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Abstract

We investigate the transmission channels of climate policy uncertainty (CPU) to the U.S. capital market using a Bayesian Structural VAR estimated on monthly data from 1994 to 2023. By jointly modeling CPU alongside the VIX and the Financial Stress Index (FSI), we isolate the mechanisms through which climate-related regulatory uncertainty affects equity valuations. Three findings emerge. First, CPU shocks significantly depress the S&P 500 index and price–dividend ratios while raising financial stress. Second, unlike conventional uncertainty shocks – which produce demand-type disinflationary contractions – CPU innovations generate supply-driven recessions, characterized by rising goods prices alongside falling asset prices, consistent with transition-cost pressures. Third, counterfactual exercises that selectively mute financial channels reveal that systemic financial stress is the dominant propagation mechanism: shutting down the FSI channel renders equity-market responses statistically insignificant, whereas muting the VIX leaves them intact. The findings are robust across a range of identification and specification exercises, including the construction of economic confidence bands from 240 alternative recursive specifications. These results establish CPU as a structurally distinct driver for financial markets, whose transmission to valuations is critically mediated by credit and intermediation frictions rather than by forward-looking volatility.

Keywords: Financial Stress, Financial Uncertainty, VIX, Stock Prices, Stock Valuations, Climate Policy Uncertainty, Climate Change.
JEL Codes: C32, E31, E44, G15, Q54.

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1 Introduction

Climate change has emerged as a first-order concern for investors, financial intermediaries, and policymakers, with profound effects on asset prices, risk premia, and the stability of the financial system (Battiston et al., 2017; Giglio et al., 2021). Financial markets face two broad categories of climate-related risk: physical risks, arising from extreme weather events and structural shifts in climate patterns, and transition risks, arising from the shift to a low-carbon economy, where regulatory changes and policy uncertainty may lead to unexpected shifts in asset valuations and credit conditions across sectors (Krüger et al., 2020). Of these two categories, transition risk is arguably the more immediate concern to portfolio managers and financial decision-makers, because it operates through channels - regulatory ambiguity, stranded-asset exposure, and compliance-cost uncertainty - that directly affect firms' cash flows and investors' required rates of return (Barnett, 2023; Dang et al., 2023). Yet, despite its relevance, the *transmission mechanism* through which climate policy uncertainty (CPU) propagates to equity valuations and financial conditions remains insufficiently understood (Hong et al., 2020; Campiglio et al., 2023). The key issue is therefore not only whether climate transition shocks are driving prices, but also the mechanisms through which uncertainty about the policy path of the transition affects financial markets at the aggregate level.

The challenge is particularly pressing because the regulatory landscape governing the low-carbon transition is itself a source of persistent uncertainty. Commitments made under the 2015 Paris Agreement aimed to limit global warming to well below 2°C, but the credibility and consistency of national pledges remain in question, and markets continue to react to evolving expectations about future regulatory paths. This ongoing policy ambiguity has spurred abrupt fluctuations in the valuations of carbon-exposed assets and has contributed to episodes of financial stress that extend well beyond the energy sector (Van der Ploeg and Rezai, 2020). A growing literature models how climate-related regulatory uncertainty raises discount rates and compresses equity valuations (Pastor and Veronesi, 2012; Barnett, 2023), and cross-sectional evidence confirms that transition risk is priced in U.S. equity markets (Faccini et al., 2023; Bolton and Kacperczyk, 2021). However, the aggregate, system-level dynamics through which CPU shocks affect asset prices - and, crucially, the financial channels that amplify or attenuate these effects - have received limited empirical attention. This gap is particularly relevant because treating CPU as a generic uncertainty shock may obscure the specific financial frictions through which transition risk may be priced. In particular, a shock that operates through broad credit and funding stress has different implications from one that is absorbed mainly by equity-market volatility.

This paper examines the effects of CPU shocks on U.S. financial markets, using monthly

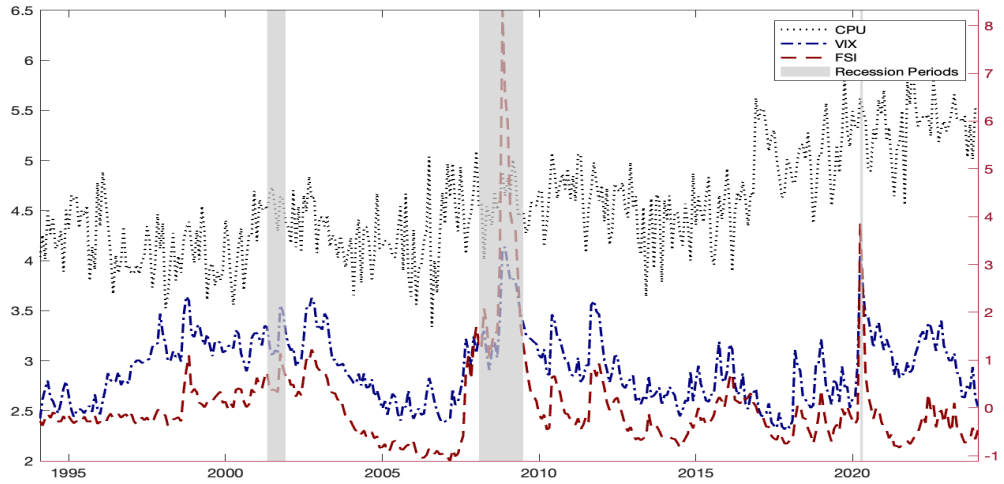
data over a January 1994–December 2023 sample. We employ a Bayesian structural VAR (SVAR) framework that includes the Gavriilidis (2021) CPU index alongside the VIX, the St. Louis Fed Financial Stress Index (FSI), the log of the S&P 500 index, and the S&P 500 log price-dividend ratio, complemented by standard U.S. macroeconomic controls (the federal funds rate, log-CPI, and log-industrial production).[1] A distinctive feature of our approach is the systematic comparison of CPU shocks with shocks to two established financial risk measures - the VIX, which captures forward-looking equity-market volatility, and the FSI, which captures system-wide stress in funding, credit, and intermediary balance sheets (Hakkio and Keeton, 2009). This comparison allows us to assess whether climate policy uncertainty is simply an alternative manifestation of conventional financial uncertainty or whether it operates through distinct channels with a different asset-pricing signature. We ask whether the equity-market response to a CPU shock is fully absorbed once the VIX and FSI channels are accounted for - or whether, instead, climate policy uncertainty activates financial stress as a distinct propagation mechanism that conventional volatility measures alone cannot capture. The answer matters to both portfolio risk management and financial stability policy: if CPU transmits primarily through credit-intermediation stress rather than equity-implied volatility, then standard VIX-based hedging strategies will understate transition-risk exposures (Engle et al., 2020), and macro-prudential frameworks that monitor only market volatility will miss the channel through which climate policy shocks become systemic (Battiston et al., 2017). Moreover, this implies that climate transition-risk exposures should be monitored through broad financial stress indicators rather than volatility indices alone; in the case of policymakers, this emphasizes the need to incorporate credit-intermediation channels into climate stress-testing frameworks (Stroebel and Wurgler, 2021).

Figure 1 plots the three uncertainty measures used in this paper. The VIX and FSI spike during NBER recessions, while the CPU index captures climate-specific events - the Paris Agreement (December 2015), COP25 (February 2019), the Climate Action Summit (September 2019), and COP26 (November 2021) - and exhibits a steadily rising trend that is largely independent of the business cycle, reflecting the growing prominence of climate-related transition risk. The low co-movement between CPU and the two financial indicators suggests that climate policy uncertainty is not simply a relabelling of conventional financial risk, lending credibility to the separation of shocks in our SVAR.

Our empirical strategy proceeds in two stages. First, we estimate structural impulse response functions (IRFs) to trace the dynamic responses of the full system of variables to

[1]FSI is widely interpreted as capturing stress in the core of the intermediation system, with a particular emphasis on banking-sector conditions such as balance-sheet fragility, funding pressure, credit spreads, and liquidity shortages (Kliesen et al., 2012).

Figure 1
Uncertainty Measures



Uncertainty measures used in the paper: Climate Policy Uncertainty (CPU), Volatility Index (VIX) in natural logs, and Financial Stress Index (FSI). Sample: 1994m1–2023m12. The grey areas represent NBER recessions.

CPU, VIX, and FSI shocks. Second, we construct counterfactual VAR models that selectively mute the VIX and FSI channels, following Giuliodori (2005), to isolate the contribution of financial stress and market volatility to the transmission of CPU shocks. As Battiston and Monasterolo (2018) emphasize, standard climate-economy models abstract from the architecture of modern financial markets, overlooking the fact that the financial system acts simultaneously as a transmitter of shocks - through leverage, interconnected balance sheets, and pricing externalities - and as a provider of hedging and diversification. Our BSVAR counterfactual approach addresses this gap by explicitly quantifying how much of the equity-market response to CPU shocks is mediated by the financial system.

Our results yield three main findings. First, a CPU shock significantly raises both the VIX and the FSI, depresses equity valuations - as reflected in persistent declines in both the S&P 500 index and the log price–dividend ratio - and triggers an accommodative monetary policy response. These equity-market effects are consistent with an increase in the climate-transition risk premium: heightened CPU raises the discount rate investors apply to cash flows exposed to regulatory ambiguity, compressing valuation ratios (Brogaard and Detzel, 2015; Barnett, 2023). Second, the asset-pricing signature of CPU shocks is qualitatively distinct from that of VIX and FSI shocks. While conventional financial shocks depress both asset prices and goods prices (a demand-type pattern), CPU shocks depress equity valuations while generating moderate inflationary pressure, consistent with a supply-side

channel in which regulatory ambiguity raises firms' marginal costs and widens the valuation wedge between clean and carbon-intensive assets (Dang et al., 2023; Acemoglu et al., 2012). Hence, climate policy uncertainty is not simply a relabelling of conventional financial risk but a distinct disturbance with a supply-side, transition-cost signature. Third, and most importantly in a transmission perspective, our counterfactual analysis reveals that the equity-market impact of CPU shocks is primarily mediated through broad financial stress rather than through equity-implied volatility. Muting the FSI channel substantially attenuates the responses of the price–dividend ratio and S&P 500 index, rendering them statistically insignificant over intermediate horizons, whereas muting the VIX channel leaves the impulse responses largely intact.[2] This finding implies that it is the activation of credit-intermediation frictions and balance-sheet stress - rather than a simple rise in market volatility - that transmits climate policy uncertainty to asset prices (Battiston et al., 2017; Dunz et al., 2021).[3]

Our results are robust to an extensive set of identification and specificaton robustness checks. In particular, we construct economic confidence bands from 240 alternative recursive Cholesky specifications, thereby moving beyond reliance on a single benchmark ordering to systematically assess the sensitivity of the estimated transmission mechanism to a range of economically plausible identifying restrictions. Specifically, we explore alternative recursive structures of the financial block while preserving the identification of the climate policy uncertainty shock. Additional robustness checks consider different lag structures, a different recursive ordering of the monetary policy variable, prior distributions (Normal–Wishart, Independent Normal–Wishart, and dummy observation priors), alternative sets of macroeconomic control variables (including consumer sentiment or obtained by replacing industrial production with the unemployment rate), the use of a shadow interest rate during the zero-lower-bound period, and a sample truncation to exclude the COVID-19 episode. The findings complement Faccini et al. (2023), who show that U.S. climate transition risk is priced in the cross section of equity returns, by addressing a different question: not *whether* transition risk commands a risk premium, but *through which financial channel* aggregate climate policy uncertainty shocks propagate to equity valuations.[4]

[2]Quantitatively, muting the FSI channel reduces the peak S&P$\tilde{5}$00 response to a CPU shock by approximately one-third, while muting the VIX alone reduces it by only one-sixth, implying that credit-intermediation stress is the dominant amplifier of climate policy uncertainty's impact on equity valuations.

[3]This result does not imply that CPU shocks are unimportant in isolation. In the baseline SVAR, a CPU shock produces statistically significant increases in both the VIX and the FSI and persistent declines in equity valuations. The counterfactual exercise identifies the *channel* through which these effects reach asset prices: CPU is the originating disturbance, while financial stress is the propagation mechanism. Shutting down the FSI channel attenuates the equity response because it removes the route through which CPU transmits, not because the shock itself is economically negligible.

[4]Our results also reinforce the perspective of Krüger et al. (2020) on the financial-market relevance

Our paper makes three contributions to the literature. First, we provide novel evidence on the aggregate financial-market effects of climate policy uncertainty, moving beyond the firm-level or sector-specific analyses that dominate the existing literature (Basaglia et al., 2025; Fried et al., 2021; Dang et al., 2023). By embedding the CPU index within a system that includes both equity-market and financial-stress variables, we characterize the full dynamic response of the U.S. financial system to climate transition-risk shocks. Second, we document that CPU shocks have a distinct asset pricing signature - depressed valuations with inflationary rather than disinflationary pressure - that sets them apart from conventional financial uncertainty. This distinction has direct implications for investors seeking to hedge or diversify transition-risk exposures, as it implies that standard volatility-based hedging strategies may be insufficient. Third, through our counterfactual design, we identify the financial stress channel as the dominant transmission mechanism from CPU to equity markets, establishing that broad credit-intermediation stress rather than equity-implied volatility is the key amplifier. This finding is relevant for both financial stability policy and portfolio risk management, as it highlights that monitoring the FSI provides a highly informative signal about the consequences of climate policy shifts.

The paper is organized as follows: Section 2 reviews the related literature, Section 3 describes the data and methodology, Section 4 presents the main results and discusses their implications, Section 5 reports a robustness analysis, and Section 6 concludes.

2 Related Literature

Our paper is related to several strands of literature. First, a large literature examines how uncertainty affects financial markets and asset prices.[5] Popular proxies include the VIX as a measure of implied financial volatility, Baker et al. (2016)'s Economic Policy Uncertainty (EPU) index, and Ludvigson et al. (2021)'s macroeconomic and financial uncertainty measures. Although disentangling shocks to uncertainty from movements in real activity is empirically challenging because of reverse causality, there is broad agreement that uncertainty is countercyclical (Bloom, 2014).[6] Of course, in a finance perspective, uncertainty is tightly linked to equity returns, risk premia, and measures of financial stress (Pastor and

of climate risk, while adding a new dimension by identifying the FSI - and therefore the banking and credit-intermediation channel - as the primary amplification mechanism.

[5]For an extensive literature review see Bloom (2014) and Castelnuovo (2023).

[6]For example, much of the empirical literature on uncertainty shocks relies on recursive identification schemes in vector autoregressions (VARs). This strategy may be problematic because it imposes zero contemporaneous effects of uncertainty on real activity, potentially leading to a biased measurement of the true impact of these shocks, see Ludvigson et al. (2021).

Veronesi, 2012; Christiano et al., 2014; Brogaard and Detzel, 2015; Ge et al., 2024). Within structural VAR frameworks, Bloom (2009) shows that uncertainty shocks generate sharp but temporary downturns, and Caldara et al. (2016) document that their real effects are substantially amplified when they coincide with a tightening of financial conditions.[7]

Closely related is the literature on financial stress. The Financial Stress Index (FSI) summarizes tensions in the financial system by aggregating information from credit spreads, stock market volatility, and indicators of banking-sector risk. High FSI readings are typically interpreted as episodes of elevated systemic risk, reflecting increased investor risk aversion and a higher likelihood of disruptions in financial markets. Liang et al. (2023) show that the Global Financial Stress Index has superior predictive power for long-horizon realized stock market volatility relative to the VIX or the EPU index, thus emphasizing the relevance of stress measures for equity-market risk assessment.

A second strand of research concerns the construction of climate policy risk measures and their asset pricing implications. Engle et al. (2020) develop a newspaper-based Climate Change News Index and show that a mimicking-portfolio strategy can hedge innovations in this index, thereby linking climate to asset returns. Bua et al. (2024) construct text-based indicators of transition and physical climate risk for European markets and document the emergence of economically significant risk premia for both, after 2015. Faccini et al. (2023) extract market-wide climate risk factors from Reuters news and find that transition risk associated with U.S. climate policy is priced in equity markets, whereas proxies for physical risks do not earn a significant risk premium. Gavriilidis (2021) construct a CPU index via textual analysis of articles from eight major newspapers - the climate analogue of Baker et al. (2016)'s EPU - and show that their index spikes around major climate policy events and is associated with a significant decline in aggregate CO2 emissions. Ji et al. (2024) build a global CPU index and document that global climate policy uncertainty exerts a significant, though predominantly short-run, effect on financial markets. At the firm level, Basaglia et al. (2025) show that higher CPU is associated with declines in capital expenditures and R&D spending - effects that are particularly pronounced among carbon-intensive firms - and with heightened stock volatility.

A third strand of work, and the one directly connected to our paper, examines how climate risk propagates through the financial system. Battiston et al. (2017) provide a comprehensive overview, emphasizing that climate risk is systemic, nonlinear, and characterized by fat-tailed distributions - features that imply the possibility of tipping points and persistent financial distress. Network linkages among financial institutions can amplify these dynamics, allowing

[7]Additional evidence on the financial effects of uncertainty is provided by Gilchrist and Zakrajšek (2012), Jurado et al. (2015), and Basu and Bundick (2017).

losses to spread system-wide (Battiston et al., 2017). Monasterolo (2020) models climate transition risk as arising from unexpected regulatory or policy shifts, identifying three drivers: (i) technological shocks that lower production costs in low-carbon sectors; (ii) regulatory shocks that penalize "brown" firms relative to greener counterparts; and (iii) changes in climate-related sentiment (Dunz et al., 2021).

Against this backdrop, a growing literature documents how capital markets internalize climate-related costs via adjustments in prices, credit spreads, and risk premia, thereby steering capital toward sustainable assets (Giglio et al., 2021; Bolton and Kacperczyk, 2021; de Jonge et al., 2025). In fact, the transition to a low-carbon economy can induce substantial asset re-pricing, creating new sources of systemic risk (Zhai et al., 2024). While the view that "green" firms tend to outperform "brown" firms is broadly supported (Pastor and Veronesi, 2012), some studies nuance this conclusion: Görgen et al. (2021) identify a "green premium," and Ardia et al. (2023) show that the relative performance of green versus brown stocks varies with fluctuations in climate change concerns, with the differential driven primarily by discount-rate news rather than cash-flow revisions.[8] Recent evidence also links climate risk directly to the stability of financial intermediaries: Bakkar et al. (2026) show that greater exposure to climate risk, and to transition risk in particular, significantly weakens bank stability.

To sum up, existing evidence underscores the critical role of uncertainty and financial stress in shaping asset prices and capital allocation, with a particular emphasis on how climate policy uncertainty affects investor behavior, equity valuations, and transition-risk exposures. Our paper contributes to this literature by adopting a Bayesian SVAR framework to identify the causal effects of CPU shocks on the financial system - showing that they significantly raise financial stress and depress equity valuations - and, through counterfactual exercises, to demonstrate that this transmission operates primarily via credit-intermediation stress rather than through equity-implied volatility alone.

3 Data and Methodology

Our empirical analysis employs eight variables that span the climate policy, financial uncertainty, asset pricing, and macroeconomic dimensions of the U.S. economy. The financial and climate-risk variables are: the natural logarithm of the climate policy uncertainty index

[8] In an intertemporal asset pricing perspective, such episodes of high realized returns are compatible with lower expected returns going forward: in a Campbell–Shiller log-linear present-value framework, large current returns associated with rising valuations can be interpreted as discount-rate news that compress risk premia and thereby reduces the conditional expectation of future returns.

(CPU), the natural logarithm of VIX (the index of 30-day implied volatility from options written on the S&P500 index), the St. Louis Fed Financial Stress Index (FSI), the S&P 500 log price-dividend ratio (PDR), and the natural logarithm of the S&P500 index. The macroeconomic (control) variables are: the Federal Funds Rate (FFR), the natural logarithm of the Consumer Price Index (CPI) and the natural logarithm of the U.S. industrial production index (IP). The data span the sample January 1994 – December 2023. This period is determined by data availability, as in particular, the FSI is only available from 1994. The CPI, industrial production, interest rate, S&P 500 index, and the FSI were pulled from the FRED database, while the log price-dividend ratio and the VIX were sourced from Bloomberg. Details regarding the dataset, along with the corresponding descriptive statistics and sample correlation matrix, are provided in the on-line Appendices A and B.

The inclusion of both VIX and FSI allows us to distinguish between implied volatility, which captures forward-looking market uncertainty, and a measure of realized stress in funding and credit markets, encompassing funding liquidity, credit risk, and intermediary balance-sheet conditions(Hakkio and Keeton, 2009). The log price–dividend ratio and the S&P 500 index serve as complementary equity-valuation measures: the former captures long-horizon discount-rate variation that is central to asset pricing research (Brogaard and Detzel, 2015), while the latter reflects shorter-horizon return dynamics. This dual representation is particularly relevant in the climate finance context, where both discount-rate and cash-flow channels may be affected by transition risk (Barnett, 2023).

We begin our analysis by examining the effects of CPU, VIX and FSI on the full set of endogenous variables by employing the structural VAR (SVAR) methodology . Additionally, we adopt a Bayesian specification to address potential non-stationarity in the data and to allow for greater model flexibility, tackling any potential problem with overparameterization and exhaustion of the available degrees of freedom (Sims et al., 1990).[9] The *reduced-form* VAR(p) model:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \varepsilon_t, \tag{1}$$

where y_t is a 8×1 vector of endogenous variables (CPU, VIX, FSI, PDR, S&P500, FFR, CPI, IP), $\varepsilon_t \sim N(0, \Sigma)$ and Σ is the residual covariance matrix. Given the monthly frequency of the data, we select a priori the number of lags to equal $p = 12$ and let the Bayesian approach handle the implications of this flexible specification.[10]

[9] In practice, the use of Bayesian priors provides a form of shrinkage toward more parsimonious dynamics, which stabilizes estimation in small samples and yields impulse responses that are less sensitive to the high persistence and near-unit-root behavior that typically characterize macro-financial time series (Bańbura et al., 2010).

[10] We show in the robustness section 5.2 that our main results are robust to the selection of alternative lag order specifications.

A common issue with this reduced form is that the shocks ε_t are typically correlated, as the empirical estimates of Σ generally turn out not to be diagonal. This correlation prevents a causal interpretation of impulse response functions (Kilian and Lütkepohl, 2017), which remain our main tool of empirical investigation. To address this issue, we turn to a SVAR modelling strategy, which allows for orthogonal shocks. The *structural* VAR model is expressed as

$$D_0 y_t = D_1 y_{t-1} + D_2 y_{t-2} + \cdots + D_p y_{t-p} + \eta_t, \tag{2}$$

where $\eta_t \sim N(0, \Gamma)$ is a vector of structural shocks with covariance Γ. We assume that Γ is diagonal, ensuring that the shocks η_t are orthogonal and uncorrelated. The resulting IRFs admit a causal interpretation, as in Bretscher et al. (2020) and Hilscher et al. (2022).

For convenience, let us define: $D = D_0^{-1}$. By pre-multiplying both sides of equation (1) by D, we can relate it to equation (2) as follows:

$$A_i = DD_i, \quad \varepsilon_t = D\eta_t. \tag{3}$$

Therefore, the covariance matrix Σ becomes simply $\Sigma = E(\varepsilon_t \varepsilon_t') = D\Gamma D'$. To achieve identification, we impose a Cholesky factorization of the reduced-form covariance matrix, corresponding to a recursive short-run identification scheme that is standard in applied SVAR work and widely used in macro-finance applications (e.g., Cortes et al., 2022). This method ensures the model follows a block-recursive structure, whereby the covariance matrix Σ is represented as a lower-triangular matrix. Without loss of generality, we normalize the covariance matrix of the structural shocks to the identity matrix, $\Gamma = I$. Each structural shock therefore has unit variance, and any scaling is absorbed into D. For the sake of clarity and to focus on economically meaningful disturbances, we report impulse responses scaled to a two-standard-deviation structural shock. This choice allows us to study the effects of sizable and intensive climate, financial uncertainty, and financial stress shocks, which are of primary interest in our analysis.[11] Under this normalization, identification is obtained by finding a matrix D such that $DD' = \Sigma$, with Σ being a symmetric matrix. This corresponds to the definition of Cholesky factorization, which guarantees that the shocks are orthogonal and

[11] Scaling IRFs to shocks larger than one standard deviation is common in the uncertainty literature. Bloom (2009) defines uncertainty shocks as stock-market volatility innovations exceeding 1.65 standard deviations above the detrended mean and, as an alternative, considers a threshold of two SDs (see his Appendix A). Jurado et al. (2015) scale their macro-uncertainty shocks to four SDs, comparable to the VXO-based shocks in Bloom (2009)'s VAR. Ludvigson et al. (2021) similarly focus on "big" shocks whose magnitudes exceed two SDs, noting that "infrequent big shocks, when they hit, can have large effects." Our two SDs scaling follows this tradition and is motivated by the observation that the most policy-relevant CPU episodes, such as the Paris Agreement, major regulatory reversals, or COP summits, correspond to large, infrequent disturbances rather than routine fluctuations.

the system is properly identified.

In summary, given a recursive approach and the ordering of our variables, we assume that within a given month, under Gaussian errors, CPU is independent of shocks to VIX, FSI, PDR, S&P500, FFR, CPI, and IP, while VIX may respond to the shocks to CPU but not to shocks to other variables; FSI is allowed to respond to shocks to both CPU and/or VIX, but it is not affected by the remaining variables. Hence, this identification scheme assumes that climate policy uncertainty is the "most exogenous" variable, because we are primarily interested in the measurement of the effects of shocks to CPU on both the financial system and on the real economy. In this sense, we leverage on the common interpretation of CPU (Gavriilidis, 2021; Faccini et al., 2023) as an indicator likely to capture exogenous variations stemming from shifting political priorities or regulations outside the financial and real economic systems (at least in terms of their contemporaneous relationships).[12] Our approach aligns with the structural VAR literature that explores the financial effects of uncertainty (see, for example, Bloom (2009); Basu and Bundick (2017); Bonaime et al. (2018); Gavriilidis (2021)). Specifically, the ordering we chose is the same as in Bloom (2009)'s seminal paper. However, as discussed in Section 2, we are fully aware of the endogeneity issues related to uncertainty (see Castelnuovo (2023)), particularly in light of its counter-cyclical nature. Indeed, in Section 5 devoted to robustness checks, we show that our findings remain robust to alternative Cholesky orderings. This restriction is plausible at the monthly frequency because the Gavriilidis (2021)'s index is constructed from newspaper coverage of climate policy, whose publication cycle - from event occurrence through editorial selection, drafting, and print - introduces an inherent delay that makes within-month feedback from financial variables unlikely. Furthermore, the index is constructed from articles that explicitly reference climate policy debates and regulatory developments, rather than from coverage of financial-market events as such. A sharp deterioration in financial conditions — whether an equity sell-off or a rise in broader financial stress — would therefore not mechanically translate into greater climate-policy coverage within the same month, unless the market movement had itself been triggered by a climate-policy announcement, in which case causality would run from CPU to financial markets, consistent with our recursive ordering. As noted by Caggiano et al. (2014), at worst by placing CPU first in our Cholesky ordering, we would be attributing all one-step-ahead forecast errors in CPU to its own, climate uncertainty

[12]Clearly, a VAR model allows, through the lags in the conditional mean function, that past financial returns and valuation ratios may affect CPU. The same applies to the lagged relationships between past VIX and FSI and current CPU. What the Cholesky identification rules out is the possibility that contemporaneous shocks to financial or real variables trigger unexpected changes in CPU in the same month. Our main results are robust to alternative VAR orderings, as discussed in Section 5.1.

shocks, implying that our results provide an upper bound on the impact of these shocks.[13] Finally, Section 5.4 shows that the results survive when consumer sentiment is ordered ahead of CPU, so that the identified shock is purged of contemporaneous confidence innovations.

As implied by the Bayesian methodology we apply, each parameter of interest is treated as a random variable with an associated (posterior) probability distribution, and inference about these parameters is based on Gibbs sampling. To avoid unduly influencing our results, we select a normal-diffuse prior, known for its result-neutral, non-informative nature (Kadiyala and Karlsson, 1997), as in Pástor and Stambaugh (1999). This choice is particularly suitable when the researcher seeks to remain agnostic regarding the specific values that Σ, the covariance matrix, may assume.[14]

Our Gibbs sampling is based on 100,000 iterations, with 50,000 used as a burn-in. We set the hyperparameters to standard values in the literature (Sims and Zha, 1998; Giannone et al., 2015; Dieppe et al., 2016): overall tightness $\lambda_1 = 0$, cross-variable weighting $\lambda_2 = 1$, lag decay $\lambda_3 = 1$, and exogenous variable tightness $\lambda_4 = 100$.[15] Our results are not sensitive to the choice of hyperparameters or the priors employed, with robustness further ensured through the use of the Giannone et al. (2015)'s optimization procedure, which is explained below. For additional details about the prior robustness, refer to the robustness Subsection 5.3, as well as the on-line Appendix D.[16]

Following Giannone et al. (2015) and Lenza and Slacalek (2024)), we also estimate the model by maximizing the marginal likelihood with respect to the prior hyperparameters using a grid search. The hierarchical modeling approach optimally adjusts the degree of prior shrinkage by balancing the number of unknown parameters with the available data, automatically tightening or loosening the priors as needed. This shrinkage level is optimized using maximum likelihood, which takes into account both the in-sample fit and model complexity,

[13] By placing the CPU as the first variable in the Cholesky ordering, all one-step-ahead forecast errors involving the CPU are attributed exclusively to shocks to the CPU itself. This implies that any unexplained variability in the CPU is considered to be entirely derived from climate uncertainty shocks, rather than from other variables. This provides an "upper bound" on the effect of CPU shocks.

[14] Given that Σ governs the interdependencies between variables, as well as how uncertainty in one variable propagates to others, imposing strong priors on Σ would otherwise force the model to believe in predefined relationships or correlation structures involving the variables, regardless of whether these relationships are supported by the data. Such restrictive assumptions may bias the estimation process, potentially distorting the results, see also the discussion in Müller (2012).

[15] The overall tightness parameter (λ_1) regulates the variance of the autoregressive coefficients, with smaller values reflecting a stronger prior belief in their proximity to zero. The cross-variable weighting parameter (λ_2) governs the variance associated with cross-lagged influences. The lag decay parameter (λ_3) determines the rate at which the significance of past lags decreases. Finally, the exogenous variable tightness (λ_4) influences the variance of coefficients on exogenous variables. See the on-line Appendix C.

[16] With respect to the robustness of the different hyperparameter choices, the corresponding estimates are available upon request.

ensuring appropriate regularization in the BVAR estimation.

Moreover, to assess the role of the financial channel in the propagation of CPU shocks, we construct a counterfactual VAR model by muting the influences of the VIX and FSI channels, following among others the approach in Giuliodori (2005), Bachmann and Sims (2012) and Samarina and Nguyen (2024)). To do so, we estimate a VARX (Vector Autoregression with Exogenous Variables) model with 12 lags that however excludes the equations for the VIX and the FSI while retaining their lagged values as exogenous variables in the remaining system equations. The difference between the IRFs in this counterfactual scenario and those from the baseline model measures the contribution of the financial channel to the transmission mechanism. Specifically, by re-estimating the model without the equations for VIX and FSI, these variables will neither respond to CPU shocks nor to other variables thus muting their power to contribute to the propagation of any baseline, primitive CPU shock. We present the counterfactual results under three alternative specifications: 1) shutting down the VIX channel, 2) shutting down the FSI channel, and 3) closing off both VIX and FSI channels. The statistical significance of the difference between the IRFs of the baseline model and those of the counterfactual scenarios are then tested using a standard t-ratio.

4 Main Empirical Results

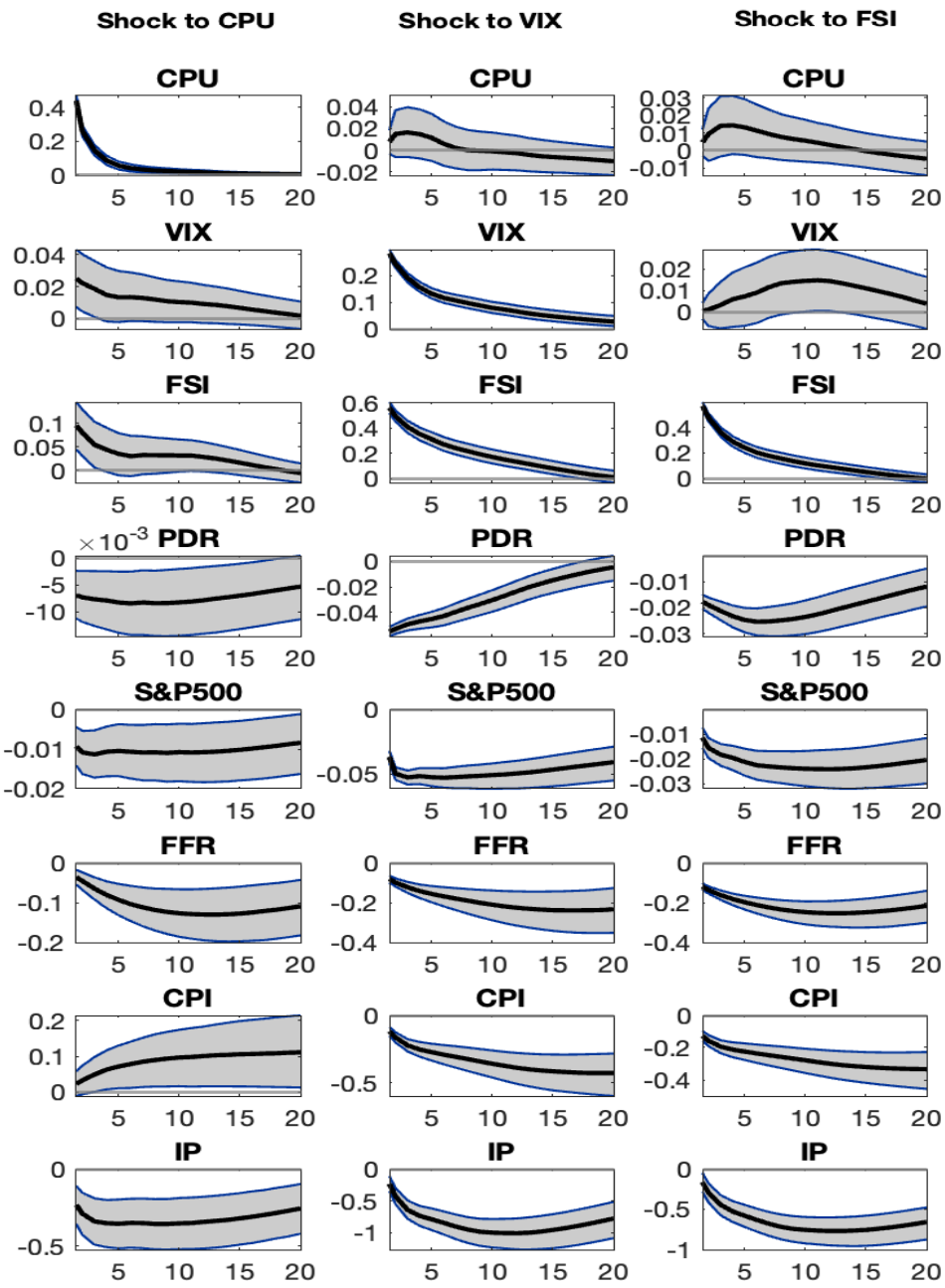
Figure 2 shows the estimated dynamic responses to a two-standard-deviation structural shock to CPU, VIX, and FSI, each displayed in a different column of the set of diagrams.[17] Table 1 displays the magnitude of the estimated impulse responses of each variable to each shock at the moment of impact, on average, and at the peak (maximum or minimum) of the effect.[18]

Concerning the shock to the VIX, used as a proxy for financial uncertainty, the impulse responses in the second column of Figure 2 display a pronounced and statistically significant increase in the Financial Stress Index, which peaks at approximately 62 percent. At the same time, both the price–dividend ratio and equity returns decline markedly. This pattern is consistent with episodes of market turbulence in which elevated implied volatility spills over into broader financial stress, compressing equity valuations through higher discount rates (Brogaard and Detzel, 2015). In parallel, monetary authorities respond endogenously by easing policy: the short-term policy rate falls by about 0.24 percentage points at its maximum

[17] In the on-line Appendix E, we include all the graphs from the paper presented with the same vertical scale by row, i.e., for each type of shock, enhancing visibility and facilitating a clearer visual understanding of our results.

[18] Our baseline reports 68% credibility intervals, corresponding to one-posterior-standard-deviation bands, a standard convention in Bayesian SVAR analysis, see Kilian and Lütkepohl (2017). All qualitative results are robust to 90% and 95% bands.

Figure 2
Baseline Results. Impulse Response Functions.



Impulse responses for a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI), respectively. Sample: 1994m1–2023m12. The variables enter the VAR in natural logarithms. The impulse responses of CPI, FFR and IP should be interpreted in percentage points. The gray area represents the 68% highest posterior density credible sets for the impulse response functions, while the black lines indicate the pointwise median IRFs using our baseline identification.

Table 1: Baseline IRF

Shocks	CPU			VIX			FSI		
	Impact	**Mean**	**Peak**	**Impact**	**Mean**	**Peak**	**Impact**	**Mean**	**Peak**
Variables									
CPU	**0.62**	0.06	**0.62**	0.014	0.000	0.016	0.010	0.004	0.014
VIX	**0.02**	0.02	**0.02**	**0.32**	0.10	**0.32**	0.002	0.010	**0.014**
FSI	**0.12**	0.04	**0.12**	**0.62**	0.20	**0.62**	**0.66**	0.16	**0.66**
PDR	**-0.006**	0.008	**-0.008**	**-0.06**	-0.02	**-0.06**	**-0.016**	-0.02	**-0.02**
S&P500	**-0.008**	-0.010	**-0.012**	**-0.02**	-0.04	**-0.06**	**-0.008**	-0.02	**-0.02**
FFR	**-0.02**	-0.10	**-0.14**	**-0.06**	-0.20	**-0.24**	**-0.10**	-0.22	**-0.26**
CPI	**0.14**	0.08	**0.12**	**-0.08**	-0.34	**-0.42**	**-0.10**	-0.26	**-0.34**
IP	**-0.18**	-0.32	**-0.36**	**-0.04**	-0.82	**-1.00**	**-0.04**	-0.64	**-0.78**

Impulse responses for a two-standard-deviation structural shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. The variables enter the VAR in natural logarithms. The impulse responses for CPI, FFR and IP should be interpreted in percentage points. The values of impact and peak in boldface font are significant at the 68% level.

response. Real activity reacts adversely as well, with industrial production reaching a trough of roughly 1 percentage points. The price level (CPI) also declines, so that the overall pattern resembles a demand-type disturbance, consistent with the findings of Leduc and Liu (2016) and Caggiano et al. (2014).

Turning to the impulse responses to an FSI shock (third column of Figure 2), the responses exhibit a broadly contractionary pattern that is qualitatively close to the one obtained under a VIX shock, but with weaker and less precisely estimated spillovers to market-based uncertainty. The FSI itself increases sharply on impact and then decays gradually, while the VIX rises only modestly and with noticeably wider credibility bands.This configuration is consistent with the FSI capturing a dimension of financial conditions - funding and credit-market stress - that is distinct from option-implied equity volatility, so that an FSI innovation need not coincide one-for-one with the volatility component captured by the VIX.[19] Asset-price responses to a financial stress shock are uniformly negative: the price–dividend ratio and the S&P 500 index both decline persistently, while monetary policy eases. Price level falls rather than rises, confirming that the dominant transmission operates through a demand and financial-intermediation channel.

Finally, in line with the main objective of the paper, the first column of Figure 2 reports the impulse responses to a shock in climate policy uncertainty. The shock generates a clear increase in financial uncertainty, although the response gradually loses statistical significance after roughly five months. Financial stress also rises, peaking at about an elasticity of 12 percent. Equity markets react sharply: both the price–dividend ratio and S&P 500

[19]Because FSI innovations reflect funding and credit-market conditions rather than equity-market expectations, they need not translate one-to-one into the uncertainty component captured by the VIX, see Hakkio and Keeton (2009).

returns decline persistently and remain statistically significantly perturbed over the relevant horizons. These equity-market effects are consistent with an increase in the climate-transition risk premium: heightened CPU raises the discount rate that investors apply to future cash flows exposed to regulatory ambiguity, compressing valuation ratios even in the absence of immediate earnings revisions (Barnett, 2023; Giglio et al., 2021). On the macroeconomic side, the policy interest rate falls, with a maximum decline of approximately 14 basis points, while IP contracts more strongly, reaching a trough of around -0.36 percentage points. By contrast, price level increases in a persistent manner, with a peak response close to 12 basis points, suggesting that climate policy uncertainty shocks may entail supply-side or cost-related pressures alongside their adverse effects on financial markets and real activity.

Several implications emerge from these results. First, shocks to climate policy uncertainty exert economically meaningful and statistically significant effects on the financial system. This finding is consistent with a growing literature that emphasizes the relevance of climate-related regulatory and transition risks for investors and financial intermediaries (Krüger et al., 2020; Faccini et al., 2023). In particular, it resonates with the evidence in Ji et al. (2024), who document that global climate policy uncertainty generates sizable, albeit temporary, reactions in financial markets.

Second, the transmission of a CPU shock differs markedly from that of VIX and FSI shocks, particularly in its asset pricing signature. While VIX- and FSI-driven disturbances are associated with declining asset prices and disinflationary pressures typical of demand-type shocks, a CPU shock is instead accompanied by depressed equity valuations but rising goods prices. From a financial perspective, this pattern implies that CPU shocks increase the required return on equity without compressing nominal cash-flow expectations proportionally, which is consistent with a transition-risk channel in which regulatory ambiguity widens the wedge between clean and brown asset valuations (Dang et al., 2023). The supply-side origin of the inflationary pressure - driven by firms adjusting production technologies, investing in green capital, or reconfiguring supply chains (Acemoglu et al., 2012; Pankratz et al., 2023)—further distinguishes CPU from conventional financial shocks.

Third, the estimated impulse responses to CPU shocks are characterized by substantially wider credibility intervals than those associated with VIX or FSI shocks. This feature points to greater heterogeneity in the transmission of climate policy uncertainty to financial markets, reflecting the complex and evolving nature of climate policy frameworks and the diversity of investors' expectations and adjustment mechanisms.

Figure 3 shows the results of the same shocks investigated above, using an identical identification while adopting Giannone et al. (2015)'s optimization approach. Even when we select the ranges of hyperparameters that maximize the model's marginal likelihood, both

the results and conclusions remain unchanged.

Overall, CPU shocks play a significant role in influencing capital markets. Given the interplay between climate and financial uncertainty, a key question arises: to what extent does the financial channel contribute to the propagation of CPU shocks? To address this, we apply the counterfactual VAR methodology. Figure 4 illustrates a counterfactual scenario for climate policy uncertainty shock only, showing three cases: VIX channel shut off, FSI channel shut off, and both channels shut off contemporaneously.

When the VIX channel is shut down, the impulse responses remain largely unchanged: all variables preserve their qualitative dynamics and statistical significance across horizons. This indicates that the effects of climate policy uncertainty are not primarily driven by equity-implied volatility, and that the baseline responses do not mechanically reflect movements in the VIX (Bloom, 2009).

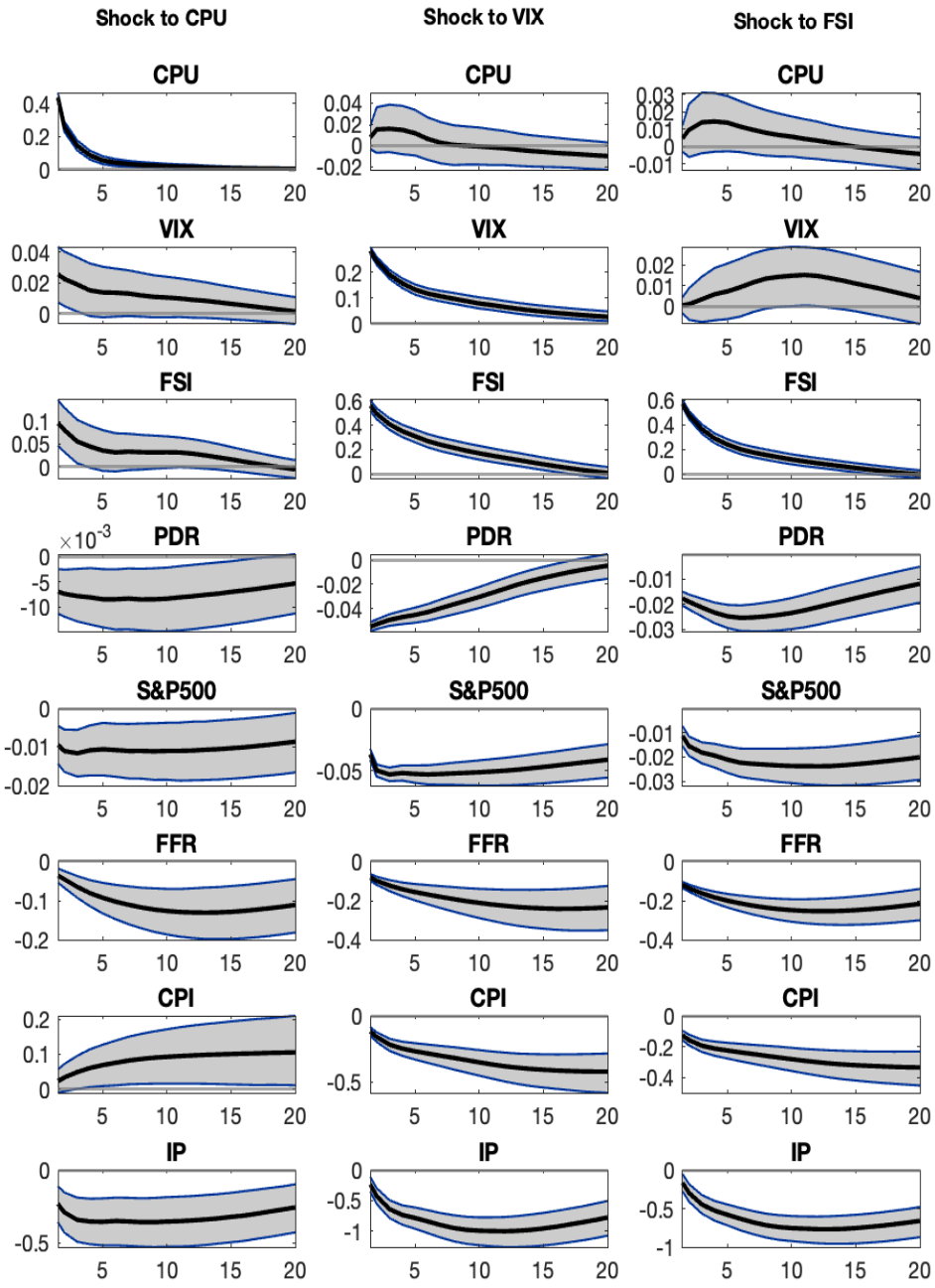
By contrast, muting the FSI channel leads to a meaningful attenuation of the financial market responses. In particular, the reactions of the price–dividend ratio and the S&P 500 lose statistical significance over intermediate horizons, with the price–dividend ratio becoming insignificant approximately between three and six months, and equity returns between five and ten months. This pattern highlights the central role of system-wide financial stress as an amplification mechanism: once broad stress conditions are dampened, the persistence and strength of the equity-market effects of the CPU are substantially reduced (Gilchrist and Zakrajšek, 2012; Brunnermeier and Sannikov, 2014).

The clearest separation emerges when both the VIX and FSI channels are muted simultaneously. In this case, the response of stock returns becomes statistically insignificant already on impact, while the responses of the remaining macroeconomic variables — monetary policy, inflation, and industrial production — remain broadly in line with the baseline specification. Taken together, these results point to a sharp distinction between financial-market and macroeconomic transmission. The impact of CPU on equity valuations is primarily mediated through broad financial stress conditions - consistent with credit-intermediation and balance-sheet channels emphasized in the climate–financial stability literature (Battiston et al., 2017) - whereas its effects on real activity operate through channels largely independent of both market-based uncertainty and stress measures.

To examine whether there are any differences in terms of magnitude of the variables' reaction across the various counterfactual scenarios, Figure 5 presents a comparison of the different scenarios, plotting the corresponding IRFs together.

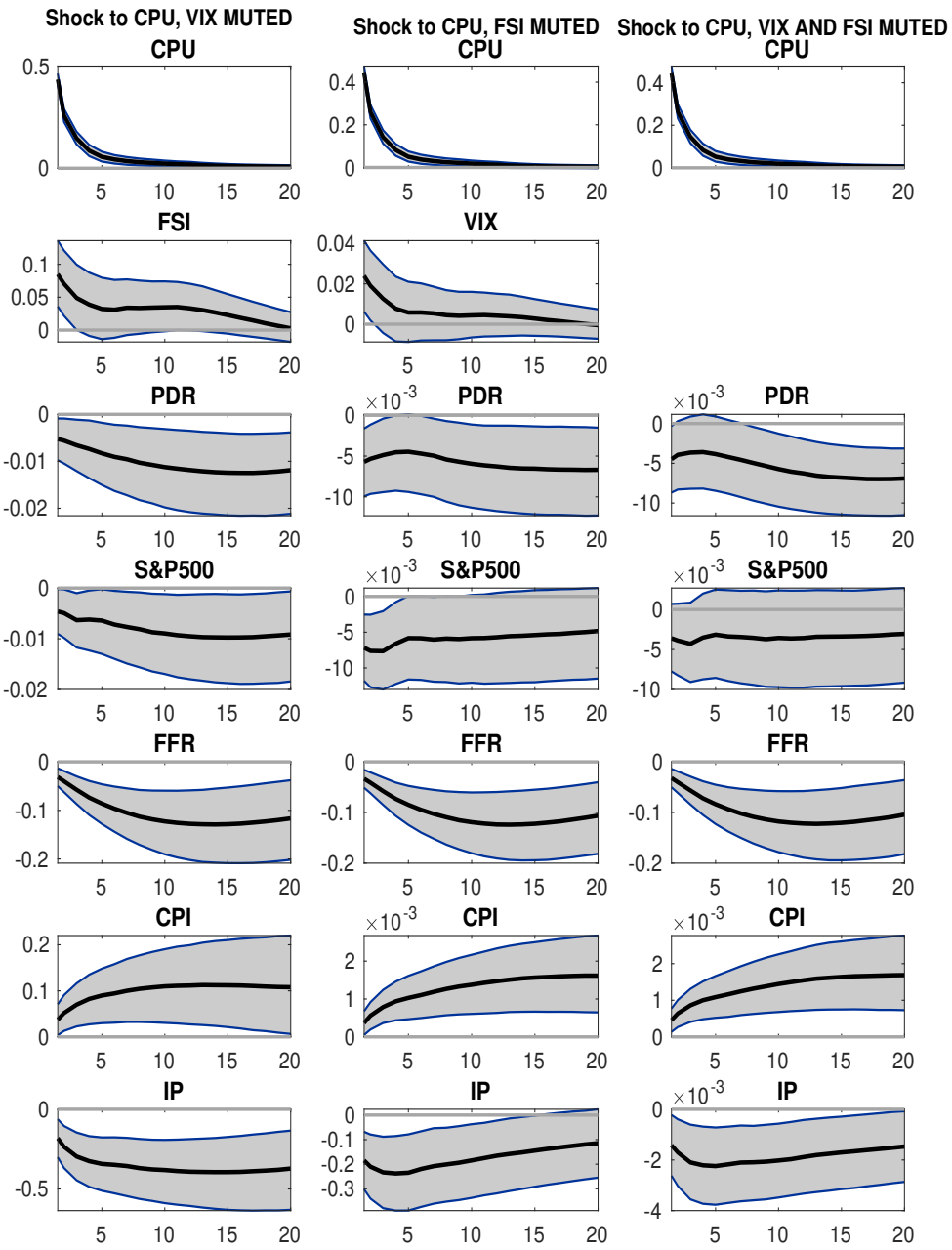
The counterfactual analysis in Figure 5 shows that when the VIX channel is muted (represented by the yellow line), the responses of the variables of interest do not deviate significantly from the baseline. In contrast, when the FSI channel is muted (purple line),

Figure 3
Baseline Results. Giannone et al. (2015)'s optimization approach. Impulse Response Functions.



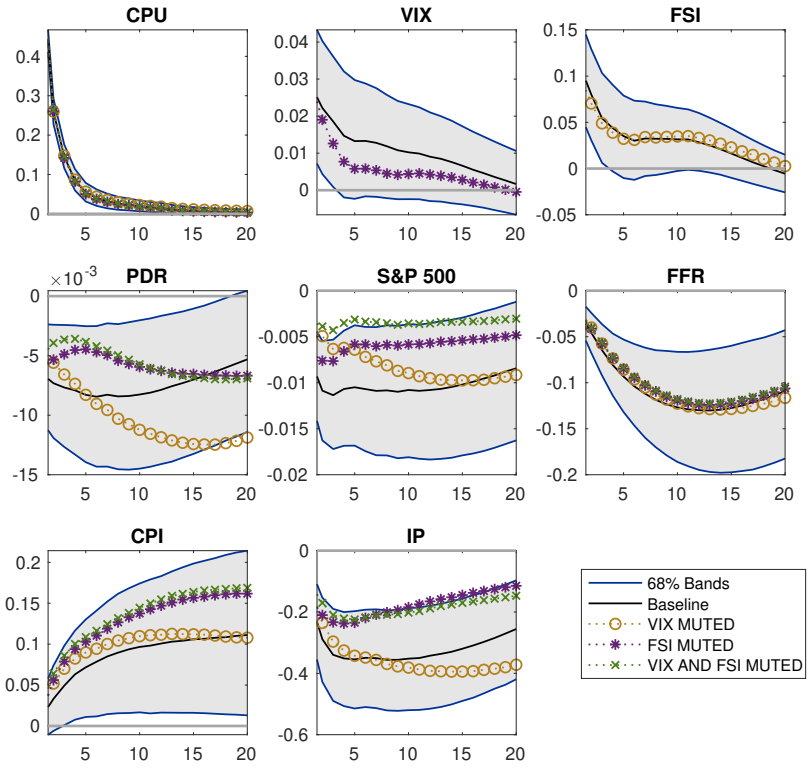
Impulse response functions of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and the Financial Stress Index (FSI). Sample: 1994m1–2023m12. Giannone et al. (2015)'s optimization is applied. The variables enter the VAR in natural logarithms. The impulse responses for CPI, FFR and IP should be interpreted as percentage point estimates. The gray area represents the 68% highest posterior density credible sets for the impulse response functions, while the black lines indicate the pointwise median IRFs.

Figure 4
Counterfactual Results. Impulse Response Functions.



Impulse responses functions of a shock to Climate Policy Uncertainty (CPU) across three different scenarios: 1) VIX channel muted (first column); 2) FSI channel muted (second column); 3) both VIX and FSI muted (third column). Sample: 1994m1–2023m12. The variables enter the VAR in natural logarithms. The impulse responses for CPI and IP should be interpreted as percentage point estimates. The gray area represents the 68% highest posterior density credible sets for the impulse response functions of each specifications, while the black lines indicate the pointwise median IRFs.

Figure 5
CPU Shock. Counterfactual Impulse Response Functions.



Impulse responses of a shock to Climate Policy Uncertainty (CPU) across three different scenarios: 1) VIX channel muted; 2) FSI channel muted; 3) both VIX and FSI muted. Sample: 1994m1–2023m12. The variables enter the VAR in natural logarithms. The impulse responses for CPI, FFR and IP should be interpreted as percentage point estimates. The gray area represents the 68% highest posterior density credible sets for the impulse response functions of each specifications under the baseline, while the black lines indicate the pointwise median IRFs.

the equity-market impact of the CPU shock is substantially attenuated, while the macroeconomic effects are also reduced. When both the VIX and FSI channels are blocked (shown by the green line), the divergence from the baseline scenario becomes significant across almost all variables. The federal funds rate is unaffected by the financial channels, as its impulse response functions perfectly overlap across scenarios. Therefore the response of climate policy uncertainty itself is virtually identical across all counterfactuals, indicating that muting the VIX and/or FSI channels does not feed back into the dynamics of CPU. This confirms that the identification of the climate policy uncertainty shock is orthogonal to contemporaneous financial conditions and supports its interpretation as an exogenous policy-related disturbance rather than a reflection of endogenous financial stress.

The macroeconomic responses display a systematic asymmetry across financial chan-

nels. Muting the FSI dampens the contraction in industrial production, while shutting down the VIX channel has almost no effect on the real-side dynamics. This reinforces the view that broad financial stress conditions and credit-intermediation frictions, rather than market volatility, are the key amplifiers of CPU's real-economy effects.[20]

Because the VIX equation remains in the system when the FSI is muted, the attenuation documented above isolates the propagation running through the component of financial stress that is orthogonal to implied volatility. Consistent with this, the two indices are not interchangeable in the baseline dynamics: a VIX innovation raises the FSI by 0.62 index points at peak, whereas an FSI innovation moves the VIX by only 0.014 (Table 1), and muting the VIX alone leaves the equity and real responses largely unchanged, whereas muting the FSI attenuates them substantially (Table 2). The dominance of the financial-stress channel therefore rests on the conditional dynamics of the system rather than on the unconditional co-movement between the two indices.

Table 2: Counterfactual Impulse Response Functions. CPU Shock (2 s.d.).

	Baseline		VIX Muted		FSI Muted		BOTH Muted	
	Mean	Peak	Mean	Peak	Mean	Peak	Mean	Peak
Variables								
CPU	0.06	0.62	**0.08**	0.62	**0.06**	0.62	0.06	0.62
VIX	0.02	0.02			**0.006**	0.02		
FSI	0.04	0.12	0.04	0.10				
PDR	0.008	-0.008	**-0.010**	-0.012	**-0.006**	-0.006	**-0.006**	-0.008
S&P500	-0.010	-0.012	**-0.008**	-0.010	**-0.006**	-0.008	**-0.004**	-0.004
FFR	-0.10	-0.14	-0.10	-0.12	-0.10	-0.12	-0.10	-0.12
CPI	0.08	0.12	**0.10**	0.12	**0.12**	0.16	**0.14**	0.16
IP	-0.32	-0.36	**-0.36**	-0.40	**-0.18**	-0.24	**-0.18**	-0.22

Impulse responses of a shock to Climate Policy Uncertainty (CPU) across four different scenarios: 1) Baseline, 2) VIX channel muted; 3) FSI channel muted; 4) both VIX and FSI muted. Sample: 1994m1–2023m12. A t-test is performed to assess the statistical significance of the differences between the response estimates obtained from the counterfactual models vs. the one from the baseline. The values that are boldfaced indicate statistically significant differences vs. the baseline, as they reject the null hypothesis at the 5% significance size.

To assess differences across counterfactual scenarios, we systematically apply t-tests to horizon-paired posterior impulse response estimates. These tests frequently reject the null hypothesis of equality with the baseline at the 5% significance level, confirming that the counterfactual responses differ in economically meaningful ways. The results are summarized in Table 2. The table reveals a clear hierarchy in financial transmission. Asset-price

[20]The divergence observed when both channels are muted is not merely quantitative but also dynamic: the CPI response becomes flatter and less persistent, while the recovery in industrial production is noticeably faster. This suggests that financial stress primarily acts as a persistence amplifier for climate policy shocks, prolonging their macroeconomic effects rather than generating them on impact.

responses—measured by the log price–dividend ratio and log S&P 500 returns—are significantly attenuated primarily when the FSI channel is muted, whereas shutting down the VIX alone has comparatively limited effects. By contrast, industrial production responds asymmetrically: muting the FSI substantially reduces the depth of the contraction (from a peak of -0.36 percentage points in the baseline to -0.24 percentage points), while muting the VIX alone slightly amplifies it. This pattern indicates that broad financial stress acts as a recession amplifier, whereas equity-market volatility does not play an analogous role for real activity. CPI inflation rises more strongly when the FSI channel (or both channels) is muted, even as output losses are mitigated. This reinforces the interpretation of CPU shocks as supply-side disturbances: financial stress disproportionately depresses real activity, and removing it allows inflationary effects to dominate. The response of CPU itself is nearly invariant across all counterfactual scenarios, in both mean and peak terms, confirming that the counterfactual exercises affect transmission mechanisms rather than shock identification or normalization.[21]

In sum, these results establish the structural distinctiveness of climate policy uncertainty shocks: they are exogenous to financial conditions, they affect asset prices mainly through broad financial stress rather than through a simple surge in forward-looking volatility, and they generate macroeconomic effects that are only weakly mediated by conventional financial uncertainty channels.

4.1 A Financial Stress Transmission Mechanism of Climate Uncertainty Shocks

When a climate policy uncertainty innovation coincides with, or triggers, broader financial distress, the relevant mechanism is not merely "more uncertainty," but the translation of policy ambiguity into system-wide stress in funding, credit, and intermediary balance sheets. Our Bayesian SVAR evidence shows that a CPU shock raises both the VIX and (more importantly) the Financial Stress Index (FSI), and is followed by weaker equity valuations (lower log-price–dividend ratio and log-S&P 500 index) and accommodative monetary policy. The intuition is that policy ambiguity induces firms and investors to revise the distribution of future compliance costs and regulation paths; when this revision is absorbed by intermediaries through tighter funding and lending constraints, discount rates rise and risk-bearing capacity

[21] The table highlights a notable stability of the monetary policy response across all scenarios. Both the mean and peak reactions of the federal funds rate are virtually unchanged when either of the purely financial channels — or both — is muted, and none of the differences are statistically significant. This suggests that the policy response to climate policy uncertainty is driven primarily by its pure macroeconomic implications, rather than by contemporaneous movements in financial stress or market volatility.

falls, compressing valuations exactly when external finance becomes more expensive. This channel is consistent with theoretical models in which climate-related regulatory uncertainty raises the required return on carbon-exposed assets (Barnett, 2023; Pástor et al., 2022), and with cross-sectional evidence that firms facing greater climate policy risk adjust their capital structure (Dang et al., 2023).

Crucially, the paper's counterfactual VAR exercises imply that the market response depends on the activation of financial stress more than on equity-implied volatility alone. Shutting down the VIX channel leaves the CPU impulse responses largely intact, whereas muting the FSI channel substantially attenuates (and can render insignificant over relevant horizons) the equity-market responses to CPU, indicating that systemic stress is the main propagation route from CPU into valuations. In other words, VIX conditions may index the market's perception of risk, but FSI conditions index whether that perception becomes binding through funding liquidity, credit spreads, and bank/intermediary frictions. Hence, CPU shocks generate the sharpest and most persistent repricing when they are accompanied by a deterioration in FSI-type conditions; when stress is muted, the same policy uncertainty has a much weaker impact on valuation ratios and returns, even if volatility remains elevated.

The equity-market response is thus most sensitive to whether the stress channel is active. This finding implies that, for investors and risk managers, monitoring broad financial stress indicators is more informative about the asset pricing consequences of climate policy shifts than tracking implied volatility alone. At the same time, the joint response pattern - declining equities, falling interest rates, and contracting output - confirms that CPU shocks are distinct disturbances whose financial-market effects depend crucially on how uncertainty translates into systemic stress and credit tightening, consistent with the broader climate–financial stability nexus (Battiston et al., 2017).

Table 2 quantifies the financial distress transmission mechanism. In the case of the S&P 500, muting the FSI channel reduces the peak equity response by one-third (from -0.012 to -0.008), while muting the VIX alone reduces it by only one-sixth (to -0.010). When both channels are shut down simultaneously, the peak response falls by roughly two-thirds (to -0.004), confirming that the majority of the equity-market impact of a CPU shock is mediated through financial channels, with the FSI contributing approximately twice the attenuation of the VIX. The mean response across horizons tells the same story: muting the FSI reduces the average S&P 500 response by 40%, compared with 20% for the VIX. The log price-dividend ratio is broadly consistent but more nuanced. Muting the FSI attenuates the peak PDR decline by one-quarter (from -0.008 to -0.006), confirming that credit-intermediation stress amplifies the valuation compression. However, muting the VIX alone amplifies the PDR response (to -0.012), suggesting that VIX partially offsets the valuation effect -possibly because

a VIX spike triggers precautionary rebalancing that limits the decline in the price–dividend ratio. When both channels are blocked, these opposing forces roughly cancel, leaving the peak PDR response at -0.008, near the baseline. This asymmetry reinforces the conclusion that the credit-stress channel is the dominant net amplifier of equity-valuation losses.

5 Robustness Analysis

We perform several additional robustness checks. Specifically, we examine (1) the robustness of the transmission of climate policy uncertainty shocks by constructing identification-related confidence bands over 240 alternative recursive Cholesky orderings of the financial block, (2) the effect of the number of lags selected when implementing model estimation, (3) an alternative recursive ordering of the monetary policy variable, (4) alternative prior distributions, (5) the potential bias resulting from omitted variables, and (6) the effects of selecting alternative indicators of real economic activity. Finally, we re-estimate the model through two additional exercises: one replacing the Federal Funds Rate with the Shadow Interest Rate during the periods in which the Zero Lower Bound (ZLB) has been binding, and another truncating the sample to exclude the post-COVID-19 period. These exercises address two concerns: first, that conventional policy rates may fail to capture the stance of monetary policy during periods of unconventional policies at the ZLB (Wu and Xia, 2016); second, that the extreme volatility and outlier behavior induced by the COVID-19 shock may distort impulse response estimation (Lenz and Posen, 2020).

5.1 Confidence Bands from Alternative Recursive Orderings

Although the recursive identification adopted in the baseline specification is well grounded in the literature, it is fair to ask whether the estimated IRFs may be sensitive to the contemporaneous ordering within the financial block of the VAR. Since CPU is the variable of interest, we keep it fixed in the first position across all specifications and vary only the ordering of the financial block, where contemporaneous feedback between market volatility and financial stress is most plausible. Specifically, we consider two recursive structures that differ in whether VIX or FSI is placed immediately after CPU; conditional on each choice, the remaining five macro-financial variables (PDR, S&P 500, FFR, CPI, IP) are permuted, yielding $2 \times 5! = 240$ economically admissible recursive specifications in total. All other elements of the empirical framework are held fixed across estimations: sample period, lag structure, Normal-Diffuse prior, hyperparameter calibration, Gibbs sampler hyperparameters (100,000 draws, first 50,000 discarded as burn-in), and shock normalization. The recursive ordering

is therefore the sole source of variation.

This exercise gauges the sensitivity of the transmission mechanism conditional on treating CPU as contemporaneously exogenous, an assumption we justify on institutional grounds in Section 3; it is not designed to test that exogeneity restriction itself. In the spirit of, among others, Guidolin et al. (2017), who assess the robustness of impulse responses through economic bands obtained under alternative assumptions on the magnitude of policy shocks, we construct our identification bands from the empirical distribution of impulse responses across the 240 specifications, here reported as 68% and 95% percentile intervals. Unlike standard Bayesian credible sets, which reflect parameter uncertainty under a fixed identification, these bands summarize identification uncertainty across alternative orderings.

Figure 6 plots the baseline impulse responses alongside the corresponding bands. Overall, the results are largely insensitive to alternative recursive orderings: across virtually all variables and horizons, the responses retain their sign, persistence, and dynamic profile, with relatively narrow economic bands. This confirms that the main conclusions of the baseline analysis are not driven by the particular ordering adopted in the benchmark specification.

5.2 Number of Lags and Monetary Policy Ordering

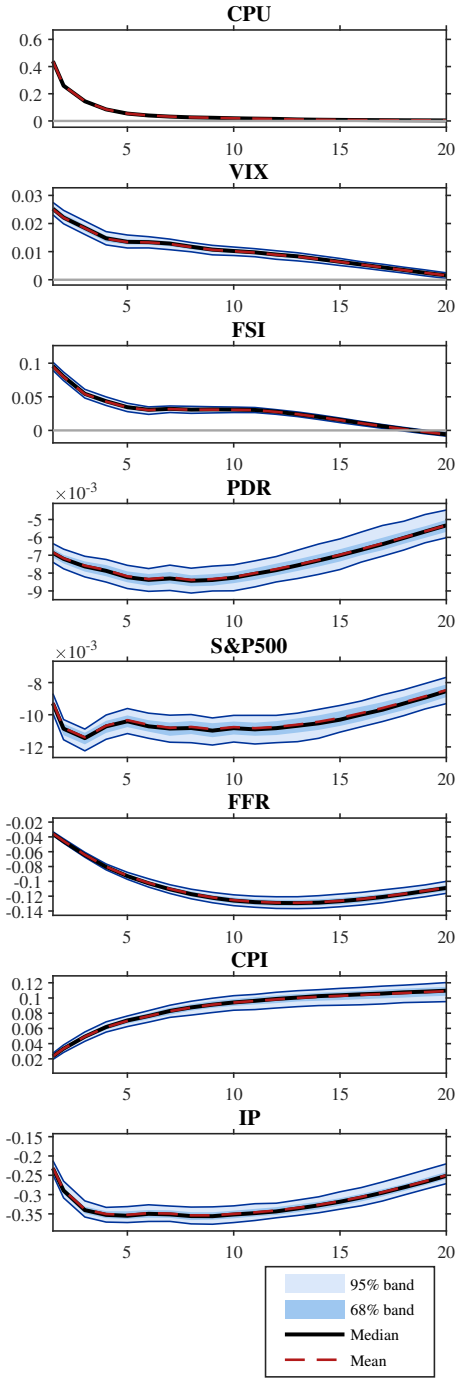
The model with 6 lags tests parsimony, while 24 lags test whether results are robust to a longer lag structure. Figure 7 shows that, even when changing the number of lags from 12 to 6 and then to 24 months, the results remain unchanged for what concerns the effects of shocks to CPU, VIX, and FSI on financial variables. Notably, in the specification with 24 lags, the effect of CPU on the VIX remains highly persistent across nearly all horizons.

We also examine the robustness of our results to various orderings of the Cholesky ordering of the monetary policy. As discussed in Section 2, while positioning the uncertainty indices as the first variables in the specification is reasonable due to their exogenous nature, regarding the ordering of monetary variables there is less unanimity. For this reason, we estimate an additional model in which we place FFR after CPI and IP, following Bernanke and Mihov (1998).[22] The variables enter y_t in the following order: CPU, VIX, FSI, PDR, S&P 500, CPI, IP, and FFR.[23] Our findings demonstrate that even when CPI and IP are placed before FFR, the CPU's effects on the financial variables are unchanged (Figure 7).

[22]For what concerns identification, early studies positioned the policy variable (e.g., the interest rate) as the first variable in the ordering (Sims, 1992), implying that it would not respond to the other endogenous variables contemporaneously. However, subsequent research reversed this ordering, placing the policy variable last (Bernanke and Mihov, 1998; Christiano et al., 1999), aligning it with a Taylor-rule approach where it responds contemporaneously to all other variables.

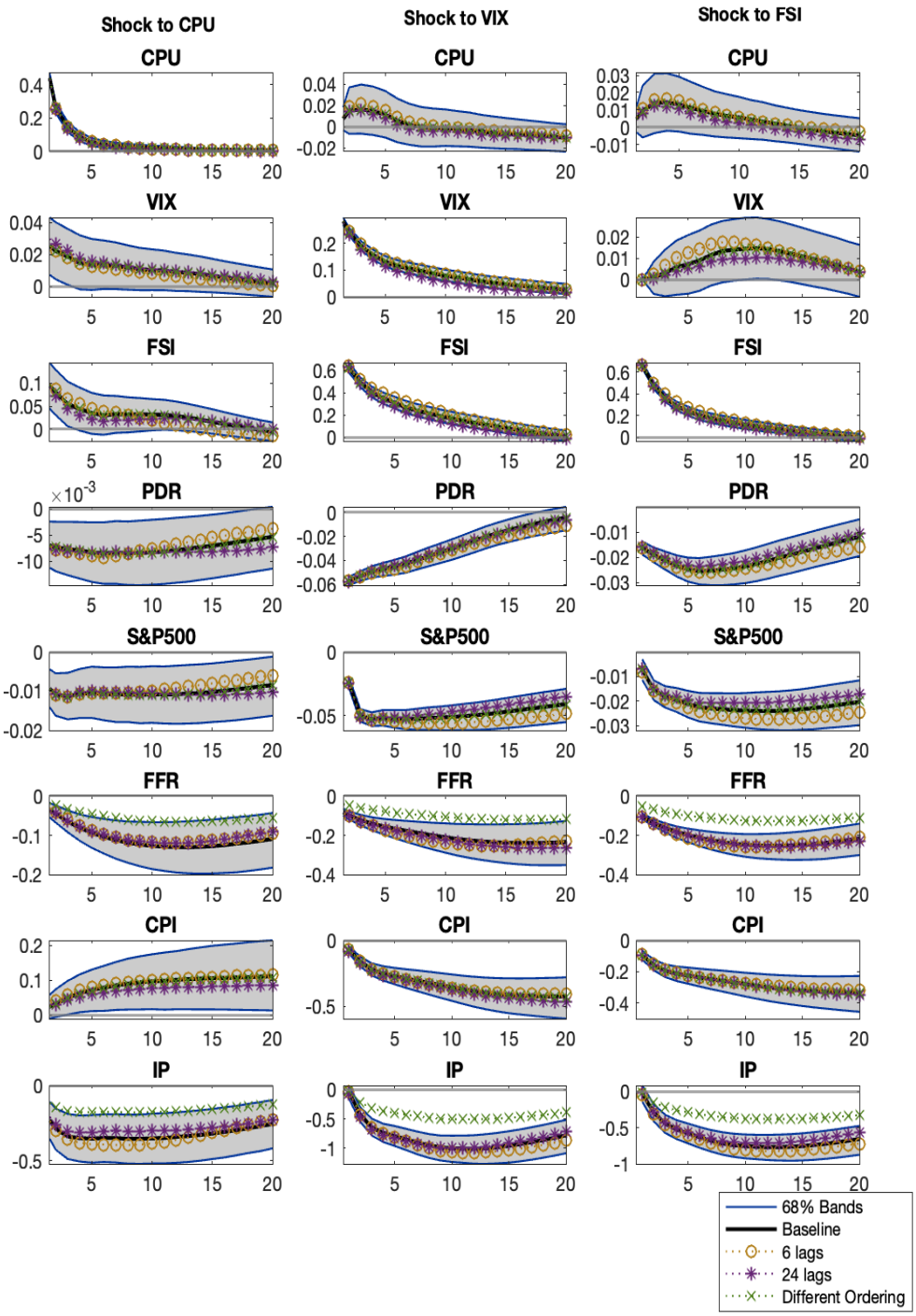
[23]In this specification we leave the number of lags the same as in the baseline model i.e. 12.

Figure 6
Identification-Driven Bands under Alternative Recursive Orderings.



Impulse responses to a two-standard-deviation structural shock to CPU, obtained from 240 alternative recursive Cholesky specifications. The black solid and red dashed lines denote the median and mean responses, respectively. The dark and light shaded areas represent the 68% and 95% economic bands, computed as empirical percentile intervals across the 240 estimations.

Figure 7
Robustness Checks. Different Lags and Ordering.



Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. Robustness analysis comparing the baseline model and its credibility bands with alternative specifications, including models with 6 and 24 lags instead of 12, and a model in which the Cholesky ordering is modified by placing CPI and industrial production before the federal funds rate.

5.3 Different Prior Distributions

We assess the sensitivity of the IRFs to the choice of prior distributions. Specifically, we replace the Normal Diffuse prior used in the baseline specification with a Normal–Wishart prior, thereby moving to a more informative prior that combines a normal prior for the VAR coefficients with a Wishart prior for the covariance matrix. We keep the hyperparameter calibration unchanged relative to the baseline to ensure that any differences are attributable to the prior family rather than to re-tuning. Figure 8 shows that our main conclusions are robust: following a CPU shock, the FSI rises and equity valuations decline, consistent with the financial transmission mechanism documented in Section 4.

Figure 8 also reports IRFs obtained under an Independent Normal–Wishart prior, which differs from the Normal–Wishart specification by imposing prior independence between the coefficient vector and the covariance matrix.[24] The resulting IRFs closely track the baseline paths in both sign and timing. Discrepancies are largely quantitative and concentrated in the persistence and peak magnitudes of some financial responses. In particular, the responses of the VIX and the FSI remain positive and display similar decay profiles across priors, indicating that the interaction between climate policy uncertainty and financial conditions is not an artifact of the baseline diffuse prior.

Moreover, across priors, the CPU shock itself is estimated with very similar persistence, suggesting that the identification of the shock is stable to prior choice. The prior sensitivity that does appear is most visible in the equity-valuation variables (price–dividend ratio and S&P 500), where the informative priors slightly smooth the responses and can shift peak effects across horizons. Overall, the close alignment of posterior medians across all three specifications supports the view that the financial-stress and equity-market responses to CPU shocks are features of the data rather than consequences of a particular prior choice.

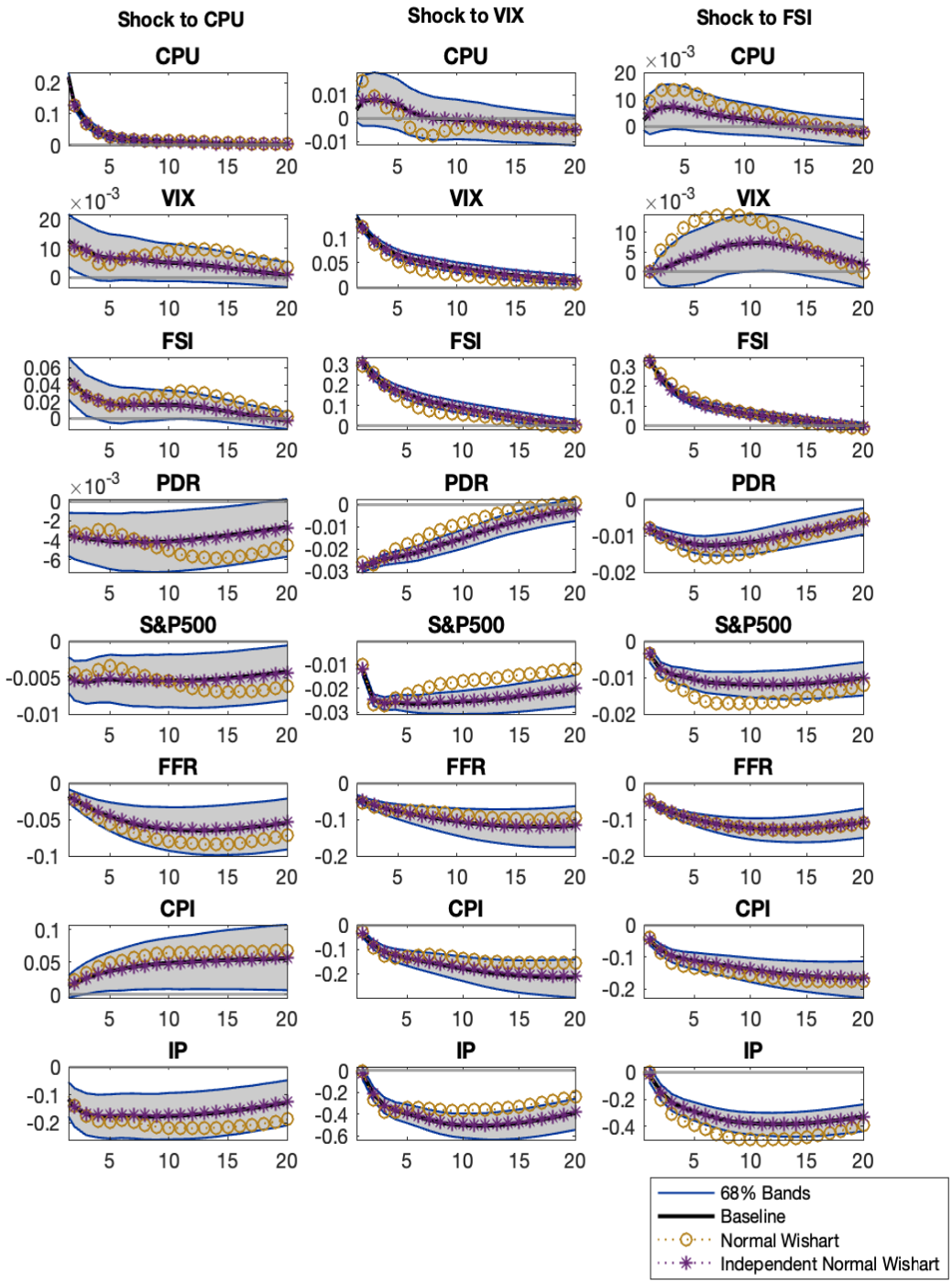
5.4 Omitted Variables

Motivated by the evidence that uncertainty shocks are closely linked to household expectations and confidence (Caggiano et al., 2014), we augment the baseline system by including the University of Michigan Index of Consumer Sentiment (SENT) from FRED as the first variable in the recursive ordering.[25] The resulting nine-variable system preserves the Cholesky identification of the remaining structural innovations.

[24] Using an Independent Normal–Wishart prior is useful because it avoids mechanically linking beliefs about dynamic propagation to assumptions about shock variances and contemporaneous correlations.

[25] Because SENT precedes CPU, this specification relaxes the baseline assumption that CPU is the most exogenous variable.

Figure 8
Robustness Checks. Alternative Prior Distributions.



Impulse responses for a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. 12 lags. Robustness analysis comparing the baseline model with its credibility bands, and two different specifications that assume either a Normal Wishart Prior or an Independent Normal Wishart Prior.

Figure 9 shows that the inclusion of SENT leaves the core qualitative results essentially unchanged. A CPU shock continues to depress equity valuations and raise financial stress, as captured by persistent declines in both the price-dividend ratio and the log-S&P 500 index and sustained increases in the VIX and the FSI. Relative to the baseline, some responses become less precisely estimated at medium horizons, consistent with the additional endogenous variable absorbing part of the short-run co-movement. Importantly, the sign patterns and relative ordering of responses remain stable, confirming that the financial repercussions of CPU shocks do not depend on omitting sentiment from the information set.

The most distinctive insight concerns the behavior of SENT itself. The CPU shock produces only a small and statistically weak response on consumer sentiment, suggesting that CPU does not immediately translate into a broad-based deterioration of household confidence. By contrast, both a VIX shock and an FSI shock generate a clearer decline in SENT on impact, consistent with the idea that households respond more strongly to episodes of generalized financial turbulence than to policy ambiguity per se. This asymmetry is economically meaningful: it suggests that CPU operates through financial intermediaries and firm-level channels rather than through household confidence, reinforcing the financial-stress transmission mechanism identified in our counterfactual analysis.[26]

5.5 An Alternative Indicator of Real Economic Activity

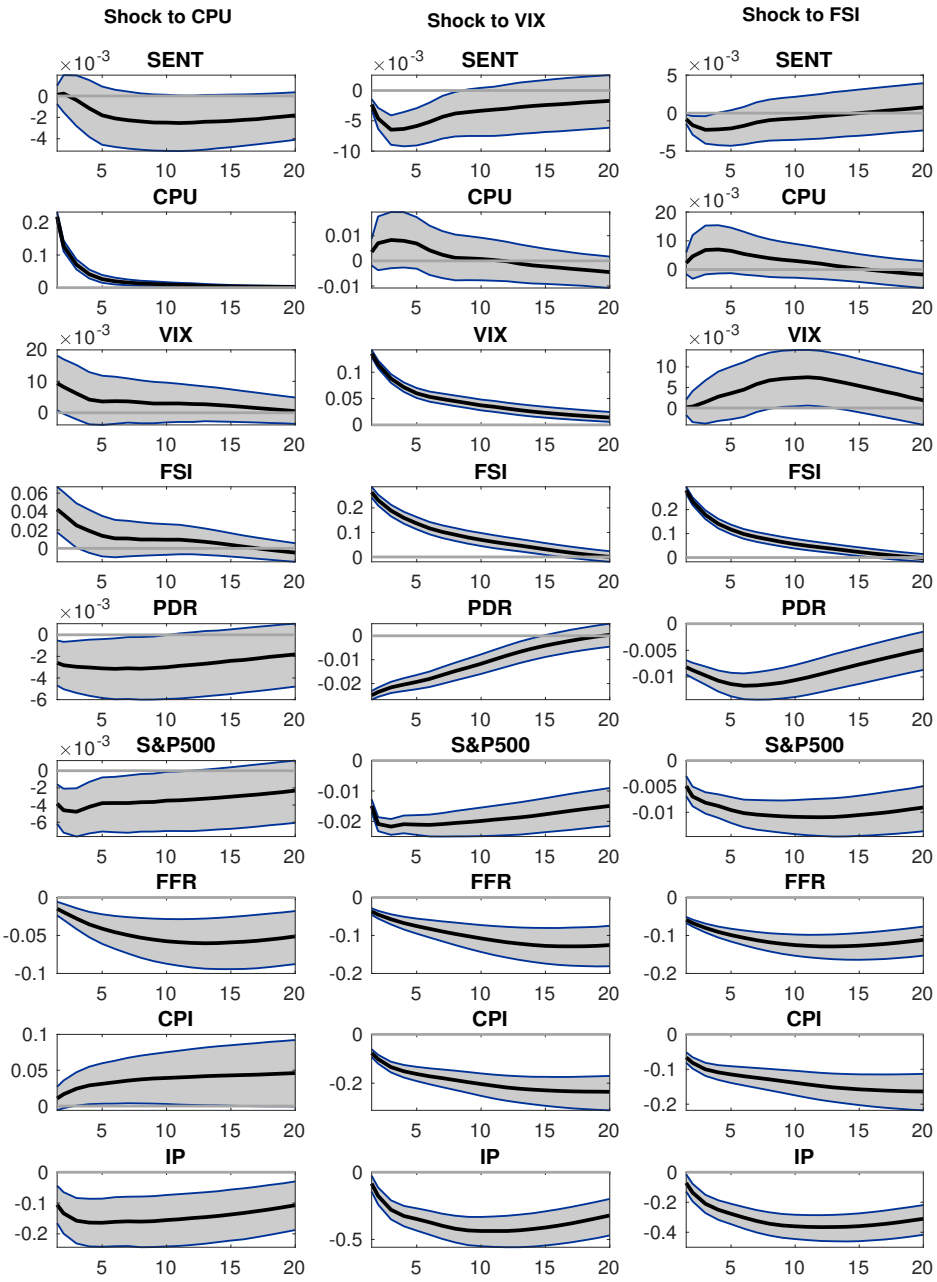
We replace IP with the unemployment rate from FRED to test whether the financial-stress responses are sensitive to the choice of real-activity measure. Figure 10 shows that the financial market responses are largely unchanged. A CPU shock continues to depress equity valuations, as reflected in persistent declines in both the price–dividend ratio and the log-S&P 500 index, while simultaneously raising financial uncertainty and stress, as captured by sustained increases in the VIX and the FSI. The contractionary effect on real activity is also confirmed, as the unemployment rate rises following a CPU shock

5.6 Using the Shadow Interest Rate and a Pre-COVID-19 Sample

We have also experimented with replacing the Federal Funds Rate with Wu and Xia (2016)'s Shadow Interest Rate over the sub-sample December 2008–December 2015 to account for

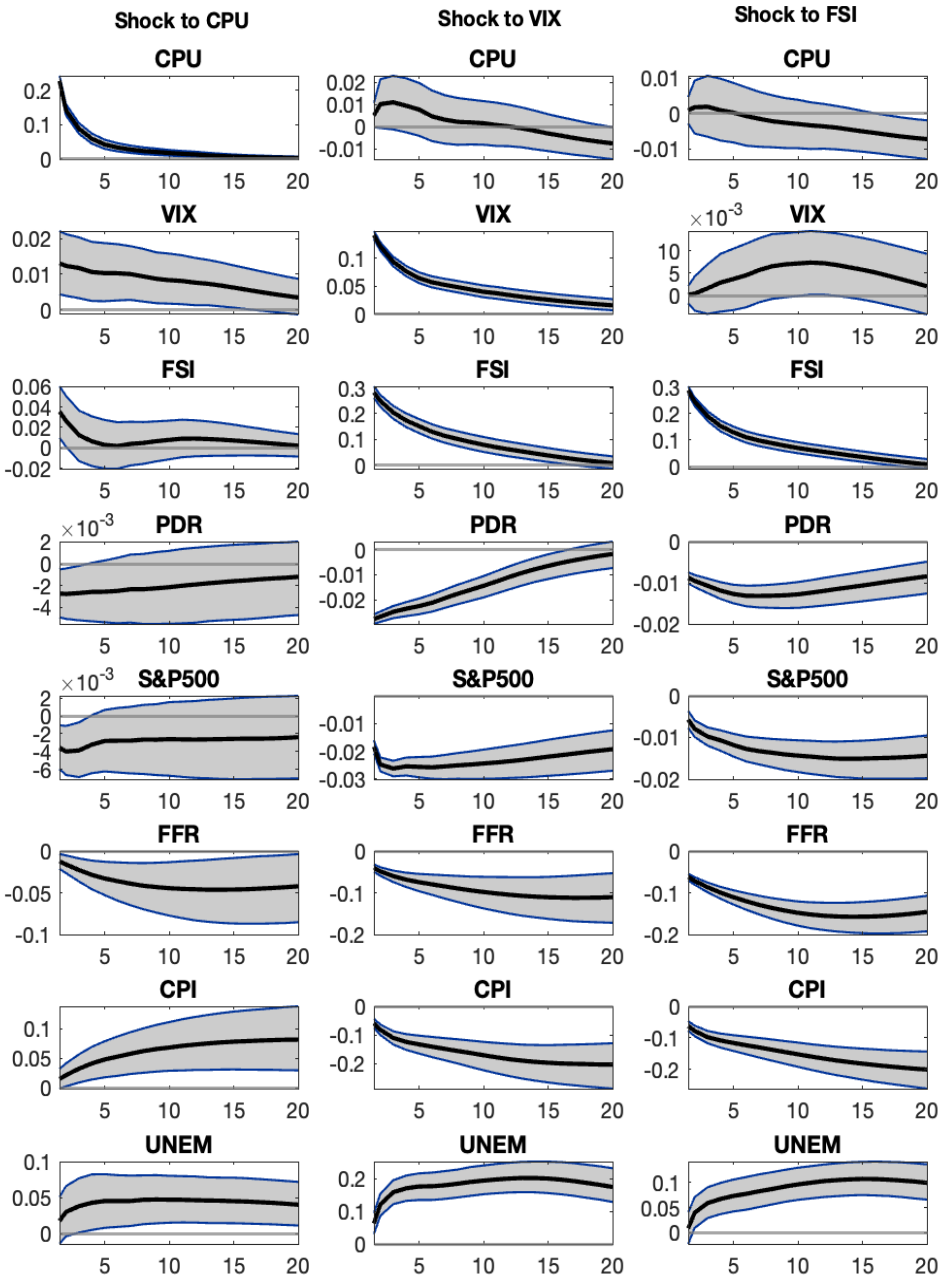
[26]CPU may primarily operate through firms' cost structures, investment decisions, and financial intermediaries, so its effects reach the broader economy through balance-sheet and pricing channels. By contrast, VIX and FSI shocks represent immediately salient financial turbulence that households can more readily perceive, see Bartram et al. (2022).

Figure 9
Consumer Sentiment Used as an Additional Variable.



Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. 12 lags. Consumer Sentiment as additional variable. The impulse responses for CPI, FFR and IP should be interpreted in percentage points. The gray area represents the 68% highest posterior density credible sets for the impulse response functions, while the black lines indicate the pointwise median IRFs using the baseline identification.

Figure 10
Unemployment Rate Replaces IP. Impulse Response Functions.



Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI), respectively. Sample: 1994m1–2023m12. The unemployment rate is used as proxy of economic (un)activity. The impulse responses for CPI, FFR and IP should be interpreted in percentage points. The gray area represents the 68% highest posterior density credible sets for the impulse response functions, while the black lines indicate the pointwise median IRFs using the baseline identification.

the ZLB experience and better measure unconventional monetary policy. For brevity, the IRFs are presented in Appendix F. As shown in Figure 25, the use of the shadow rate does not materially alter the financial market responses. Equity valuations continue to decline following uncertainty and stress shocks, as reflected in persistent drops in the price–dividend ratio and declines in the S&P 500 index, while both the VIX and the FSI remain elevated. These results confirm that the interaction between CPU and financial conditions is robust to alternative measures of the monetary policy.

Figure 26 (in the on-line Appendix F) presents the estimation results after excluding the COVID-19 period. The financial variable responses remain qualitatively intact: both the VIX and the FSI continue to rise following a CPU shock, and equity measures keep showing persistent declines. Excluding the pandemic mainly reduces the short-run volatility of the IRFs but does not overturn the main conclusion that broad financial stress is the key amplifier of CPU's effects on asset prices.

5.7 Dummy Observation Priors

As a final robustness check, we also estimate the model using a dummy observation prior (Bańbura et al., 2010) (Appendix D). This approach implements shrinkage by augmenting the dataset with artificial observations rather than by directly specifying prior moments for the VAR coefficients. The dummy observations replicate the moments of the Minnesota prior while allowing for computationally efficient estimation and facilitating unit-root–related restrictions.[27]

On-line Appendix D reports the resulting impulse response functions, keeping all other modelling choices identical to the baseline. The signs and broad magnitudes of the median IRFs are preserved across all variables, with the 68% highest posterior density credible sets closely tracking those of the baseline model. In particular, the persistent increases in the VIX and FSI following a CPU shock and the sustained declines in equity valuations remain qualitatively intact, reinforcing the conclusion that our results are driven by genuine data patterns rather than by artifacts of a specific prior parameterization.

[27]Following Bańbura et al. (2010), the dummy observations comprise three blocks: the first shrinks own-lag coefficients toward unity (or zero for mean-reverting variables) and cross-variable coefficients toward zero at a rate increasing with the lag order; the second sets the prior scale for the residual covariance matrix; and the third encodes a diffuse prior on the intercept. Stacking these artificial observations on top of the actual sample yields an augmented regression whose OLS estimates coincide with the posterior mean of the normal-inverted Wishart prior, casting Bayesian estimation as a least-squares problem.

6 Discussion and Conclusions

6.1 Implications for Financial Intermediation and Portfolio Management

Our results have direct implications for investors and portfolio managers seeking to measure, hedge, and price climate transition-risk exposures. The counterfactual analysis reveals that muting the FSI channel substantially attenuates equity responses to CPU shocks, whereas muting the VIX alone has a limited effect. For practitioners, this implies that the Financial Stress Index - which aggregates credit spreads, banking-sector risk, and yield-curve dynamics - provides a more informative real-time signal of the financial consequences of climate policy shifts than implied volatility alone. This is especially relevant for financial institutions, since the transmission mechanism operates through credit spreads, funding conditions, and intermediary balance-sheet stress rather than through equity-market volatility alone. Portfolios that condition rebalancing on volatility indicators without incorporating credit stress will underestimate the risk associated with climate policy episodes, complementing Liang et al. (2023)'s finding that the Global FSI dominates the VIX in forecasting long-horizon volatility.

Engle et al. (2020) show that mimicking-portfolio strategies can dynamically hedge innovations in a Climate Change News Index using equity portfolios sorted on environmental scores. Our contribution is to identify the *financial channel* through which such innovations affect aggregate equity returns: the FSI-mediated credit-stress pathway. This has a concrete implication for hedging: strategies that rely exclusively on equity-level volatility instruments (e.g., VIX futures) to hedge transition-risk exposures will capture only part of the total risk, because they miss the credit-intermediation component that our counterfactual identifies as the main amplifier. Effective hedging of CPU-driven equity losses should therefore pair standard volatility hedges with credit-spread instruments or financial-stress-sensitive positions.

Brogaard and Detzel (2015) demonstrate that economic policy uncertainty carries a significant and unconditional negative risk premium in the cross-section of equity returns. Bretscher et al. (2020) extend this result by showing that the impact of uncertainty shocks is strongly state-dependent: when risk aversion is high (e.g., proxied by the inverse of the surplus consumption ratio) the equity response to an uncertainty shock is roughly four times as large as in low-risk-aversion states. Our empirical finding that CPU transmits to equity valuations primarily through financial stress rather than through the VIX resonates with this mechanism: the FSI captures episodes in which credit conditions tighten, risk appetite falls, and the marginal investor's aversion to uncertainty is elevated. This suggests that the pricing of CPU risk may concentrate in high-stress regimes, implying that unconditional esti-

mates of a climate policy uncertainty premium may understate the conditional compensation investors require during financial-stress episodes.

6.2 Summary of Findings

We document how climate policy uncertainty propagates through the U.S. financial system using a Bayesian structural VAR framework with monthly data over 1994–2023. Our analysis yields three main findings. First, a CPU shock generates persistent increases in both the VIX and the Financial Stress Index, accompanied by sustained declines in the S&P 500 and the log price–dividend ratio, consistent with a compression of equity valuations driven by rising discount rates (Barnett, 2023; Brogaard and Detzel, 2015). These equity-valuation effects align with the growing cross-sectional evidence that transition risk is priced in U.S. equity markets (Faccini et al., 2023; Bolton and Kacperczyk, 2021).

Second, through a counterfactual design that sequentially mutes the VIX and FSI channels, we show that the financial stress channel is the dominant transmission mechanism from CPU to equity markets, while equity-implied volatility alone accounts for a substantially smaller share of the total effect. This finding resonates with the climate–financial stability literature, which emphasizes that climate risk is systemic and propagates through network linkages among financial institutions (Battiston et al., 2021).

Our results are robust across a wide range of alternative specifications, including the identification-driven bands from 240 alternative recursive Cholesky specifications, different lag structures, alternative recursive orderings of the monetary policy variable, variable sets, sample periods, and prior assumptions. Overall, the analysis highlights climate policy uncertainty as a significant driver of financial conditions and investor behavior. CPU shocks amplify financial stress, compress equity valuations, and operate through credit-intermediation channels rather than through market volatility alone. These findings suggest that climate policy uncertainty should be treated not only as a novel risk, but also as a source of financial-intermediation stress. For investors, this implies that volatility-based hedges may be insufficient; for policymakers and supervisors, it highlights the importance of monitoring credit and funding conditions when assessing the financial stability implications of the low-carbon transition.

6.3 Future Research Directions

Several avenues for future research emerge from our analysis. First, examining the cross-sectional dimension of CPU's financial impact - for instance, whether carbon-intensive industries exhibit stronger FSI-mediated responses - would bridge our aggregate evidence with

the firm-level findings of Basaglia et al. (2025) and with Ardia et al. (2023)'s evidence that the green–brown performance differential is driven by discount-rate news. Second, constructing tradable factor-mimicking portfolios for CPU innovations, in the spirit of Engle et al. (2020) and Brogaard and Detzel (2015), would allow direct estimation of the CPU risk premium and its variation across financial regimes. Third, our counterfactual exercise characterizes the reduced-form propagation structure of the VAR rather than a fully structural experiment. Muting the FSI equation removes all dynamic feedback running through that variable, including channels that may not map one-to-one onto credit frictions. The goal is simply to quantify how much of the response to CPU shocks travels through the financial-stress node. A fully structural decomposition is likely to require a general equilibrium framework with an explicit financial accelerator, along the lines of Christiano et al. (2014) ; we regard this as a promising avenue for future research. Finally, exploring nonlinear dynamics (e.g., Ciccarelli et al., 2023) may yield further insights into regime-dependent amplification of transition-risk premia, particularly whether the FSI transmission channel exhibits threshold effects that map onto the state-dependent risk premium as in Bretscher et al. (2020).

References

D. Acemoglu, P. Aghion, L. Bursztyn, and D. Hemous. The environment and directed technical change. *American Economic Review*, 102(1):131–166, 2012.

D. Ardia, K. Bluteau, K. Boudt, and K. Inghelbrecht. Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632, 2023.

R. Bachmann and E. R. Sims. Confidence and the transmission of government spending shocks. *Journal of Monetary Economics*, 59(3):235–249, 2012.

S. R. Baker, N. Bloom, and S. J. Davis. Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4):1593–1636, 2016.

Y. Bakkar, S. Ben Jabeur, S. Challita, and F. Shuwaikh. Climate risk and bank financial stability. *The European Journal of Finance*, 32(9):1124–1169, 2026.

M. Bańbura, D. Giannone, and L. Reichlin. Large Bayesian vector autoregressions. *Journal of Applied Econometrics*, 25(1):71–92, 2010.

M. Barnett. Climate change and uncertainty: an asset pricing perspective. *Management Science*, 69(12):7562–7584, 2023.

S. M. Bartram, K. Hou, and S. Kim. Real effects of climate policy: financial constraints and spillovers. *Journal of Financial Economics*, 143(2):668–696, 2022.

P. Basaglia, C. Berestycki, S. Carattini, A. Dechezleprêtre, and T. Kruse. Climate policy uncertainty and its impact on firms and investors. 2025.

S. Basu and B. Bundick. Uncertainty shocks in a model of effective demand. *Econometrica*, 85(3):937–958, 2017.

S. Battiston and I. Monasterolo. The climate target gap is widening: can we close it by including climate finance in SSPs? Working Paper 3266041, SSRN, 2018.

S. Battiston, A. Mandel, I. Monasterolo, F. Schütze, and G. Visentin. A climate stress-test of the financial system. *Nature Climate Change*, 7(4):283–288, 2017.

S. Battiston, Y. Dafermos, and I. Monasterolo. Climate risks and financial stability. *Journal of Financial Stability*, 54:100867, 2021.

B. S. Bernanke and I. Mihov. Measuring monetary policy. *Quarterly Journal of Economics*, 113(3):869–902, 1998.

N. Bloom. The impact of uncertainty shocks. *Econometrica*, 77(3):623–685, 2009.

N. Bloom. Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28:153–176, 2014.

P. Bolton and M. Kacperczyk. Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549, 2021.

A. Bonaime, H. Gulen, and M. Ion. Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics*, 129(3):531–558, 2018.

L. Bretscher, A. Hsu, and A. Tamoni. Fiscal policy driven bond risk premia. *Journal of Financial Economics*, 138(1):53–73, 2020.

J. Brogaard and A. Detzel. The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1):3–18, 2015.

M. K. Brunnermeier and Y. Sannikov. A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421, 2014.

G. Bua, D. Kapp, F. Ramella, and L. Rognone. Transition versus physical climate risk pricing in European financial markets: a text-based approach. *The European Journal of Finance*, 30(17):2076–2110, 2024.

G. Caggiano, E. Castelnuovo, and N. Groshenny. Uncertainty shocks and unemployment dynamics in US recessions. *Journal of Monetary Economics*, 67:78–92, 2014.

D. Caldara, C. Fuentes-Albero, S. Gilchrist, and E. Zakrajšek. The macroeconomic impact of financial and uncertainty shocks. *European Economic Review*, 88:185–207, 2016.

E. Campiglio, Y. Dafermos, P. Monnin, J. Ryan-Collins, G. Schotten, and M. Tanaka. Climate-related risks in financial assets. *Journal of Economic Surveys*, 37(3):950–992, 2023.

E. Castelnuovo. Uncertainty before and during COVID-19: a survey. *Journal of Economic Surveys*, 37(3):821–864, 2023.

L. J. Christiano, M. Eichenbaum, and C. L. Evans. Monetary policy shocks: what have we learned and to what end? *Handbook of Macroeconomics*, 1:65–148, 1999.

L. J. Christiano, R. Motto, and M. Rostagno. Risk shocks. *American Economic Review*, 104 (1):27–65, 2014.

M. Ciccarelli, F. Kuik, and C. M. Hernández. The asymmetric effects of weather shocks on euro area inflation. 2023.

G. S. Cortes, B. Taylor, and M. D. Weidenmier. Financial factors and the propagation of the

Great Depression. *Journal of Financial Economics*, 145(2):577–594, 2022.

V. A. Dang, N. Gao, and T. Yu. Climate policy risk and corporate financial decisions: evidence from the NO_x budget trading program. *Management Science*, 69(12):7517–7539, 2023.

M. de Jonge, D. Broeders, and D. Rijsbergen. The euro area carbon bond premium. *The European Journal of Finance*, 31(14):1739–1769, 2025.

A. Dieppe, R. Legrand, and B. Van Roye. The BEAR toolbox. 2016.

N. Dunz, A. Naqvi, and I. Monasterolo. Climate sentiments, transition risk, and financial stability in a stock-flow consistent model. *Journal of Financial Stability*, 54:100872, 2021.

R. F. Engle, S. Giglio, B. T. Kelly, H. Lee, and J. Stroebel. Hedging climate change news. *Review of Financial Studies*, 33(3):1184–1216, 2020.

R. Faccini, R. Matin, and G. Skiadopoulos. Dissecting climate risks: are they reflected in stock prices? *Journal of Banking & Finance*, 155:106948, 2023.

S. Fried, K. Novan, and W. B. Peterman. The macro effects of climate policy uncertainty. Finance and Economics Discussion Series 2021-018, Board of Governors of the Federal Reserve System, 2021.

K. Gavriilidis. Measuring climate policy uncertainty. *Available at SSRN 3847388*, 2021.

Y. Ge, X. Xu, C. Yu, and J. Meng. Macroeconomic uncertainty and the excess returns of stock. *The European Journal of Finance*, 31(3):260–288, 2024.

D. Giannone, M. Lenza, and G. E. Primiceri. Prior selection for vector autoregressions. *Review of Economics and Statistics*, 97(2):436–451, 2015.

S. Giglio, B. Kelly, and J. Stroebel. Climate finance. *Annual Review of Financial Economics*, 13:15–36, 2021.

S. Gilchrist and E. Zakrajšek. Credit spreads and business cycle fluctuations. *American Economic Review*, 102(4):1692–1720, 2012.

M. Giuliodori. The role of house prices in the monetary transmission mechanism across European countries. *Scottish Journal of Political Economy*, 52(4):519–543, 2005.

M. Görgen, A. Jacob, and M. Nerlinger. Get green or die trying? Carbon risk integration into portfolio management. *Journal of Portfolio Management*, 47(3):77–93, 2021.

M. Guidolin, A. G. Orlov, and M. Pedio. The impact of monetary policy on corporate bonds under regime shifts. *Journal of Banking & Finance*, 80:176–202, 2017.

C. S. Hakkio and W. R. Keeton. Financial stress: what is it, how can it be measured, and why does it matter? *Economic Review*, 94(2):5–50, 2009.

J. Hilscher, A. Raviv, and R. Reis. Inflating away the public debt? An empirical assessment. *Review of Financial Studies*, 35(3):1553–1595, 2022.

H. Hong, G. A. Karolyi, and J. A. Scheinkman. Climate finance. *Review of Financial Studies*, 33(3):1011–1023, 2020.

Q. Ji, D. Ma, P. Zhai, Y. Fan, and D. Zhang. Global climate policy uncertainty and financial markets. *Journal of International Financial Markets, Institutions and Money*, 102047, 2024.

K. Jurado, S. C. Ludvigson, and S. Ng. Measuring uncertainty. *American Economic Review*, 105(3):1177–1216, 2015.

K. R. Kadiyala and S. Karlsson. Numerical methods for estimation and inference in Bayesian VAR-models. *Journal of Applied Econometrics*, 12(2):99–132, 1997.

L. Kilian and H. Lütkepohl. *Structural vector autoregressive analysis*. Cambridge University Press, 2017.

K. L. Kliesen, M. T. Owyang, and E. K. Vermann. Disentangling diverse measures: a survey of financial stress indexes. *Federal Reserve Bank of St. Louis Review*, 94, 2012.

P. Krüger, Z. Sautner, and L. T. Starks. The importance of climate risks for institutional investors. *Review of Financial Studies*, 33(3):1067–1111, 2020.

S. Leduc and Z. Liu. Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, 82:20–35, 2016.

S. Lenz and A. S. Posen. The macroeconomic effects of COVID-19: a mid-term review. *Economic Policy*, 35(104):523–580, 2020.

M. Lenza and J. Slacalek. How does monetary policy affect income and wealth inequality? *Journal of Applied Econometrics*, 39(5):746–765, 2024.

C. Liang, Q. Luo, Y. Li, and L. D. T. Huynh. Global financial stress index and long-term volatility forecast for international stock markets. *Journal of International Financial Markets, Institutions and Money*, 88:101825, 2023.

S. C. Ludvigson, S. Ma, and S. Ng. Uncertainty and business cycles: exogenous impulse or endogenous response? *American Economic Journal: Macroeconomics*, 13(4):369–410, 2021.

I. Monasterolo. Climate change and the financial system. *Annual Review of Resource Economics*, 12(1):299–320, 2020.

U. K. Müller. Measuring prior sensitivity and prior informativeness in large Bayesian models. *Journal of Monetary Economics*, 59(6):581–597, 2012.

N. Pankratz, R. Bauer, and J. Derwall. Climate change, firm performance, and investor surprises. *Management Science*, 69(12):7352–7398, 2023.

Ľ. Pástor and R. F. Stambaugh. Costs of equity capital and model mispricing. *Journal of Finance*, 54(1):67–121, 1999.

L. Pastor and P. Veronesi. Uncertainty about government policy and stock prices. *Journal of Finance*, 67(4):1219–1264, 2012.

Ľ. Pástor, R. F. Stambaugh, and L. A. Taylor. Dissecting green returns. *Journal of Financial Economics*, 146(2):403–424, 2022.

A. Samarina and A. D. Nguyen. Does monetary policy affect income inequality in the euro area? *Journal of Money, Credit and Banking*, 56(1):35–80, 2024.

C. A. Sims. Interpreting the macroeconomic time series facts: the effects of monetary policy. *European Economic Review*, 36(5):975–1000, 1992.

C. A. Sims and T. Zha. Bayesian methods for dynamic multivariate models. *International*

Economic Review, pages 949–968, 1998.

C. A. Sims, J. H. Stock, and M. W. Watson. Inference in linear time series models with some unit roots. *Econometrica*, pages 113–144, 1990.

J. Stroebel and J. Wurgler. What do you think about climate finance? *Journal of Financial Economics*, 142(2):487–498, 2021.

F. Van der Ploeg and A. Rezai. Stranded assets in the transition to a carbon-free economy. *Annual Review of Resource Economics*, 12(1):281–298, 2020.

J. C. Wu and F. D. Xia. Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291, 2016.

P.-X. Zhai, Q. Ji, and Y.-R. Ma. Climate risks and financial market: a review of the literature. *Climate Change Economics*, 2024.

Appendix to Climate Policy Uncertainty and Financial Dynamics: Insights from a Bayesian SVAR

Appendix A: Data Sources

- **Climate Policy Uncertainty.** Climate Policy Uncertainty Index. Source: Economic Policy Uncertainty's site.

  The Climate Policy Uncertainty index has been created by Gavriilidis (2021), following a methodology similar to the one developed by Baker et al. (2016) for the Economic Policy Uncertainty index. To construct this index, a comprehensive analysis of articles from eight prominent U.S. newspapers was undertaken, concentrating on a specific set of keywords that capture the uncertainties surrounding climate policy.

- **VIX.** CBOE Volatility Index: VIX, Index, Monthly. Source: FRED.

- **Financial Stress Index.** St. Louis Fed Financial Stress Index, Monthly. Source: FRED.

- **S&P price-dividend ratio**. S&P log price-dividend ratio. Source: Bloomberg and calculations by the authors.

- **S&P 500**. S&P 500 - Price Index. Source: Bloomberg.

- **Short-term Interest Rate.** Federal Funds Effective Rate, Percent, Monthly. Source: FRED.

- **Shadow Interest Rate.** Jing Cynthia Wu's elaboration, Percent, Monthly. Source: Jing Cynthia Wu'site.

- **CPI.** Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, Index 1982-1984 = 100, Monthly. Source: FRED.

- **Industrial Production.** Industrial Production: Total Index, Index 2017 = 100, Monthly. Source: FRED.

- **Consumer Index.** University of Michigan: Consumer Sentiment, Index 1966:Q1 = 100, Monthly. Source: FRED

- **Unemployment.** Unemployment Rate, Percent, Monthly. Source: FRED.

Appendix B: Descriptive and Correlation Analysis

Table 3 reports the main descriptive statistics for the variables included in the analysis. The series exhibit marked heterogeneity in their levels and dispersion, reflecting fundamental differences between financial market indicators, macroeconomic aggregates, and measures of uncertainty and economic stress used in this paper.

The CPU index displays moderate variability over the sample period, with a mean of 4.57 and fluctuations confined to a relatively narrow range, suggesting persistent but not excessively volatile policy-related uncertainty. A similar pattern characterizes the VIX, which shows limited dispersion around its mean, consistent with its role as a forward-looking measure of market uncertainty that remains stable in tranquil periods but experiences episodic spikes during stress events. By contrast, the Financial Stress Index (FSI) is considerably more volatile, with a mean close to zero, large standard deviation, and wide support, including pronounced negative and positive extremes.

Financial and macroeconomic variables display more stable dynamics. Equity-related measures such as the price–dividend ratio and the S&P 500 index exhibit moderate dispersion around their means, reflecting long-run growth trends with cyclical fluctuations. The federal funds rate shows substantial variation over the sample, consistent with changes in the monetary policy regime, including periods of tightening, easing, and proximity to the zero lower bound. Inflation and industrial production are comparatively smooth, with low standard deviations and narrow ranges, while sentiment and unemployment display greater variability, particularly the unemployment rate. Overall, the descriptive statistics confirm that the dataset combines slow-moving macroeconomic indicators with highly volatile financial and uncertainty measures.

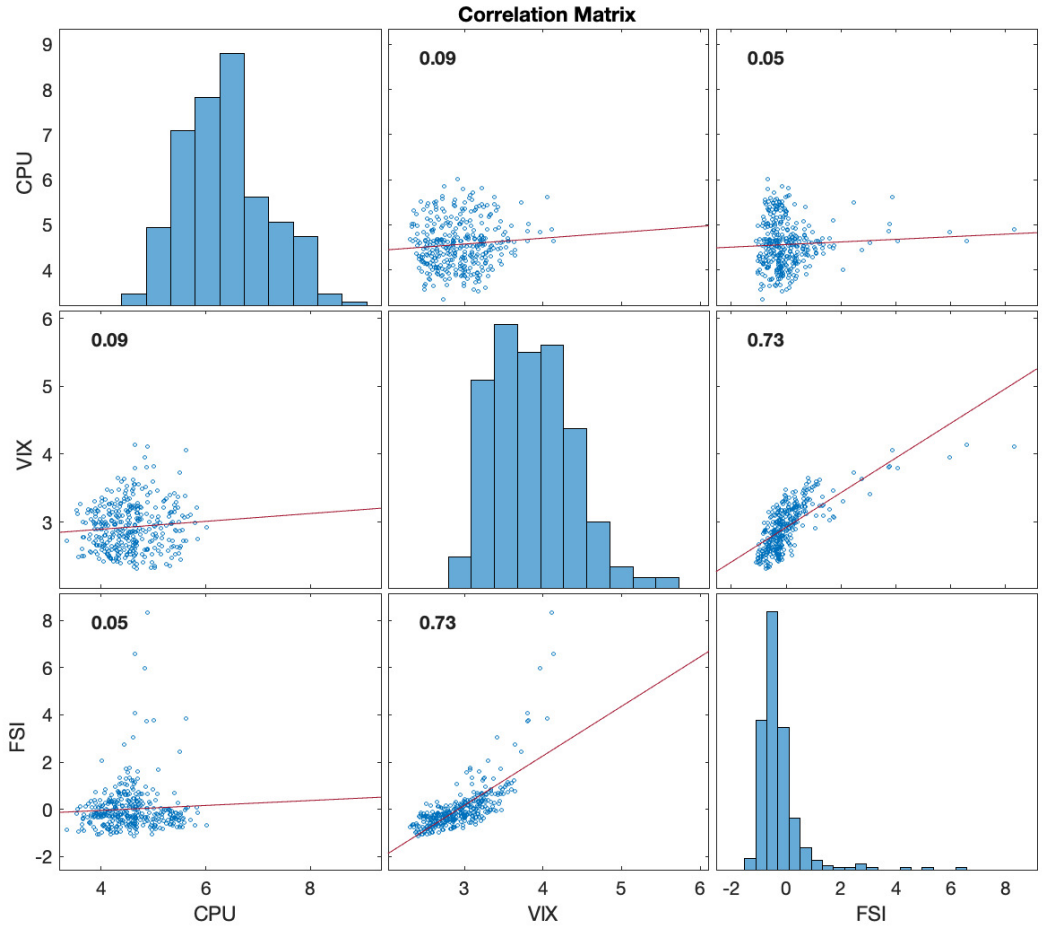
Table 3: Descriptive Statistics

U.S. Data					
Variable	Obs	Mean	Std. dev.	Min	Max
CPU	360	4.57	0.51	3.34	6.02
VIX	360	2.93	0.34	2.32	4.14
FSI	360	0.02	0.98	-1.11	8.32
PDR	360	4.00	0.22	3.32	4.51
S&P500	360	7.30	0.60	6.10	8.48
FFR	360	2.47	2.23	0.05	6.54
CPI	360	5.34	0.20	4.99	5.73
IP	360	4.53	0.11	4.20	4.65
SENT	360	4.44	0.17	3.91	4.72
UNEM	360	5.64	0.81	3.40	14.80

The sample spans the period 1994m1–2023m12. The dataset includes CPU, VIX, FSI, PDR, S&P500, FFR, CPI, IP, UNEM, and SENT. All variables are expressed in logarithms, with the exception of FSI, FFR, and UNEM, which enter the model in levels.

Figure 11 displays the correlations between the alternative uncertainty and stress measures used in the paper. While FSI and VIX appear to be highly correlated, with an estimated correlation coefficient of 0.73, the CPU shows weak correlations with both the VIX and the FSI.

Figure 11
Correlation Matrix.



Pair-wise Pearson's correlation coefficients. The uncertainty/stress measures represented in the plots are: Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12.

Appendix C: Bayesian SVAR Estimation

As a baseline model, we utilize a diffuse (Jeffrey's) prior for Σ, which represents a flexible selection. This approach is useful when one remains agnostic about the values of Σ. The

likelihood and the prior for β are expressed as follows:

$$L(\beta, \Sigma) \propto \exp\left(-\frac{1}{2}(\beta - \hat{\beta})^\top \left(\Sigma^{-1} \otimes (X^\top X)\right)(\beta - \hat{\beta})\right)$$

$$\pi(\beta) \propto \exp\left(-\frac{1}{2}(\beta - \beta_0)^\top \Omega_0^{-1}(\beta - \beta_0)\right),$$

where Σ is defined as:

$$\pi(\Sigma) \propto |\Sigma|^{-\frac{n+1}{2}}.$$

This prior is improper as it does not integrate to one but rather to infinity. Despite this, the posterior distribution remains proper because when combining the likelihood and priors, we obtain the joint posterior:

$$\pi(\beta, \Sigma|y) \propto |\Sigma|^{-\frac{T+n+1}{2}} \exp\left(-\frac{1}{2}(\beta - \hat{\beta})^\top(\Sigma^{-1} \otimes X^\top X)(\beta - \hat{\beta}) - \frac{1}{2}\text{tr}\left(\Sigma^{-1}(Y - X\beta)^\top(Y - X\beta)\right)\right)$$

By marginalizing over Σ, the conditional posterior for β is a multivariate normal distribution:

$$\pi(\beta|\Sigma, y) \sim N(\bar{\beta}, \bar{\Omega}).$$

Similarly, the conditional posterior for Σ follows an inverse-Wishart distribution:

$$\pi(\Sigma|\beta, y) \sim IW(\tilde{S}, T),$$

where $\tilde{S} = (Y - X\beta)^\top(Y - X\beta)$ is the scale matrix.

We use a Gibbs sampler within the standard Bayesian VAR framework, adapted to our inverse-Wishart specification for the variance–covariance matrix through the choice of the scale matrix and degrees of freedom. This algorithm typically involves the following steps:

1. At each iteration n:

   (a) Draw $\Sigma^{(n)}$: Given $B^{(n-1)}$, draw $\Sigma^{(n)}$ from an inverse-Wishart distribution with the following scale matrix and degrees of freedom

   $$\pi(\Sigma \mid \beta^{(n-1)}, y) \sim IW(\tilde{S}, T),$$

   where

   $$\tilde{S} = (Y - XB^{(n-1)})^\top(Y - XB^{(n-1)}),$$

   and T is the number of time periods.

   (b) Draw $\beta^{(n)}$: Conditional on $\Sigma^{(n)}$, draw $\beta^{(n)}$ from a multivariate normal distribution

   $$\pi(\beta \mid \Sigma^{(n)}, y) \sim N(\bar{\beta}, \bar{\Omega}),$$

   where

   $$\bar{\Omega} = \left(\Omega_0^{-1} + \Sigma^{-1} \otimes (X^\top X)\right)^{-1},$$

and

$$\bar{\beta} = \bar{\Omega}\left(\Omega_0^{-1}\beta_0 + (\Sigma^{-1} \otimes X^\top)y\right).$$

2. Repeat the previous steps for a number I_t of iterations.

3. Remove the first B_u iterations (burn-in phase), and use the remaining draws to construct the empirical posterior distributions for β and Σ.

Selection of Hyperparameters

In our empirical set up, we may select four key hyperparameters: λ_1, λ_2, λ_3, and λ_4, each playing a distinct role in determining the prior distributions of the coefficients:

- **Overall tightness (λ_1)**: this hyperparameter regulates the overall variance of the autoregressive coefficients. When λ_1 is low (approaches 0), the model adopts a stronger prior assumption that the coefficients should be small, effectively pulling them toward zero. Conversely, a higher λ_1 provides more flexibility, allowing the data to exercise a stronger influence on the posterior findings. In our baseline model, λ_1 is set to 0, reflecting a strong prior belief in tightly constrained-to-zero coefficients that imply no reaction by the financial variables of interest to all types of shocks we experiment with, including the climate-related ones.

- **Cross-variable weighting (λ_2)**: this hyperparameter governs the prior variance of the cross-lag coefficients, i.e., the coefficients on lagged values of other variables appearing in each VAR equation. Lower values of λ_2 imply stronger prior shrinkage toward zero for cross-variable lag coefficients, reflecting a prior belief that cross-variable dynamic effects are relatively weak. Effectively, setting $\lambda_2 = 0$ shrinks the posterior towards turning a VAR towards a collection of seemingly-unrelated AR(p) models. We set $\lambda_2 = 1$, implying no additional shrinkage on cross-lag coefficients relative to own-lag coefficients.

- **Lag decay weighting (λ_3)**: this hyperparameter governs how rapidly the influence of lagged variables decays as the lag order increases. A higher value of λ_3 implies that higher-order lags retain greater importance, whereas a lower value induces a faster decline in their relevance. Setting $\lambda_3 = 1$ corresponds to the standard assumption that the effects of past observations decay at a moderate and smoothly decreasing rate as one considers increasing lags.

- **Exogenous variable tightness (λ_4)**: this hyperparameter controls the prior variance assigned to the coefficients of exogenous variables, including the constant term. Choosing a large value of λ_4 (we set it to 100 in our specification) implies very weak prior shrinkage on these coefficients, allowing them to be estimated largely from the data with minimal prior interference.

In practice, in the case of the parameters linking a variable to its own lags, the prior variance can be written as:

$$\sigma_{a_{ii}}^2 = \left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2.$$

As for the cross-variable lag coefficients, their prior variance is

$$\sigma_{a_{ij}}^2 = \left(\frac{\sigma_i \lambda_1 \lambda_2}{\sigma_j l^{\lambda_3}}\right)^2,$$

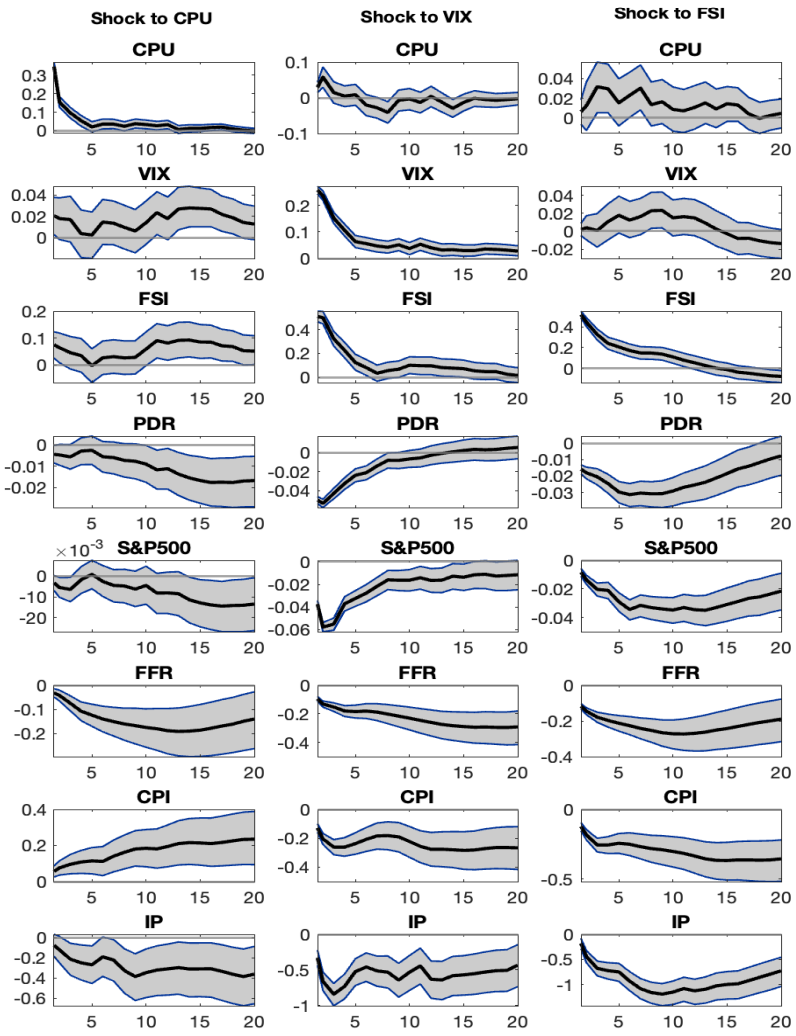
where σ_i and σ_j denote the residual variances derived from separate autoregressive models for variables i and j. In the case of the coefficients associated to the exogenous variables, the variance is:

$$\sigma_{c_i}^2 = \sigma_i^2 (\lambda_1 \lambda_4)^2.$$

Appendix D: Additional Robustness Checks

Figure 12 displays the impulse responses to a CPU shock, identified using the same baseline model as in the main text, but with a Dummy Observations set as the prior. Overall, the main results, particularly in terms of signs of the IRFs, remain unaffected.

Figure 12
Dummy Observations Prior. Impulse Response Functions.

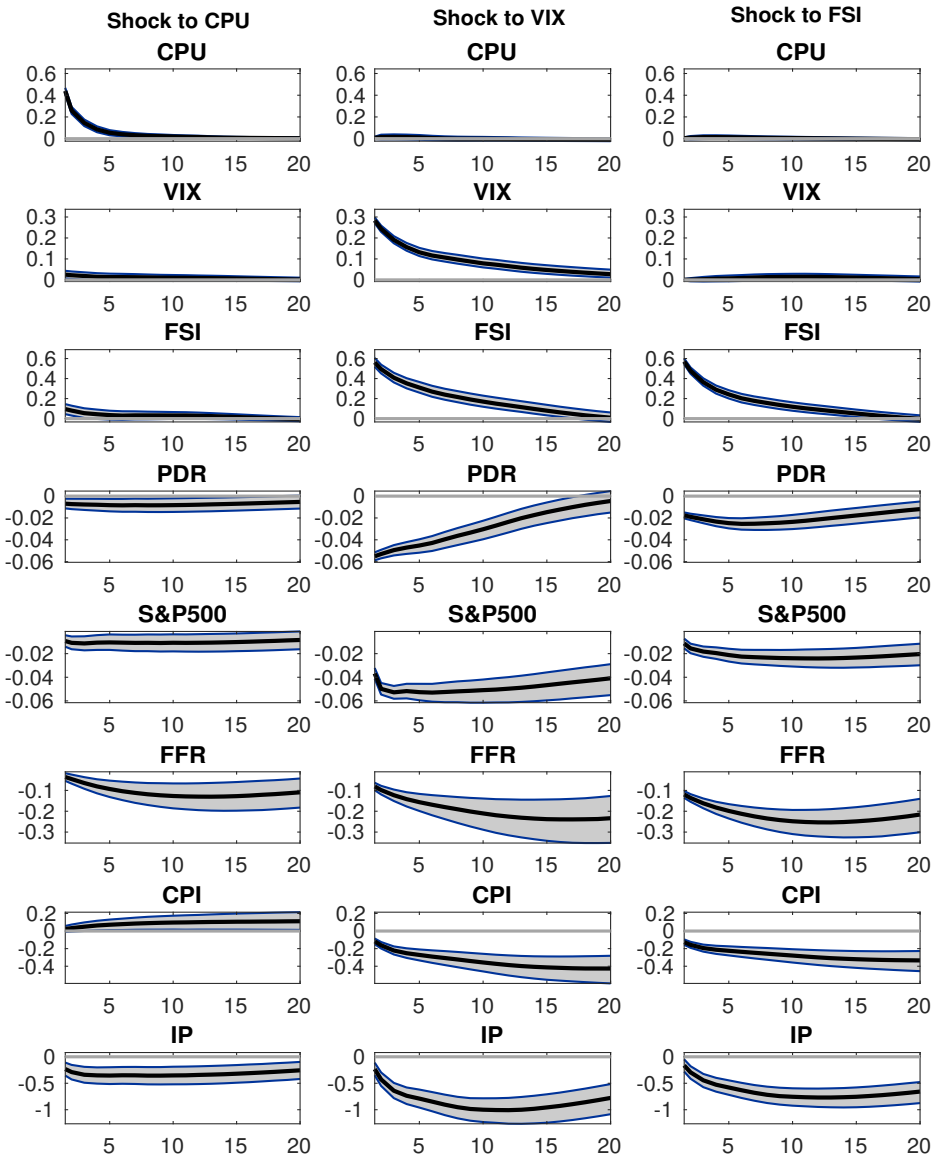


Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. 12 lags. The impulse responses for CPI, FFR and IP should be interpreted in percentage points. The gray area represents the 68% highest posterior density credible sets for the IRF, while the black lines indicate the pointwise median IRFs under the baseline identification.

Appendix E: Equally Scaled IRFs

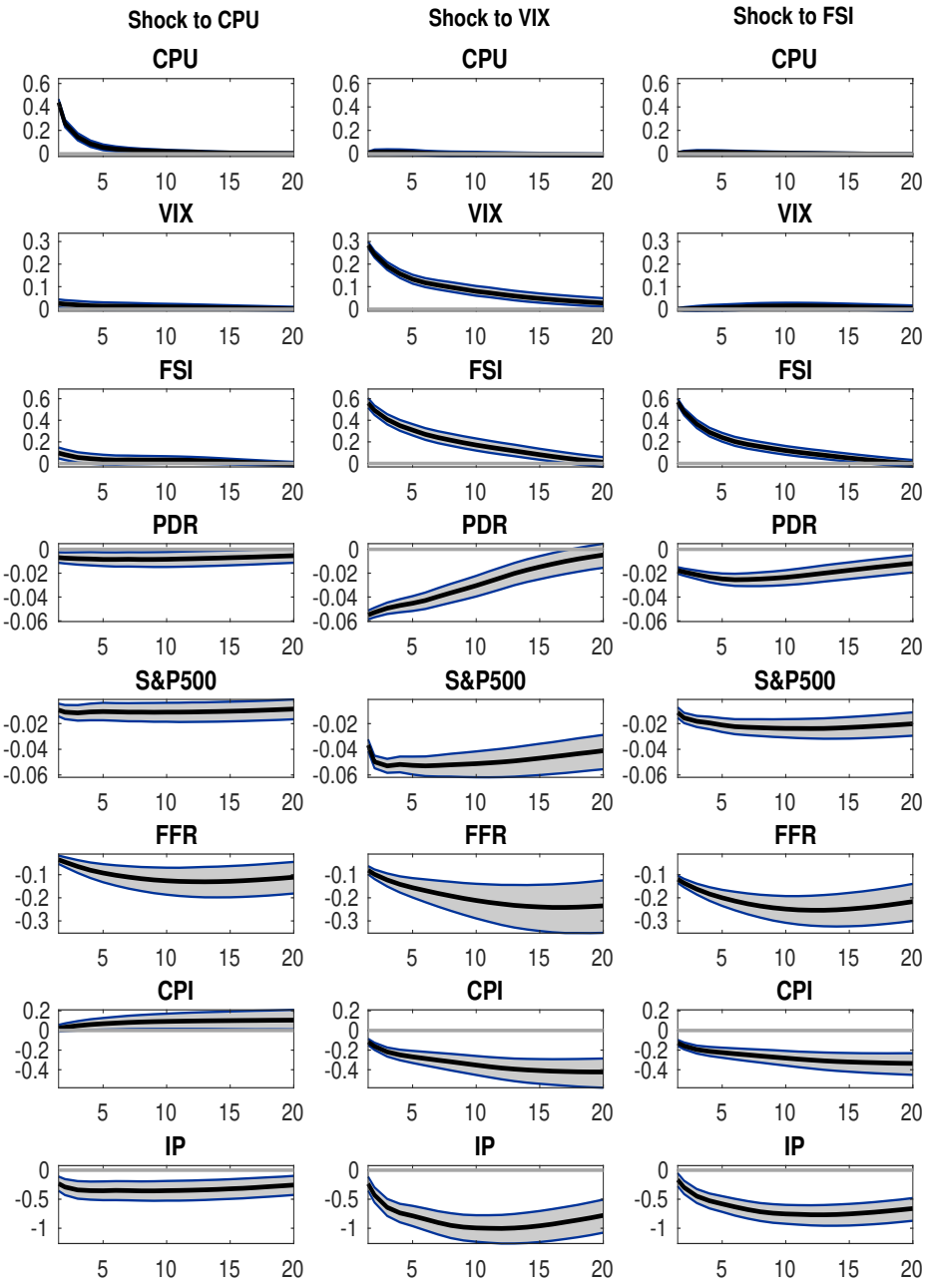
In this appendix we report IRF plots for the same shocks and exercises in the main text, when the vertical axis is identically scaled (by row) across different shocks. In particular, Figure 13 corresponds to Figure 2, Figures 15, 16, and 17 to Figure 7, Figures 18 and 19 to Figure 8, Figure 20 to Figure 9, Figure 21 to Figure 10, Figure 14 to Figure 3, Figure 22 to Figure 12, Figure 23 to Figure 25, Figure 24 to Figure 26.

Figure 13
Equally Scaled IRFs. Figure 2. Baseline Results.



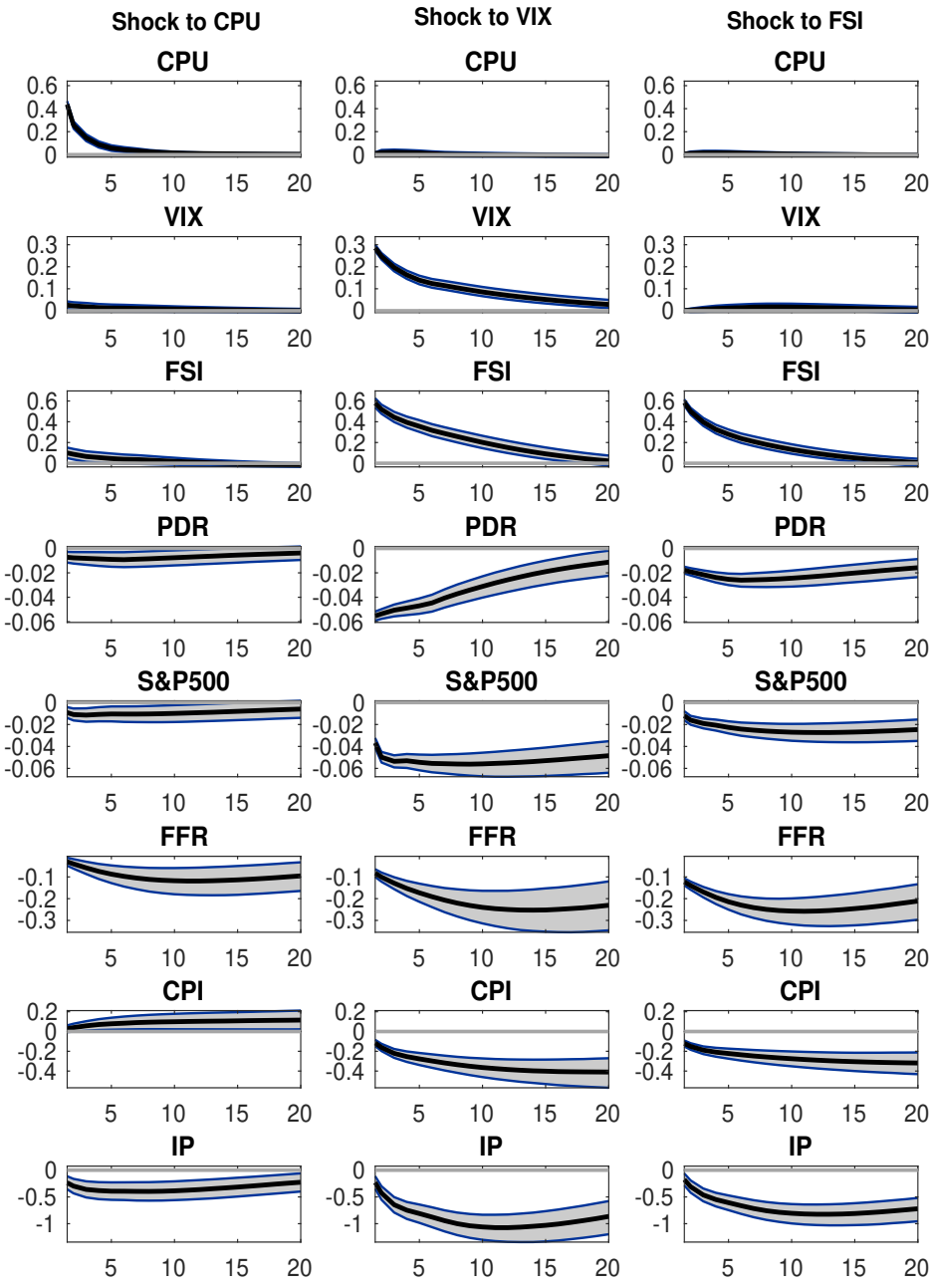
Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Baseline Case. Sample: 1994m1–2023m12.

Figure 14
Equally Scaled IRFs. Figure 3. Giannone et al. (2015)'s Optimization.



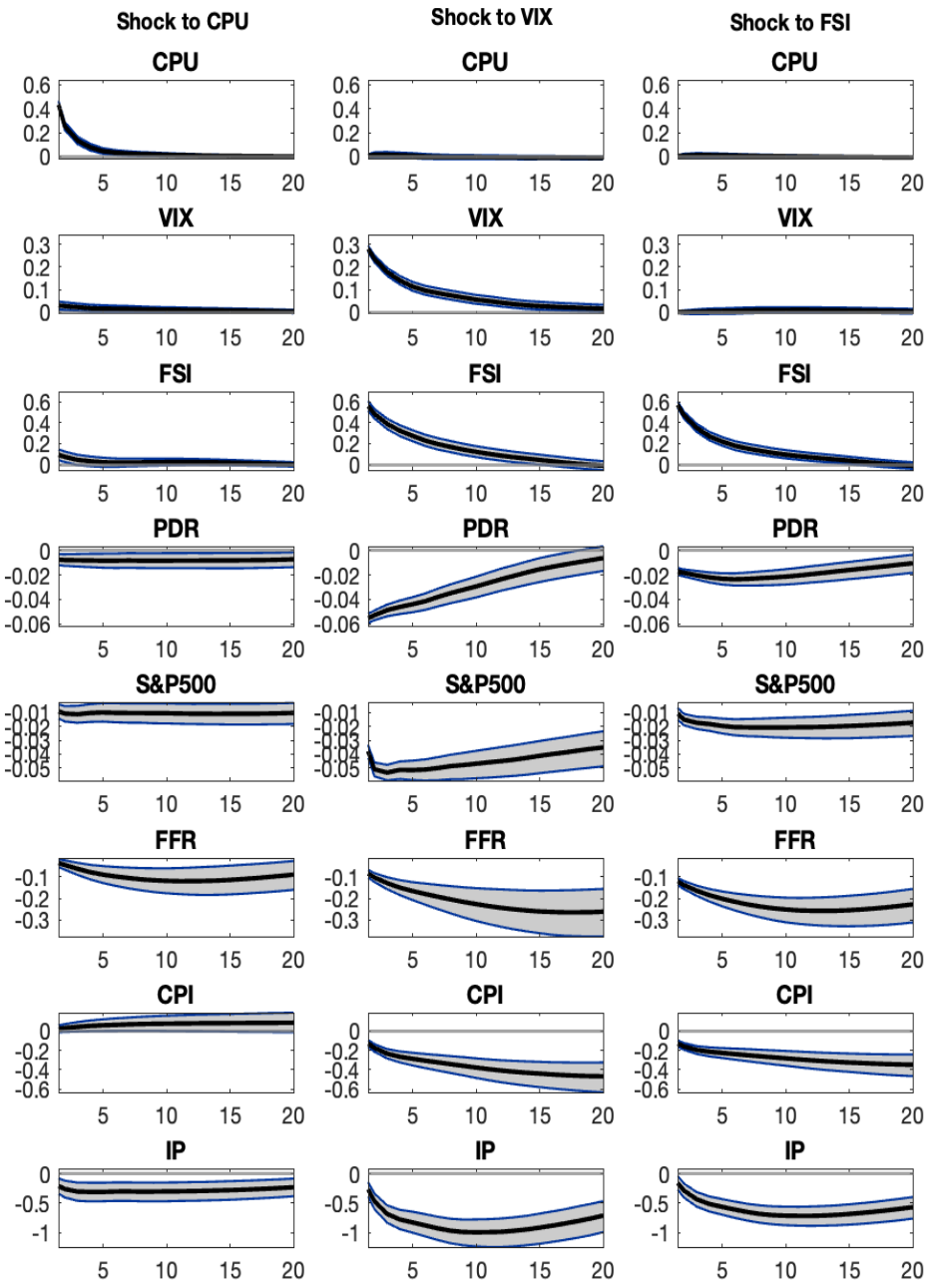
Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Giannone et al. (2015)'s optimization. Sample: 1994m1–2023m12.

Figure 15
Equally Scaled IRFs. Figure 7. 6 lags.



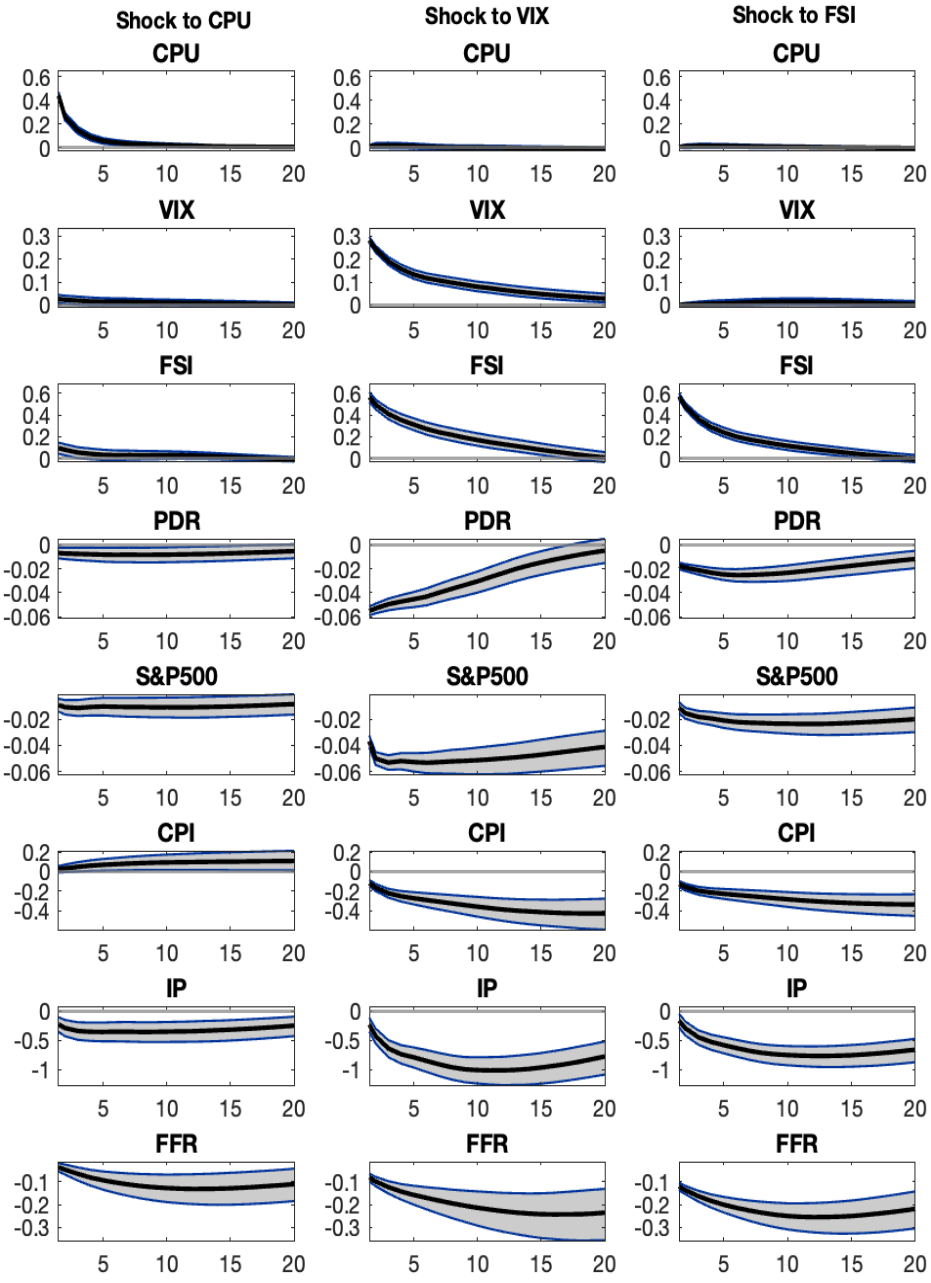
Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. 6 lags.

Figure 16
Equally Scaled IRFs Figure 7. 24 lags.



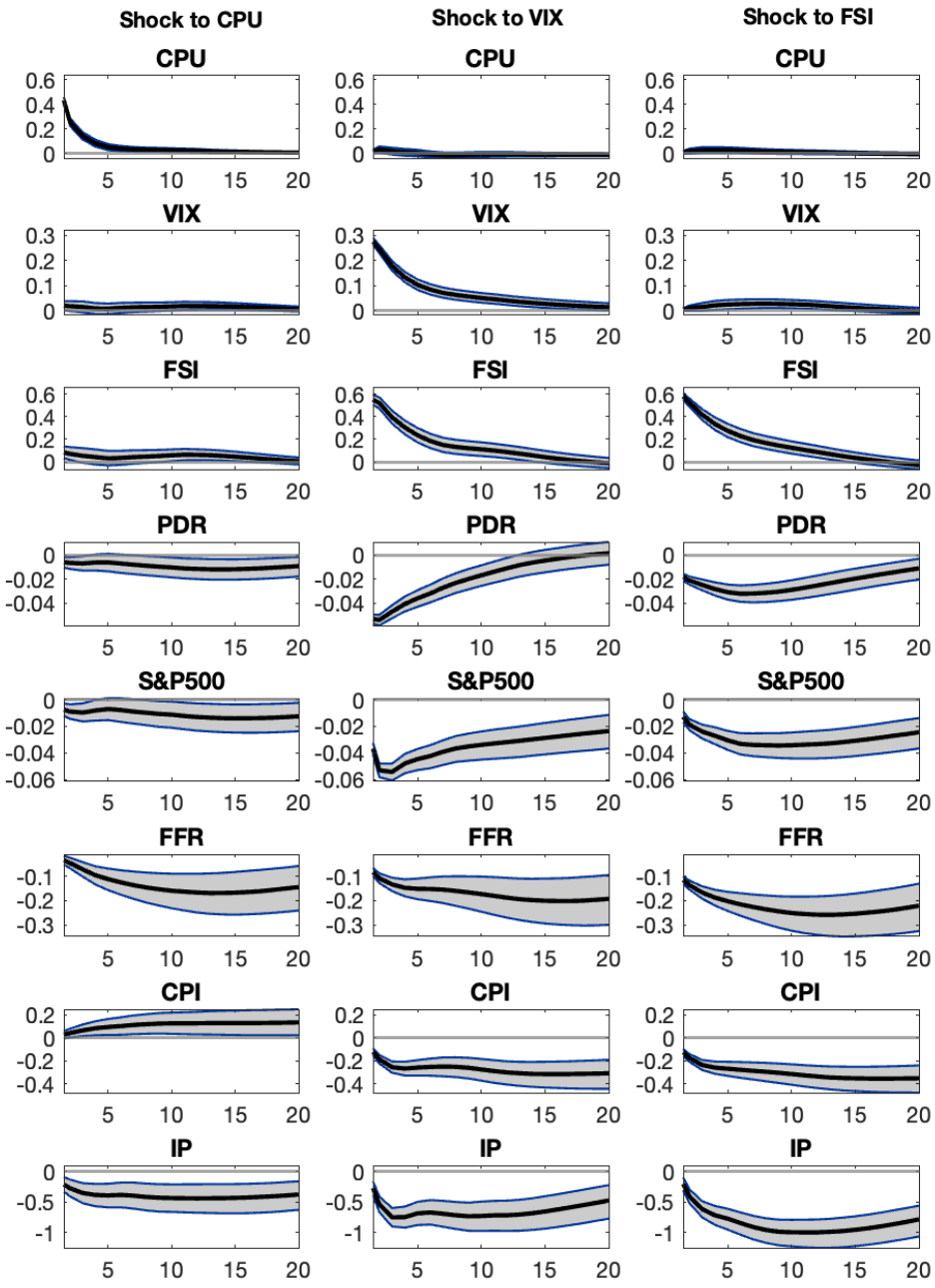
Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. 24 lags.

Figure 17
Equally Scaled IRFs Figure 7. Different Ordering.



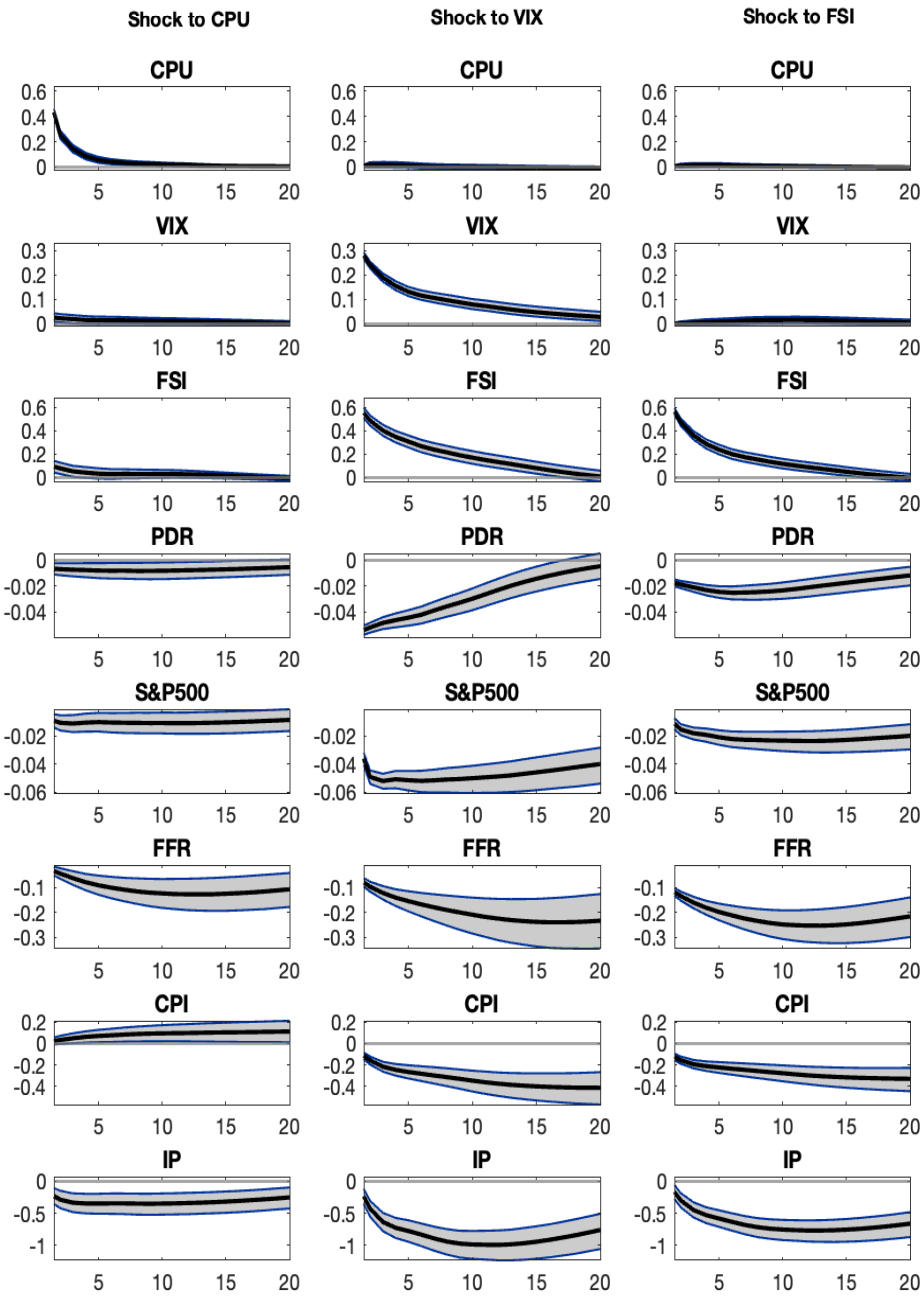
Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. FFR after CPI and IP.

Figure 18
Equally Scaled IRFs. Figure 18. Normal Wishart Prior



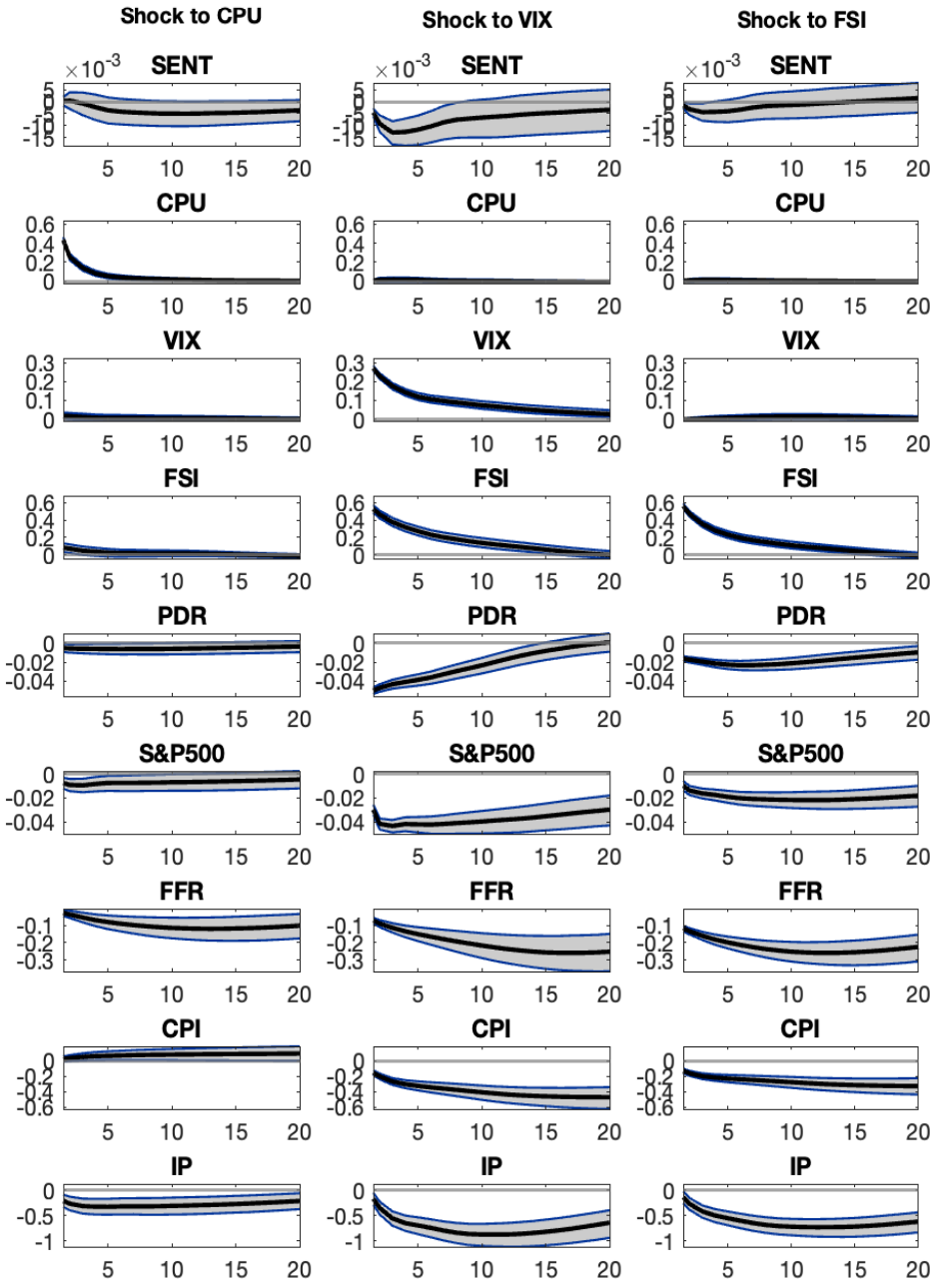
Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Normal Wishart Prior. Sample: 1994m1–2023m12.

Figure 19
Equally Scaled IRFs. Figure 18. Independent Normal Wishart Prior



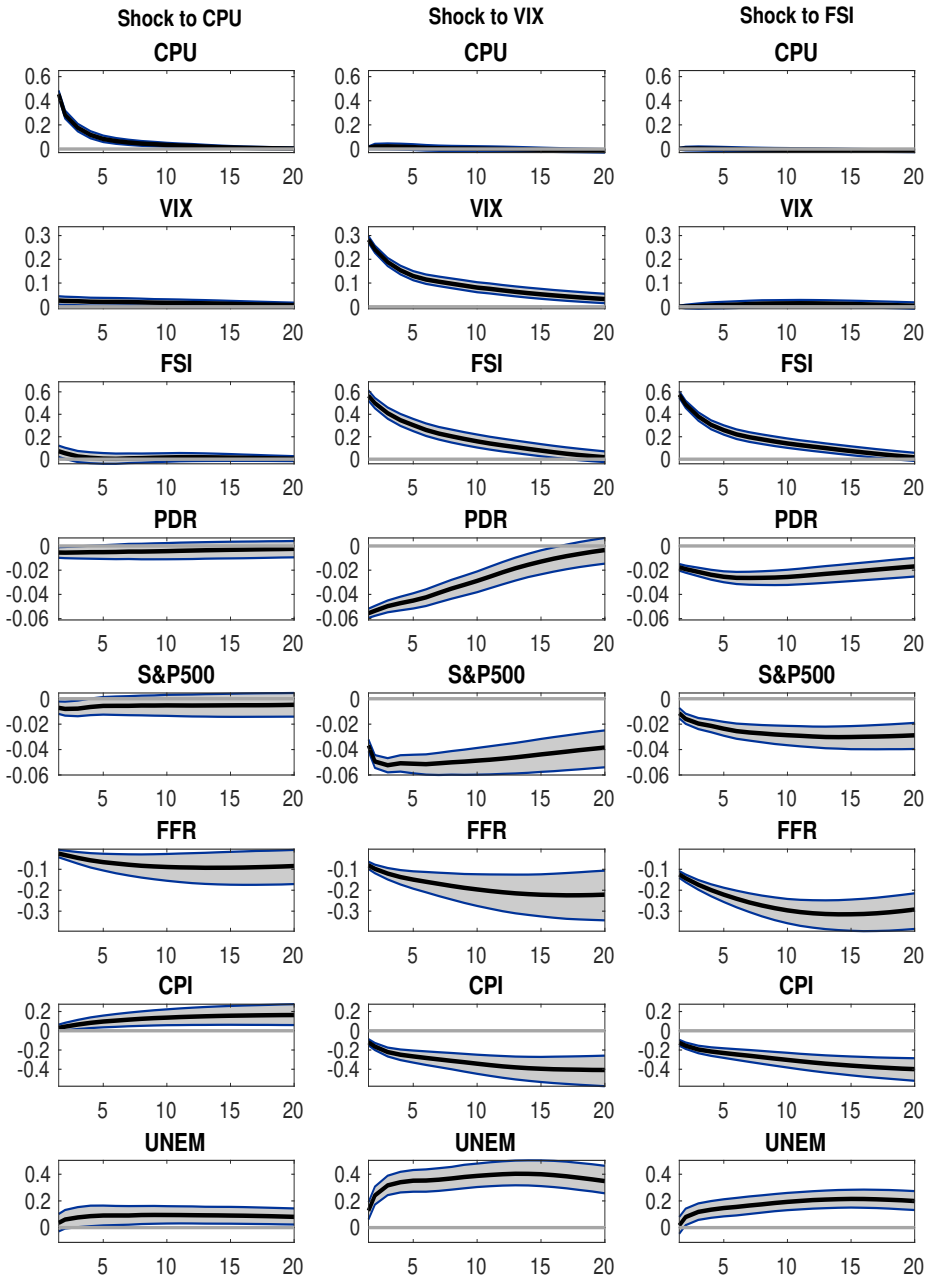
Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Independent Normal Wishart Prior. Sample: 1994m1–2023m12.

Figure 20
Equally Scaled IRFs Figure 9. Obmitted Variables



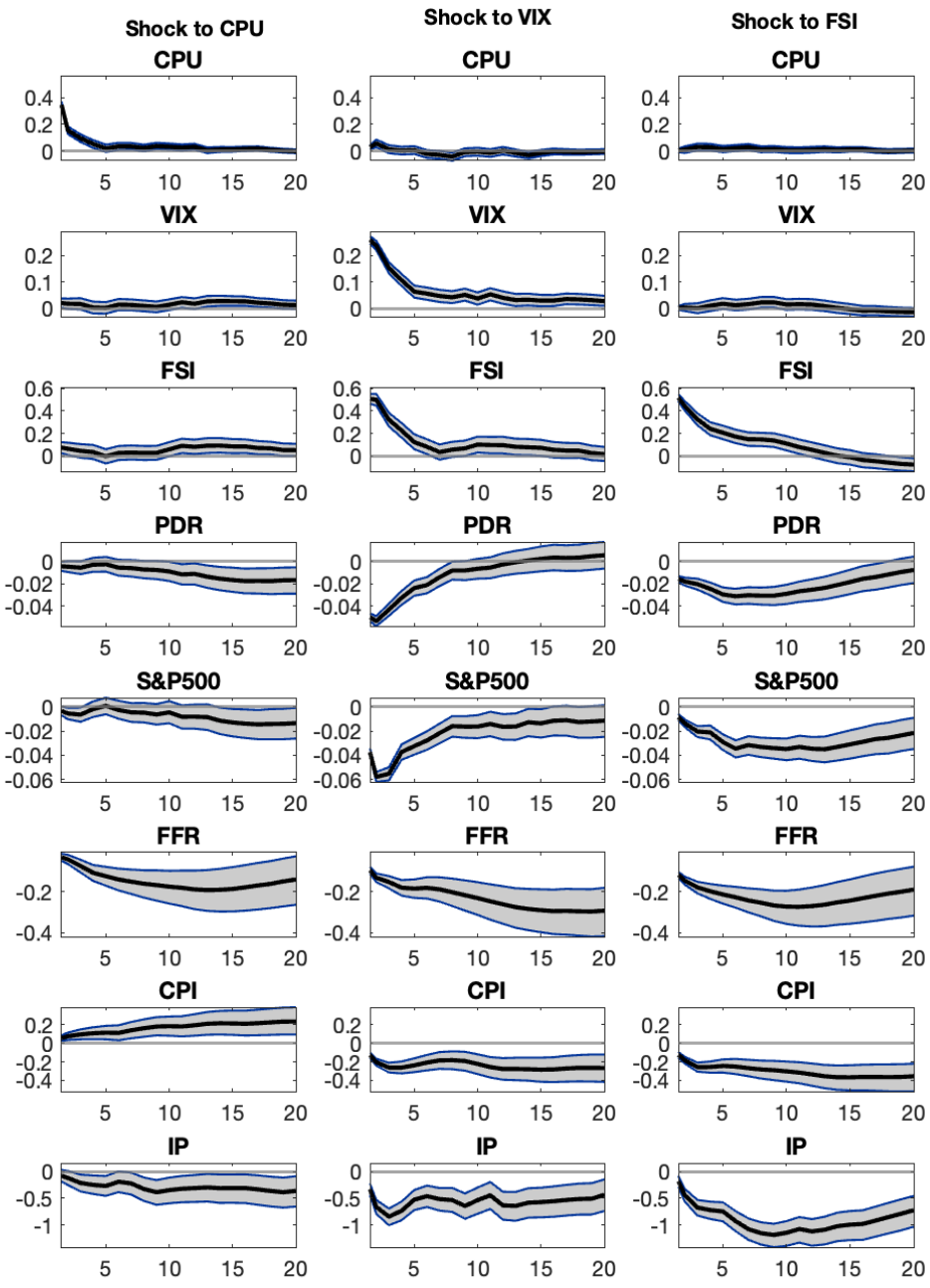
Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. Consumer Sentiment as additional variable.

Figure 21
Equally Scaled IRFs Figure 10. Unemployment



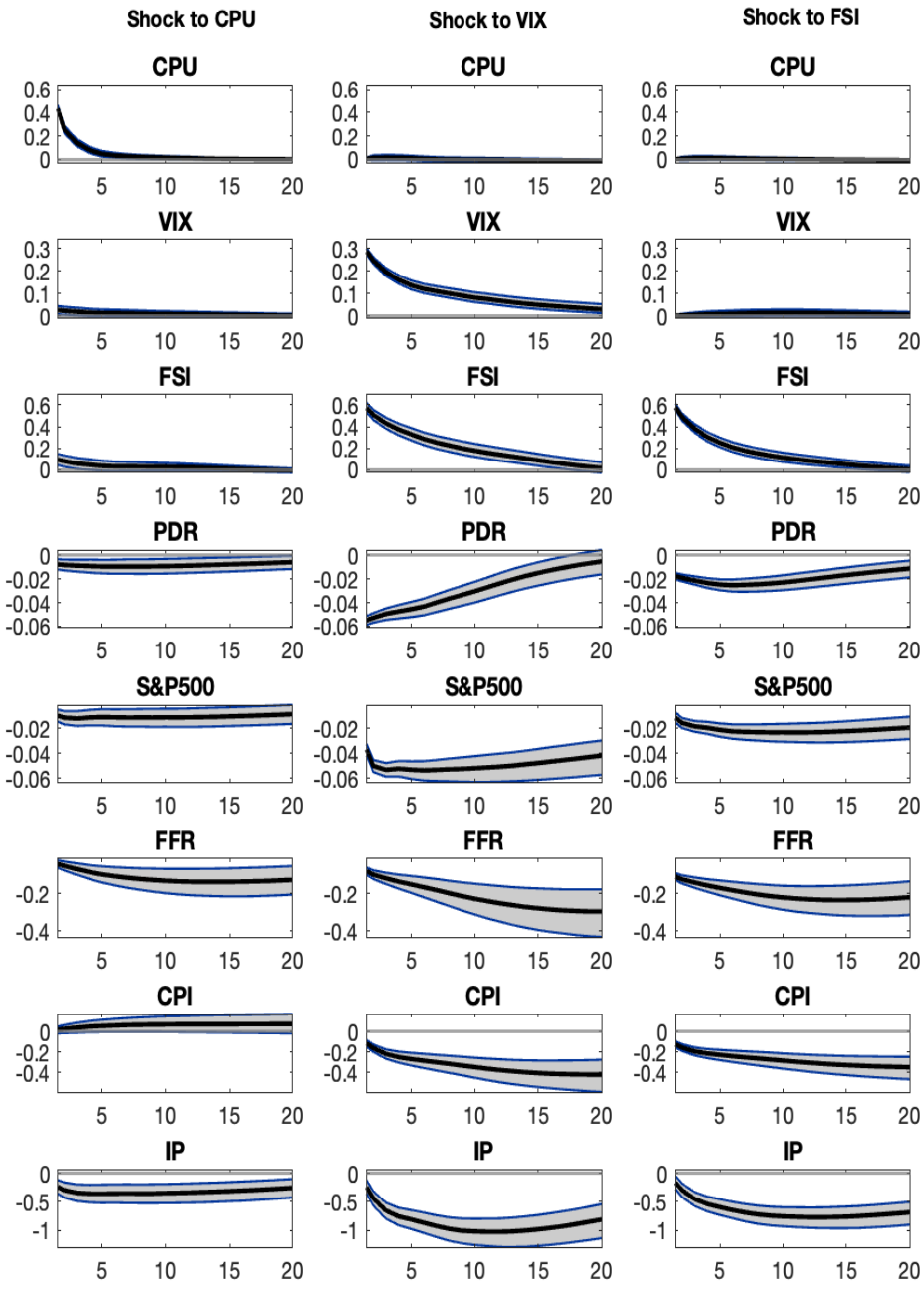
Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. Unemployment as a proxy of real economic (un)activity.

Figure 22
Equally Scaled IRFs. Figure 12. Dummy Observations Prior



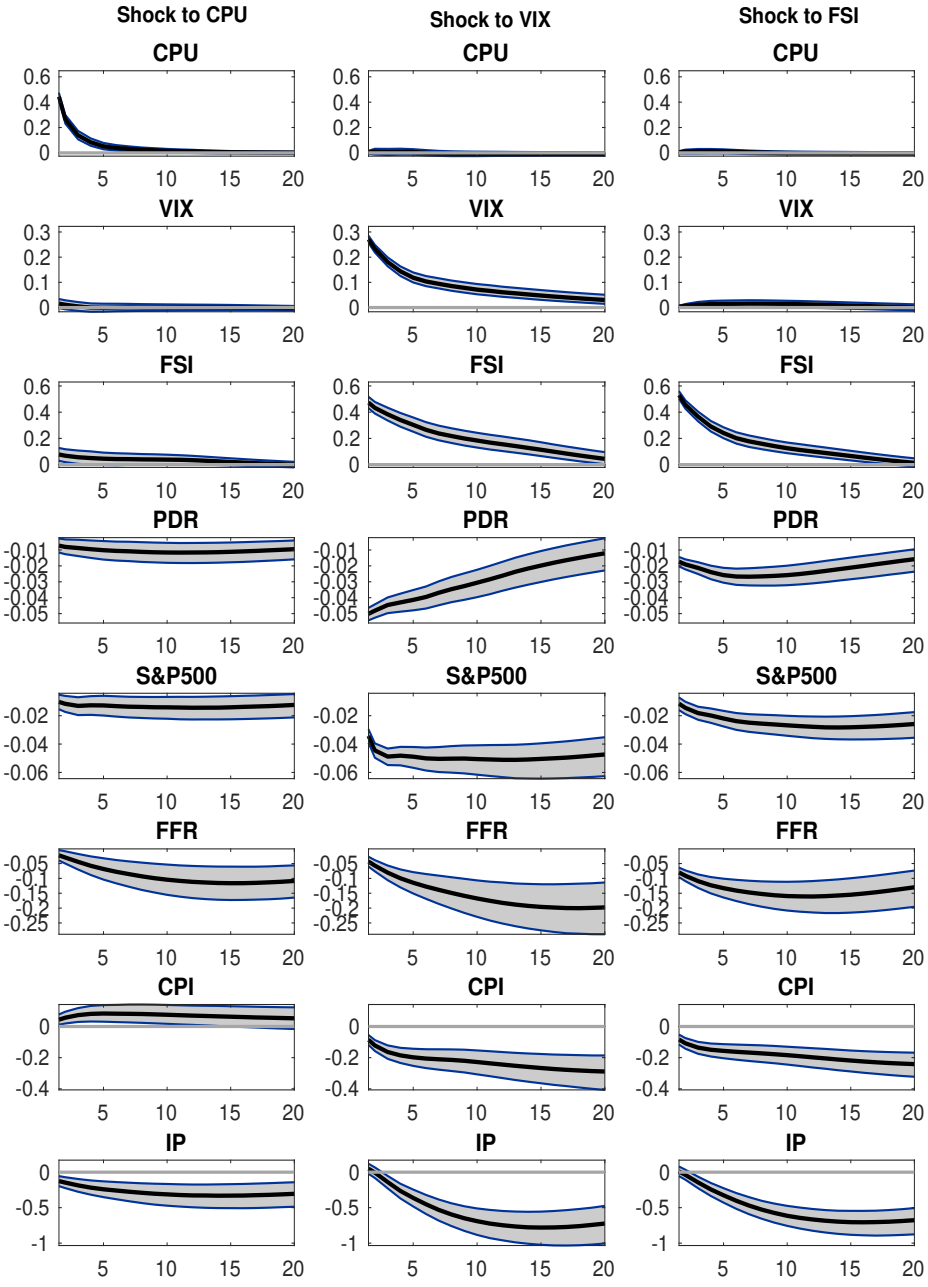
Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Dummy Observations Prior. Sample: 1994m1–2023m12. Figure 12. Same Size IRF.

Figure 23
Equally Scaled IRFs, Figure 25, Shadow Interest Rate



Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Sample: 1994m1–2023m12. Shadow Interest Rate is used from December 2008 to December 2015.

Figure 24
Equally Scaled IRFs. Figure 26. Pre Covid-19 Sample

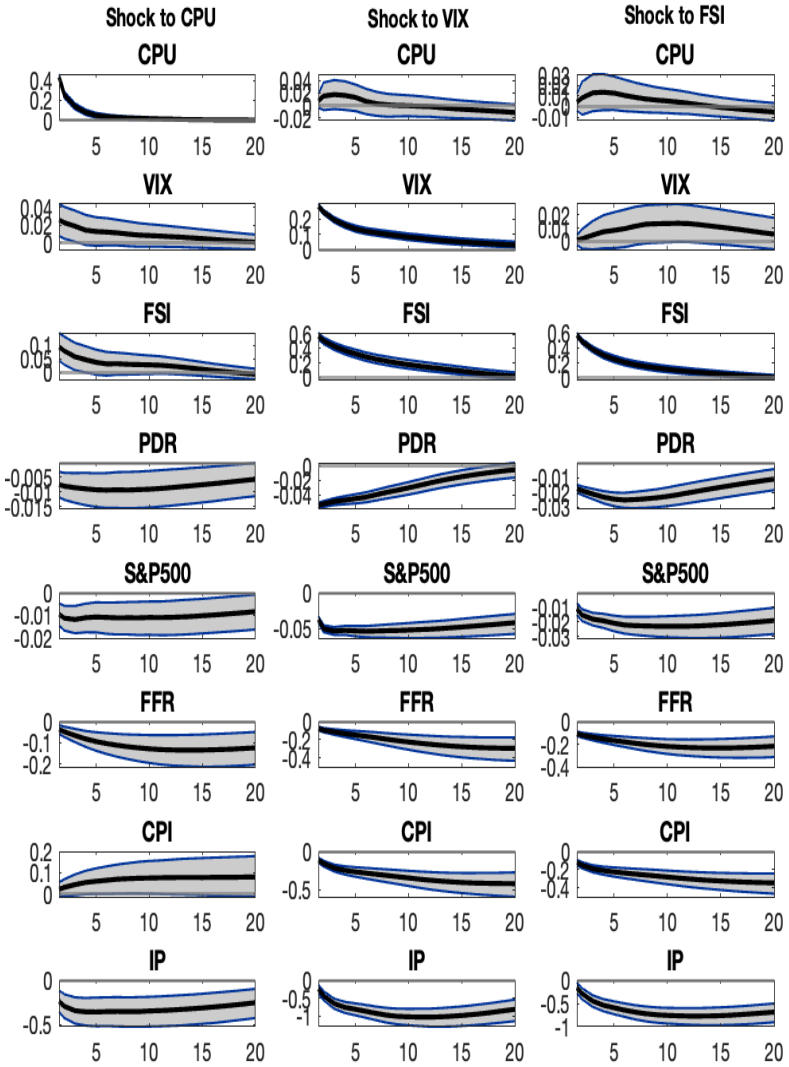


Impulse responses of a shock to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI). Pre Covid-19 Sample. Sample: 1994m1–2020m2.

Appendix F: Shadow Interest Rate and Pre-COVID-19 Impulse Response Functions

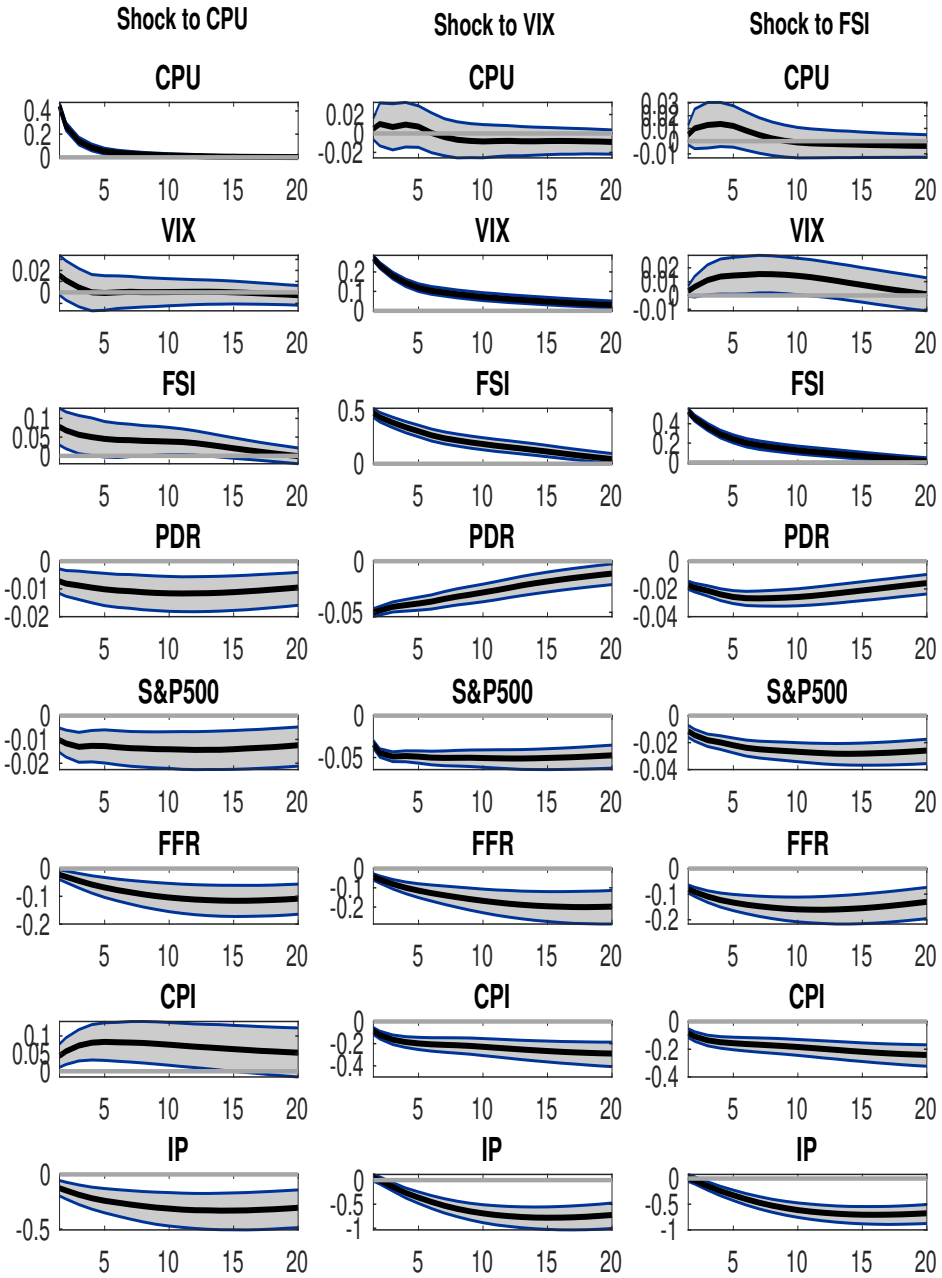
This appendix reports the IRFs from two additional exercises: first, replacing the federal funds rate with the shadow interest rate to account for the zero lower bound (Figure 25); and second, re-estimating the model on a pre-COVID-19 sample (Figure 26).

Figure 25
Shadow Interest Rate. Impulse Response Functions.



Impulse responses of shocks to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI), respectively. Sample: 1994m1–2023m12. The shadow interest rate is used in the December 2008 - December 2015 sample to replace the fed funds rate. The impulse responses of CPI and IP should be interpreted in percentage points. The gray area represents the 68% highest posterior density credible sets, while the black lines indicate the pointwise median IRFs using the baseline identification.

Figure 26
Pre Covid-19 Sample. Impulse Response Functions.



Impulse responses of shocks to Climate Policy Uncertainty (CPU), Volatility Index (VIX), and Financial Stress Index (FSI), respectively. Sample: 1994m1–2020m2. Pre Covid-19 Sample. The impulse responses of CPI, FFR and IP should be interpreted in percentage points. The gray area represents the 68% highest posterior density credible sets for the impulse response functions, while the black lines indicate the pointwise median IRFs using the baseline identification.