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The macroeconomic effects of climate policy uncertainty: Evidence from Portugal*

Hugo Morão†

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Abstract

This study examines the macroeconomic impact of policy uncertainty in climate decision-making. It employs data mining to 23 Portuguese news sources to construct a novel monthly Climate Policy Uncertainty (CPU) series, which is then used in a Structural Vector Autoregression (SVAR) model to analysis its macroeconomic effects. These responses collectively reveal significant economic restructuring in response to climate policy uncertainty. The combination of reduced industrial production and increased unemployment suggests substantial supply-side adjustment costs during the transition. However, the positive stock market response indicates that financial markets view these changes as ultimately beneficial for certain sectors, particularly those aligned with environmental sustainability.

JEL Codes: C32; E32; E61; F18; G18; Q54; L66

Keywords: Climate policy; Textual analysis; Policy uncertainty; Portugal; SVAR

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1 Introduction

Climate policy is gaining unprecedented prominence on the policy agenda, with domestic legislation and global initiatives like the Paris Agreement and national carbon pricing schemes potentially having far-reaching economic impacts. Yet, the inherent uncertainties surrounding the implementation and effects of these policies have remained largely unexplored through a macroeconomic lens. This paper fills this major gap by posing the following question: How do shocks in Climate Policy Uncertainty (CPU) impact key macroeconomic variables?

The study applies a textual analysis approach, extracting information from over a thousand news articles from 23 Portuguese newspapers to measure the level of uncertainty in climate policy. The relative frequency analysis of this news creates a monthly series of climate policy uncertainty. Using an SVAR with this resulting CPU series as a proxy, the paper explores the dynamic effects of CPU shocks on macroeconomic indicators.

Understanding CPU's macroeconomic effects is crucial for policymakers, investors, and businesses navigating the low-carbon transition. This study's importance extends beyond academic interest, offering vital insights for policy formulation in an increasingly climate-conscious world.

Climate policy uncertainty shocks produce economically significant effects. Higher uncertainty about climate policy leads to an immediate decline in industrial production and CO2 emissions, with both showing stronger responses to positive and large shocks.

The unemployment rate shows marked asymmetry - positive shocks cause steeper increases than benchmark shocks, while large shocks generate about twice the impact of small ones. Stock prices respond positively despite the production decline, suggesting markets anticipate benefits for environmentally aligned sectors. The policy uncertainty response reveals that climate policy uncertainty creates spillover effects into broader economic uncertainty. This evidence bolsters the argument that shifts in expectations about future climate policy can yield considerable impact through both size and sign asymmetries, even if some of the policies are not implemented in the short term.

This paper builds on the extensive literature studying the macroeconomic repercussions of policy uncertainty shocks, typified by the seminal work of Baker et al. (2016) and surveyed in Al-Thaqeb and Algharabali (2019).

While this literature primarily suggests that such shocks generally lead to adverse economic effects, this paper adds nuance to this understanding. This paper shows that the impacts of CPU have evolved, shifting from initially negative to positive post-2019, corresponding with increased public awareness of climate policy.

Recent studies highlight the importance of considering asymmetric effects when analyzing policy uncertainty. For instance, Gyamerah et al. (2024) examine how CPU affects green bond returns, finding significant asymmetric impacts in the short and long run. Their work emphasizes the need to consider both positive and negative shocks separately. Similarly, Kisswani and Elian (2021) demonstrate that uncertainty-based proxies can have asymmetric impacts on market volatility, suggesting that the relationship between policy uncertainty and macroeconomic variables is more complex than previously thought. The study also shows the non-linear nature of CPU impacts aligns with recent work by Nusair et al. (2024), who document significant variations in how policy uncertainty affects different economies, emphasizing the importance of country-specific analysis.

Methodologically, this study builds on the approach of Gavriilidis (2021), who pioneered the use of textual analysis to create an index for measuring climate policy uncertainty and found a negative association between CPU and CO_2 emissions. This research extends this previous work by providing novel evidence on CPU's macroeconomic effects in a European context, focusing on Portugal as an early adopter of green policies.

The European dimension of this work builds upon several recent studies. Pinar and Karahasan (2024) show that uncertainty significantly affects the effectiveness of EU policy instruments, while Basaglia et al. (2025) investigate how climate policy uncertainty influences firm and investor behavior across developed European economies. Similarly, Tedeschi et al. (2024) analyze CPU's impact on European financial markets with particular attention to time-varying effects. This paper complements these studies by examining multiple transmission channels simultaneously in Portugal, a country with unique exposure to climate risks due to its early adoption of green policies.

This research offers more than just filling a European gap. It studies various transmission channels together and shows that responses change based on the direction and size of the shock.

This paper uncovers asymmetric effects of CPU shocks that vary by both sign and magnitude, with positive shocks generally showing deeper impacts than benchmark shocks, and large shocks approximately doubling the effect of small shocks. The study examines both sign and size asymmetries in CPU impacts, revealing how responses differ based on shock characteristics. Furthermore, it investigates how CPU asymmetrically influences major macroeconomic variables, filling a gap in the literature by systematically analyzing these differential responses across various economic indicators.

This work also contributes to the growing literature on CPU's impacts on financial markets, while some studies like Ren et al. (2023) and Yu et al. (2023) have examined CPU's effects on corporate financialization and green bond market volatility, respectively. This paper's findings complement their work by showing a broader economic influence of CPU, particularly in stock market and consumer behaviors. These findings also add to the mixed results in this area, with some studies linking CPU to market volatility (Lasisi et al., 2022; Salisu et al., 2023), while others find no significant impact on sustainable green asset returns (Akpa et al., 2023). The mixed nature of these findings is further illustrated by Batabyal and Killins (2021), who find that policy uncertainty has asymmetric effects on stock market returns, with different implications for short-run and long-run market behavior.

This analysis enriches the corporate sector literature by examining CPU's impact on industrial production and consumer prices. This provides insights into how businesses adjust to evolving climate policy landscapes. The findings complement studies on CPU's effects on corporate green innovation (Huo et al. (2023), Mao and Huang (2022)), adoption of pollution-reducing technologies (Wang, 2022), and corporate investment (Huang and Sun, 2023; Gao and Zhang, 2023). The focus on production is particularly relevant given Adil and Roy (2024) finding that uncertainty affects investment decisions through both direct and indirect channels.

This paper provides a comprehensive understanding of CPU's effects on a set of macroeconomic indicators and demonstrates how these effects can drive historical fluctuations. This approach addresses the significant challenge highlighted by Tay (2023) of accurately quantifying climate change effects on the financial system and broader economy.

Roadmap. In what follows, Section 2 details the methodology for measuring CPU and describes the main events associated with it. Section 3 examines the model and data used to quantify the effects of changes in climate policy uncertainty. Section 4 focuses on the macroeconomic consequences of CPU shocks. The paper concludes with Section 5 providing some policy implications and concluding remarks.

2 Measuring climate policy uncertainty

The study collected monthly data from an extensive set of news sources from January 1997 to December 2022. These sources comprised two news agencies, seven national newspapers, five business newspapers, two regional newspapers and two online newspapers, which together represent over 90% of Portugal's news coverage by readership and a list is provided in Table A. All searches were restricted to Portuguese language content with Portugal as the geographic focus to avoid capturing international political discussions unrelated to domestic policy. The methodology draws on established approaches from Baker et al. (2016) and the CPU construction approach in Gavriilidis (2021) adapted to the Portuguese context by Morão (2025c). The index construction involved gathering monthly article frequencies from each news outlet containing specific terminology related to climate policy uncertainty. Articles qualified for inclusion only when they contained terminology from three distinct categories: climate-related terms (C), policy-related terms (P), and uncertainty-related terms (U). To ensure data quality, the analysis implemented several content filters. Only substantive articles between 99-2000 words were considered, providing sufficient depth while excluding excessively long or brief content. The methodology excluded news summaries, calendars, corporate reports, rankings, routine financial updates, interviews, opinion pieces, and headline-only stories, focusing exclusively on substantive news reporting. The search parameters consisted of the following terms:

(i) **Climate (C)** - This group includes terms related to climate change and environmental issues such as ”Carbon Dioxide”, ”CO2”, ”Carbon Emissions”, ”Carbon Neutrality”, ”Carbon Neutral”, ”CO2 Reduction”, ”Carbon Reduction”, ”Greenhouse Gases”, ”Greenhouse Effect”, ”Global Warming”, ”Acid Rain”, ”Climate Change”, ”Renewable Energy”, ”Green Energy”, ”Wind Energy”, ”Solar Energy”, and ”Solar Panel/s”.

(ii) **Policy (P)** - This group contains terms related to governmental and policy-making entities or processes, including ”Parliament”, ”São Bento Palace”, ”Government”, ”Ministry of Finance”, ”Environmental Fund”, ”European Commission”, ”Deficit”, ”Budget”, ”tax/es”, ”Legislation”, ”Reforms”, ”Standards”, ”normatives”, ”regulations”, ”rules”, and ”laws”.

(iii) **Uncertainty (U)** - This group consists of words that convey uncertainty, instability, or risk, such as ”uncertain”, ”uncertainty”, ”instability”, ”unpredictability”, ”unstable”, ”indefiniteness”, ”insecurity”, ”doubt”, ”indecision”, and ”risk/s”.

The constructed index reveals multiple peaks, all corresponding to major events, ei-

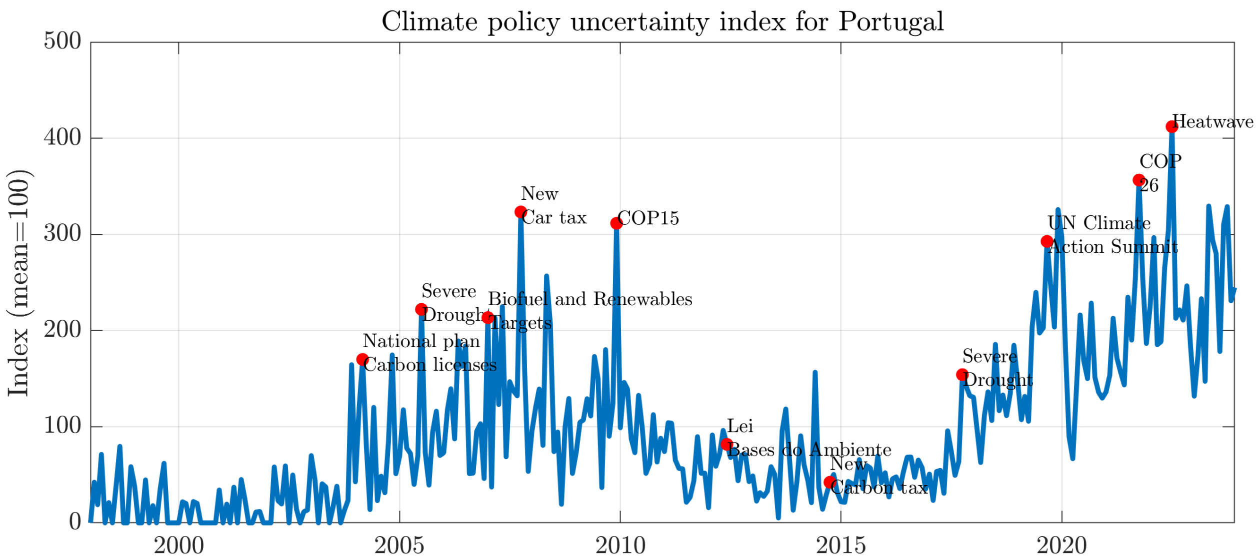


Figure 1: The new climate policy uncertainty index for Portugal

ther localized in Portugal or those related to broader global climate phenomena. In March 2002, Portugal received unfavorable attention due to its subpar environmental track record, as highlighted in a report by a European Agency. The proposal of Carbon and Car taxes in December 2003 led to changes in legislation in the following years. 2004 marked the introduction of the National Carbon Licenses Plan. This plan was designed to be compatible with the European Union's Emissions Trading System (EU ETS), which initiated its Phase I in 2005. The objective was to regulate greenhouse gas emissions by establishing a nationwide cap and issuing carbon licenses to companies. Works such as those by Känzig (2023) and Morão (2024b, 2025a) go into the economic effects of this carbon licensing framework. In 2005, Portugal faced a severe drought, an event the government viewed as a probable manifestation of altered climate patterns. This understanding served as a catalyst, spurring a series of policy initiatives geared towards renewable energy and environmental conservation.

In 2007, the Portuguese climate landscape witnessed two main events. The first came when the government demonstrated its commitment to clean energy by setting targets for new biofuels and other renewables. Finally, a restructuring of the car tax system was proposed during the budget proposal discussions in October. This tax initiative sought to discourage the usage of fossil fuels by imposing higher taxes on less efficient vehicles.

The Barroso Commission[1] faced a challenge in 2008. While there was a strong push to increase the biofuel component in the fuel mix as a move toward sustainable energy, simultaneous concerns arose that this measure could inadvertently contribute to escalating food prices during the global food price crisis that year. This situation underscored the complex relationship between climate policy decisions and broader socioeconomic issues like food security. The year 2009 was marked by transformative moments in global environmental policy. In the US, the Obama administration signaled a notable policy shift toward environmental conservation and climate change mitigation. The same year, Portugal participated in the COP15, a major international climate change conference, showing its commitment to the global climate change mitigation efforts.

In 2012, key environmental legislation, known as the 'Lei de Bases do Ambiente' was proposed. This legislation was instrumental in shaping Portugal's strategies and initiatives related to environmental conservation and climate change mitigation. Through this law, the country aimed to articulate a cohesive and comprehensive set of guidelines acting as a strategic framework to guide Portugal's subsequent initiatives in these critical domains.

The announcement by the right-wing government coalition in 2014 to integrate a new carbon tax into fuel prices also marked a substantive shift in environmental policy. This policy was a significant step toward aligning economic incentives with environmental sustainability goals. Focusing on carbon-intensive sectors like transportation and energy production, the policy offered economic incentives to actively reduce their carbon footprints.

The 2017 Iberian drought followed an exceptionally low rainfall period during the hydrological year 2016-2017. This period marked a significant climatic challenge for both Spain and Portugal, exacerbating existing water scarcity issues and affecting a wide range

[1] The European Commission led by José Manuel Barroso, who served as President from 2004 to 2014

of socio-economic sectors.

In 2019, global strikes were organized in the lead-up to UN Climate Action Summit, serving as a powerful demonstration of public sentiment on these issues. These protests aimed to galvanize international leaders to take substantive action on climate change.

The second major peak in the series was the highly attended COP26 conference in 2021. The conference concluded with a resolution that was less stringent than anticipated, partly due to concessions from China and India regarding the complete phase out of coal power. Nonetheless, it achieved key objectives, such as swifter reductions in greenhouse gas emissions and pledges for increased climate financing to help developing countries adapt to climate impacts. This outcome is evidenced by the rising climate risk premiums in European equity markets, as examined by Bua et al. (2023) through textual analysis. In this same year, Portugal experienced an unprecedented heatwave that broke existing records by lasting longer and spreading across a larger geographical area than any other July heatwave documented since 1941.

Comparing with other indexes Another important aspect of this CPU index is its alignment with major peaks in other climate-related indexes found in literature, particularly at key points of interest. Firstly, it aligns with the climate change news index developed by Engle et al. (2020) using textual analysis. For this particular index, major worldwide climate events, like international conferences, are expected to correlate due to their repercussions on domestic policy. This is exemplified by its major peak during the Copenhagen UN Climate Conference in 2009, confirming the influence of global climate events on this CPU index.

Furthermore, the index correlates with climate-induced events, such as those detailed in Morão (2023), which investigates the effects of water uncertainty. Notably, there is a significant overlap between our index and major water-related climate events. For instance, both indexes prominently feature the severe drought that engulfed all of Portugal in 2005, the worst on record. Another major overlap occurs during the Iberian drought and the catastrophic forest fires in Portugal in October, which resulted in a significant number of fatalities. These events greatly impacted agriculture, energy production, forestry, and water resources, creating a pressing demand for policy intervention. They were also frequently associated with climate change in media coverage, highlighting the expected increase in frequency and intensity of such events in the future.

3 Empirical framework

This section outlines the empirical framework, identification strategy, and dataset.

3.1 Model

The empirical analysis begins with a vector autoregression framework containing n endogenous variables, m exogenous variables and p is the lag order expressed as:

$$y_t = \mathcal{A}_1 y_{t-1} + \ldots + \mathcal{A}_p y_{t-p} + \mathcal{C} x_t + \varepsilon_t \qquad \varepsilon_t \sim \mathcal{N}(0, \Sigma) \tag{3.1}$$

In this specification, y_t represents an n-dimensional vector capturing the endogenous variables of interest, while the coefficient matrices $\mathcal{A}_1$ through $\mathcal{A}_p$ each have dimensions $n \times n$. The model accommodates exogenous influences through, $n \times m$ coefficient matrix $\mathcal{C}$ operating on the m-dimensional exogenous vector x_t. The disturbance term ε_t follows a multivariate normal distribution characterized by a zero mean vector and variance-covariance matrix Σ, which is positive definite. For estimation efficiency, the explanatory variables can be consolidated into a combined matrix.

$$y = \bar{X}\beta + \varepsilon \tag{3.2}$$

with $\bar{X} = I_n \otimes X$, where $X = [y'_{t-1}, y'_{t-2}, \ldots, y'_{t-p}, x'_t]$ is a $T \times (np + m)$ dimensional matrix of lagged endogenous variables and exogenous variable. Then $\beta = \text{vec}\left([A_1, A_2, \ldots, A_p, C]'\right)$, $y = \text{vec}\left([y_1, y_2, \ldots, y_T]'\right)$, and $\varepsilon = \text{vec}\left([\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_T]'\right)$. The Bayesian estimation employs an independent Normal-Wishart prior for the unknown parameters. This prior of the VAR slope is $\beta \sim \mathcal{N}(\beta_0, \Omega_0)$, where the prior mean β_0 is set to zero and Ω_0 is a diagonal matrix is approximated as the residual variance of an AR(1) regression[2], and $\Sigma \sim \mathcal{IW}(S_0, \alpha_0)$ with α_0 prior degrees of freedom, and S_0 scale matrix[3]. Hyperparameters are set based on generally accepted values in the academic literature, and listed in Table 4.

For estimation purposes, it should be noted that the joint posterior distribution $\mathbb{P}(\beta, \Sigma | y)$ lacks a closed-form expression. However, the conditional posterior distributions $\mathbb{P}(\beta | \Sigma, y)$ and $\mathbb{P}(\Sigma | \beta, y)$ are analytically accessible. While conceptually straightforward, this sampling approach requires substantial computational resources. For technical details regarding Gibbs sampling within Bayesian vector autoregressions using independent normal inverse-Wishart priors, readers may consult Dieppe et al. (2016). BVAR estimations were conducted using MATLAB R2025a, with the BEAR 5.0 toolbox for the BVAR models. The algorithm is configured to execute a total of 5000 iterations, discarding the first 4000 as a burn-in period.

Identifying CPU shocks The effects of climate policy uncertainty on the Portuguese economy are estimated using a structural VAR. The study employs a SVAR approach for several reasons. *First*, it allows us to identify structural shocks without imposing strong restrictions on contemporaneous relationships between the endogenous variables. *Second*, it enables us to use the CPU index as a variable, leveraging the information contained in news coverage. This approach particularly fits for studying policy uncertainty, where timing and anticipation effects are quite important. The SVAR analysis involves identify-

[2]Similar to what is described in Litterman (1986)

[3]This follows what is described in Karlsson (2013).

ing using the Cholesky decomposition as in Baker et al. (2016); Morão (2025b) the $n \times n$ $\mathcal{D}$ matrix, which linearly relate the reduce-form innovations ε_t with the structural shocks $\eta_t : \varepsilon_t = \mathcal{D}\eta_t$.

3.2 Empirical specification

The baseline specification uses six variables to capture key aspects of the Portuguese economy affected by climate policy uncertainty. The BVAR model employs the vector $y_t = [c_t, \pi_t, u_t, s_t, co2_t, epu_y]'$, where:

y_t measures industrial production, capturing overall economic activity. π_t is the headline inflation, measuring price stability and broader macroeconomic effects. u_t is the unemployment rate, capturing shock impacts on employment. s_t is the stock market index price, indicating asset valuation and investment conditions, thus reflecting financial market reactions. Finally, $co2_t$ measures CO2 emissions, tracking firms' environmental responses to uncertainty. epu_t captures economic policy uncertainty, revealing spillovers from climate to broader policy uncertainty.

This set of variables enables us to trace CPU shock transmission through various economic channels, from immediate market responses to more longer-term labor market adjustments.

The data is monthly and covers from January 1998 to December 2022. For the empirical analysis, the specification includes six lags of the endogenous variables alongside a constant term. Additionally, the model incorporates the Portuguese Economic Policy Uncertainty Index developed by Morão (2024a) as an exogenous control variable. The estimation is conducted using variables in their level form rather than differences. You can see additional source details in Table 3. However, the results are robust across all these choices, as shown in Appendix C. Figure 2 illustrates the temporal evolution of all variables included in the baseline specification throughout the sample period.

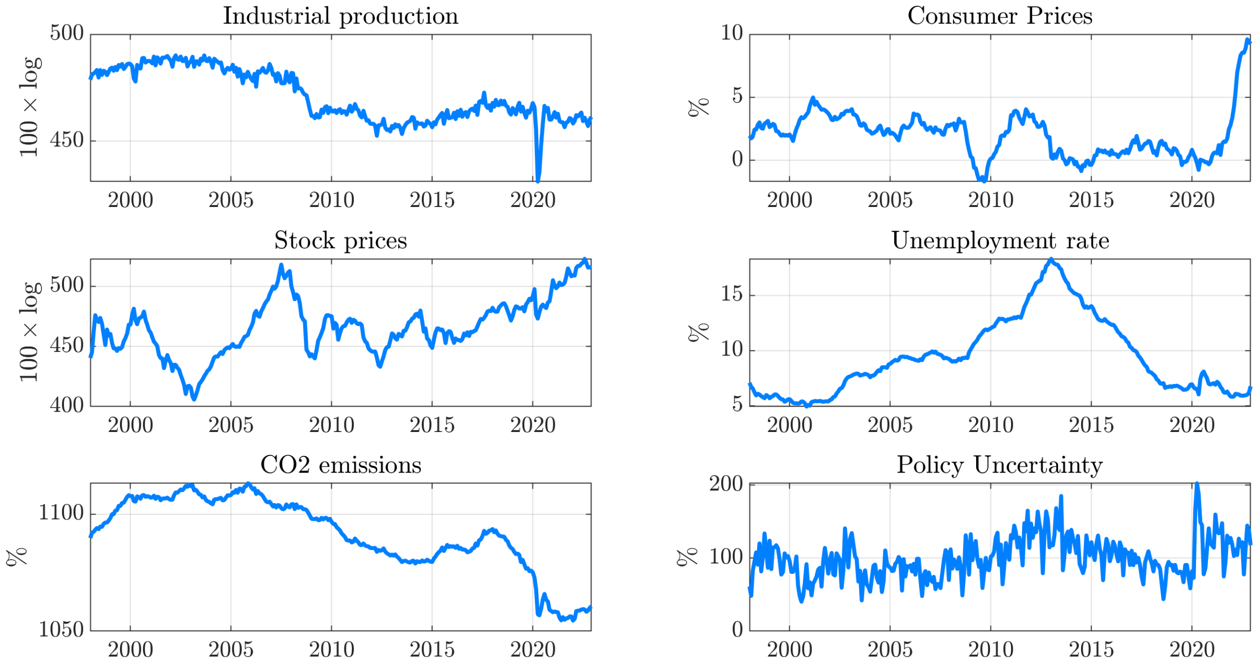


Figure 2: The macroeconomic data series in the baseline model

4 The macroeconomic effects

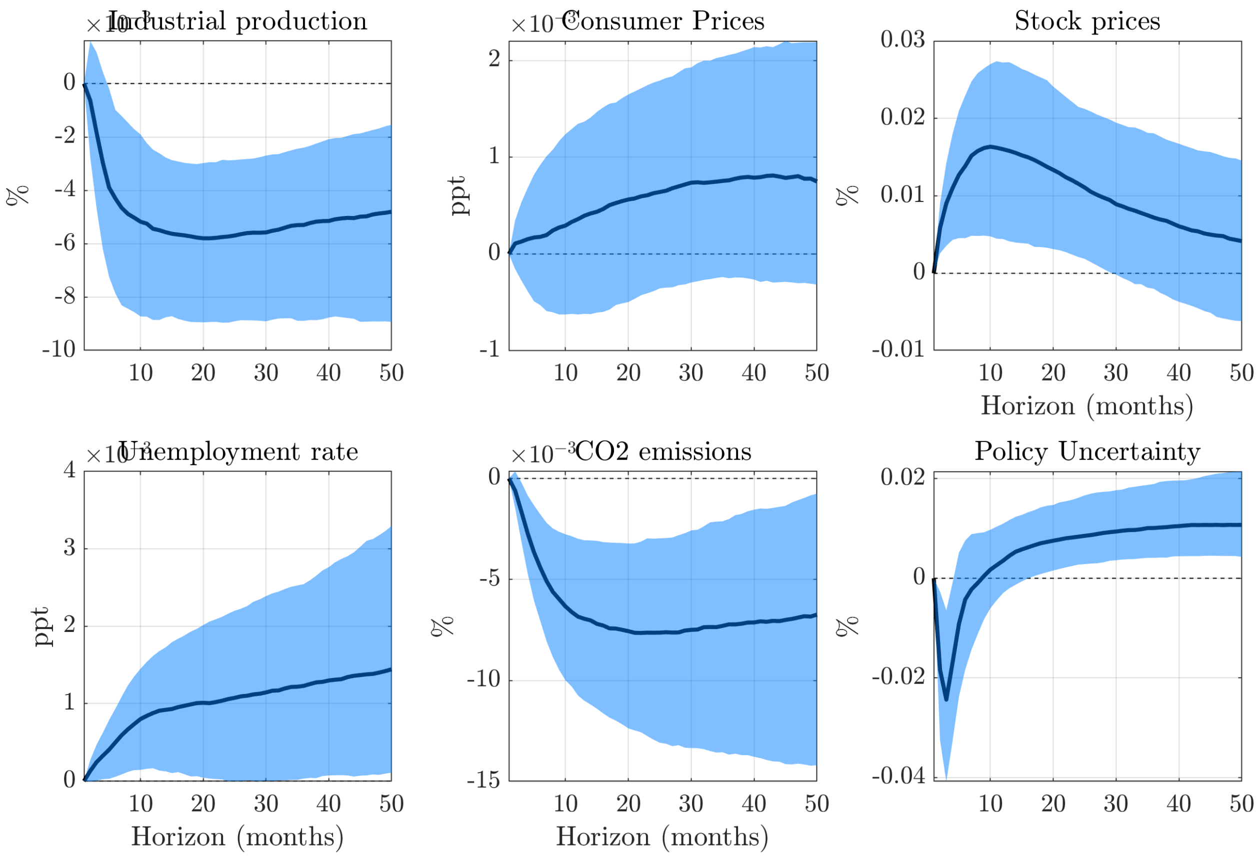
This section evaluates the macroeconomic repercussions of the climate policy uncertainty using the Impulse Response Functions (IRF) from the SVAR and assessing the asymmetries using local projection described in the seminal work of Jordà (2005)[4]. Structural analysis tools, particularly Impulse Response Functions (IRF), demonstrate how the macroeconomic variables in the model change over time after a CPU shock.

4.1 IRF analysis

Figure 3 illustrates the impact of climate policy uncertainty shocks on Portuguese macroeconomic variables from the SVAR.

The responses reveal the complex transmission mechanisms of climate policy uncer-

[4]Using *locproj* package in Stata 14



Note: The solid black line represents the posterior median estimate and the shaded areas 68% credible bands.

Figure 3: Impulse responses to a CPU shock

tainty shocks through the economy.

Starting with industrial production, the immediate and sustained negative impact, lasting for 40 months, reaching a substantial decline of approximately 5%. This persistent contraction suggests that firms significantly reduce their production activities when facing high climate policy uncertainty. The persistence and magnitude of this decline indicates that firms do not merely make temporary adjustments but rather implement longer-term operational changes, particularly in carbon-intensive sectors navigating an uncertain regulatory landscape.

The stock market response shows an interesting dynamic - a positive impact peaking around 1.5% that persists for about 20 months. This seemingly counterintuitive reaction reflects major investors were bullish on sectors that would benefit from stricter climate policy changes, such as renewable energy and green technology. Supporting this, Bouri et al. (2022) used ETFs data to show that a higher CPU correlates with stronger performance for green stocks compared to those of environmentally unfriendly companies. Portugal's early adoption of green policies amplifies this effect, as investors foresee these shocks as likely accelerating the green transition, leading to portfolio reallocations that favor green initiatives. However, this can also reflect speculative behavior as investors try to preempt which sectors will benefit when the uncertainty eventually resolves.

Consumer prices demonstrate a gradual but steady increase, reaching about 0.8 percentage points. The credible bands are wide meaning there is some uncertainty in the estimates. This pattern points to businesses initially absorbing costs due to being constrained by various frictions or pre-existing contracts but eventually pass them on to consumers. Hoang (2022) describes how firms adopt ”wait-and-see” strategies during periods of high policy uncertainty, delaying major decisions while gradually adjusting prices to maintain profitability under potential new regulatory constraints.

The CO2 emissions response reveals an important sequencing in how firms adapt to uncertainty. Both metrics drop quickly in the first year, but CO2 emissions continue falling more steeply until near the second year, while industrial production's decline moderates earlier. This sequence suggests that firms first implement the easiest responses which are cutting production levels. Only then they make structural changes to reduce their emissions intensity like switching to cleaner energy sources, upgrading to more efficient equipment, or shifting product mix toward less carbon-intensive goods.

The unemployment rate shows a persistent upward trend, reaching approximately 1.5 percentage points higher. This signals a longer-term and structural adjustment in response to the persistent climate policy uncertainty. Industries facing potential regulatory changes and not fully aligned with the green transition are likely to hesitate to keep their workforce intact, particularly in sectors that might face higher operational costs under stricter environmental policies.

The policy uncertainty response shows an initial negative spike followed by a gradual return to positive territory. The initial negative spike captures the confusion when new climate legislation is proposed or debated, while the gradual return to positive territory represents the normal progression of legislation through parliament.

These responses collectively paint a picture of a significant economic restructuring going on in response to climate policy uncertainty. The combination of reduced industrial production, increased unemployment, and rising consumer prices suggests substantial adjustment costs during the transition. However, the positive stock market response indicates that financial markets view these changes as ultimately beneficial for certain sectors, particularly those aligned with environmental sustainability.

4.2 Evidence of asymmetries

This section examines asymmetric impacts of CPU shocks using Jordà (2005) local projections implemented through Ugarte-Ruiz (2023). The first analysis focuses on size-based asymmetries by splitting CPU shocks into small and large categories. The large shocks, classified as those above the 90th percentile of the distribution, correspond to major events like climate conferences or environmental disasters.

$$y_{t+h} = \alpha_h + \theta_h^{small} \eta_t^{CPU} \mathcal{I}(|\eta_t^{small}| \leq z_{0.9}) + \theta_h^{large} \eta_t^{CPU} \mathcal{I}(|\eta_t^{large}| > z_{0.9}) + X_t' \beta_h + \varepsilon_{t+h} \quad (4.1)$$

where θ_h^{small} are the dynamic causal effects of small and θ_h^{large} are the dynamic causal effects of large CPU shocks. Figure 4 displays the impacts of small and large CPU shocks. The effects mirror the baseline responses but with greater magnitude. Positive shocks demonstrate stronger impacts, though their estimates carry wider credible bands compared to specifications including all shocks. This increased uncertainty justifies the baseline approach of incorporating both positive and negative shocks.

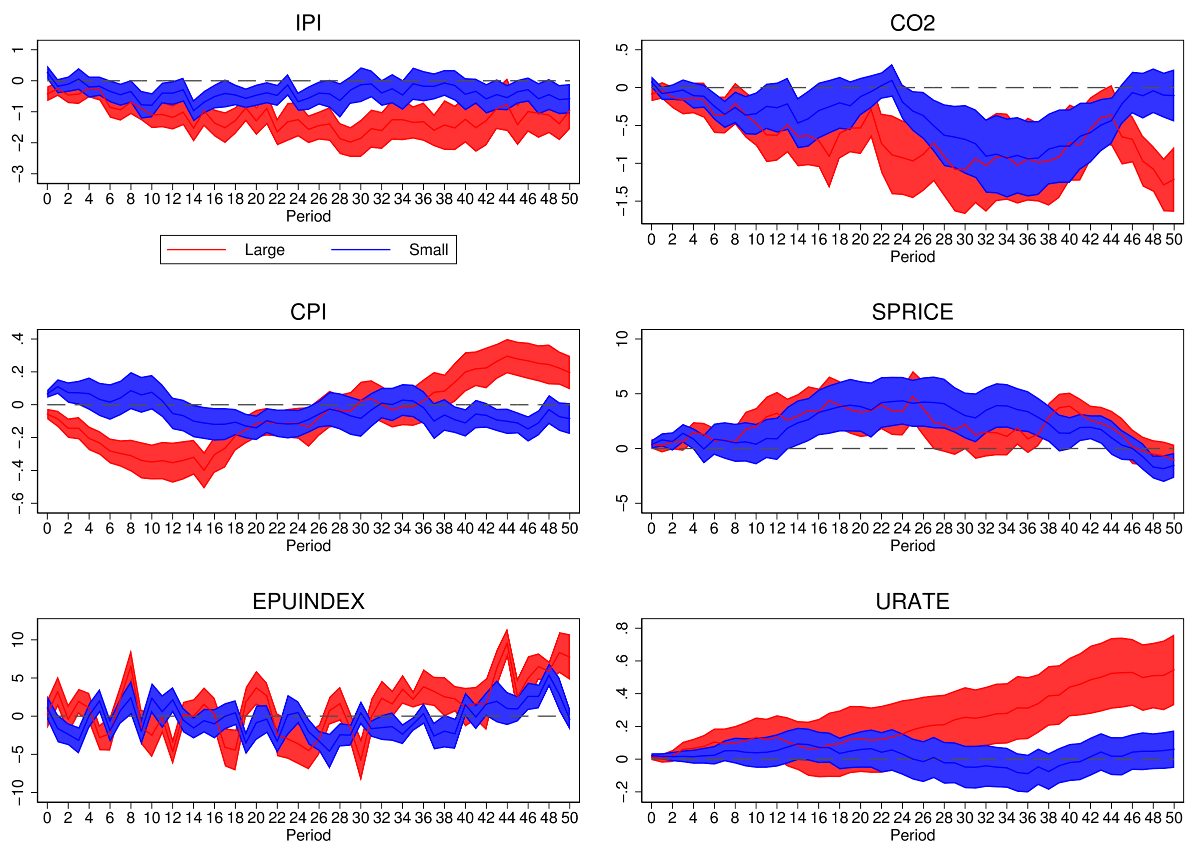


Figure 4: Impulse responses to a large (red) and small (blue) CPU shock

Industrial production shows asymmetric responses to shock sizes. Large shocks (red line) create modestly larger negative impacts compared to small shocks (blue line). At peak times, large CPU shocks reduce industrial output by 2%, while small shocks cause a 1.5% decline. Similarly, CO2 emissions display strong size effects. Large shocks drive the emissions down by around 1.5% in the long run, compared to small shocks, which cause only minor fluctuations around zero. These size asymmetries suggest that, after big climate policy shocks, firms cut both production and emissions more preparing for strict future regulations. Consumer prices also reveal size-dependent dynamics. Large shocks initially decrease prices by up to 3% before causing a significant increase after period 30. Small shocks, however, just create minimal price movements. This pattern shows that high policy uncertainty first makes firms hesitant to raise prices, but, it eventually forces larger price hikes to cover costs. Stock prices respond similarly to both shock sizes in the medium term. Yet, large shocks seem to create more volatility reflecting greater uncertainty about their impact. The EPU response shows that large CPU shocks and create more volatile initial reactions also lead to lasting increases in policy uncertainty. The economic mechanism should work through the interconnection of policy channels. When firms face climate policy concerns, they create uncertainty affecting energy regulations, industrial standards, and trade agreements. The unemployment rate demonstrates the most asymmetric size effects. Large CPU shocks lead to a significant rise in unemployment, while small shocks result in only slight changes in employment suggesting that labor markets can handle small uncertainty shifts. But they face major adjustments during large climate policy uncertainties.

The second analysis focuses on sign-based asymmetries by splitting CPU shocks into positive and negative, as described in Equation 4.2.

$$y_{t+h} = \alpha_h + \theta_h^{neg} \eta_t^{CPU} \mathcal{I}(\eta_t^{neg} \leq z_{0.9}) + \theta_h^{pos} \eta_t^{CPU} \mathcal{I}(\eta_t^{pos} \leq 0) + X_t' \beta_h + \varepsilon_{t+h} \tag{4.2}$$

where θ_h^{pos} are the dynamic causal effects of positive and θ_h^{neg} are the dynamic causal effects of negative CPU shocks. Figure 5 displays the impacts of positive and the regular CPU shocks estimated in the SVAR model.

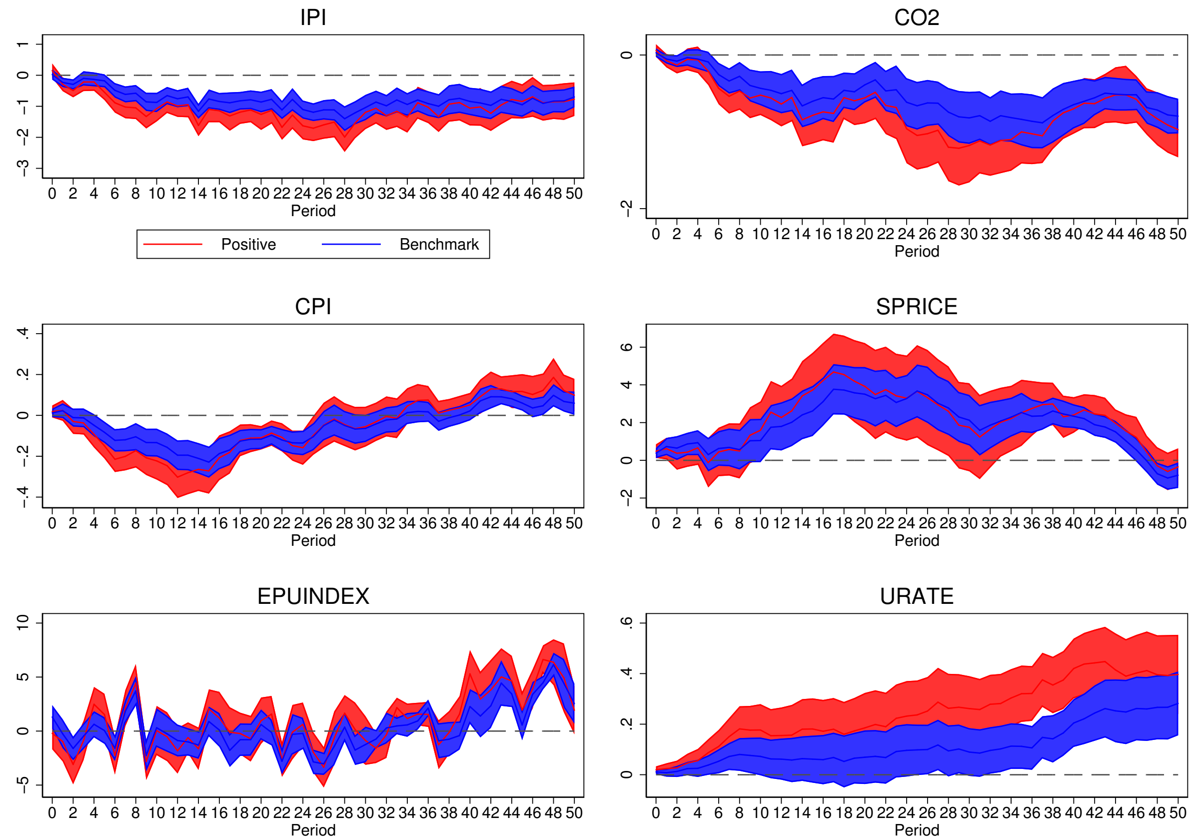


Figure 5: Impulse responses to a positive CPU shock

It can be observed that while there is some sign asymmetry, it is not severe enough to change the main interpretation of the model. Industrial production and CO2 emissions move in the same direction. Positive shocks (red line) tend to result in larger declines compared to benchmark shocks (blue line). Industrial production gradually decreases by about 1.5% under positive shocks compared to roughly 1% for benchmark shocks. This suggests that climate policy uncertainty lowers production. It does so, regardless of whether the shock is positive or negative, but with varying intensities. Consumer prices do not display much sign of asymmetry in their timing or size. Stock prices show the same sign but a bit more. They respond more positively than the benchmark. CPU shocks cause larger price increases that peak at around 4% (versus 3% for the benchmark) before the second. This may mean that equity markets prefer the changes in rising climate policy uncertainty over its reduction. Both shocks show similar volatility regarding policy uncertainty. Yet, after period 30, positive CPU shocks lead to slightly higher economic policy uncertainty. This may mean that climate policy uncertainty harms broader economic policies. The unemployment rate reveals initially similar responses that diverge over time. Both shock types lead to rising unemployment. Yet, positive shocks cause a steeper rise, reaching about 0.4% by period 50. In contrast, benchmark shocks show a more gradual increase to about 0.25%. This pattern shows that labor markets react more to positive uncertainty shocks it reflect firms' reluctance to create jobs amid increased policy ambiguity.

Additional results and robustness analysis This section outlines the results of various robustness checks on the SVAR estimation, grouped into three main categories detailed in the following subsections. First, the assessment of different subsamples is conducted to determine if substantial changes in the previously discussed findings occur. Second, the effect of alternative modeling settings, such as hyperparameters and alternative priors, is evaluated to understand how these could lead to different results. The findings that CPU shocks have a significant effect on the macroeconomy remains robust across alternative model priors, different subsamples, and various model tuning approaches.

Pandemic. One possible area for scrutiny when examining the effect of CPU is the unique economic conditions created by the COVID-19 pandemic and the Russian war. These unparalleled shocks disrupted many macroeconomic variables and could engage with CPU in complex ways.

However, a visual analysis clearly indicates an upward trend in CPU starting from 2017. To address this concern and isolate some of the effects of these shocks in the baseline model, the analysis re-estimates the BVAR specification for periods including the COVID-

19 pandemic. Isolating these unique periods of economic upheaval provides a clearer understanding of CPU's impacts on the Portuguese macroeconomy.

Figure 6 compares the IRFs from the benchmark with the scenario that add the COVID-19 pandemic (green line). Visual inspection indicates that the central conclusions of this

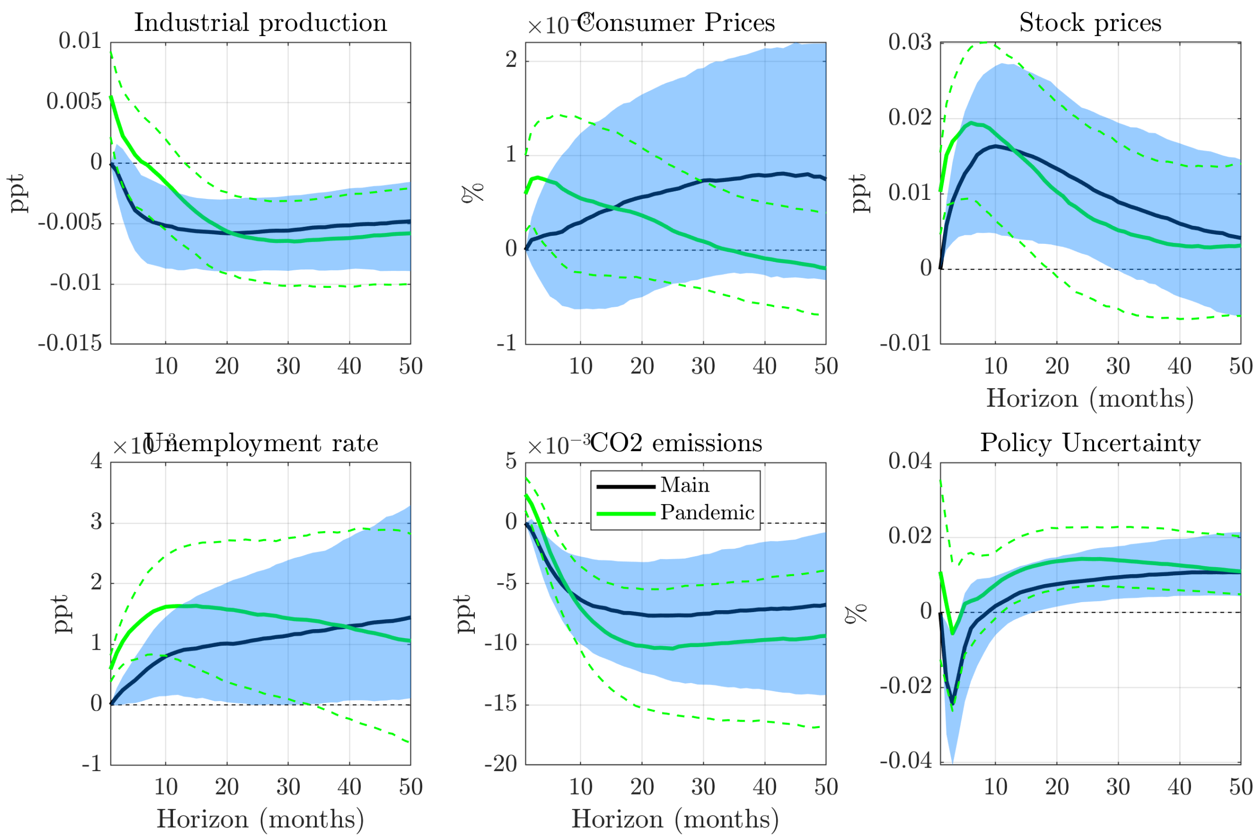


Figure 6: Adding pandemic

study remain robust. While some variations in the estimates do occur due to these extraordinary events, the main finding is that CPU significantly impacts macroeconomic variables remains consistent.

Model specification. Robustness checks are crucial for validating the results derived from the SVAR analysis in this paper. This includes the introduction of an alternative exogenous variable, specifically, the Global Economic Policy Uncertainty Index (GEPU), (Figure 8) as well as running the model without any exogenous variables (Figure 9). The analysis explores the effects of changing lag lengths (Figures 10 and 11), and different priors (Figures 12 and 13). Additionally, the analysis assesses the sensitivity of the results to variations in hyperparameters (Figures 14, 15, and 16), alternative assumptions regarding the S_0 matrix (Figure 17), and the possibility of a unit root or cointegration process (Figure 18). The relevant figures can be found in Appendix C.

5 Conclusion and policy implications

Climate policy is gaining prominence in the policy toolkit, and its importance in shaping macroeconomic trajectories cannot be overstated. This study reveals how uncertainty around climate legislation impacts various economic indicators in Portugal, providing insights for policymakers navigating the green transition.

The primary channel operates through industrial production, where firms demonstrate a strategic response to uncertainty about future environmental regulations. This, in turn, lowers CO2 emissions suggesting a two-stage adaptation pattern. Firms first cut output in response and then go for deeper changes to reduce emissions intensity.

Financial markets show a positive response, with rising stock prices. This suggests that financial markets expect gains for sectors that support stricter environmental rules. This is especially true in Portugal's green-focused market.

The labor market exhibits a gradual but persistent adjustment, reflected in slowly rising unemployment rates as industries prepare for potential regulatory changes. Meanwhile, consumer prices show a modest but steady increase over time, suggesting that firms eventually transfer the costs of regulatory uncertainty to end consumers.

These findings suggest several concrete policy recommendations: First, governments should establish clear legislative timelines for climate policies. Setting specific carbon pricing and emissions standards would help firms. It would allow them to plan investments and adjust their workforces. Second, implement regulatory changes in stages. Announce detailed guidelines well in advance. Portugal's energy sector transition demonstrates how early policy signals enable proactive adaptation. Third, targeted support should help industries hit hardest by climate policies include tech adoption incentives and workforce training programs. Fourth, simplifying approval processes for green projects would reduce uncertainty while maintaining environmental standards. Fifth, transparent monitoring frameworks would help markets anticipate and adapt to policy adjustments. Looking ahead, Portugal's experience shows how legislative uncertainty shapes economic restructuring. Climate policy uncertainty raises costs due to lower production and higher unemployment. But, the stock market's rise shows optimism about long-term sustainability. Future research should examine how different economies manage this transition, it should also explore ways to reduce uncertainty in laws while meeting environmental goals.

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APPENDIX FOR PUBLICATION

A Appendix: CPU index

search query The search query used in DJ Factiva was the following: wc¿99 AND wc¡2000 AND ((ns=gclimt OR dióxido de carbono OR redução NEAR4 emissões OR taxa carbono OR efeito estufa OR CO2 OR aquecimento global OR alteraç* climática* OR energia verde OR energi* renováv* OR energia eólica OR energia solar OR pain* solar*) AND (parlamento OR assembleia da republica OR govern* OR ministério das finanças OR fundo ambiental OR comissão europeia OR agência portuguesa do ambiente or défice or orçament* or (o or de or do or um or por or este or esse or aquele) w/1 imposto$1 or legisla* OR regula* OR burocracia* or lei or leis) AND (incert* OR instabil* OR indefini* OR indecis* OR imprev?si* OR insegur* OR risco$1)) NOT ns=(nsum OR ncdig OR ncal OR nran OR nrmf OR nnam OR niex OR nedc OR nhoc OR npdn OR nrgn OR nhrd OR nlet OR namt OR npan OR nobt OR nitv OR niex OR nhrd)

Alternative climate index A useful climate awareness index can be obtained by removing the Policy and Uncertainty blocks from the search.

B Appendix: Data and Model

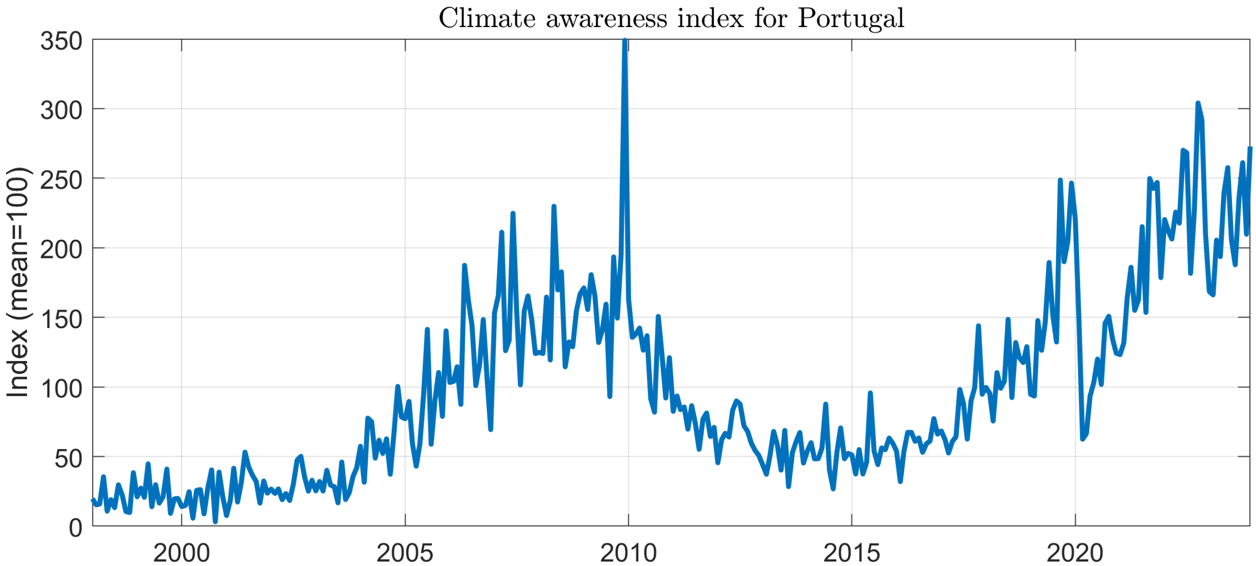

Figure 7: Climate Awareness index

Table 1: Sources

name	Freq	Type	fry	frm	frd	toy	tom	tod
Journal de Notícias	D	National newspaper	1998	1	1	2023	3	31
Correio da Manha	D	National newspaper	2008	12	1	2023	3	31
Diário de Notícias	D	National newspaper	2010	5	1	2023	3	31
Publico	D	National newspaper	2010	11	1	2023	3	31
Espresso	W	National newspaper	2013	9	1	2023	3	31
Journal I	D	National newspaper	2013	12	1	2023	3	31
O Sol	W	National newspaper	2017	1	1	2023	3	31
Vida Económica	D	Business newspaper	1998	1	1	2023	3	31
Diário Económico	D	Business newspaper	1998	2	1	2016	5	31
Journal de Negócios	D	Business newspaper	2011	10	1	2023	3	31
Dinheiro Vivo	W	Business newspaper	2014	4	1	2023	3	31
O Journal Economico	W	Business newspaper	2017	7	1	2023	3	31
Açoriano Oriental	D	Regional newspaper	2010	6	1	2023	3	31
Journal do Fundão	W	Regional newspaper	2011	7	1	2018	7	31
Observador		Online newspaper	2017	7	1	2023	3	31
ECO		Online newspaper	2019	2	1	2023	3	31
Executive Digest		Magazine	2019	11	1	2023	3	31
Reuters		News agency	1998	1	1	2023	3	31
Agência Lusa		News agency	2001	2	1	2023	3	31

Notes: fry = from year; frm = from month; frd = from day; toy = to year; tom = to month; tod = to day. These columns indicate the start and end dates of data collection for each news source.

Table 2: Major events in Portugal highlighted by 1

Y	M	Event
’03	Dec	Proposal for carbon emission and vehicle taxes
’04	Mar	Initiation of national carbon licenses plan
’05	Jul	Severe drought
’07	Jan	Speech on new biofuels and renewables targets
’07	Oct	Road tax increase
’09	Dec	COP 15
’12	Jun	Implementation of ”Lei de Bases do Ambiente”
’17	Nov	Severe drought
’19	Sep	UN Climate Action Summit
’21	Oct	COP 26 climate conference
’22	Jul	Heatwave

Table 3: Data Description and Sources

Label	**Description**	**Source**
y_t	Industrial production in Portugal	FRED
$co2_t$	CO2 emissions for Portugal	Own
π_t	Headline inflation rate for Portugal	FRED/Own
u_t	Harmonized Unemployment Rate	FRED
s_t	Total Share Prices for All Shares for Portugal	FRED
epu_t	Economic Policy Uncertainty Iodex for Portugal	Morão (2024a)

Notes: Data series are monthly and covering 1998m1-2022m12 period in the main specification.

Table 4: Hyperparameters

	Value	Description	Observation
ρ	1	autoregressive coefficients	Used in all models
λ_1	0.1	overall tightness	$\lambda_1 = 1000$ in model 15 & $\lambda_1 = 1$ in model 16
λ_2	0.5	cross-variable weighting	$\lambda_2 = 2$ used in model 18
λ_3	1	lag decay	Used in all models
λ_4	10^5	exogenous variable tightness	Used in all models

C Appendix: Sensitivity analysis

C.1 Robustness: GEPU

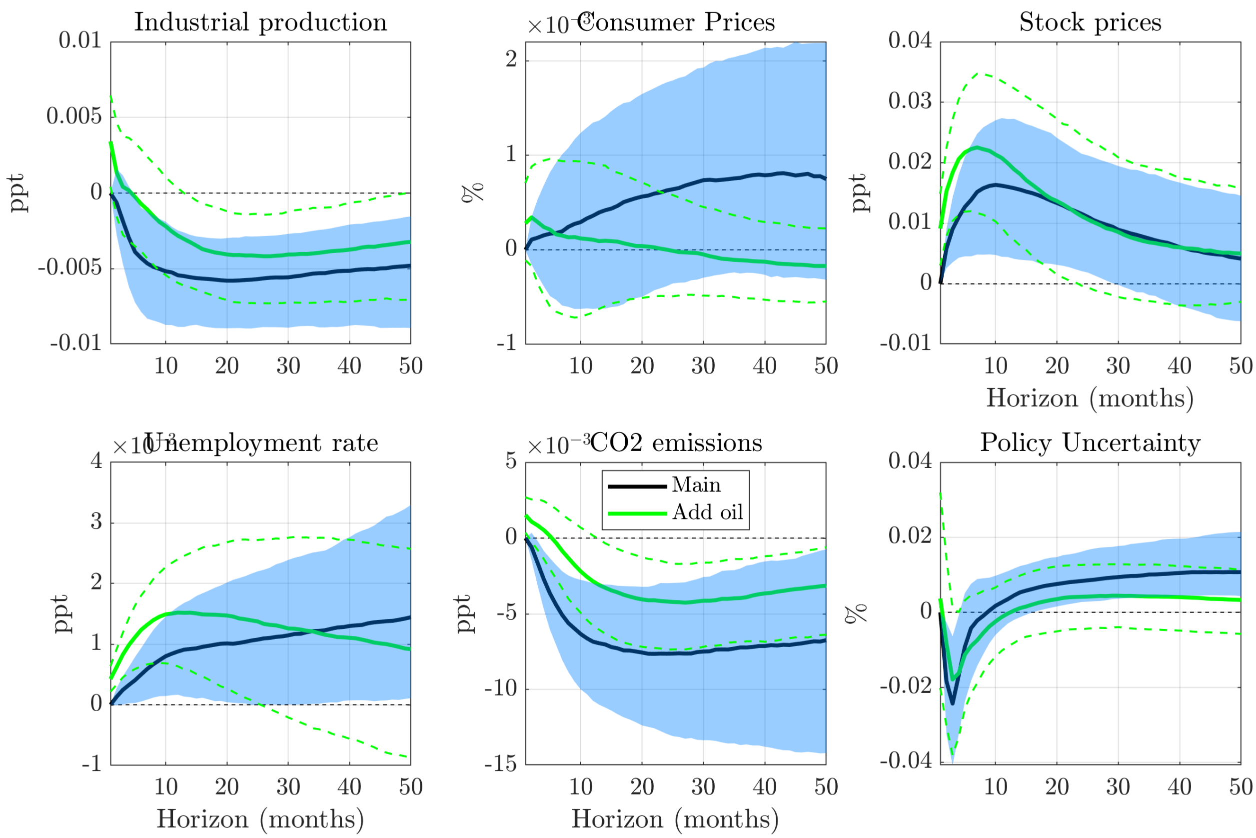

Figure 8: Model including GEPU as exogenous variable

C.2 Robustness: No exogenous variables

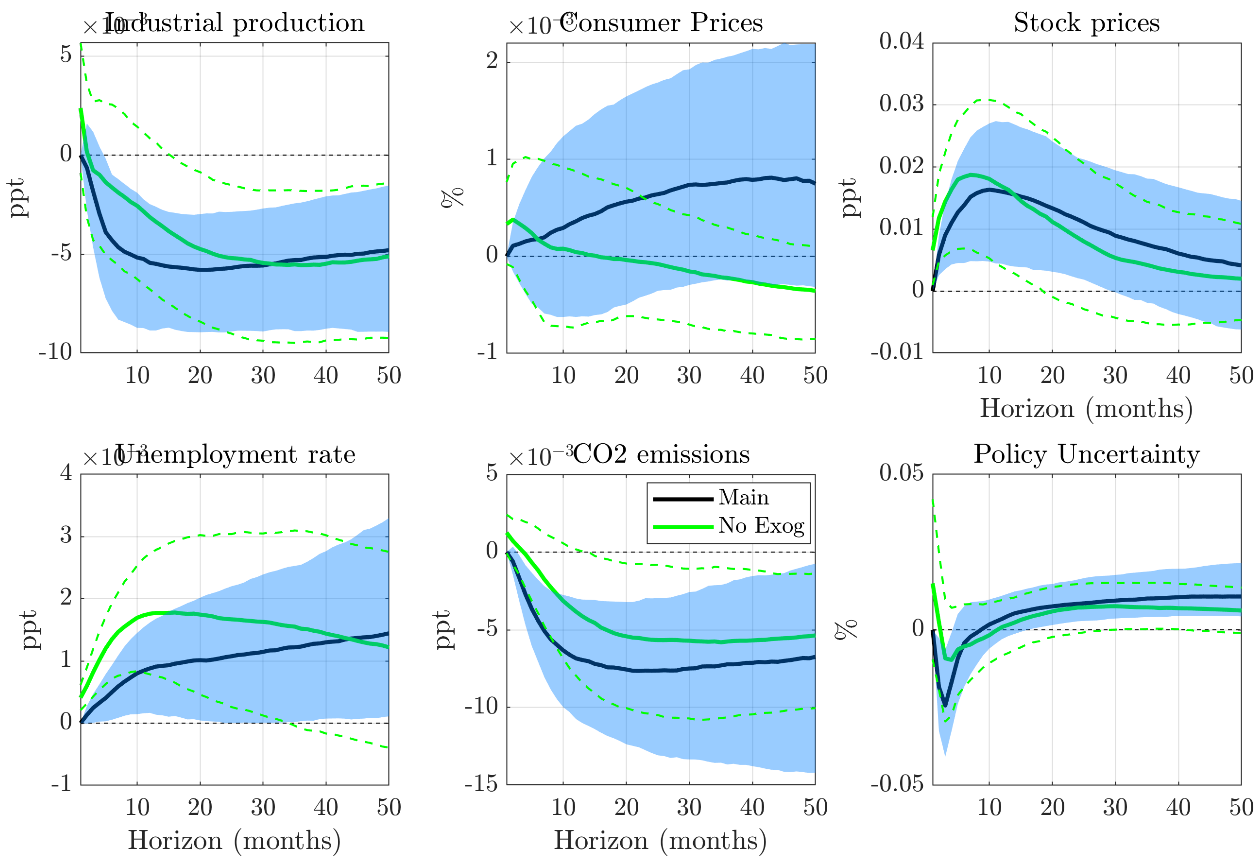

Figure 9: Model excluding the exogenous variable

C.3 Robustness: 3 lag

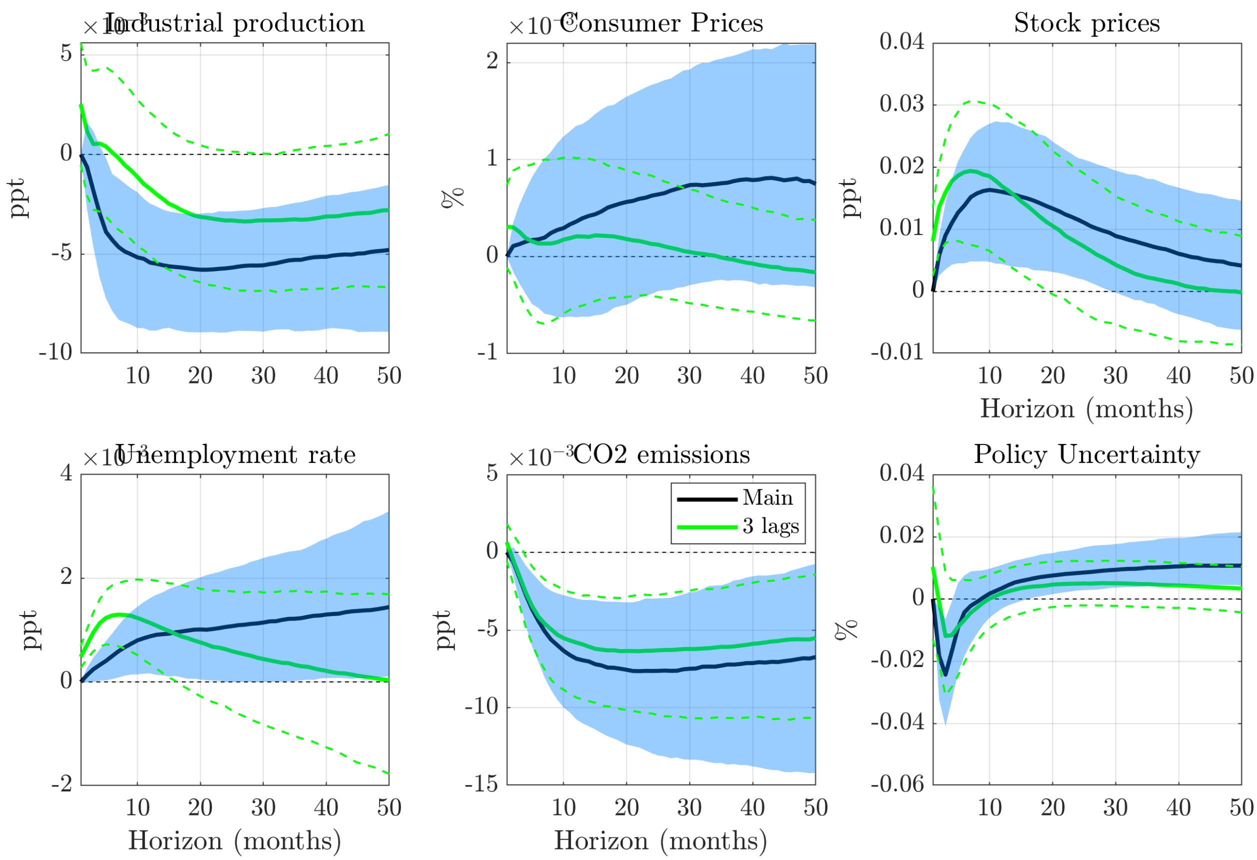

Figure 10: Results from a BVAR(3)

C.4 Robustness: 12 lags

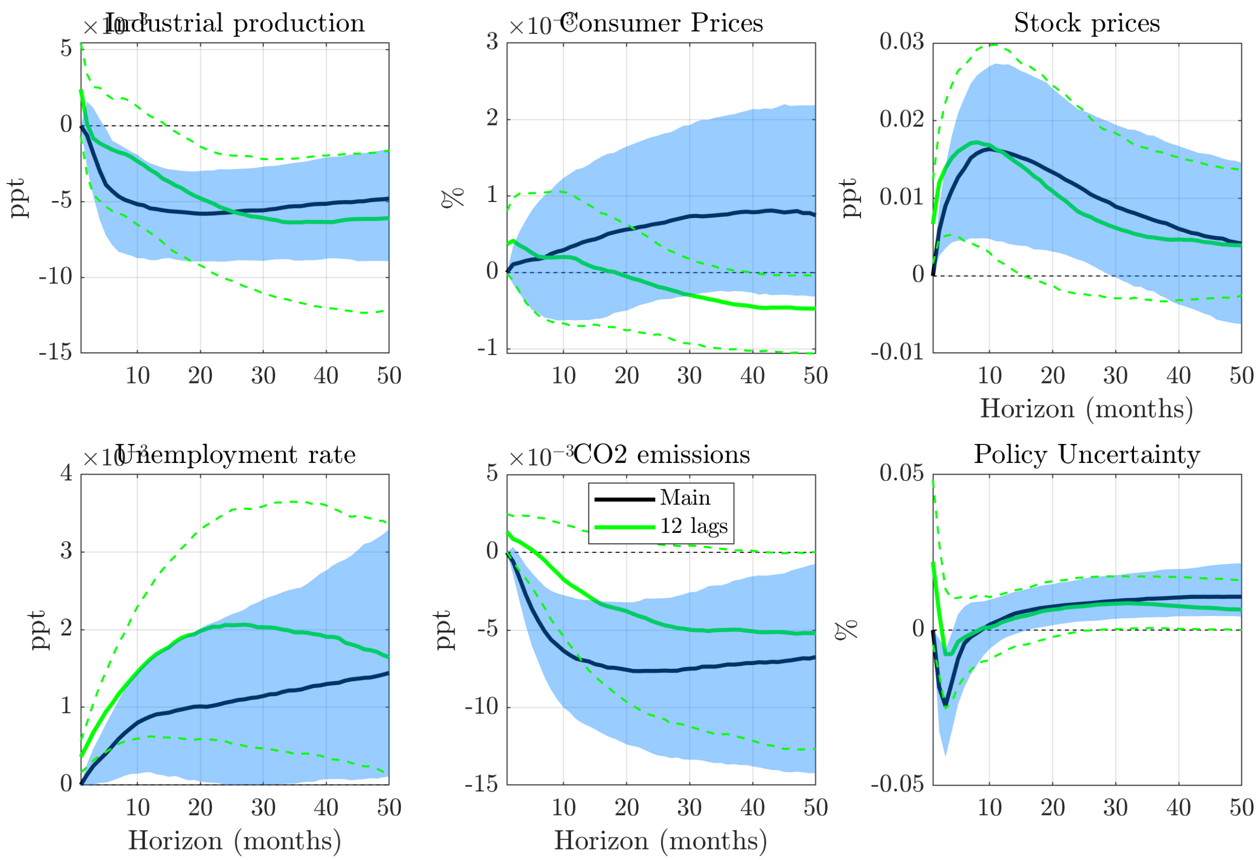

Figure 11: Results from a BVAR(12)

C.5 Robustness: $\mathcal{NW}$ prior

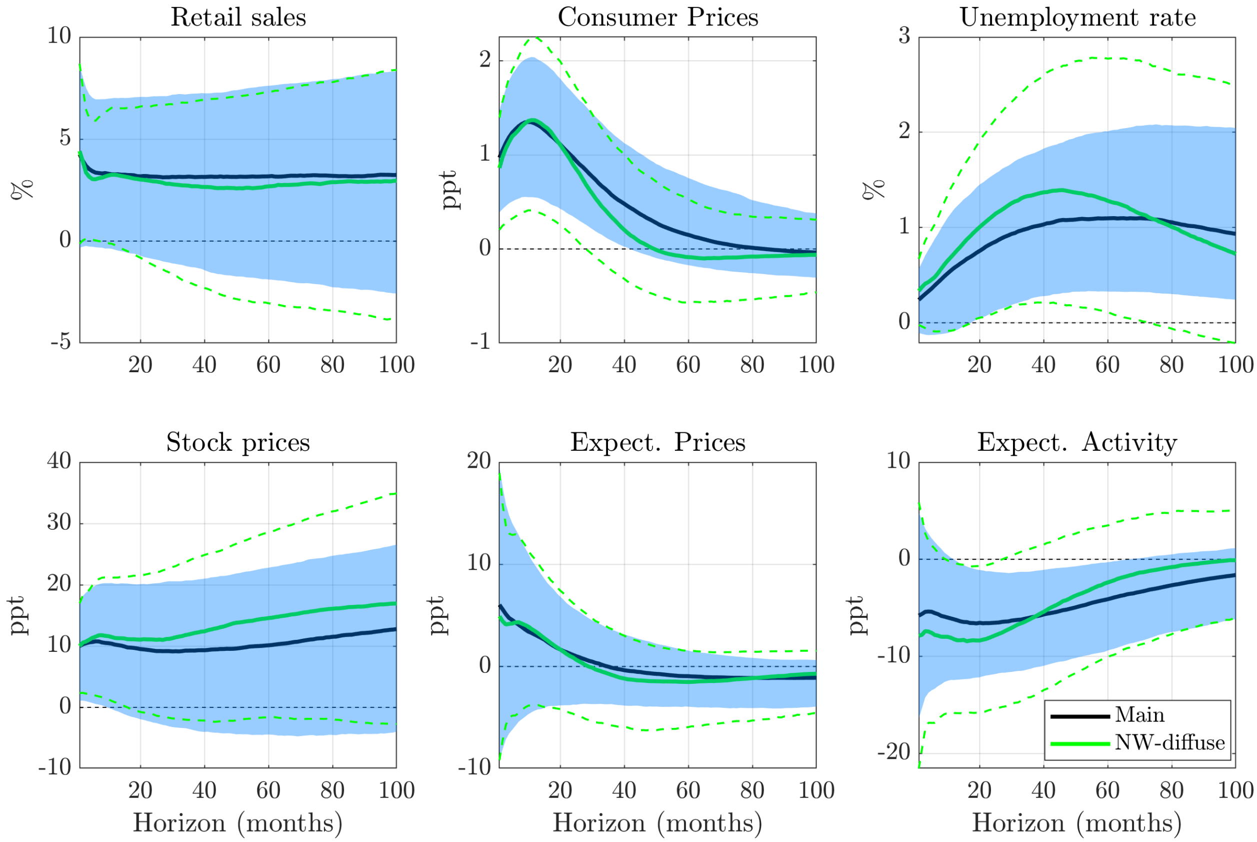

Figure 12: BVAR with Normal-Whishart prior

C.6 Robustness: Normal-Diffuse prior

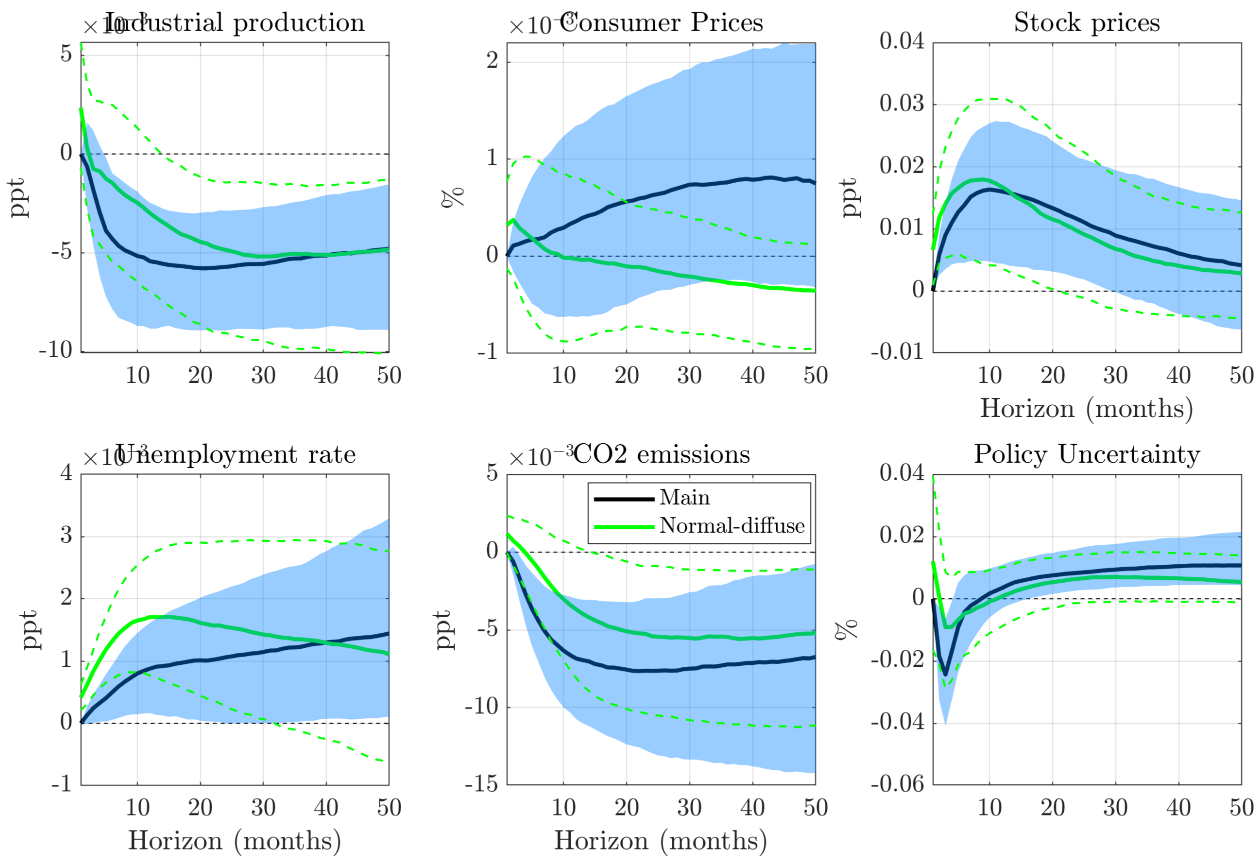

Figure 13: BVAR with Normal-Diffuse prior

C.7 Robustness: Normal-Whishart diffuse prior

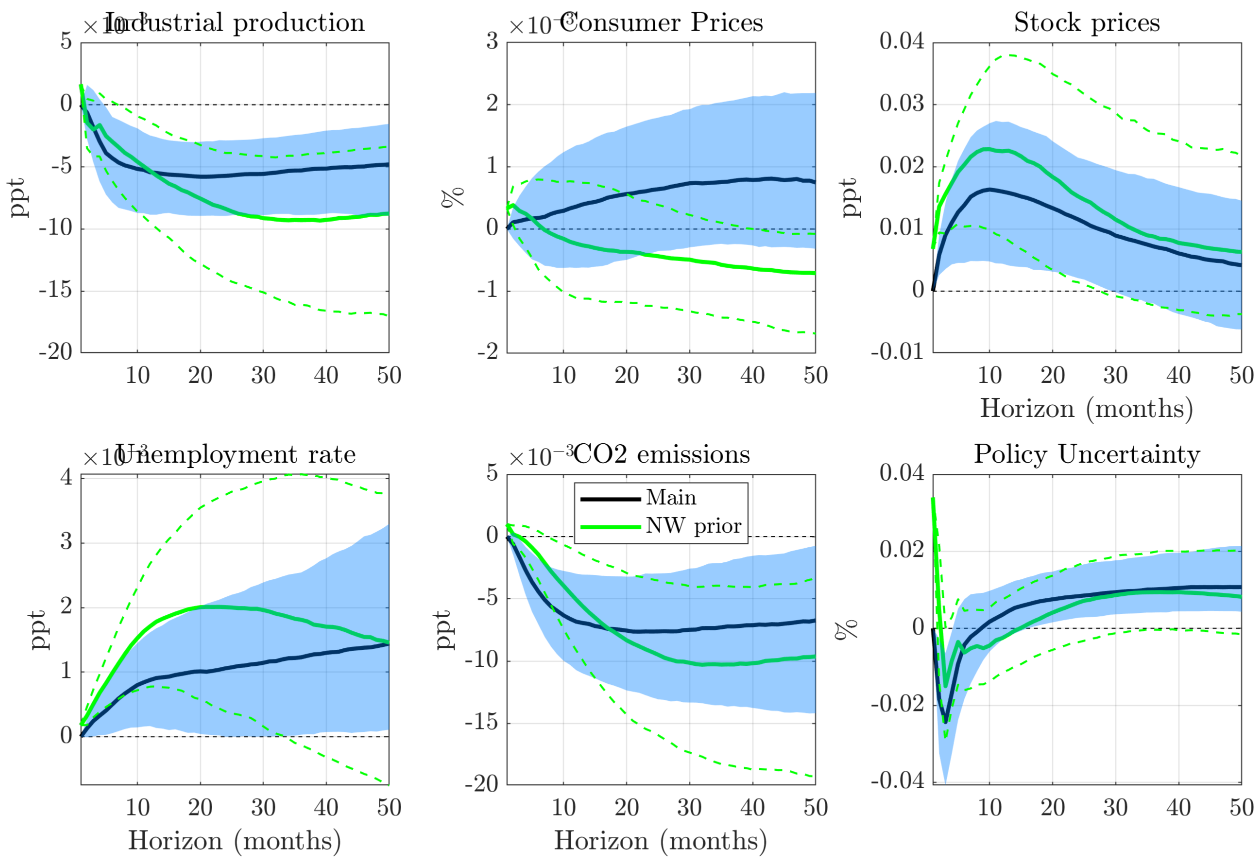

Figure 14: BVAR with Normal-Whishart diffuse prior with $\lambda_1 = 1000$

C.8 Robustness: VAR-OLS

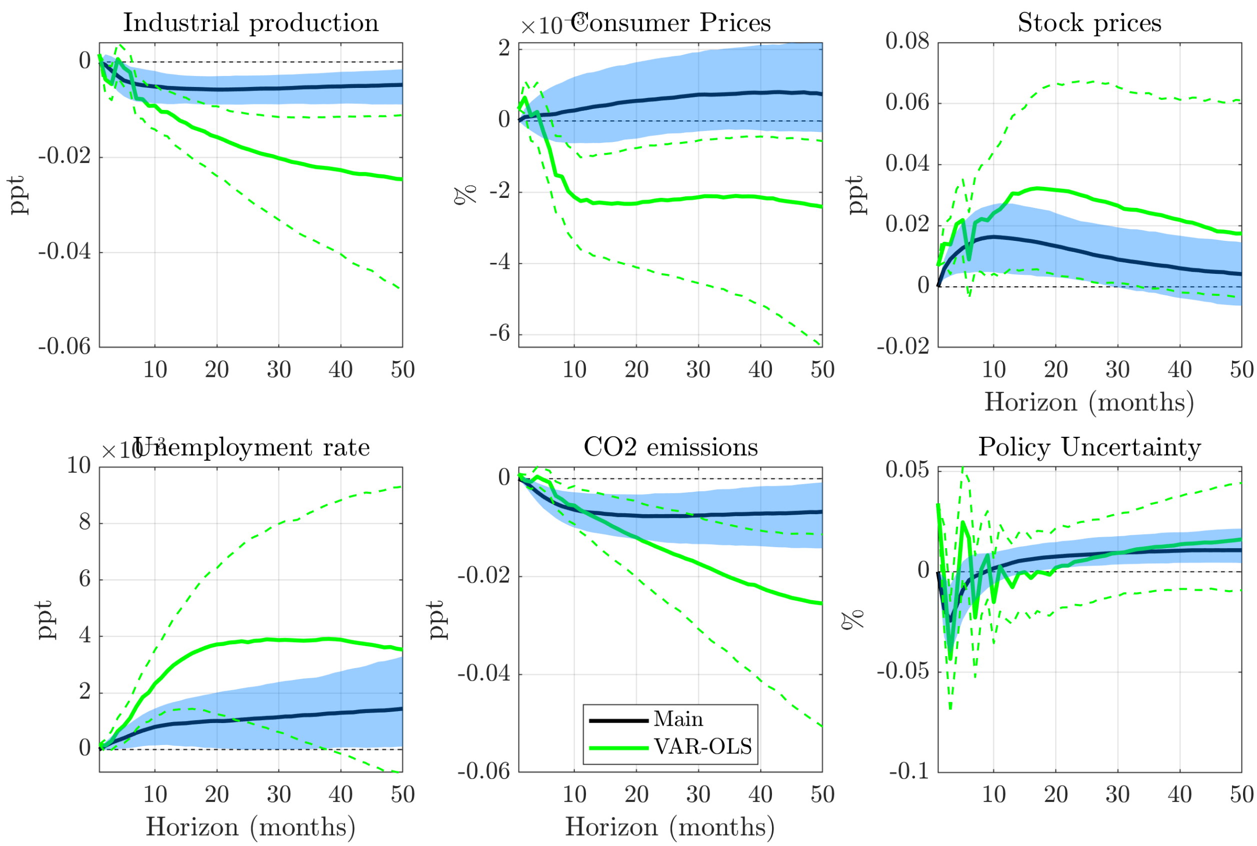

Figure 15: BVAR with $\lambda_1 = 1$ and $\lambda_2 = 2$

C.9 Robustness: Hyperameters optimized

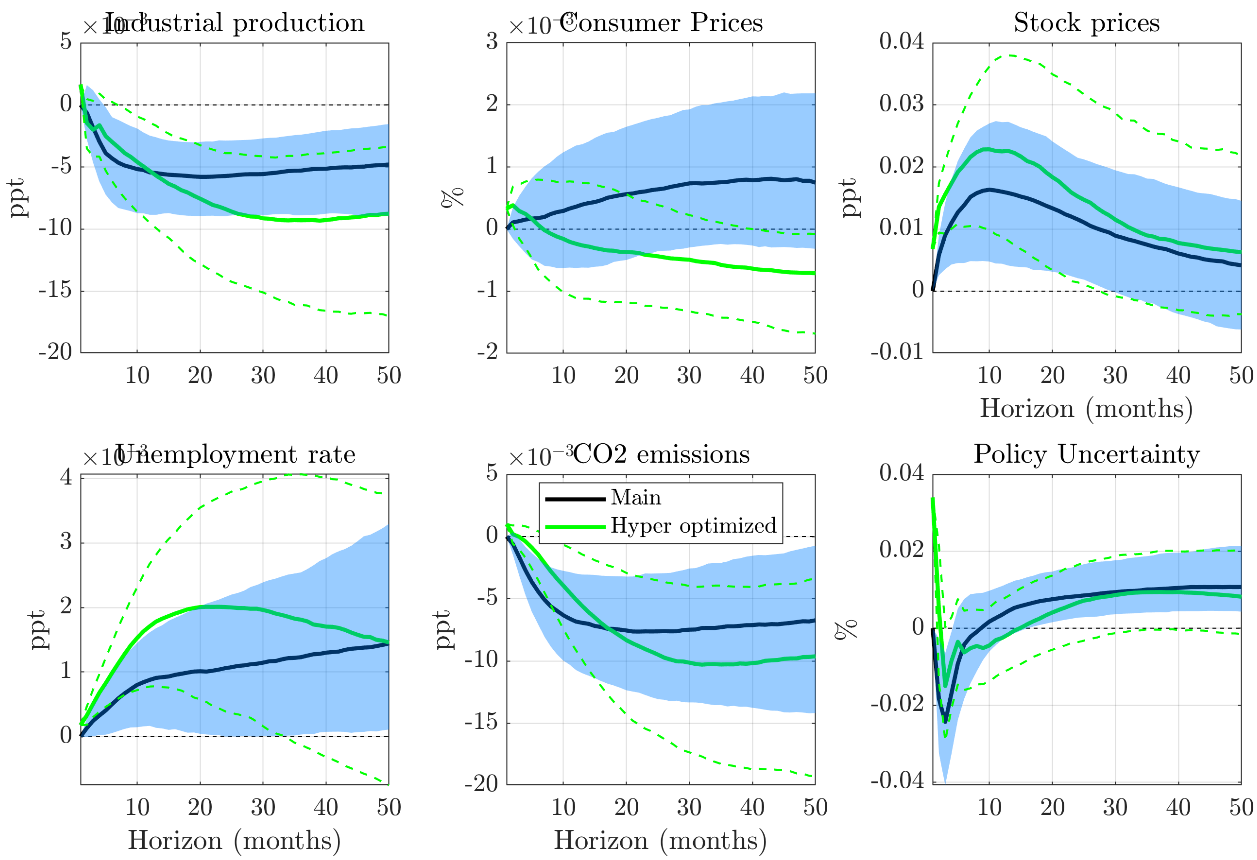

Figure 16: BVAR with hyperparameters optimized by grid search

C.10 Robustness: S_0 identity matrix

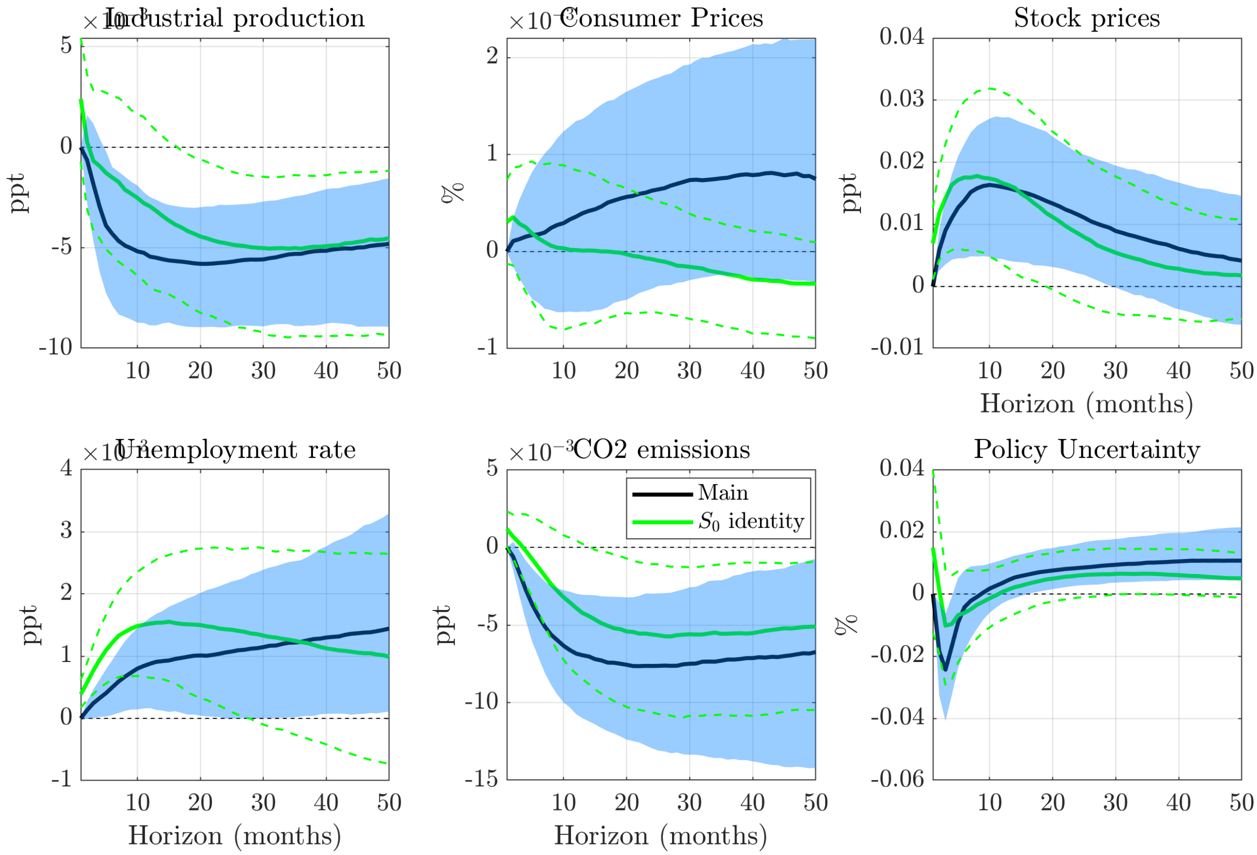

Figure 17: BVAR with S_0 identity matrix

C.11 Robustness: SoC and Dummy prior

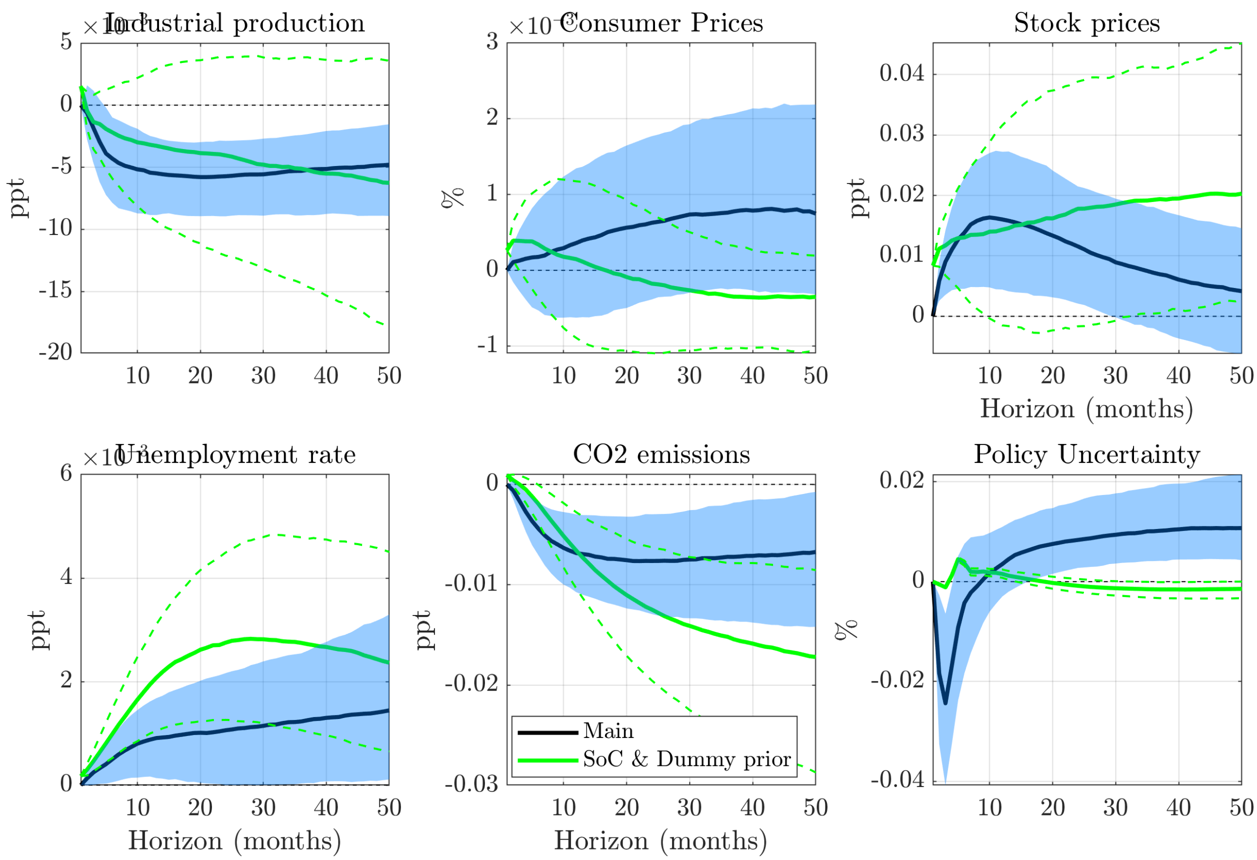

Figure 18: BVAR with sum-of-coefficient and dummy prior