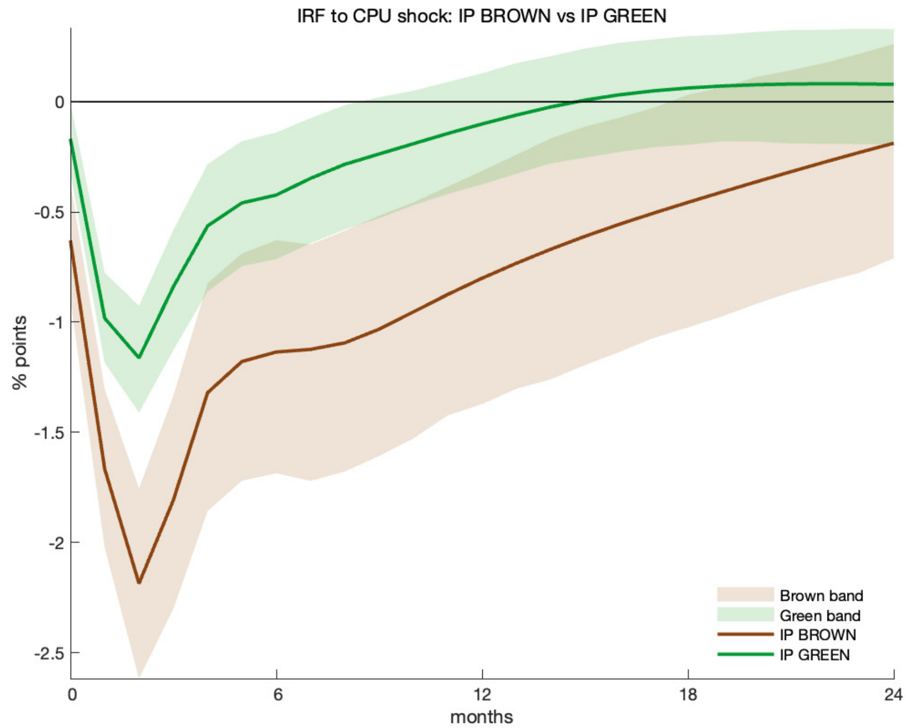

Figure 6
Sectoral Industrial Production Responses to a climate uncertainty Shock.
Impulse response functions to the identified climated uncertainty shock for green and brown industrial production indices estimated from the Bayesian Proxy-SVAR. The specification includes the VIX, aggregate IP, PCE, PD, FFR, and sectoral IP for green and brown industries. Sectoral indices are equal-weighted averages of the constituent NAICS sectoral IP series: *Brown* = Utilities (2211–2212), Oil and Gas Extraction (211), Petroleum and Coal Products (324); *Green* = Computers and Electronic Products (334), Electrical Equipment (335). Shaded areas denote 68% posterior credible intervals. IRFs are reported in percentage points. Sample: January 2014–January 2025.

weighted means.[16]

As in earlier analysis, we re-estimate the BVAR including sectoral PD ratios for green and brown industries, using the same specification, the same data and sample period, and identification strategy as in the baseline model. Figure 7 shows that climate uncertainty shocks initially depress asset valuations in both groups, consistent with a tightening of financial conditions and an increase in risk premia. However, over intermediate horizons of 4-12 months, the PD ratio of green sectors rebounds more quickly and often overshoots its pre-shock level, while brown sector valuations remain persistently depressed, significantly so for up to 20 months after the initial shock. This pattern suggests that heightened climate-policy uncertainty triggers a temporary

[16]The Fama–French industry portfolios are based on the SIC classification, which is the same system used for industrial production data before NAICS replaced it in 1997. This means that the sectoral mappings in the PD analysis follow the SIC structure and therefore line up with the older industrial production categories.

flight to safety away from all stocks issued in all sectors and a subsequent reallocation of wealth that reflects a shift in investor preferences toward greener industries and away from brown.

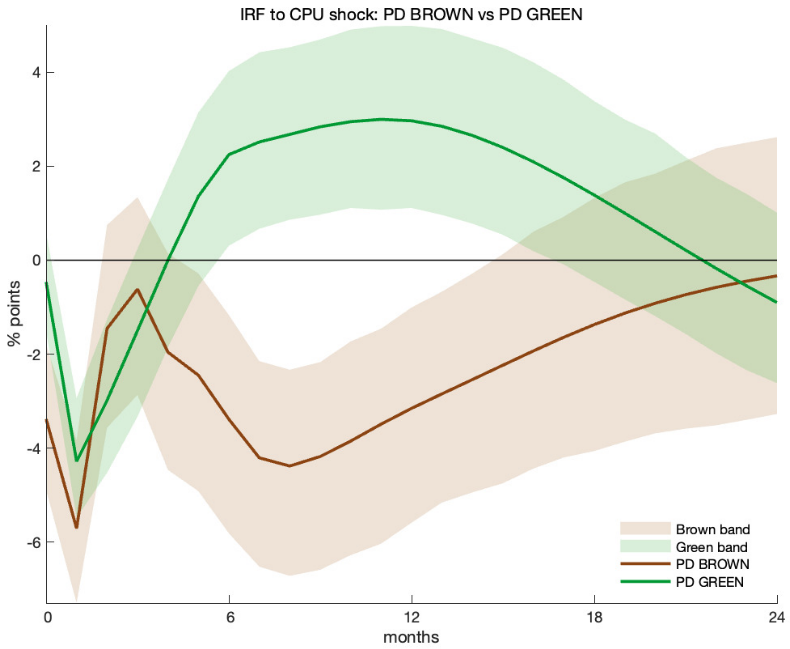

Figure 7
Sectoral Price–Dividend Ratio Responses to a climate uncertainty Shock.
Impulse response functions to the identified climated uncertainty shock for green and brown sectoral price–dividend ratios in the Bayesian Proxy-SVAR. The specification includes VIX, IP, PCE, PD, FFR, and sectoral PD ratios for green and brown industries. Sectoral indices are equal-weighted averages of constituent SIC groups: *Brown* = Oil (30; Petroleum & Natural Gas), Utilities (31; Electric & Gas), Coal (29; Coal Mining); *Green* = Chips (37; Electronic Equipment & Components), ElcEq (22; Electrical Equipment). Shaded areas denote 68% posterior credible intervals. IRFs are reported in percentage points. Sample: January 2014–January 2025.

This mechanism is consistent with asset pricing models in which forward-looking investors revise expected cash flows and discount rates asymmetrically across sectors when climate transitions uncertainty rises (see Pástor et al. (2022)): green firms benefit from stronger optionality on future regulation and lower expected compliance costs, whereas carbon-intensive firms face greater downside risk due to the potential tightening of emissions constraints (Lemoine and Traeger (2016); Barnett et al. (2020); Bolton and Kacperczyk (2023)). Empirically, studies show that periods of elevated climate uncertainty are associated with declines in brown asset valuations and relative inflows into low-carbon or high ESG score-tilted assets, reflecting both risk-based rebalancing and evolving investor beliefs about long-term transition pathways (see, e.g., Ceccarelli et al. (2024); Cornelli et al. (2025). Moreover, evidence from green–brown return spreads corroborates the idea that markets tend to reward firms perceived to be better aligned with expected future policy regimes during episodes of regulatory uncertainty, reinforcing the asymmetric dynamics observed in the PD ratios (see, e.g., Basaglia et al. (2025)).

Overall, these results reveal a pronounced *green–brown asymmetry* in both real and financial responses to climate uncertainty shocks. While climate-related uncertainty depresses aggregate activity, its effects are unevenly distributed across sectors: carbon-intensive industries experience deeper and more persistent contractions, whereas low-carbon and technology-oriented sectors display greater resilience and faster recovery. The estimated impulse responses indicate that a rise in climate-related financial uncertainty reduces overall economic activity, with stronger and longer-lasting effects on brown industries. In terms of market valuations, the price–dividend ratio initially declines across all sectors following a climate shock, but subsequently rebounds for green industries, suggesting a reallocation of investors' wealth towards transition-resilient assets as the economy adjusts. These findings support the view that the asymmetric responses of the two sectors are particularly important, because they highlight how climate transition shocks are likely to redistribute risks and investment opportunities across the economy, accelerating capital flows towards greener industries while exposing carbon-intensive activities to higher financial vulnerability. Such heterogeneity across sectors aligns with firm-level evidence showing that firms with greater exposure to climate and transition risks tend to react more negatively to increases in climate-policy uncertainty (Känzig et al., 2025; Basaglia et al., 2025).

6.2 Granular Sectoral Heterogeneity

The previous green vs. brown analysis already highlighted meaningful asymmetries in how broad groups of industries respond to climate transition risk shocks. To obtain a more granular and comprehensive picture of how climate policy uncertainty propagates across the economy, we extend the analysis to the full cross-section of U.S. industries. Specifically, we disaggregate real activity using the complete set of 23 NAICS industrial production series from the Federal Reserve's G.17 database, and we examine sectoral valuation dynamics using a wide sub-set of the 49 Fama–French industry portfolios. This finer sector-by-sector approach uncovers pronounced differences in both the magnitude and the persistence of real and financial responses across U.S. industries—patterns that are largely obscured in more aggregated analyses—and crucially allows us to match each sector to its corresponding EPA supply-chain emission intensity, thereby linking observed sectoral responses to their underlying carbon exposure.

6.2.1 Sectoral Disaggregation: Industrial Production and Emission-Based Heterogeneity

In this subsection, we estimate a separate Bayesian VAR for each of the 23 industrial production sectors reported in the Federal Reserve's G.17 release, following the official NAICS industry-group classification. Each sectoral VAR has exactly the same specification adopted in the main model, with the only difference being the inclusion of one sectoral IP index at a time. This ensures that the identification and dynamic structure remain fully comparable across models and that the sectoral setup closely mimics the propagation of the same aggregate climate uncertainty shock. Identification is based on the *same* external instrument used in the aggregate Proxy-SVAR—namely, the innovation to the realized volatility of the ICE U.S. Carbon Futures Index. This setup guarantees that differences across sectors reflect genuine heterogeneity in the estimated transmission mechanism, rather than differences in the way shocks are identified and constructed or model specification.

Table 4 reports the mean impulse responses of each sector over horizons of 0–24 months. The results reveal substantial heterogeneity. Carbon-intensive and energy-related activities exhibit the sharpest output contractions. Oil and Gas Extraction displays the largest decline in IP, with an average response of –1.75%, followed by Motor Vehicles and Parts (–1.28%), Coal Mining (–1.11%), and Natural Gas Distribution (–0.88%). These sectors are characterized by high reliance on fossil-fuel inputs, technologically rigid production processes, and strong exposure to climate- and regulatory-driven demand shifts. Other heavy industries, such as Primary Metals or Plastics and Rubber, also respond negatively to climate transition risk shocks but with lower magnitudes.

In contrast, several lower-emission manufacturing sectors exhibit muted or slightly positive responses. These include for example Computer and Electronic Products sector. Figure 8 provides a visual ranking of all sectors by their exposure to climate transition uncertainty shocks, highlighting the systematic concentration of negative responses among fossil-fuel-based or energy-intensive activities (colored in brown). Even among sectors that are not overtly fossil-fuel-based, the responses appear ordered in a way that correlates closely with their indirect energy dependence, capital intensity, and position within upstream supply chains. Industries such as Primary Metals, Plastics and Rubber Products, and Electrical Equipment display moderately negative responses, consistent with their indirect reliance on energy-intensive inputs and carbon-exposed supply chains. By contrast, more innovation-oriented or less energy-dependent sectors—such as Computer and Electronic Products, Machinery, or Furniture—show negligible or mildly positive

IP Sector (NAICS)	Mean IRF (0–24)
Oil and Gas Extraction (211)	-0.01746
Motor Vehicles and Parts (3361–3)	-0.01280
Coal Mining (2121)	-0.01063
Natural Gas Distribution (2212)	-0.00878
Aerospace and Misc. Transport (3364–9)	-0.00731
Petroleum and Coal Products (324)	-0.00659
Printing and Related Support (323)	-0.00592
Primary Metals (331)	-0.00252
Plastics and Rubber Products (326)	-0.00252
Electrical Equipment (335)	-0.00221
Computer and Electronic Products (334)	-0.00173
Furniture (337)	-0.00096
Machinery (333)	-0.00096
Electric Power Generation (2211)	-0.00028
Nonmetallic Mineral Products (327)	-0.00010
Apparel and Leather (315,6)	-0.00008
Food, Beverage, and Tobacco (311–2)	0.00099
Paper (322)	0.00165
Fabricated Metal Products (332)	0.00165
Misc. Durable Goods (339)	0.00217
Wood Products (321)	0.00242
Chemicals (325)	0.00302
Textiles (313–4)	0.00388

Table 4: Mean IRF of Industrial Production Sectors to a climate uncertainty Shock (0–24 Months).
The Mean IRFs represent the average response over 24 horizons, estimated from a sector-specific VAR. The sectoral VAR includes VIX, aggregate IP, PCE, PD, FFR, and the sectoral IP index. Sample: January 2014–January 2025.

responses, underscoring the role of technological flexibility, lower emissions intensity, and greater adaptability to regulatory shifts.

Linking climate uncertainty Sensitivity to IP Emission Intensity

To explain the cross-sectional pattern of responses uncovered earlier, we match each sector with its supply-chain greenhouse gas emission intensity using the U.S. Environmental Protection Agency's harmonized dataset of NAICS-level emission factors. These data provide total GHG intensity (in kg CO_2e per 2022 USD of output) at a granular 6-digit level.[17] Since industrial production sectors are defined at a coarser NAICS aggregation, sector-level emissions are computed as averages of the corresponding 6-digit emission factors.[18]

Table 5 reports the resulting emission-intensity ranking. A strong alignment emerges between the highest-emission industries (e.g., Coal Mining, Natural Gas Distribution, Oil and Gas

[17] EPA Supply-Chain Greenhouse Gas Emission Factors by NAICS data are accessible through the U.S. Government Open Data Portal at this link.

[18] Electric Power Generation (NAICS 2211) is omitted due to missing EPA margin adjustments, those corrections that align industry-level emissions or energy-use data with economic activity measures by correcting for wholesale and retail trade margins, transportation margins, and other distributional markups embedded in the use of intermediate goods.

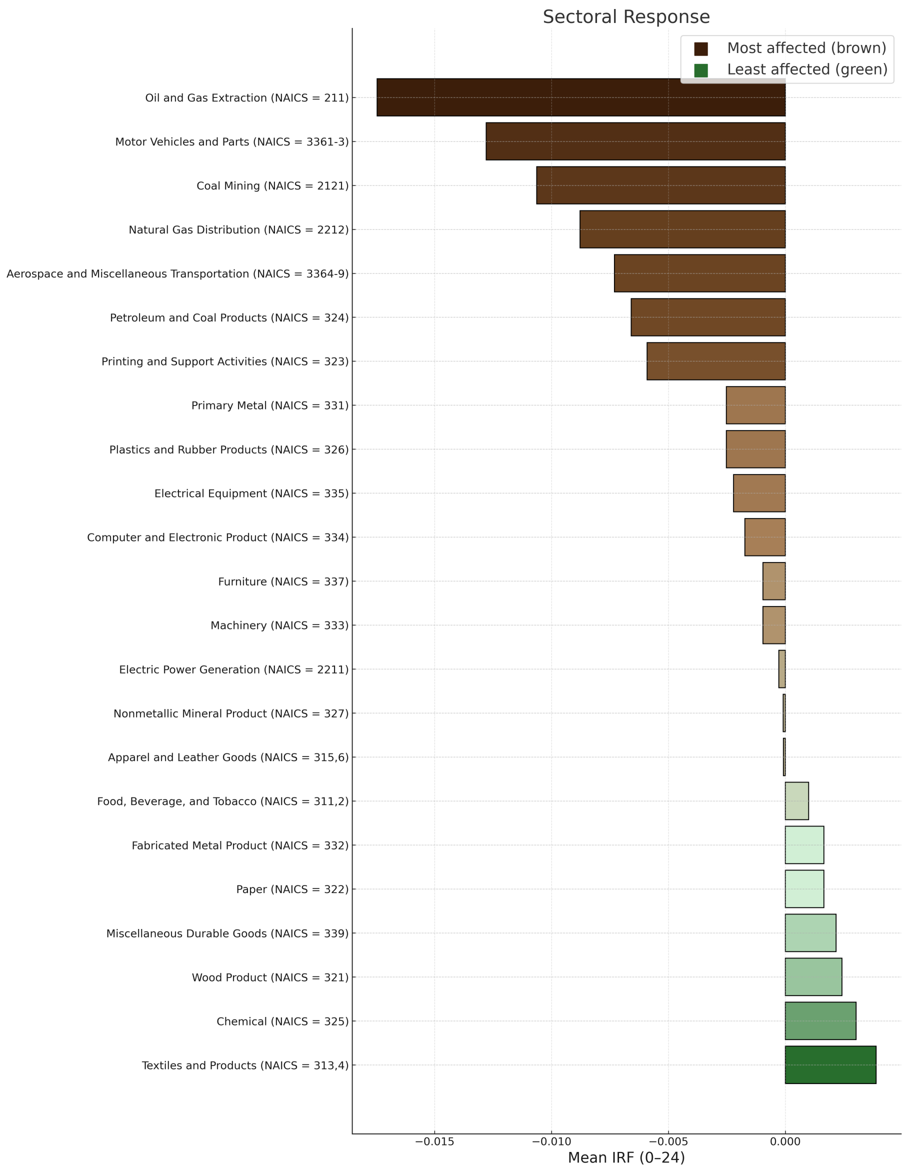

Figure 8
Industrial Production Sectoral Exposure to Climate Uncertainty Shocks. Ranking of IP sectoral mean impulse responses to a climate uncertainty shock. Brown- (Green-) coded sectors represent the most (least) negatively affected industries. The sectoral responses represent the average response over 24 horizons, estimated from a sector-specific VAR. Each sectoral VAR includes VIX, aggregate IP, PCE, PD, FFR, and the sectoral IP index. Sample: January 2014–January 2025.

Extraction, Plastics and Rubber, Primary Metals) and the sectors most negatively exposed to carbon futures-implied uncertainty shocks.

To develop a clearer statistical understanding of the relationship between emission intensity and the real effects of climate uncertainty shocks, we plot the sectoral mean IRFs against their corresponding emission measures. Figure 9 provides a visual illustration of this link: sectors with higher greenhouse-gas intensities tend to cluster in the lower part of the scatter, indicating more adverse output responses to a climate shock. For estimation purposes, emission intensities are rescaled by dividing by 1000 (so that one unit corresponds now to one ton of CO_2e per USD), which improves numerical comparability in the subsequent regression. The blue line in the figure depicts the fitted regression line, which corresponds to the specification we formally discuss below. Regressing the sectoral mean IRFs on the scaled emission intensity yields an estimated slope coefficient of $\hat{\beta} = -0.0014$, statistically significant at the 10% level, confirming the partial reliability of the negative relationship seen in the scatter plot: more (less) carbon-intensive sectors experience systematically more (less) adverse responses to climate transitionrisk shocks. Overall, the results support the idea that the climate shock proxy systematically hits "brown" sectors harder: higher-emission industries exhibit more negative IRF responses, with larger magnitudes and greater persistence over the forecast horizon. In contrast, lower-emission and technology-enabling sectors display milder reactions to the shock.

Sector (IP)	NAICS	Emissions (kg CO2e per USD)
Coal Mining	2121	747.0
Natural Gas Distribution	2212	532.0
Paper	322	469.48
Oil and Gas Extraction	211	377.0
Plastics and Rubber Products	326	365.44
Primary Metal	331	336.08
Chemical	325	309.00
Petroleum and Coal Products	324	308.62
Nonmetallic Mineral Product	327	303.53
Food, Beverage, and Tobacco	311–2	302.85
Aerospace and Misc. Transport	3364–9	209.68
Printing	323	205.0
Fabricated Metal Products	332	203.34
Textiles and Products	313–4	198.00
Machinery	333	175.34
Motor Vehicles and Parts	3361–3	170.19
Wood Products	321	163.93
Electrical Equipment	335	145.45
Furniture	337	139.19
Miscellaneous Durable Goods	339	118.0
Apparel and Leather Goods	315–6	101.08
Computer and Electronic Products	334	51.10

Table 5: Emission Intensity by Sector (kg CO_2e per USD).
Sector-level emission intensities are obtained by matching each industry to the U.S. Environmental Protection Agency's harmonized dataset of NAICS-based supply-chain greenhouse gas emission factors, reported at the 6-digit level and provided without margins.

6.2.2 Sectoral Disaggregation: Price–Dividend Ratio and Emission-Based Heterogeneity

To complement the real-side analysis, we examine now the occurrence of any heterogeneous valuation effects across industries. We construct sectoral price–dividend ratios using the Fama–

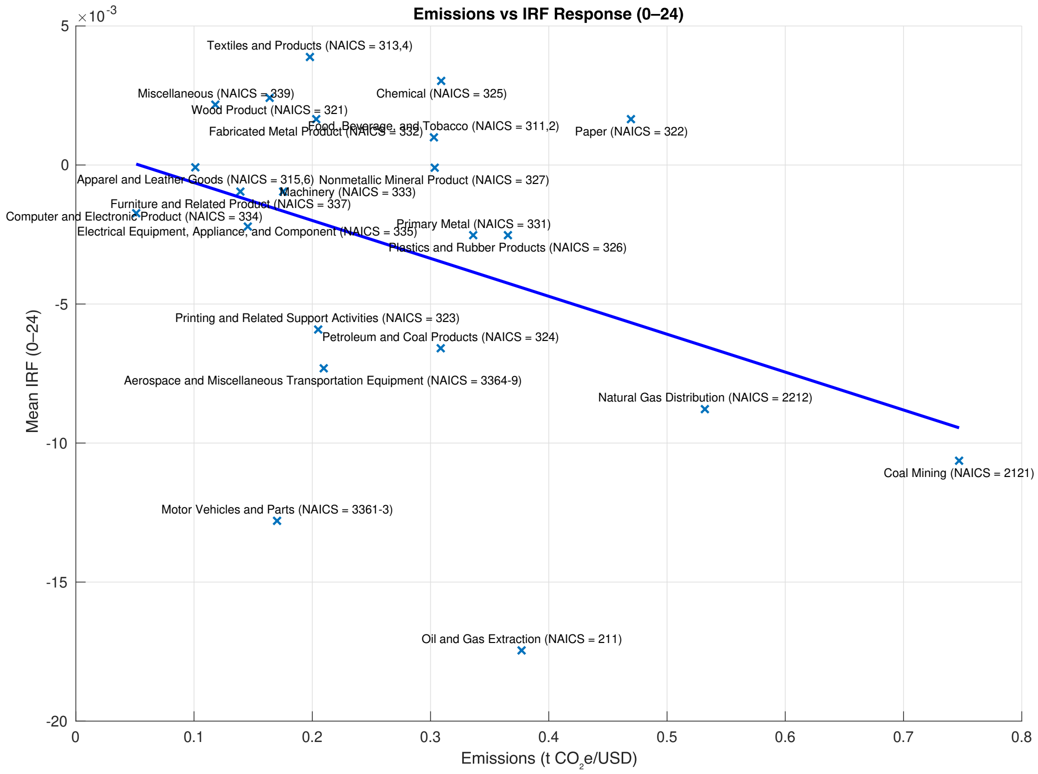

Figure 9
Emissions vs. Sectoral IP Responses. The scatter plot illustrates the existence of a negative correlation between emission intensity and average impulse responses to climate uncertainty shocks. The blue line represents the fitted regression line. Emission intensities are rescaled by dividing by 1000 (so that one unit corresponds now to one ton of CO_2e per USD).

French 49 Industry Portfolios, based on stock returns and dividends from Kenneth French's data library.[19] Of the original 49 industries, we retain 40 sectors whose dividend histories are available over the full sample, ensuring consistency in the construction of the valuation series. Importantly, the Fama–French industry portfolios are classified according to the historical SIC system, which underlies all portfolio groupings in this dataset.

We estimate a separate BVAR for each sector, following the same specification used in the industrial production analysis. The vector of the endogenous variables now includes the VIX, aggregate IP, PCE, PD, FFR, and, one at a time, the sectoral PD ratio.

Table 6 reports the mean impulse responses of the sectoral PD ratios to a climate uncertainty shock over the horizon 0–24 months. The results reveal substantial cross-sectional variation. Real Estate, Medical Equipment, Textiles, and Laboratory Equipment exhibit the largest negative responses, followed by sectors such as Oil, Insurance, Business Services, and Chemicals. In

[19] Fama–French 49 Industry Portfolios, available through Kenneth French's Data Library at this link.

contrast, several industries show positive or strongly positive long-run responses to the shock, including Chips, Electrical Equipment, Retail, and Entertainment. Beyond the clear dispersion in mean PD responses, the ranking suggests a deeper economic structure. The sectors at the lower end of the distribution—Real Estate, Medical Equipment, Textiles, Oil, and Insurance—share features that amplify their sensitivity to uncertainty shocks, such as heavy reliance on physical capital, exposure to regulatory or input-cost risks, and dependence on long-duration cash flows. These characteristics make their valuations particularly responsive to shifts in discount-rate premia induced by climate-related uncertainty. Conversely, sectors with positive long-run PD responses tend to be more innovation-intensive (Chips, Electrical Equipment), more flexible in adjusting business models (Retail), or oriented toward discretionary consumption and digital content (Entertainment), all of which make them more resilient to transitional uncertainty or even attractive destinations for investor rebalancing.[20]

Sector	**Mean IRF**	**Sector**	**Mean IRF**
Real Estate (RlEst)	-0.05950	Tobacco (Smoke)	0.00686
Medical Equipment (MedEq)	-0.04346	Building Materials (BldMt)	0.00701
Textiles (Txtls)	-0.04200	Finance (Fin)	0.00889
Laboratory Equipment (LabEq)	-0.02546	Wholesale (Whlsl)	0.00895
Petroleum & Natural Gas (Oil)	-0.02291	Banking (Banks)	0.00441
Miscellaneous (Other)	-0.02160	Computers (Hardw)	0.01026
Agriculture (Agric)	-0.01668	Telecommunications (Telcm)	0.01138
Insurance (Insur)	-0.01460	Restaurants, Hotels & Motels (Meals)	0.01260
Business Services (BusSv)	-0.01313	Food Products (Food)	0.01383
Chemicals (Chems)	-0.01240	Electronic Components (Chips)	0.01519
Shipbuilding & Railroad (Ships)	-0.00912	Electrical Equipment (ElcEq)	0.02077
Coal (Coal)	-0.00793	Retail (Rtail)	0.02177
Utilities (Utilities)	-0.00758	Aircraft (Aero)	0.02406
Steel Works (Steel)	-0.00346	Transportation (Trans)	0.02607
Drugs (Drugs)	-0.00194	Books/Printing (Books)	0.02930
Household Goods (Hshld)	0.00270	Toys/Recreation (Toys)	0.03293
Construction (Cnstr)	0.00292	Apparel (Clths)	0.03364
Shipping Containers (Boxes)	0.00548	Mining (Mines)	0.03537
Beer & Liquor (Beer)	0.00556	Automobiles & Trucks (Autos)	0.16114
Machinery (Mach)	0.00590	Entertainment (Fun)	0.21897

Table 6: Mean IRF of Sectoral Price–Dividend Ratios to a Climate Uncertainty Shock (0–24 Months).
The IRFs represent the average response over 24 horizons, estimated from a sector-specific VAR. Each sectoral VAR includes VIX, aggregate IP, PCE, PD, FFR, and the sectoral PD index. Sample: January 2014–January 2025. The "Miscellaneous" sector includes residual or unclassified industries, including niche utilities and small-scale service providers.

[20]This pattern is consistent with the view that climate uncertainty reshapes the relative attractiveness of economic activities not only through direct emissions exposure, but also through broader channels such as technological adaptability, capital intensity, and sectoral demand elasticities.

Emission Mapping and Valuation Responses

To examine whether the heterogeneity in valuation responses is related to transition risk, we map each SIC-based sector into its underlying NAICS industries and match these to the EPA supply-chain emission factors. Because the SIC and NAICS classification systems are not mutually consistent, the mapping follows the official SIC–NAICS crosswalk, which may associate a single SIC code with several NAICS industries and, conversely, link some NAICS codes back to multiple SIC categories.[21] This structural mismatch reflects the different classification logics underlying the two taxonomies. Such non-one-to-one correspondence naturally introduces cross-code variation in the resulting sector-level emission measures, as the NAICS industries linked to a given SIC sector may differ substantially in their emission intensities. To ensure that the mapped emission proxies remain coherent and comparable across sectors, we apply a log-dispersion filter. Specifically, we compute for each SIC sector the difference $\Delta_{\log} = \log(\max) - \log(\min)$ across all associated NAICS emission factors and retain only those sectors with internal dispersion below the threshold $\Delta_{\log} \leq 8.5$. This procedure excludes sectors whose internal emission profiles are excessively heterogeneous and leaves a final sample of 33 sectors for which the mapped emission intensity can reasonably be interpreted as a meaningful summary measure.[22]

Figure 10 plots the mean PD response against the corresponding emission intensity. As in the real-side analysis of the averaged IRFs for industrial production, the scatter plot reveals a clear downward pattern: higher-emission sectors tend to exhibit more negative valuation responses to climate uncertainty shocks. A simple regression of sectoral mean PD responses on rescaled emission intensity yields a slope coefficient of $\beta = -0.0448$, statistically significant at the 10% level. This confirms that carbon-intensive portfolios systematically experience more negative valuation effects in response to climate-policy uncertainty shocks. Importantly, the sensitivity of valuations to climate-policy uncertainty is not confined to a handful of extreme polluters but reflects a gradient visible throughout the cross-section. Although the most carbon-intensive sectors (Coal Mining, Oil and Gas Extraction, Natural Gas Distribution) anchor the lower end of the distribution, the negative association extends across the entire emissions range. For instance, mid-emission manufacturing industries—such as Plastics and Rubber Products or Petroleum and Coal Products—also lie meaningfully below zero, whereas low-emission sectors cluster closer to or above zero. Moreover, no sectors can be found to display both high emissions and positive

[21] Available at NAICS crosswalk's link.

[22] The excluded sectors are: Business Services (BusSv), Automobiles & Trucks (Autos), Entertainment (Fun), Computers (Hardw), Retail (Rtail), Transportation (Trans), and Textiles (Txtls).

PD responses. The empty quadrant reinforces the idea that, under uncertainty about future climate regulation, it is difficult for carbon-intensive industries to generate valuation gains, even if they are not directly regulated in the short run. Investors appear to treat emissions intensity as a structural exposure that scales downside risk. Finally, the dispersion around the fitted line is asymmetric, with low-emission sectors showing more vertical spread, including several mildly positive responses. This suggests the presence of factors—such as technological adaptability, intangible capital, or expected demand shifts—that can offset the negative discount-rate effect for greener sectors but rarely do so for brown ones.

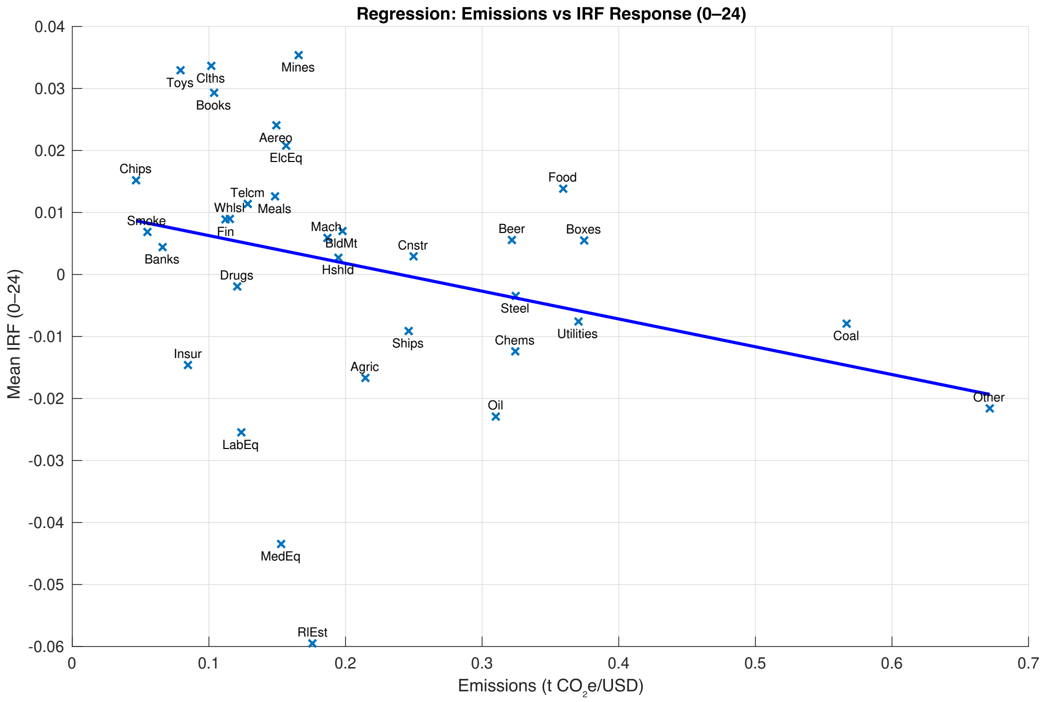

Figure 10
Emissions vs. Sectoral PD Responses. The scatter plot illustrates the existence of a negative correlation between emission intensity and average impulse responses to climate uncertainty shocks. The blue line represents the fitted regression line. Emission intensities are rescaled by dividing by 1000 (one unit equals one ton of CO_2e per USD).

Overall, and similarly to the findings for IP responses, the evidence indicates that climate uncertainty shocks propagate asymmetrically across valuation measures: carbon-intensive industries experience larger and more persistent declines in PD ratios, while low-emission and transition-enabling sectors display milder or even positive valuation adjustments. This valuation asymmetry mirrors the real-side sectoral heterogeneity and reinforces the interpretation of carbon future-driven climate shocks as a disturbance that disproportionately affects brown industries.

Taken together, the granular results in this section show that emission intensity is a key driver of sectoral vulnerability to climate shocks: industries with higher carbon intensity are systematically hit harder, both in terms of real activity and equity valuation losses. In addition, on the financial side, several low-emission sectors even display a positive valuation response in the form of higher price-dividend ratios. This is consistent with a reallocation of investor wealth toward industries perceived as more resilient or less exposed to transition risk (Pástor et al., 2022; Ardia et al., 2023).

6.3 Green Re-Pricing Mechanism

To gain additional insights, we next examine what the asymmetric adjustments reported above may imply for long-horizon valuation spreads across brown and green sectors. To analyse how climate-policy uncertainty is differentially prices across industries, we construct a sectoral Climate Valuation Response (CVR), defined as the cumulative price-dividend impulse response over a 24-month horizon. This measure captures the long-run discount-rate adjustment induced by a climate uncertainty shock and provides a natural metric for comparing sectoral reactions as a reflection of their heterogeneous exposures to transition risk.[23]

To organise our cross-sectional analysis, we group sectors by their emission intensity score. For each $k = 1, \ldots, 5$, we compute the average CVR across the k most carbon-intensive industries (*Top-k*), and the k least emission-intensive industries (*Bottom-k*):[24]

$$CVR_{(k)} = \frac{1}{k} \sum_{i \in \text{group}(k)} CVR_i.$$

Two patterns clearly emerge from Table 7. First, the CVR is negative for all Top-k groups, indi-

[23]For instance, the Campbell–Shiller's approximate identity (Campbell and Shiller, 1988) implies that innovations in the log price–dividend ratio $pd_t \equiv p_t - d_t$ can be decomposed into revisions of expected future dividend growth and revisions in expected future returns,

$$\Delta pd_{t+1} \approx \text{cash flow news}_{t+1} - \text{discount rate news}_{t+1},$$

where discount-rate news is the revision in future expected returns induced by a shock. The literature has documented that the price-dividend ratio predicts returns over horizons ranging from months to a few years much more reliably than it predicts dividend growth; variance decomposition exercises—based on monthly vector autoregressions—quantify the relative contributions of discount-rate and cash-flow news to unexpected returns and valuation movements and find discount-rate news explains a large share of return innovations. This empirical evidence implies that valuation-ratio fluctuations are primarily driven by discount-rate news rather than cash-flow news, see Cochrane (2011) and references therein. In this section, we are therefore measuring the differential of the discount rate news term under the assumption that the climate uncertainty shocks do not represent cash flow news or that the green-brown differential in the cash flow news they induced is negligible.

[24]For expositional purposes we present results for values of k up to 5, but the emission-based gradient is fully robust to alternative choices of k: Top-k minus Bottom-k groupings deliver the same qualitative separation across all specifications.

cating that carbon-intensive sectors experience persistent valuation declines following a futures-implied climate shock, consistent with heightened transition-risk exposure and sustained increases in discount rates. Second, the Bottom-k groups exhibit strictly positive CVR values for all $k \leq 5$, pointing to a medium-run re-pricing of low-emission, transition-resilient industries. This contrast reflects the fact that climate uncertainty shocks shift investor demand toward sectors with lower regulatory and technological exposure to the transition, generating a *green re-pricing effect.*

Top 5 Sectors	**Emission Intensity**	**CVR**
Miscellaneous (Other)	0.672	−0.540
Coal	0.567	−0.198
Boxes	0.375	−0.089
Utilities	0.371	−0.309
Food	0.359	−0.198
Bottom 5 Sectors	**Emission Intensity**	**CVR**
Chips	0.047	0.380
Smoke	0.055	0.276
Banks	0.066	0.221
Toys	0.079	0.371
Books	0.104	0.444

Table 7: Climate Valuation Responses Averaged by Emission Scores. Top 5 vs Bottom 5 Sectors.
Thietable reports the 24-month cumulative price-dividend responses (CVR) to a climate-policy uncertainty shock for the five highest-emission (Top 5) and the five lowest emission sectors (Bottom 5). Emission intensities are scaled by 1,000.

To provide a clear visual representation of the emission-based differential in climate valutation responses, Figure 11 plots the average CVR for the Top-k and Bottom-k emission groups, constructed cumulatively for $k = 1, \ldots, 5$. The Top-k curve aggregates the k most carbon-intensive sectors, while the Bottom-k curve aggregates the k least emission-intensive sectors, so that increasing the values for k expands the corresponding cluster. The figure also reports the spread (dashed red line), defined as the difference $CVR_{\text{Bottom-}k} - CVR_{\text{Top-}k}$. The pattern is highly asymmetric: the Top-k CVR remains persistently negative for all values of k, whereas the Bottom-k CVR increases monotonically with k, resulting in a consistently negative and widening spread. The magnitude of the spread, which ranges between approximately -0.95 and -0.55, indicates that transition-resilient, low-emission industries systematically load more heavily on the discount rate risk associated to climate uncertainty shocks. This provides direct support to a *green re-pricing mechanism*, whereby climate uncertainty induces stronger valuation adjustments for industries that are more exposed to investor reallocation flows away from the effects of transition risks.

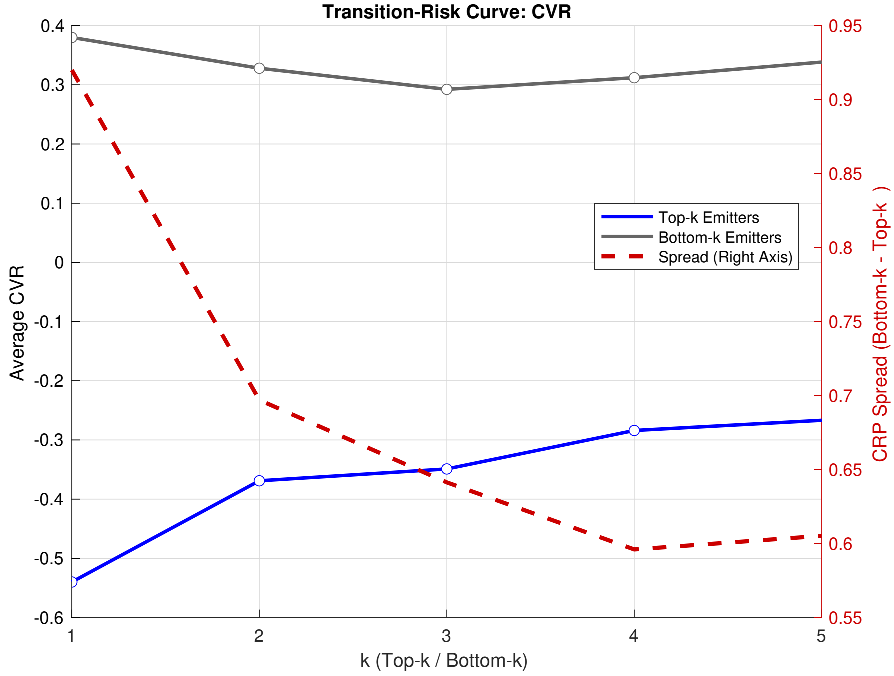

Figure 11
Transition-risk cluster CVR curves for the Top-k highest-emission sectors (blue) and the Bottom-k lowest-emission sectors (grey), plotted along with the corresponding spread (red, right axis).

To further characterise sectoral heterogeneity in the transmission of climate-policy uncertainty shocks to financial markets, and to illustrate how this differential repricing unfolds over time, Figure 12 provides a summary of the *green–brown PD IRF spread*, defined as the difference between the average price–dividend IRFs of the five least carbon-intensive sectors and of the five most emission-intensive sectors. While the CVR spreads offer a *cumulative* estimate of the heterogeneity in the valuation effects of forward-looking climate uncertainty shocks between green and brown sectors, the spread in Figure 12 concerns the differences at the margin and can be taken as a horizon-decomposition of $CVR_{(Bottom-Five)} - CVR_{(Top-Five)}$.

The spread exhibits a distinctive dynamic pattern. From month 4 onward the spread becomes positive and increases monotonically up to a horizon of 14 months. In particular, from a 9-month horizon, the differential response turns statistically significant, in the sense that the 90 percent credibility region fails to contain zero. Then it stabilizes and slightly reverses between horizons of 16 and 24 months, although it remains positive (and statistically significant, at leat until horizon 23). The green sectors recover rapidly and exhibit medium-run positive re-pricing (higher log PD ratio), consistent with (unexpectedly) declining discount-rates and heightened

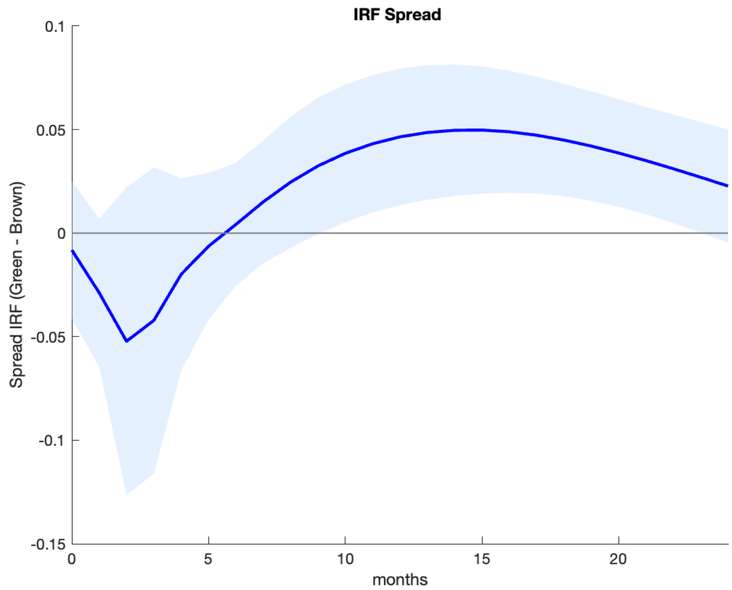

Figure 12
Impulse-response spread between the Top 5 carbon-intensive sectors and the Bottom 5 low-emission sectors, computed as the difference between their average price-dividend IRFs in response to a climate uncertainty shock.

demand for transition-resilient assets that support positive cash flow news. Brown sectors, by contrast, experience persistent valuation erosion, consistent with elevated transition risk and weaker long-horizon cash-flow expectations. Formally, if the impact on cash flow news is assumed to be moderate, a negative spread implies that carbon-intensive sectors face stronger upward adjustments in discount rates following climate uncertainty shocks. Moreover, once the short-run adjustment dissipates, the green sectors recover while brown sectors continue to depreciate, driving the persistent valuation gap across emission tiers.

Together, the CVR asymmetry and the persistent green-brown IRF spread reveal a consistent green re-pricing effect: climate uncertainty shocks differentially increase the discount rates applied to carbon-intensive activities and this shifts capital and invrestment towards transition-resilient industries. This systematic re-pricing mechanism reinforces the deep segmentation of asset valuations along the emission spectrum.

7 Conclusion

This paper provides new evidence on the macro-financial effects of climate-related uncertainty in the United States. Using a monthly Bayesian Proxy-SVAR identified with an external instrument derived from the realized volatility of ICE U.S. Carbon Futures log-price changes, we document how unexpected increases in transition risk tighten financial conditions and propagate to the real economy.

A rise in climate uncertainty leads to a marked increase in the VIX, accompanied by declines in aggregate industrial production, the prices of goods and services, and equity market valuations, as well to as a loosening of monetary policy through lower policy rates. Consumer prices exhibit a modest but negative reaction, suggesting that short-run demand effects dominate. This mild deflationatory response indicates that our proxy mainly captures the *second-moment dimension of uncertainty* rather than direct policy actions on carbon pricing, whilst first-moment effects are likely remain consistent with what reported in the literature. Whereas actual climate-policy interventions that raise carbon prices tend to be inflationary—-reflecting higher production costs, tighter energy supply, and cost-push pressures—-our measure captures instead the uncertainty surrounding such actions, which primarily affects expectations and financial conditions.

Notably, the adjustment dynamics of financial variables, such as the VIX, the equity price-dividend ratio, and the policy short-term rate, appears considerably more persistent than that of the macroeconomic variables like industrial production and consumer prices. This persistence is consistent with a financial transmission channel through which climate uncertainty spreads across the economy, operating via risk re-pricing, shifts in asset valuations, and changing financial conditions. Overall, these dynamics suggest that climate policy uncertainty acts as a financial amplifier of macroeconomic fluctuations. These results remain robust across a range of specifications, including alternative lag structures, prior choices, and identification settings.

Next, we classify sectors according to their exposure to transition risk: *brown* industries include energy-supply and fossil-fuel-based activities such as utilities, oil and gas extraction, and petroleum refining; *green* sectors comprise low-emission and transition-enabling manufacturing, such as electrical equipment and electronic components. At the sectoral level, we uncover a pronounced *green–brown asymmetry* in the transmission of climate uncertainty shocks. Carbon-intensive industries experience deeper and more persistent contractions in output, while low-emission and technology-oriented sectors display greater resilience and faster recovery. In financial markets, equity valuations decline on impact for all industries but rebound and overshoot in the case of green sectors, suggesting a reallocation of capital toward transition-resilient assets. These findings support the view that the asymmetric responses of the two groups are particularly important, as they highlight how transition uncertainty shocks redistribute risks and investment opportunities across the economy, by accelerating capital flows toward greener industries while exposing carbon-intensive activities to greater financial vulnerability.

To complement this broad two-sector decomposition, we also estimate a fully granular, sector-by-sector specification. The granular sector-by-sector analysis further strengthens these conclusions. By linking each industry to its EPA supply-chain emission intensity, we uncover a clear cross-sectional gradient: sectors characterized by higher carbon intensity exhibit systematically larger and more persistent real and financial contractions following a climate uncertainty shock. This confirms and extends the green–brown asymmetry documented earlier, showing that the severity of climate-induced adjustments increases monotonically with emission intensity.

Methodologically, our contribution lies in developing and exploiting a market-based, forward-looking proxy of climate uncertainty derived from the estimated *innovation* of an autoregressive process applied to realized carbon futures returns realized variance. This innovation-based proxy captures unexpected revisions in investors' expectations about the credibility and timing of climate regulations, offering a cleaner identification of the transition uncertainty channel. By linking carbon market dynamics to broader macro-financial conditions, our approach bridges the literatures on climate-policy risk, financial transmission, and macroeconomic volatility.

In a policy perspective, our findings emphasize the importance of predictable and credible climate policies in mitigating the macro-financial costs of the energy transition. Our results indicate that uncertainty about the timing and stringency of future regulation operates as an amplifier of macroeconomic fluctuations, raising risk premia, depressing investment, and disproportionately affecting carbon-intensive industries. This aligns with theoretical analyses showing that regulatory ambiguity can delay or distort firms' adjustment decisions, leading to inefficient capital stranding, higher transition costs, and lower welfare (Lemoine and Traeger (2016); Barnett et al. (2020)). In financial markets, the heightened volatility and risk re-pricing associated with transition uncertainty echo the asset-pricing evidence that carbon-intensive firms command higher required returns due to their exposure to downside policy risk (Bolton and Kacperczyk (2021b); Bolton and Kacperczyk (2023)), while predictable regulatory trajectories help compress risk premia and support the financing of green investment.[25] Together with our empirical findings, this body of work suggests that by anchoring expectations and alleviating the second-moment shocks that propagate through financial markets, credible climate policy can therefore sustain investment, reduce transition risk premia, and promote a more orderly, efficient, and financially stable path to decarbonisation.

[25] At the macro level, general equilibrium models indicate that policy credibility is a key determinant of the pace and cost of decarbonisation. When agents have confidence in a clear long-run policy path, the transition unfolds with smoother capital reallocation, lower precautionary savings, and more sustained innovation (see Acemoglu et al. (2016); Van der Ploeg and Rezai (2020)).

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Appendix A: Sources of the Data

1 Data Source

Country: United States Monthly Frequency — February 2014 to January 2025		
Variable	**Definition**	**Construction and Source**
VIX$_t$	CBOE Volatility Index. Benchmark measure of aggregate financial uncertainty implied by S&P 500 options.	Monthly average of daily VIX values. Measures expected equity market volatility over a 30-day horizon. Source: Federal Reserve Economic Data (FRED).
RVUS$_t$	Realized volatility of ICE U.S. Carbon Futures Index. Market-based proxy for climate policy uncertainty.	Computed from daily log-returns of ICE U.S. Carbon Futures prices. Monthly realized volatility: $$RV_m = \sqrt{\frac{30}{n_m}\sum_{d=1}^{n_m} r_d^2}$$ where n_m is the number of trading days in month m. Prices obtained from Bloomberg. Futures reference allowances from the Western Climate Initiative (WCI) and the Regional Greenhouse Gas Initiative (RGGI).
ε_t^{RV}	Climate uncertainty shock (external instrument).	Innovation component of carbon futures realized volatility, constructed as the residual from: $$RV_t = \alpha + \beta RV_{t-1} + \varepsilon_t$$ Estimated over the full sample. The residual isolates unanticipated, forward-looking revisions in climate-policy uncertainty.
IP$_t$	Industrial Production Index. Measure of real economic activity.	Seasonally adjusted aggregate industrial production index from the Federal Reserve G.17 release. Source: Federal Reserve Economic Data (FRED).
UR$_t$	Unemployment Rate. Measure of labor market slack.	US Unemployment rate, seasonally adjusted. Percent. Monthly Frequency. Source: Federal Reserve Economic Data (FRED).

Table (continued)

Variable	**Definition**	**Construction and Source**
$\mathbf{IP}_{s,t}$	Sectoral Industrial Production (NAICS-based).	Sector-level IP series from the Federal Reserve G.17 dataset. Industries classified according to NAICS codes. Green and brown aggregates constructed as equal-weighted averages of selected sectors.
$\mathbf{PCE}_t$	Personal Consumption Expenditures Price Index. Inflation measure.	Chain-type PCE price index, monthly and seasonally adjusted. Source: Federal Reserve Economic Data (FRED).
$\mathbf{FFR}_t$	Effective Federal Funds Rate. Monetary policy instrument.	Percent. Monthly average of the effective federal funds rate. Source: Federal Reserve Economic Data (FRED).
$\mathbf{PD}_t$	Aggregate S&P 500 price–dividend ratio. Forward-looking valuation measure.	Computed from Robert Shiller's S&P 500 prices and dividends. Dividends annualized using a trailing 12-month window. Source: Shiller Dataset. https://shillerdata.com
$\mathbf{SP500}_t$	S&P 500 stock market index. Broad measure of U.S. equity prices.	Monthly S&P 500 index level from Robert Shiller's dataset. Used as an alternative valuation indicator to the price–dividend ratio in robustness checks. Source: Shiller Dataset. https://shillerdata.com
$\mathbf{PD}_{s,t}$	Sectoral price–dividend ratios (SIC-based).	Constructed from Fama–French 49 Industry Portfolios. Dividends computed over a trailing 12-month window (36 months for coal). Source: Kenneth French Data Library.
$\mathbf{Emissions}_s$	Sectoral supply-chain greenhouse gas emission intensity.	EPA supply-chain emission factors by NAICS (kg CO_2e per USD of output). Sector-level intensities obtained as averages of corresponding 6-digit NAICS codes. Source: U.S. Environmental Protection Agency. U.S. Environmental Protection Agency.

Data sources, definitions, and construction of variables. This table reports the variables used in the analysis, together with their definitions, construction details, and original data sources.

Appendix B: Robustness to the Number of Lags

This appendix assesses the robustness of the impulse response functions to alternative choices of the BVAR lag length. In addition to the baseline specification with six lags, we re-estimate the model using three, twelve, and twenty-four lags. The comparison allows us to evaluate whether the dynamic responses to the identified shock are sensitive to the lag structure of the VAR.

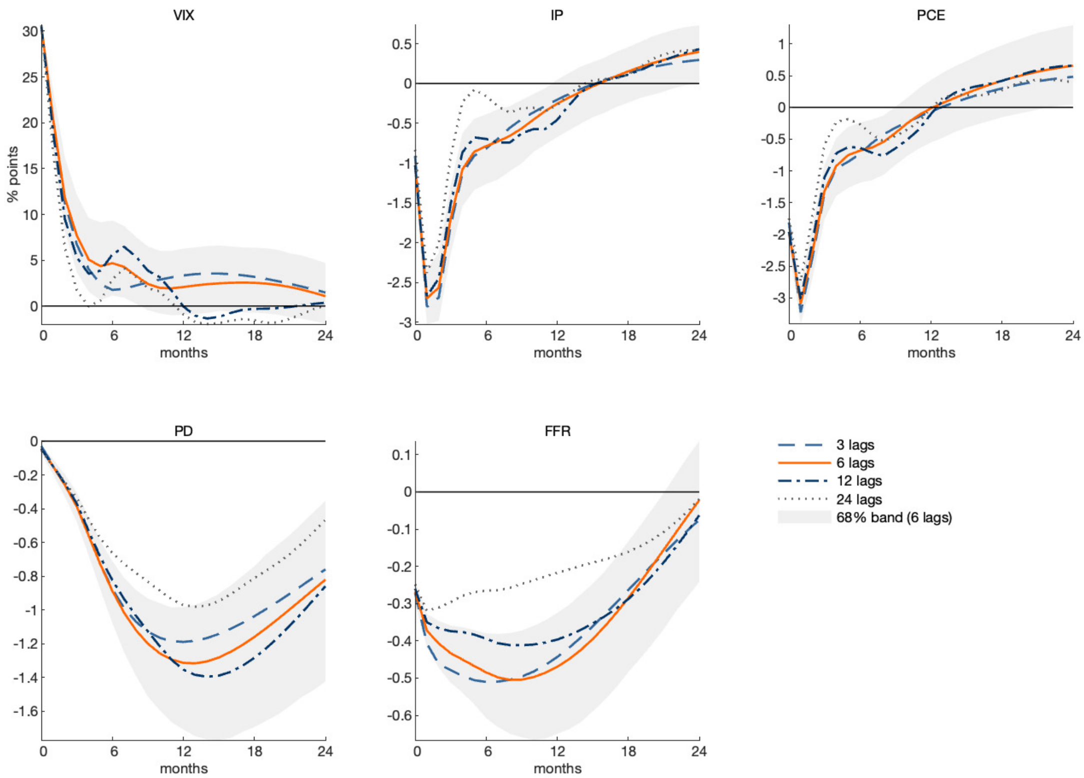

Figure 13
Robustness to the number of Lags

Impulse response functions estimated using alternative VAR lag lengths (3, 6, 12, and 24 lags). Solid and dashed lines report point estimates for each specification. Shaded areas denote 68% posterior credible intervals for the baseline specification with six lags. IRFs are reported in percentage points. Sample: February 2014–January 2025.

Overall, the impulse responses are highly robust across alternative lag specifications. The magnitude, sign, and timing of the responses are remarkably similar for the 3-, 6-, and 12-lag models across all variables. When using 24 lags, some attenuation in the responses emerges, most notably for the federal funds rate, whose path lies partially outside the 68% credible interval of the baseline specification at intermediate horizons. This behavior is consistent with the loss of degrees of freedom and weaker parameter precision associated with highly parameterized monthly VARs. Importantly, even in this case, the qualitative dynamics—including the direction of the responses and their overall persistence—remain unchanged. Taken together, these results indicate that the baseline findings are not driven by the choice of lag length and are robust to alternative dynamic specifications.