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Uncertainty in climate policy and energy industry*

Hugo Morão†

September 13, 2025

Abstract

This study looks at how the the climate policy uncertainty (CPU) shocks affect Portugal's energy sector, specifically examining their effects on turnover, output prices, and labor market dynamics. The structural vector autoregression (SVAR) analysis shows that CPU shocks lead to a significant increase in domestic turnover. Output prices rise both at home and abroad, but foreign prices are more sensitive. The labor market shows a more nuanced reaction, hours worked marginally increase and wages remain unchanged. Furthermore, the study finds that CPU has been a key driver of historical variations in the energy sector, particularly during global policy events like COP26 and domestic policy changes like carbon or car tax changes. These findings establish CPU as significant driver in energy prices and underscore the importance of judicious climate policymaking.

JEL Codes: C32; E62; F18; H23; Q48; L94; G18

Keywords: climate policy; climate policy uncertainty; SVAR; energy crisis; Portugal

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1 Introduction

In a era defined by climate change and sustainability imperatives, policy uncertainty is becoming increasingly important. Governments globally face the challenge of crafting appropriate climate policies that can meet the targets without disrupting existing industries. The energy industry, a cornerstone in modern economies, finds itself in the middle of complex policy decisions balancing economic benefits and climate goals.

This paper examines a pressing question: how does climate policy uncertainty (CPU) specifically impact the energy industry? The relevance of this question is twofold. Firstly, it aligns with the significant question of the trade-offs environmental stewardship and economic stability - a tension that despite shaping policy it remains empirically under-explored. Secondly, this paper addresses a gap in the literature by analyzing how the sector-specific responses to the uncertainty created by many policy initiatives directly affect the energy industry, particularly in terms of adaptability and resilience, thus capturing heterogeneity in the market responses.

Related literature and contribution. Building on the pioneering work of Gavriilidis (2021) there is a growing literature studying the consequences of climate policy uncertainty shocks. This author introduced a news-based index to quantify CPU and employed a recursive SVAR to establish its link with lower CO2 emissions. Apergis et al. (2023) further explored this concepts and linked CPU with air-travel demand. This study extends the literature by using a Portuguese CPU index developed by Morão (2025b) with a novel Portuguese sectoral-level survey data from Portugal's energy industry. This investigation focuses in the interplay between CPU and key variables such as turnover, labor, and pricing within the energy sector. A Bayesian SVAR model is used to analyze these dynamics, with the CPU shock identified through a proxy-based approach as outlined by Ludvigson et al. (2021).

Recent literature on CPU's economic impacts can be split into financial market effects

and firm-level behavior. Several studies look at how CPU affects market volatility. Yu et al. (2023) focuses on stocks, Lasisi et al. (2022) on bonds, Wu et al. (2022) on carbon markets, and Salisu et al. (2023) on oil markets. Also, Xiao and Liu (2022) shows that since the Paris Agreement, CPU has played a bigger role in causing fear in the oil market.

Regarding firm-level impacts, Zhu et al. (2023) use unbalanced panel data to show that CPU positively influences on corporate innovation. This finding is echoed by Huo et al. (2023), who argues that CPU encourages corporate green innovation – a viewpoint that contrasts with Mao and Huang (2022), who asserts that this policy uncertainty reduces green innovation by making financing more challenging. Additionally, Wang (2022) notes that firms adopt pollution-reducing technologies in response to CPU. However, Gao and Zhang (2023) argues that higher levels of CPU discourage corporate investment. Furthermore, Huang and Sun (2023) observes that in China firms invest less when confronted with higher CPU. Similarly, Fried et al. (2021) suggests that CPU lowers carbon footprint firms by driving to invest in more eco-friendly capital stock. In contrast, Khalil and Strobel (2023) argues that CPU negatively impacts the market valuation of sectors with carbon emissions compared to those with low carbon emissions.

Overall, this paper enriches the existing literature by providing a comprehensive study of CPU's effects on the energy sector, thereby complementing firm-level studies and shifting focus toward real-sector impacts.

Preview of results. The study finds that CPU shocks wield a considerable impact on Portugal's energy sector. The SVAR analysis reveals that the shock rise domestic turnover, as well as home and foreign output prices, highlighting the considerable impact on the industry. Contrarily, non-domestic turnover and labor hours show only a marginal response, while gross wages remain unchanged. In periods of high CPU, Portuguese energy firms anticipate favorable market conditions by increasing the levels of investments in low-carbon technologies. This leads to a sustained rise in turnover for over a year. How-

ever, in non-domestic markets, firms display a muted reaction to CPU, likely holding off awaiting for policy clarity. Gross wage remain largely static, pointing to firms' preference for capital investments in green technologies over adjustments in labor costs. There is also a small increase in hours worked, which can be seen as a short-term requirement for firms to be able to adapt through new technology adoption or process conversion. Interestingly, the results show a price elasticity differential between home and foreign markets in response to CPU. Prices in foreign markets are more responsive, likely due to stricter environmental regulations in foreign markets which may yield higher returns in case of the firms being early adopter and highly invested in green technology and sustainable practices.

Through historical decomposition, the study concludes that a significant share of fluctuations in the energy industry can be attributed to CPU. For instance, during key episodes like the car tax hike or on major climate conferences, CPU shocks meaningfully contributed to shifts in the domestic turnover and output prices. This underscores CPU crucial role in policy planning within the energy sector. The analysis reveals a significant shift in the historical contribution of CPU on the energy industry around 2018/2019, coinciding with major climate policy events like COP26. Prior to this period, the effects of CPU had adverse effects on the sector. However, the sign of these effects change, a shift attributed to the rising of many sustainability-focused firms within the energy sector and the positive effects of many climate policies implemented over the last decade.

Finally, while the study provides a comprehensive understanding the SVAR specification used is robust to many changes in specification leaving some room for future research to explore non-linearities that might arise from global crises.

Validation. Portugal offers an ideal setting to study the impact of climate policy on the energy sector, given its extensive dataset sales, labor, and output price data in the energy industry. Its rapid transition towards renewables, while still maintaining traditional en-

ergy sources like natural gas, creates a dynamic environment highly responsive to policy shifts. Portugal's EU membership adds complexity, as national climate initiatives interact with broader EU directives. This mix of factors makes the Portuguese energy sector particularly sensitive to policy uncertainty, allowing us to observe clear and varied industry responses. Though this study focuses on Portugal, it helps us see how climate policy uncertainty impacts energy sectors in other countries facing similar transitions.

Roadmap. The paper unfolds as follows: Section 2 outlines the methodology and data sources. The empirical results are presented in Section 3. Section 4 presents sensitivity checks and some model extensions. Section 5 concludes with a few policy implications.

2 Methodology and data

This section presents the empirical approach used to analyze how climate policy uncertainty affects Portugal's energy sector. Before diving into technical details, let us outline the key components of the methodology. The analysis rests on three main pillars. First, the model used is a Vector Autoregression (VAR) - essentially a system of equations that captures how different aspects of the energy sector interact over time, much like running several related regressions simultaneously. Second, the analysis employs Bayesian methods to incorporate prior knowledge about the energy sector, such as the fact that more recent events typically have stronger effects than distant ones. Third, the strategy used to identify climate policy shocks using a state-of-the-art approach that treats our climate policy uncertainty index as an external variable, similar to standard instrumental variables regression.

2.1 SVAR model

Consider an SVAR model with six endogenous variables $n = 6$ corresponding to $y_t = [t_t, t_t^*, w_t, h_t, \pi_t, \pi_t^*]'$, where t_t is the index of domestic turnover, t_t^* is the index of non-

domestic turnover, w_t is the index of gross wages and salaries, h_t is the index of hours worked in industry, π_t represents home-market output prices, and π_t^* represents foreign-market output prices. The model has p lags:

$$y_t'\mathcal{D}_0 = \mathcal{C} + \mathcal{D}_1 y_{t-1}' + \ldots + \mathcal{A}_p y_{t-p}' + \eta_t' \tag{2.1}$$

Here, $\mathcal{D}_1, \ldots, \mathcal{D}_p$ are p coefficient matrices, each of size $n \times n$. Additionally, $\mathcal{C}$ is an $n \times 1$ parameter matrix. η_t is an $n \times 1$ vector of structural shock, and $\mathcal{D}_0$ is invertible. We can combine these regressors into a single matrix:

$$y_t'\mathcal{D}_0 = x_t'\mathcal{D}_+ + \eta_t' \tag{2.2}$$

where $x_t' = [1, y_{t-1}', \ldots, y_{t-p}']$ and $\mathcal{D}$ is a $n \times (np+1)$ dimensional matrix of lagged variables. $\mathcal{D}_+' = [\mathcal{C}', \mathcal{D}_1 \ldots \mathcal{D}_p']$. $\mathcal{D}_0$ and $\mathcal{D}_+$ are the structural parameters.

The reduced-form equation is then:

$$y_t = x_t'\beta_t + \varepsilon_t' \tag{2.3}$$

where $\beta = \mathcal{D}_+\mathcal{D}_0^{-1}$, $\varepsilon_t' = \eta_t'\mathcal{D}_0^{-1}$ and $\mathbb{E}[\varepsilon_t\varepsilon_t'] = (\mathcal{D}_0\mathcal{D}_0')^{-1} = \Sigma$.

β and Σ serve as reduced-form parameters for VAR coefficients and covariance matrix. The model uses Bayesian analysis. It employs an independent Normal-Wishart for estimating parameters. β has a normal distribution with mean β_0 and covariance matrix Ω_0. While, Σ follows an inverse Wishart distribution. This distribution is defined by a scale matrix S_0 and α_0 degrees of freedom. This approach is like the Minnesota prior in Litterman (1986), but does not condition the prior for β on Σ. The Gibbs sampling with an independent normal-Wishart prior described in Dieppe et al. (2016)[1]. This gives us tractable posterior distributions and simplifies the Bayesian inference process while re-

[1]More exposition on the Gibbs sampling can be seen in Karlsson (2013).

ducing the computational burden of the model. Robustness checks were conducted to address concerns about prior selection, using alternative priors such as Normal-Diffuse and optimized hyperparameter priors. The results are displayed in Figures 11-15 in Appendix B. The algorithm runs for 5000 iterations, discarding the first 2000 as a burn-in. Hyperparameters are set based on values commonly reported in the literature (see Table 3 for details). This framework captures the energy industry's variable interactions while accounting for uncertainty in the parameter estimates.

Why an SVAR? The choice of an SVAR model for this analysis is grounded in the unique economic features of the energy sector. It provides a solid foundation for studying the impacts of climate policy shocks on the energy industry. The energy sector is defined by long-term capital investments. These investments are highly sensitive to policy changes and have complex interdependencies with various economic variables. Policy shifts often cause delayed and non-linear responses.

These features often need a model that can capture both immediate impacts and delayed effects of policy uncertainty shocks. The sector experiences simultaneous causality between policy uncertainty and economic outcomes while facing frequent structural changes due to technology and major policy shifts.

The SVAR model excels in handling these complexities. It provides tools, like impulse response function (IRF) and forecast error variance decomposition (FEVD). These make it valuable in untangling the links between climate policy uncertainty and energy sector dynamics.

This approach not only allows for the isolation of specific impacts of policy uncertainty shocks, but it also provides insights crucial for effective policy design in a fast-changing industry.

2.2 The identification of the climate policy uncertainty shocks

In a standard SVAR model, the innovations ε_t are linear combinations of the structural shocks η_t. This is shown in Equation 2.4.

$$\varepsilon_t = \mathcal{D}_0 \eta_t \tag{2.4}$$

Herein, D_0 is an $n \times n$ matrix encapsulating the contemporaneous interactions among the variables, while η_t is an $n \times 1$ vector of structural shocks. The methodology assumes that these shocks follow a normal distribution with a zero mean and a diagonal covariance matrix, i.e., $\eta_t \sim \mathcal{N}(0, I)$.

This paper seeks a more nuanced identification strategy to generate the CPU shock than the conventional recursive approach. The departure from this approach stems from its overly restrictive assumptions. They may not align with some economic intuitions. The approach limits responses to uninteresting shocks. Instead, the scheme in Ludvigson et al. (2021) will be used. It implements correlation restrictions on the shocks. This approach allows us to use the CPU index, not as an endogenous variable in the VAR, but as an proxy for identifying the structural CPU shocks. Specifically, following correlation restriction is imposed:

$$\rho_1 = \text{corr}\left(S_t, \eta_{1,t}\right) \geq \bar{c} \tag{2.5}$$

Where S_t is the CPU index developed by Morão (2025b), $\eta_{1,t}$ is the structural shock used to identify the CPU shock, and $\bar{c}$ is a threshold correlation. This framework ensures a strong connection between the CPU shock and the index. It allows for flexibility in the relationships between the endogenous variables.

The methodology follows the seminal paper of Baker et al. (2016). It counts articles that have *at least* one keyword from these categories: "climate" (C),"policy" (P), and "uncertainty" (U). The search parameters consisted of the following terms:

(i) **Climate (C)** - This group includes terms related to climate change and environmen-

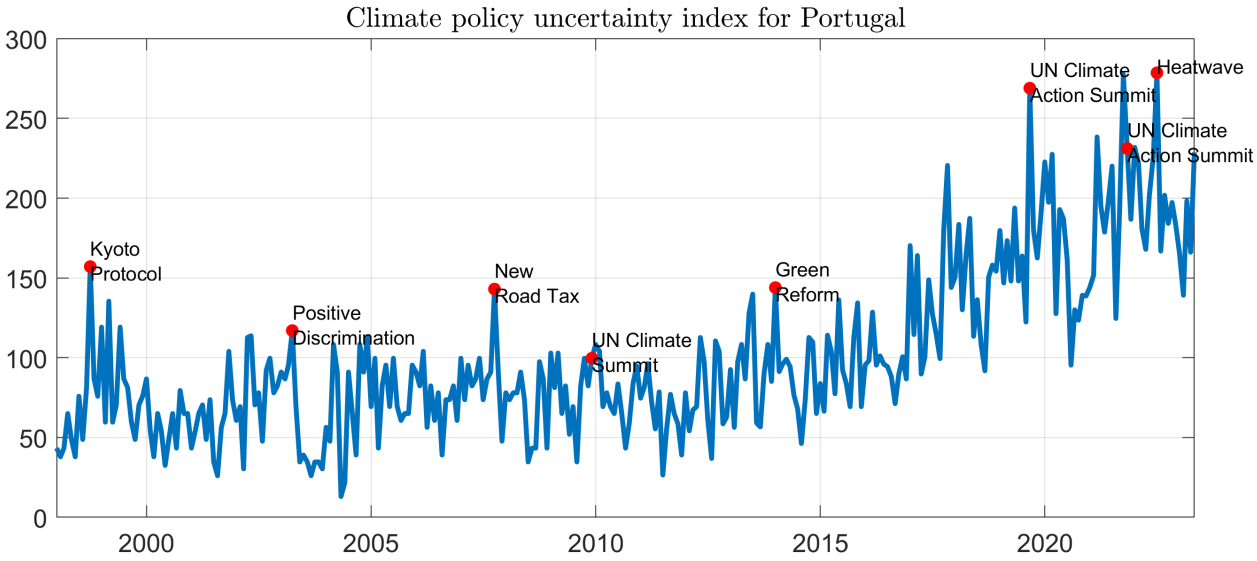


Figure 1: The climate policy uncertainty series (index points)

tal issues. These are "carbon dioxide", "CO2", "carbon emissions", "carbon neutrality", "carbon neutral", "CO2 reduction", "carbon reduction", "greenhouse gases", "greenhouse effect", "global warming", "acid rain", "climate", "renewable energy", "green energy", "wind energy", "solar energy", and "solar panel/s".

(ii) **Policy (P)** - This group contains terms related to governments and their policies. It includes "parliament", "government", "ministry of finance", "environmental fund", "European Commission", "deficit", "budget", "tax/es", "legislation", "standards", "normatives", "regulations", "rules", and "laws".

(iii) **Uncertainty (U)** - This group includes words that convey uncertainty, instability, or risk. They include "uncertain", "uncertainty", "instability", "unpredictability", "unstable", "indefiniteness", "insecurity", "doubt", "indecision", and "risk/s".

2.3 Empirical specification

Understanding the Portuguese energy sector requires analyzing domestic, labor, and foreign factors. This analysis uses a dataset that covers January 2005 to December 2022. It includes six important variables. Each one plays a different role, but they are all linked

together. The index of domestic turnover (t_t) show the revenues from the energy industry in Portugal. The index of non-domestic turnover (t_t^*) tracks revenues from exports and global transactions. It helps assess the industry's exposure to climate policies worldwide. This employs a dataset spanning January 2005 to December 2022, consisting of six key variables, each serving distinct yet interconnected roles. Moving to labor dynamics, the index of gross wages and salaries, w_t, act as an indicator of the labor costs, which are closely tied to regulatory changes. Positives changes in this variable might suggest that climate-related regulation, such as carbon pricing, are seen as likely to inflates the industry's cost structure. The index of hours worked in industry, h_t, provides insight into labor inputs in the energy industry, and may show how labor allocation changes in response to policy uncertainties, which is particularly relevant since climate policy may require adjustments to many production processes. π_t denotes the home-market output prices. These are the prices that producers get for goods sold in Portugal. They also reveal how domestic climate policies affect consumer prices. For instance, an announcement of a domestic carbon tax is likely to be passed onto consumers, thereby it will affect this index, see Morão (2025a, 2024b) Conversely, foreign output prices (π_t^*) encapsulate the prices for energy goods sold abroad and are likely to be influence climate policies in trading partner countries. Swings in this index can signal the industry's international competitiveness.

The study uses six lags. It also includes a constant term and the Economic Policy Uncertainty Index (EPU) for Portugal, as introduced by Morão (2024a) The VAR model is estimated in log annual rates. Further source details are provided in Table 2. The results stay robust across all these choices, as shown in Appendix B. Figure 2 shows the series in the baseline VAR for the sample period.

Upon close examination of each variable, domestic turnover displays a distinct pattern shows high volatility, stabilizes, and then becomes volatile again towards the end of the sample. This resurgence in volatility is driven by disruptions like the pandemic and major shifts in energy markets, particularly an increased emphasis on climate poli-

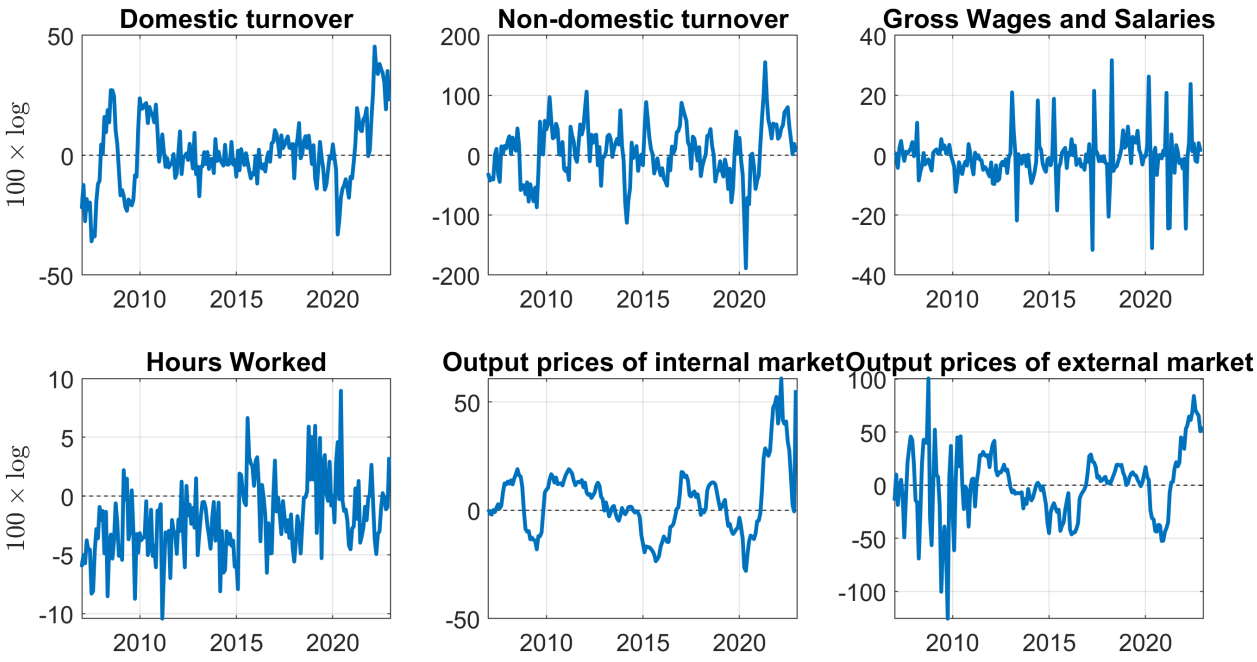


Figure 2: The energy industry data series in the baseline model

cies. The fluctuations suggest that domestic turnover is sensitive to external shocks and policy changes, highlighting its complexity. Non-domestic turnover is the series that exhibits larger fluctuations, notably during the pandemic-induced downturn and subsequent recovery. Despite initial sluggishness in the early 2010s, this metric shows a solid growth, particularly in 2010. This growth is spurred by two main factors: the Portuguese energy sector's strategic focus on international markets to counter domestic stagnation, and its successful adoption of competitive renewable energy technologies, incentivized by a decade of favorable policies. Gross wages experience a notable decline in wages around the portuguese debt crisis and rebound with some spikes wage negotiation periods. The years of 2018 and 2019 stand out by the high growth aligning with the upward trend in CPU. This suggests that wages in the industry are now subject not only to economic cycles but are also influenced by uncertainties in climate policy. Hours worked series presents the a negative growth in the majority of the time until 2015 due to broader structural decline in all portuguese industries associated with desindustrialization. After 2015 the sector start to some growth mainly to the good adaption of the portuguese en-

ergy to decarbonization and other sustainability practices. Home market output prices are shaped by production costs, such as fuel prices, and to a lesser extent, changes in economic activity (industrial production). The demand for cleaner energy amplified by programs EU ETS, also played an important role in shaping these prices. In contrast, foreign market output prices are more volatile and influenced by global energy prices and international regulations. Towards the sample period's end, home and foreign prices synchronize indicating growing integration between Portuguese and EU markets, likely due to coordinated policy efforts like the EU ETS and the adoption of common environmental standards.

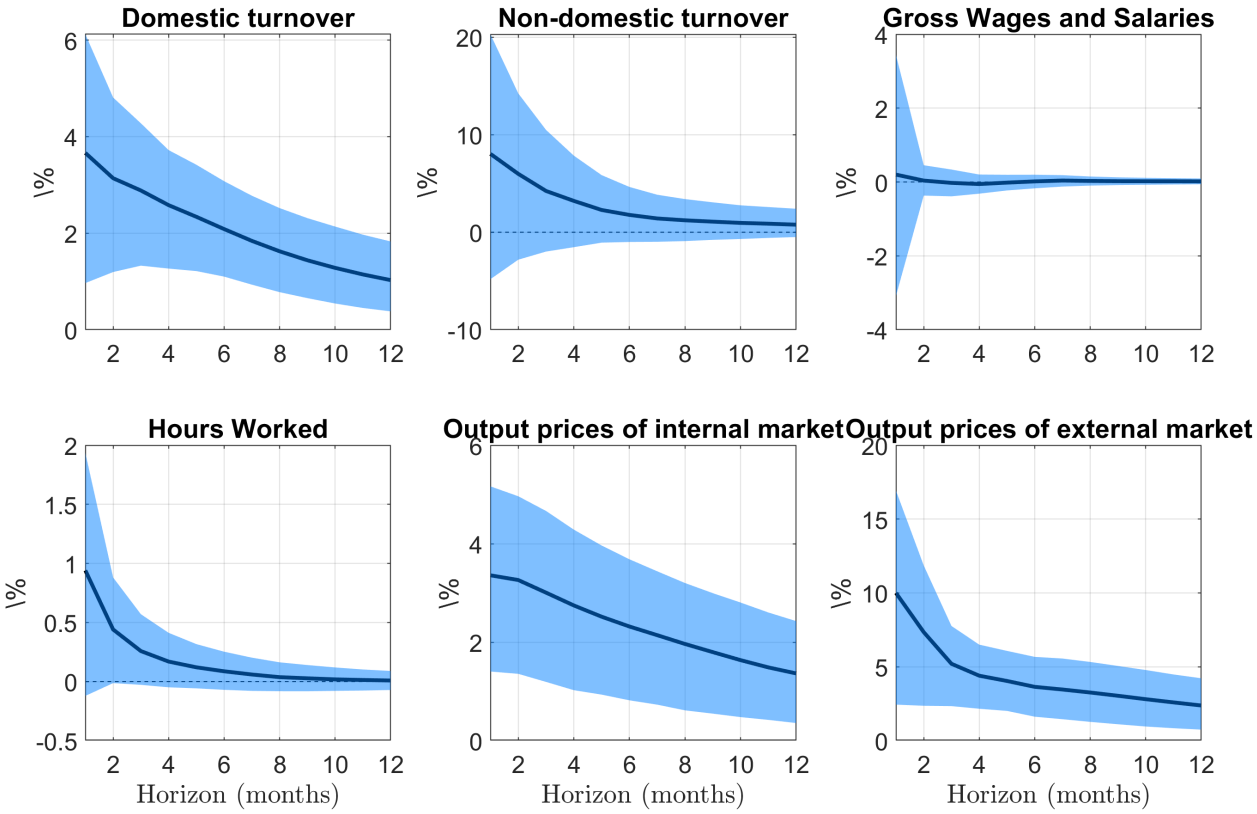
3 The impact on the energy industry

The section unfolds in three parts: First, the IRFs to see how energy market variables react to changes in climate uncertainty. Second, the FEVD to find out how CPU contribute to these changes in the energy industry. Finally, Historical Decomposition (HD) explores how CPU have historically affected the energy market.

3.1 IRF analysis

This subsection examines the impulse responses from the model described earlier. The analysis looks at how climate uncertainty impacts the energy sector. It focuses on a rise in climate policy uncertainty. The focus will be on sales, output prices, wages, and employment. Figure 3 shows how shocks from climate policy uncertainty affect all variables in the energy industry. The x-axis shows time (in months) after the shock. The y-axis shows the % deviation from the baseline.

In the response to higher climate policy uncertainty, domestic turnover in Portugal exhibits a strong and persistent positive response. Firms may interpret the uncertainty as foreshadowing favorable market conditions for sustainability, leading them to invest



Note: Note: Impulse responses to climate policy uncertainty shocks are normalized to show a 10% increase in foreign market prices at impact. The solid black line shows the posterior median estimate, while the shaded areas indicate the 68% credible bands.

Figure 3: Impulse responses to a climate uncertainty policy shock

in low-carbon technologies, thus driving up their turnover for a period extending over a year.

Non-domestic turnover manifests a positive effect but with a muted significance, indicated by wider credible bands. This suggest lower sensitivity to domestic policy changes, likely because energy firms involved in international transactions are probably already be under some global regulations, making them less reactive to domestic uncertainties. Alternatively, these international firms can also adopt wait-and-see approach until the policy and regulatory landscape becomes clearer.

While turnover responds in varying degrees, gross wages remain largely unaffected. This indicates that firms prioritize capital investments in new technologies or practices as an immediate response to the climate policy uncertainty, rendering labor costs secondary as they not experience significant changes.

In terms of hours worked, there is a marginally significant increase in hours worked in the industry. This small uptick can be attributed to firms' rapid adaptation to expected policy changes, possibly via the adoption of new green technologies or reconverting some processes that will demand more labor hours temporarily.

Home and foreign market output prices both exhibit a persistent and positive response to CPU shocks. This price increase is a response to companies grappling with increased costs for carbon reduction. There is a price differential between the two markets, as foreign markets are more sensitive to policy uncertainty — around 10% (normalized) compared to 4% for the home market. This indicate higher awareness of climate issues among foreign buyers, leading to international market pressures or more stringent regulations that will eventually spillover to domestic policy or the amplification of effects by other variables like exchange rate risks. Either way, the influence of domestic climate policy uncertainty seems to have far-reaching consequences, affecting prices in international markets as well.

3.2 Historical importance

Variance decomposition analysis. The preceding analysis confirms that CPU shocks have significant effects on the energy industry. Next, we must ask: to what extent CPU shocks explain historical variations in key variables? A forecast error variance decomposition (FEVD) addresses this. This analysis complements the IRF results. It reveals whether CPU shocks have a greater impact on short-term or long-term energy sector dynamics. This information is valuable for policymakers. It shows how their climate policies might affect different aspects of the energy industry over various time horizons.

Table 1 presents the CPU shock's percentage contribution to the variance of each variable at three distinct forecast horizons: 1 months, 6 months, and 12 months.

Table 1: Forecast error variance decomposition

h	t_t	t_t^*	w_t	h_t	π_t	π_t^*
1	29.20	12.80	9.83	16.66	35.90	27.38
6	36.35	13.39	10.00	16.19	35.12	29.90
12	35.18	13.82	10.00	16.10	34.39	29.04

Notes: The table presents the median values for forecast error variance decomposition. These results are for climate policy uncertainty shocks at three time frames: 1 month, 6 months, and 12 months.

At $(h = 1)$, the CPU shock explains a substantial 29.2% of the variance in domestic turnover. This strong and fast impact is due to the capital-intensive and long-term nature of energy firms, which prompts them to swiftly adjust operations and investment strategies. Typically, this involves reducing fossil fuel-based operations and ramping up renewable energy projects to mitigate adverse effects of policy uncertainty.

Non-domestic turnover is comparatively less affected, with only 12.80% of its variance being explained by the CPU shocks, potentially because many of these firms' international operations benefit from contractual obligations that shield them temporarily from some of the immediate effects of Portugal's domestic policy uncertainty.

For gross wages, the CPU shocks only explain 9.83% of the variance. Wages tend to be

a less flexible operational cost for energy firms, often due to existing labor contracts and regulation that insulate them from immediate adjustments in response to sudden policy changes. Consequently, firms are more likely to focus on other cost-cutting or efficiency measures.

Regarding hours worked shows a 16.66% contribution. This suggests a that labor market adjustment is more elastic in labor demand, likely as short-term response to higher costs and operational changes required by the new climate policy landscape.

Home market output prices exhibit the most immediate and significant response, contributing to about 36% of the variance. This implies that Portuguese energy firms are quick to transfer the increased production costs arising from policy uncertainty to domestic consumers through upward price adjustments (IRF). From the foreign markets counterpart, the CPU shocks account for 27.38% of the variance. Despite being less impacted than home prices, this significant effect indicates that even if these prices are for foreign markets, they are not fully insulated from domestic climate policy uncertainties.

As the forecast horizon extends to $h = 6$ and $h = 12$, the sensitivity of these sectors to climate policy uncertainty largely remains, albeit some changes like in domestic turnover. This uptick is indicative of a lagged adjustment process among Portuguese energy firms. Initially, firms employ quick fixes, such as delaying immediate investments. However, as uncertainty lingers, they increasingly opt for structural adjustments, like supply chain modifications and long-term investment reevaluations, or diversify into less policy-sensitive energy markets.

Historical decomposition analysis. As observed, CPU shocks can significantly impact the Portuguese energy market. An equally important question is the role of these policy shifts are in shaping the trends and variations in Portugal's energy markets. A historical decomposition is performed to examine this.

Figure 4 delineates the historical contribution of climate policy uncertainty shocks to

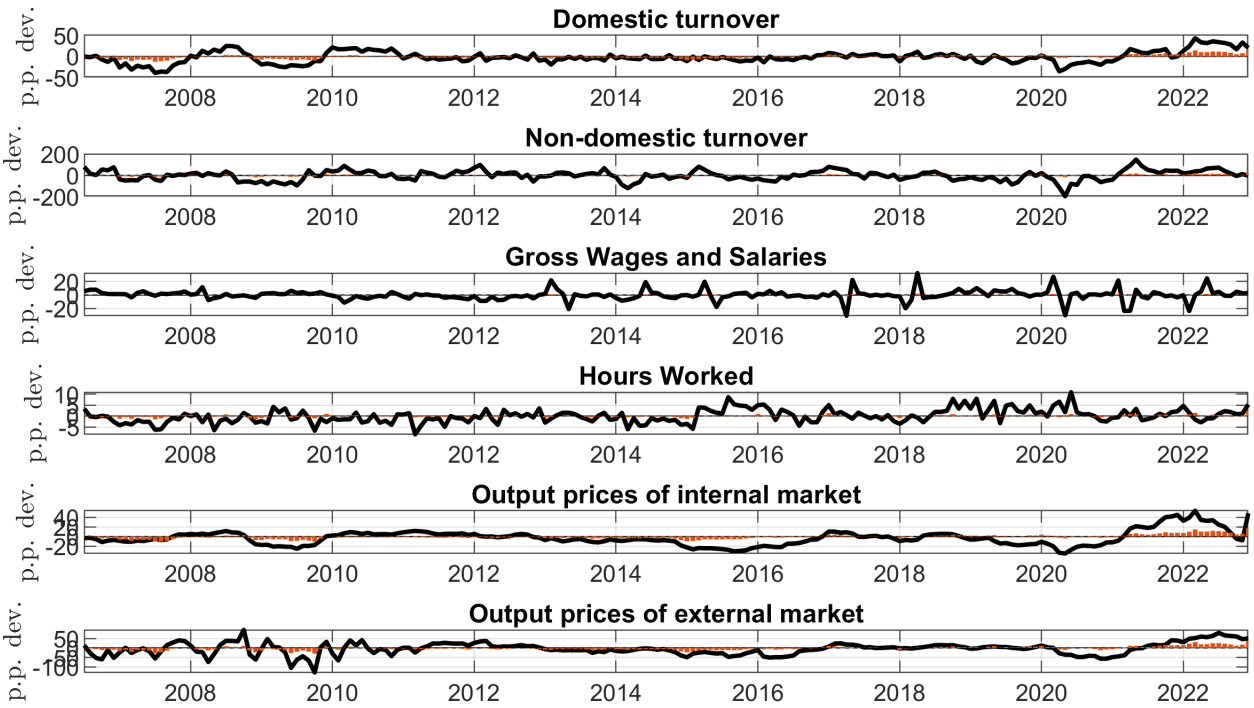


Figure 4: Historical decomposition of energy industry variables

Note: The solid bar shows the median estimate. The black line represents the time series of the variables in % deviations.

energy variables from 2005 to 2022. As mentioned earlier, the effects on wages are insignificant and therefore omitted from the plot.

The visible first insight across all variables is that CPU shock contribution that is procyclical i.e. decrease when the variation are negative and increase when they are positive in terms of p.p. deviations. Domestic turnover has a significant contribution except in three specific episodes which are the Great Financial Crisis, Portuguese financial crisis (2010 and 2011) and the COVID-19 pandemic. In the periods with higher variation as 2007, 2009 and mid 2022 the shock accounted for about a third of all variation. From 2012 to 2016 it contributed for about half or a bit higher however the whole variation of the series remains low. The modest contribution of CPU shocks to non-domestic turnover aligns well with the uncertainty observed in the bounds of the IRF analysis, and is further substantiated by the high variance noted in the series on the y-axis. Hours worked follows a similar dynamics but with a much lower variability in the series this likely due

to the downward trend in the industry until around 2015. This was a common trend in all portuguese industries.

In terms of output prices, the years 2007 and 2009 stand out for their substantial negative contributions from CPU shocks, which pushed prices downward. This matches aligns well consistent with key policy events of that era, such as the European Commission's scrutiny of biofuel viability and the policy shift under the Obama administration in the US. In 2007, CPU accounted for the majority of the variation in output prices, while in 2009 it explained about half. For foreign market output prices, CPU's contribution was also significant but relatively less significant compared to its impact on internal prices. This difference can be attributed to the high volatility in foreign markets, particularly in the early sample period. During 2010 to 2012, the contribution of CPU to output prices is minimal, aligning with a general waning in focus on climate issues amid the Portuguese debt crisis. This trend reversed with the proposals of new environmental laws and carbon tax proposals. Interestingly, despite the sign of the CPU's contribution being the same across both home and foreign markets, CPU can explain more of the dynamics in foreign markets than in internal ones.

Lastly, the contribution of CPU shocks is time-varying. Initially, these shocks had a dampening effect on domestic turnover and output prices. This feature persisted until 2018, a period that saw a rising in CPU linked to global events such as COP26. The changing dynamic is particularly evident in output prices where the negative contributions gradually receded and turned positive after 2018. This shift can be attributed to the rising of many sustainability-focused firms within the energy sector. Despite the new costs associated with carbon licenses and taxes these firms are investing in low-carbon technologies giving Portugal an edge in terms of climate policy.

4 Additional results and robustness analysis

This section conducts two additional tests to ensure the robustness of the study's results. First, alternative setups of the main study's model are examined, with direct attention to a common identification scheme called Cholesky decomposition, to assess if it changes the main findings. Second, the effects of some changes in model settings are assessed to determine if they lead to different outcomes. Ultimately, the main finding remains unchanged: CPU shocks have a significant impact on the Portuguese energy industry, a results that holds across the tests conducted.

Cholesky decomposition. Recent literature by Kilian et al. (2022) emphasize the vulnerability of SVAR models that rely on Cholesky decomposition identification unless the identifying restrictions are substantiated by external evidence. Despite these concerns, it remains a common practice in the economic uncertainty literature, particularly following Baker et al. (2016) which explore recursive orderings of the variables in SVAR models. In Figure 6, the median response identified using the proxy approach is juxtaposed with the alternative approach, indicated by the green line, that employs recursive ordering for identification.

Upon initial inspection, the recursive approach appears more optimistic regarding the impact of shocks on the energy sector. The effects on domestic turnover and both types of output prices considerably more persistent. Some responses even double compared to the the main benchmark after the first year. The most notable distinction is that the recursive model generates significant hump-shaped responses in hours worked and home output prices. Furthermore, non-domestic turnover gains significance within the first four months, although wage response continue to lack statistical significance.

Model specification. The SVAR model's findings are assessed by applying several changes. One key change is adding an exogenous variable REER, as noted in Figure 7. The model

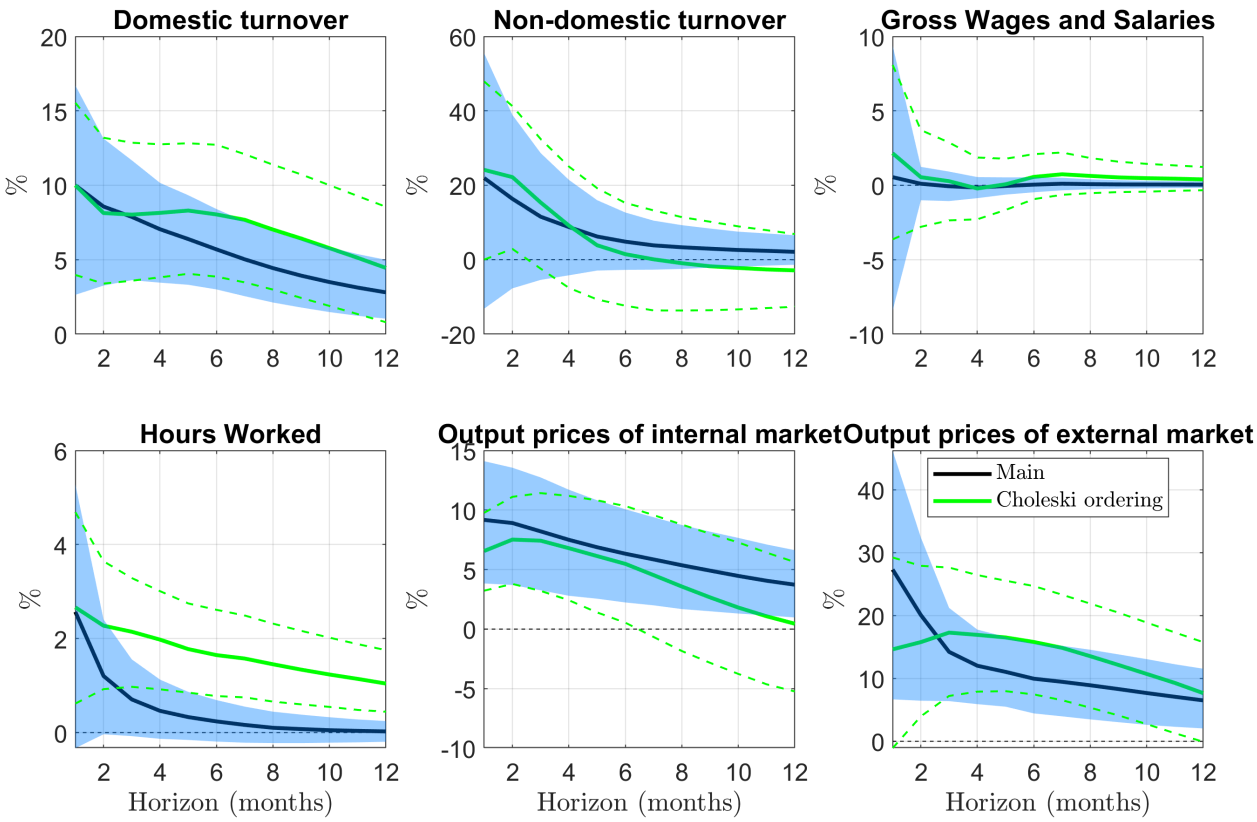


Figure 5: Model with recursive identification

is also run without any exogenous variables as indicated in Figure 8. Further checks include changing some model'a parameters, like lag lengths (see Figures 9 and 10), and employing different priors (see Figures 11 and 12). Hyperparameter sensitivity analysis allows us to measure the model's responsiveness to changes in hyperparameters, as displayed in Figures 13, 14 and 15. The influence of different assumptions about the S_0 matrix (see igure 16) and the inclusion of constant and trend terms (see Figures 17 and 18). The results from all tests are consistent, increasing confidence in the study's conclusions. The strength of the benchmark model shows it's ready for further improvements. See Appendix B for more details.

5 Conclusion and policy implications

The primary contribution of this study is that Climate Policy Uncertainty shocks have a significant impact on the energy industry. Sectoral-level survey data from Portugal and an SVAR model are used, employing the Portuguese CPU series as a proxy for identification. The impact of CPU is heterogeneous across different variables such as turnover, labor and prices variables, with particular sensitivity observed in domestic turnover and output prices within home and external markets. Historical decomposition analysis supports the hypothesis that uncertainty in climate policy has greatly affected the ups and downs in the energy sector. This research builds upon existing literature, such as presented by Morão (2025a), which examined the macroeconomic effects but without explicitly considering the sectoral effects of policy uncertainty. Although the SVAR model employed herein is robust across different specifications and benefits from a more rigorous proxy-based identification. Future research may explore these non-linearities in greater detail and extend the analysis to other industries. From a policy standpoint, this study emphasizes the need for predictable climate policies to minimize the negative effects of uncertainties in the energy sector. Policymakers should pay attention to how CPU affects different facets of the industry, particularly the areas most sensitive to fluctuations and

tailoring interventions. Overall, this paper improves our comprehension of how climate policy uncertainties propagate through the energy markets, offering key insights for academics and policymakers alike. While this study focuses on Portugal, its findings apply to other similar countries. The results likely apply most to nations with a mix of energy sources, those undergoing energy transitions. However, the size and mechanisms of these effects may vary. They depend on each country's characteristics, like energy market liberalization and economic structure. Future research should compare these dynamics across countries to establish broader generalizability of these results.

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Appendix For Publication

A Appendix: Data and Model

Table 2: Data Description and Sources

Label	Description	Source
S_t	Climate policy uncertainty in Portugal	Morão (2025a)
t_t	Index of domestic turnover in industry	INE/Own
t_t^*	Index of non-domestic turnover in industry	INE/Own
h_t	Index of gross wages and salaries in industry	INE/Own
w_t	Index of hours worked in industry	INE/Own
π_t	Indexes of output prices (home)	INE/Own
π_t^*	Indexes of output prices (foreign)	INE/Own
epu_t	Economic policy uncertainty Index for Portugal	Morão (2024a)

Notes: Data series are monthly and covering 2006m1-2019m12 period in the main specification.

Table 3: Hyperparameters

	Value	Description	Observation
ρ	1	autoregressive coefficients	Used in all models
λ_1	0.1	overall tightness	$\lambda_1 = 1000$ in model 14 & $\lambda_1 = 1$ in model 15
λ_2	0.5	cross-variable weighting	$\lambda_2 = 2$ used in model 17
λ_3	1	lag decay	Used in all models
λ_4	10^5	exogenous variable tightness	Used in all models

B Appendix: Sensitivity analysis

B.1 Robustness: Pandemic

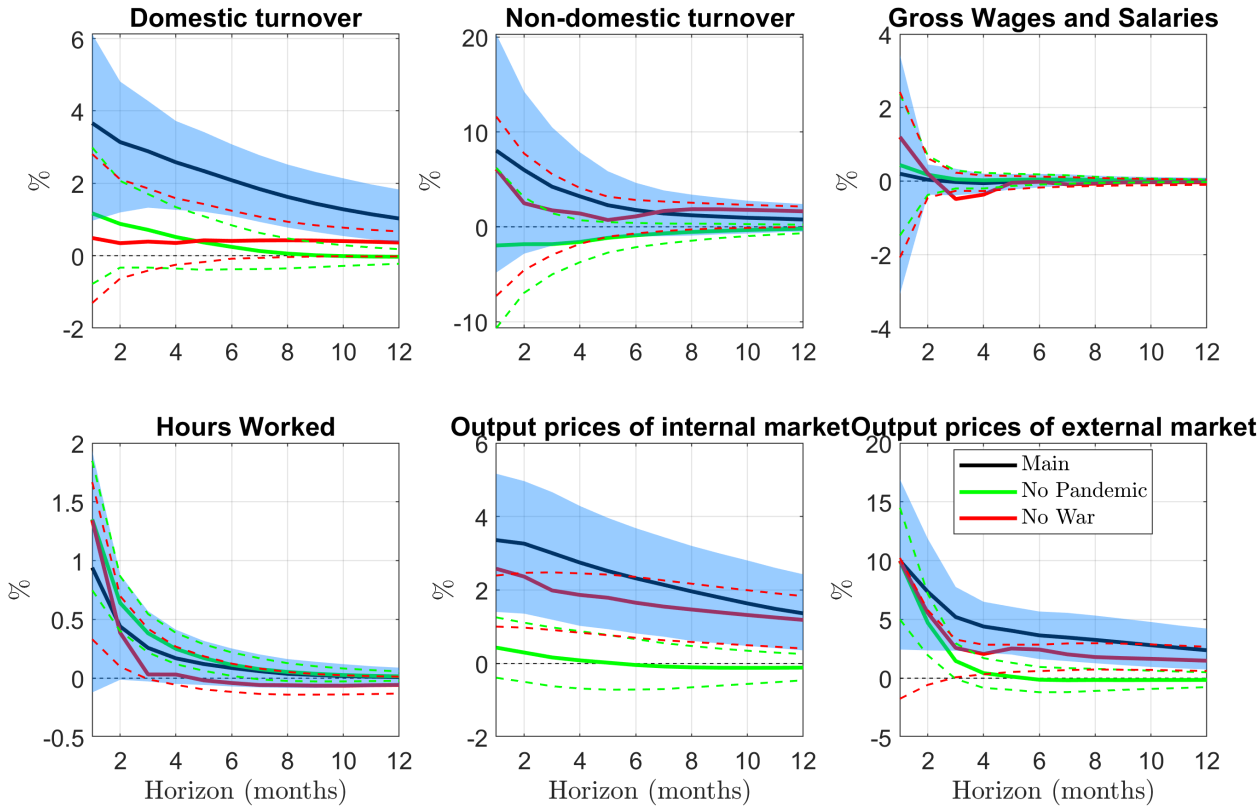

Figure 6: Removing pandemic and war

B.2 Robustness: REER

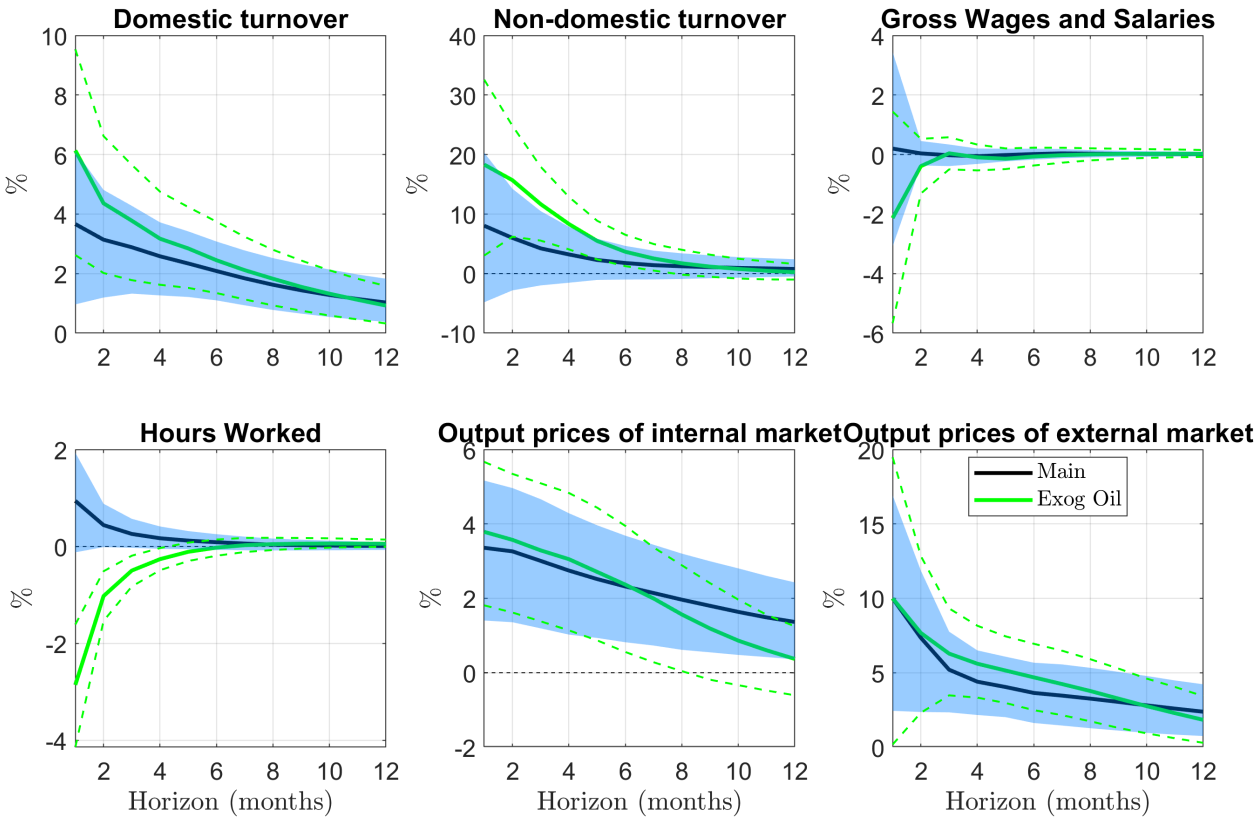

Figure 7: Model including REER as exogenous variable

B.3 Robustness: No exogenous variables

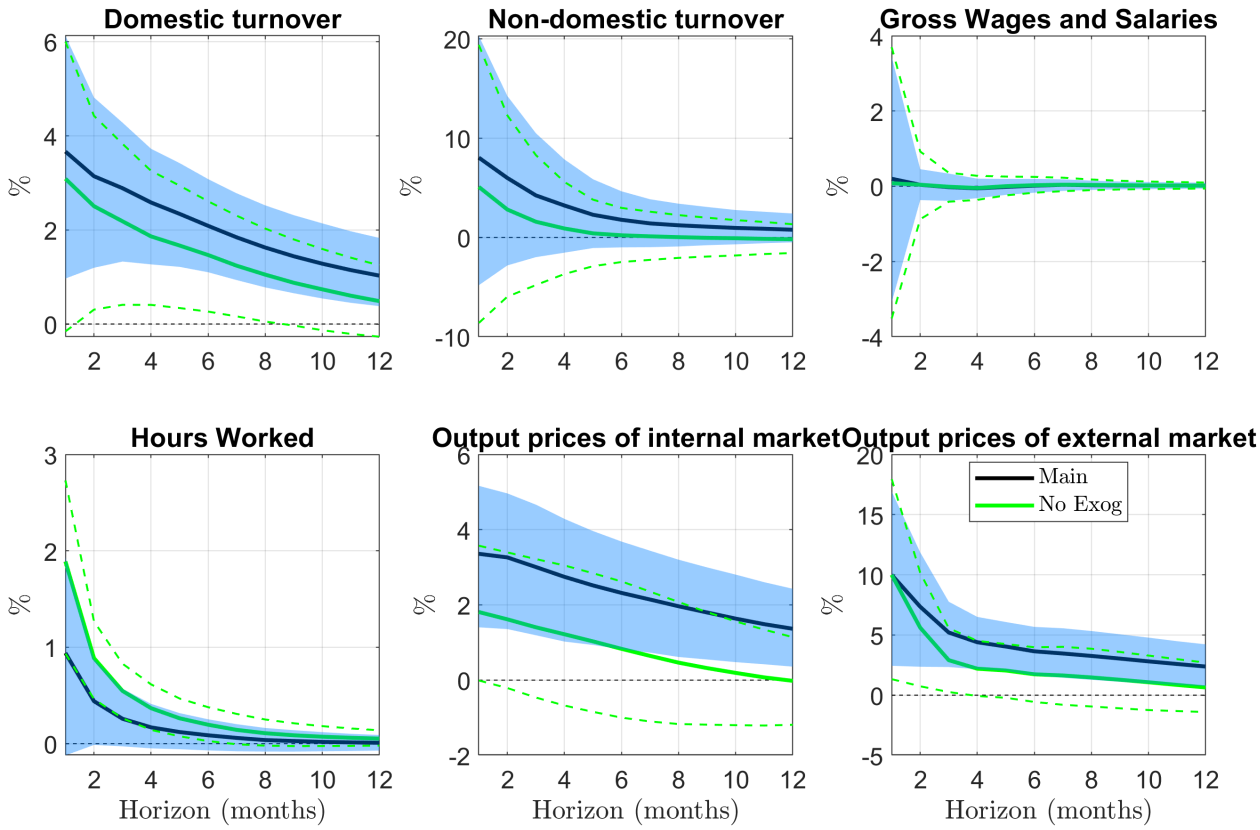

Figure 8: Model excluding the exogenous variable

B.4 Robustness: 4 lags

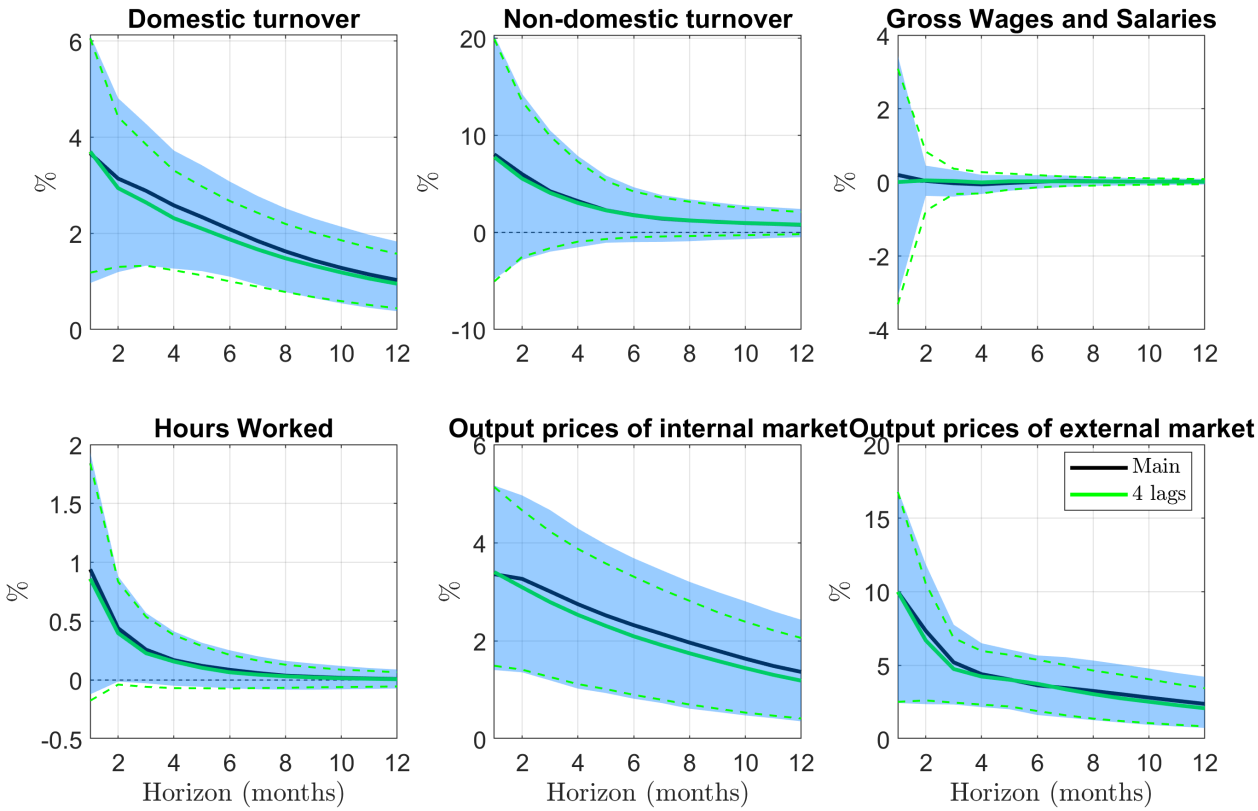

Figure 9: Results from a BVAR(4) following AIC

B.5 Robustness: 1 lags

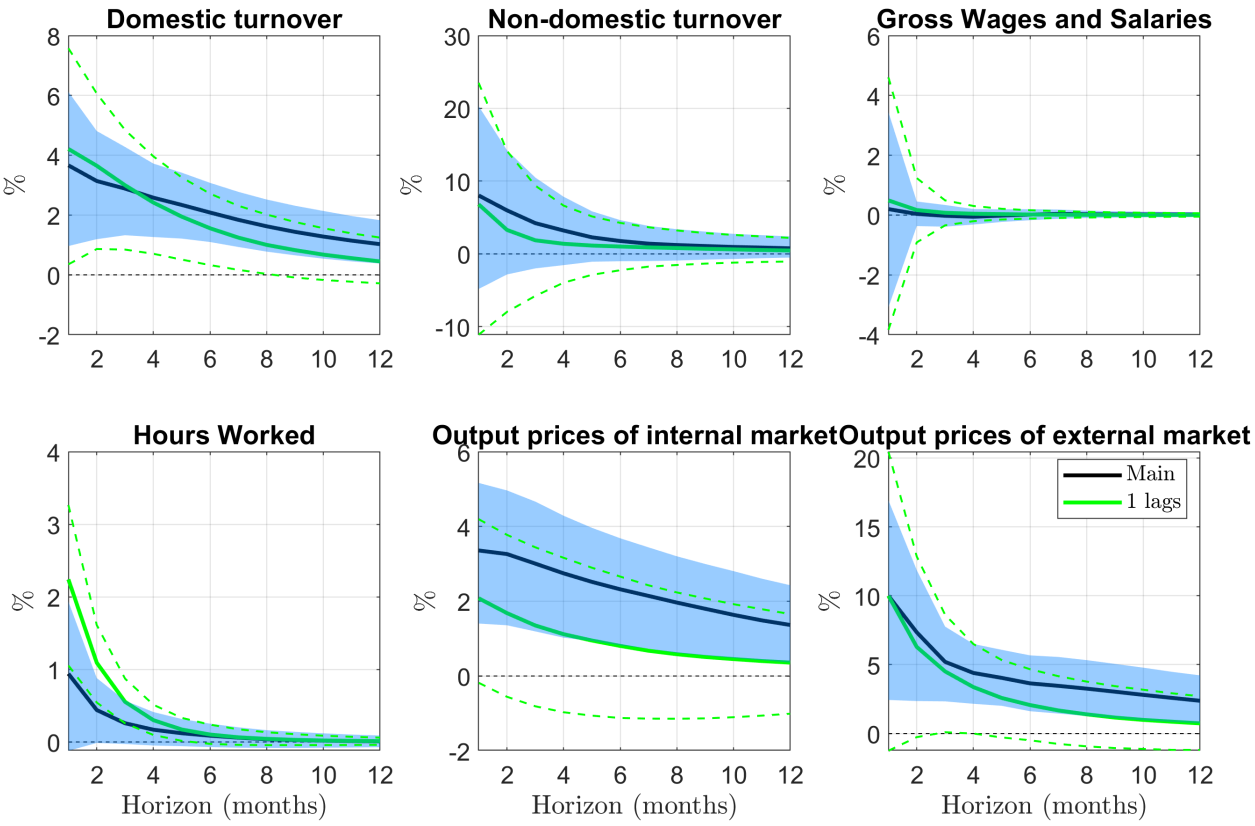

Figure 10: Results from a BVAR(1) foloowing LR

B.6 Robustness: $\mathcal{NW}$ prior

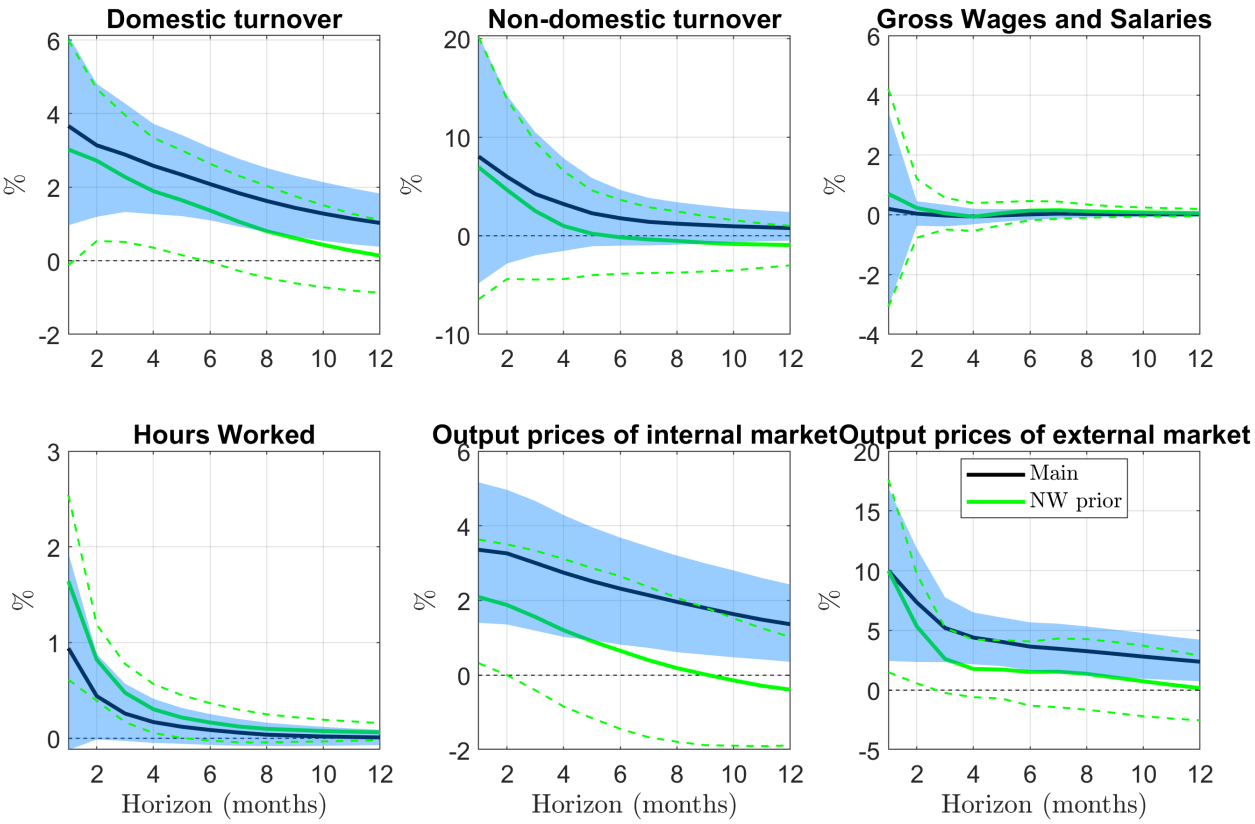

Figure 11: BVAR with Normal-Whishart prior

B.7 Robustness: Normal-Diffuse prior

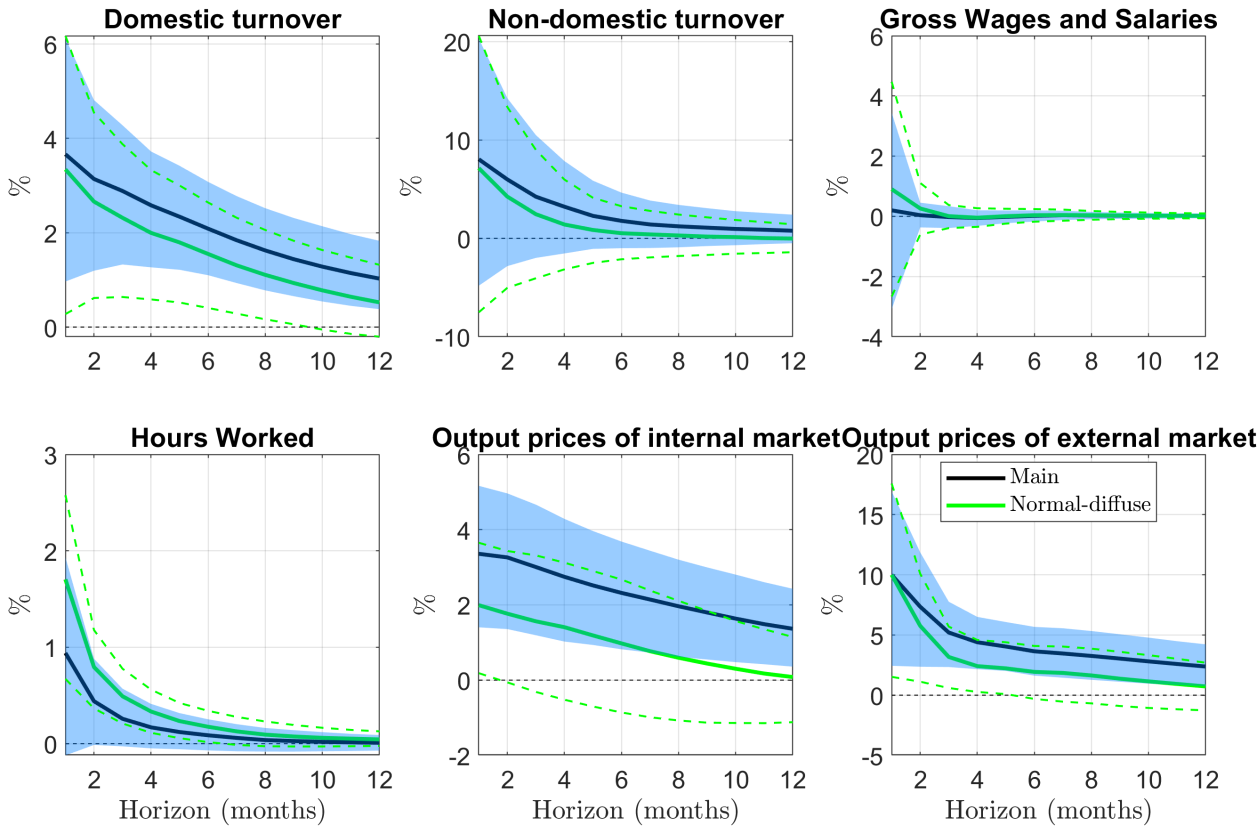

Figure 12: BVAR with Normal-Diffuse prior

B.8 Robustness: $\mathcal{NW}$ diffuse prior

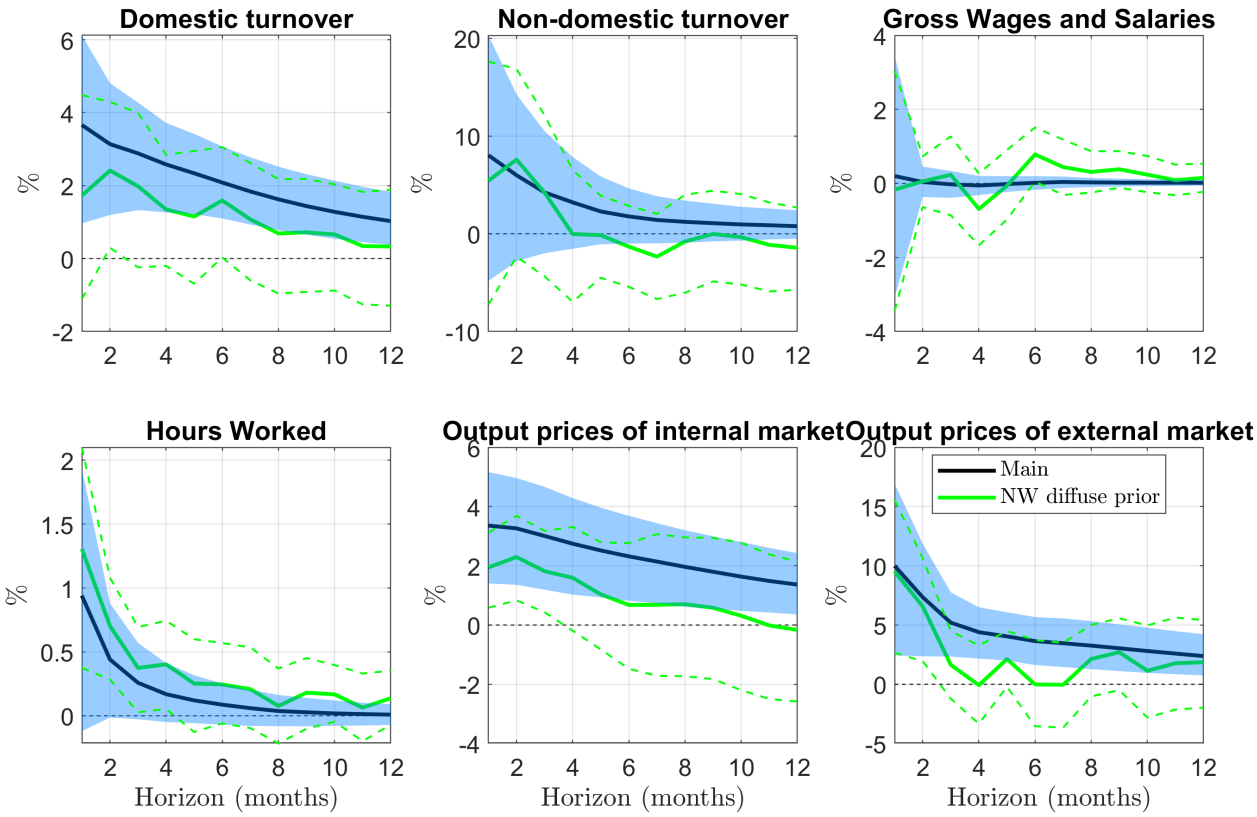

Figure 13: BVAR with Normal-Whishart diffuse prior with $\lambda_1 = 1000$

B.9 Robustness: VAR-OLS

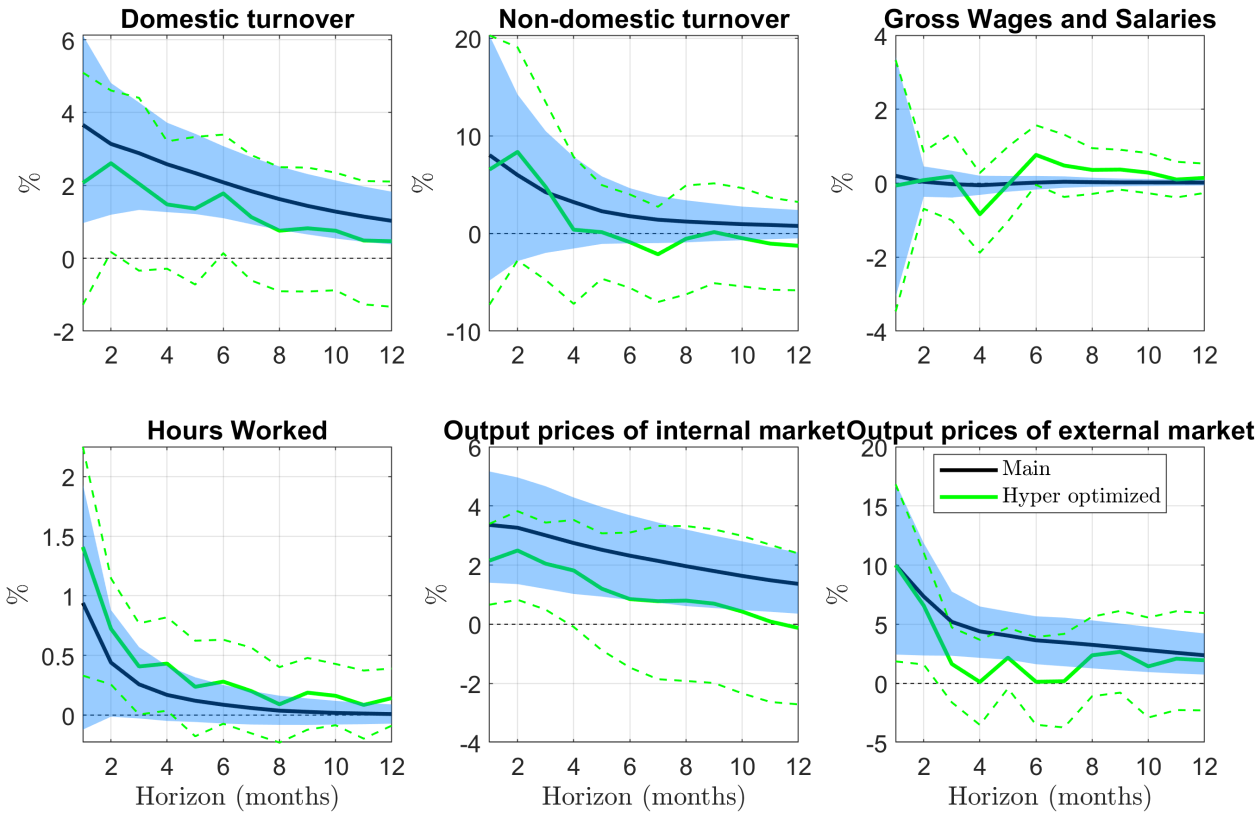

Figure 14: BVAR with $\lambda_1 = 1$ and $\lambda_2 = 2$

B.10 Robustness: Hyperameters optimized

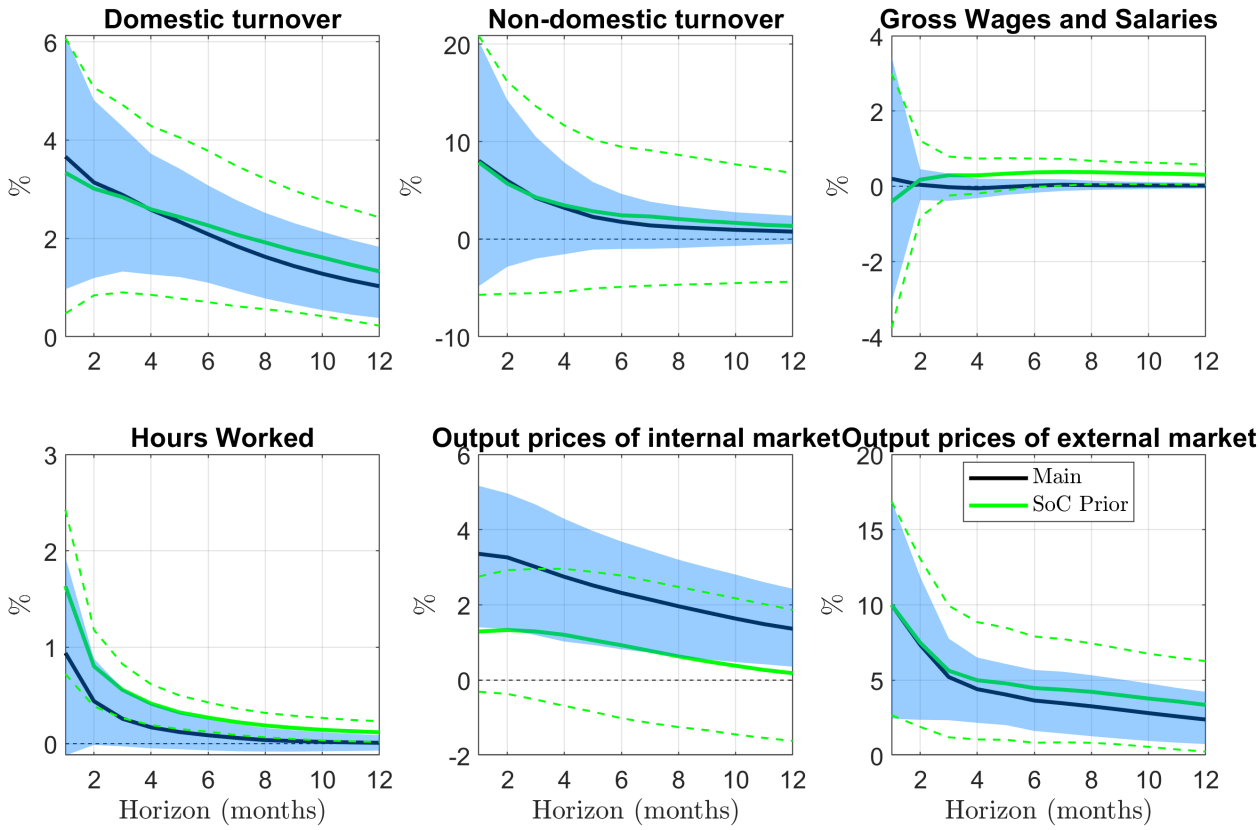

Figure 15: BVAR with hyperparameters optimized by grid search

B.11 Robustness: S_0 identity matrix

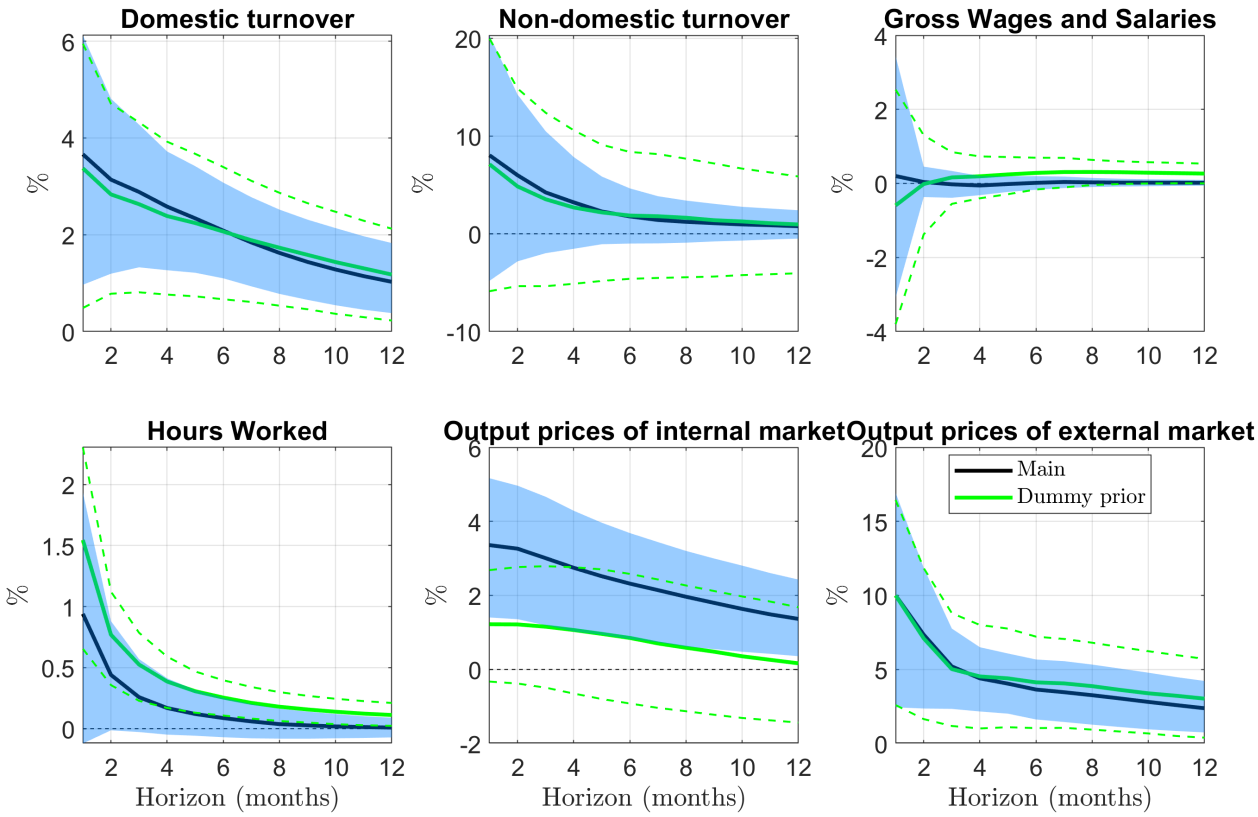

Figure 16: BVAR with S_0 identity matrix

B.12 Robustness: linear trend

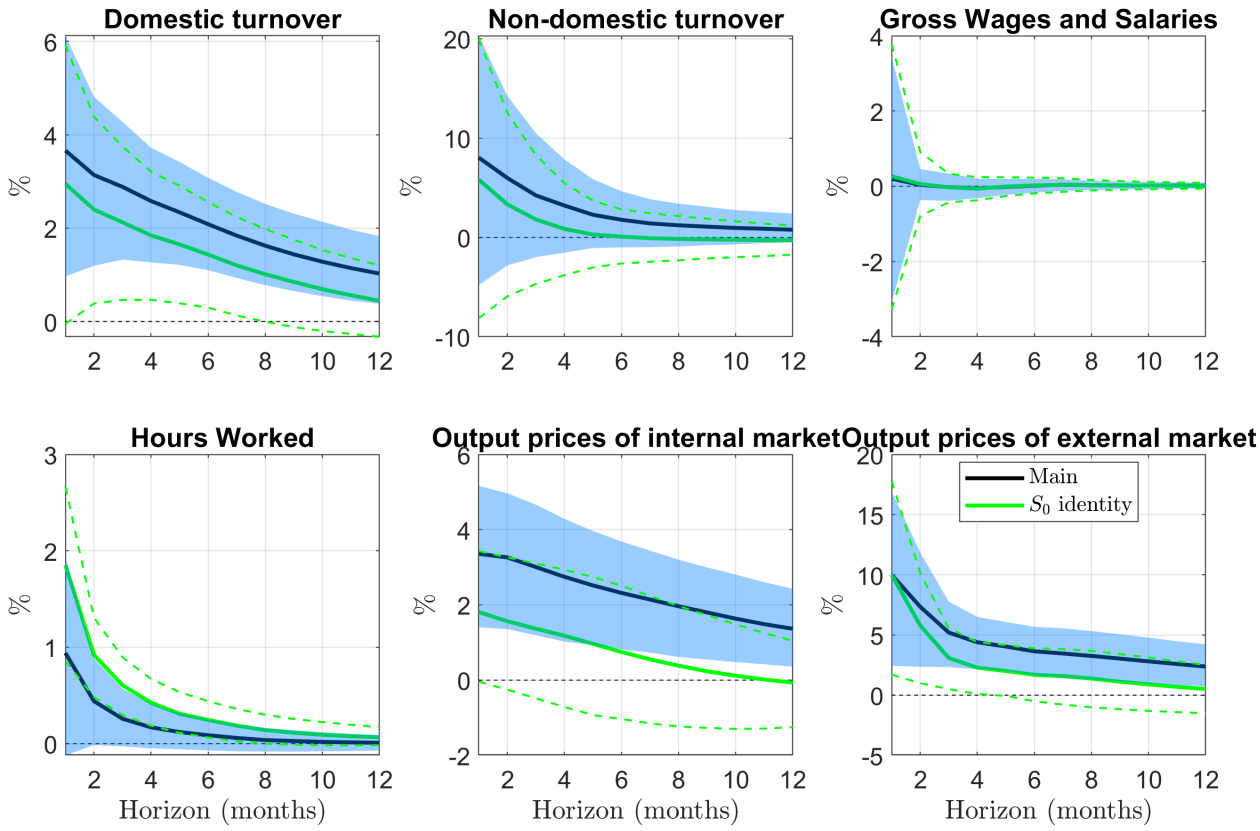

Figure 17: BVAR with linear trend

B.13 Robustness: No constant

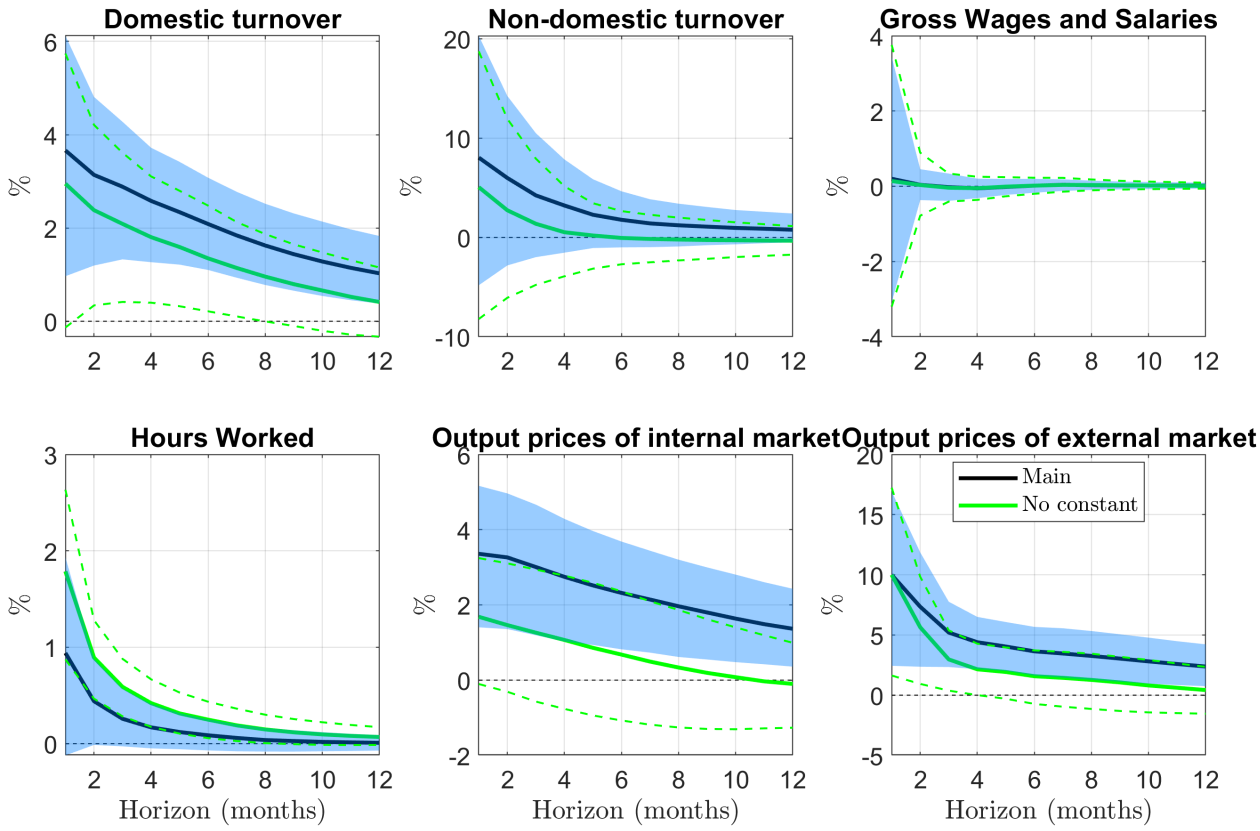

Figure 18: BVAR without a constant

B.14 Robustness: 12 lags

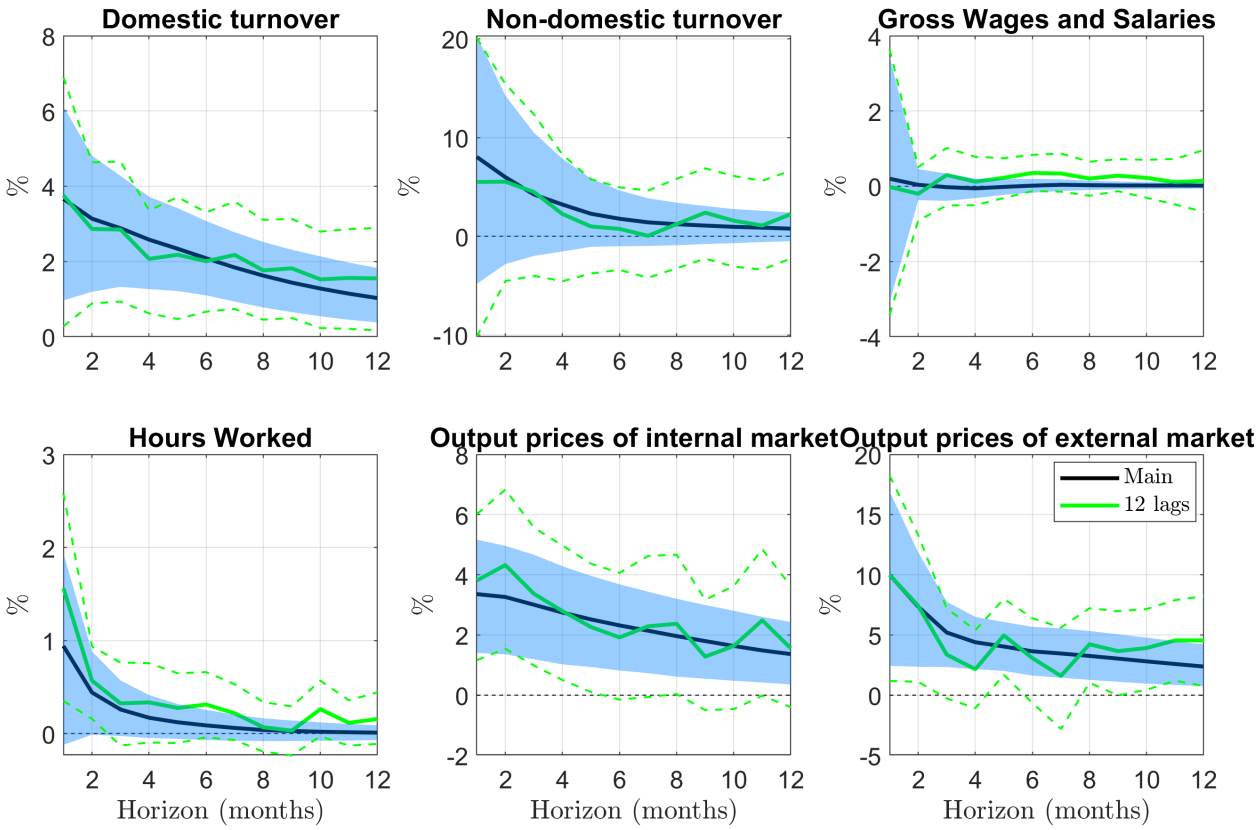

Figure 19: BVAR(12) following LR

B.15 Robustness: 5% threshold

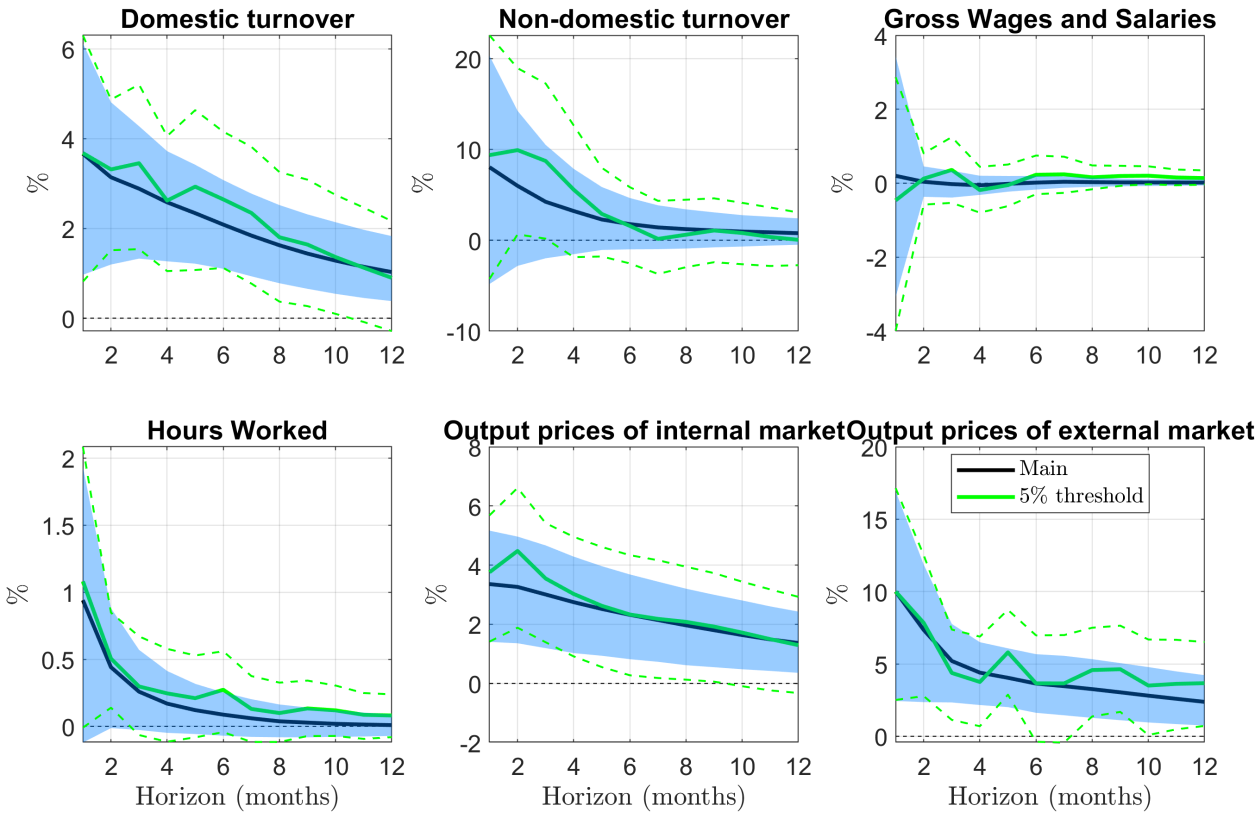

Figure 20: BVAR identified with 5% correlation threshold

B.16 VAR coefficients

Endogenous: DT

	Median	St.dev	Low.bound	Upp.bound
DT(-1)	0.708	0.050	0.662	0.760
DT(-2)	0.063	0.041	0.023	0.105
DT(-3)	-0.008	0.029	-0.034	0.022
DT(-4)	0.013	0.023	-0.011	0.037
DT(-5)	-0.009	0.019	-0.028	0.011
DT(-6)	-0.004	0.016	-0.020	0.012
NDT(-1)	0.011	0.009	0.002	0.019
NDT(-2)	0.001	0.006	-0.005	0.007
NDT(-3)	0.000	0.004	-0.003	0.004
NDT(-4)	0.001	0.003	-0.002	0.004
NDT(-5)	-0.001	0.002	-0.003	0.002
NDT(-6)	-0.001	0.002	-0.003	0.001
W(-1)	-0.075	0.039	-0.115	-0.035
W(-2)	0.003	0.023	-0.019	0.026
W(-3)	0.005	0.015	-0.010	0.020
W(-4)	0.001	0.012	-0.011	0.013
W(-5)	-0.001	0.010	-0.010	0.009
W(-6)	0.001	0.008	-0.007	0.009
H(-1)	0.085	0.109	-0.024	0.190
H(-2)	-0.009	0.064	-0.072	0.057
H(-3)	0.007	0.045	-0.038	0.052
H(-4)	0.001	0.034	-0.033	0.034
H(-5)	0.003	0.028	-0.025	0.030
H(-6)	-0.001	0.023	-0.023	0.023
PI(-1)	0.068	0.044	0.026	0.114
PI(-2)	0.007	0.030	-0.022	0.038
PI(-3)	0.007	0.021	-0.014	0.027
PI(-4)	0.002	0.016	-0.013	0.018
PI(-5)	0.000	0.013	-0.012	0.014
PI(-6)	-0.001	0.011	-0.012	0.009
PE(-1)	0.013	0.013	-0.001	0.026
PE(-2)	-0.001	0.008	-0.009	0.007
PE(-3)	-0.003	0.006	-0.009	0.002
PE(-4)	-0.001	0.004	-0.005	0.003
PE(-5)	-0.000	0.003	-0.004	0.003
PE(-6)	-0.001	0.003	-0.004	0.002
Constant	-0.098	0.582	-0.691	0.490

Sum of squared residuals: 10305.64
R-squared: 0.736
adj. R-squared: 0.677

Table 4: Domestic turnover VAR coefficients

Endogenous: NDT

	Median	St.dev	Low.bound	Upp.bound
DT(-1)	0.127	0.150	-0.019	0.277
DT(-2)	-0.052	0.097	-0.146	0.046
DT(-3)	-0.019	0.070	-0.082	0.051
DT(-4)	-0.029	0.053	-0.082	0.023
DT(-5)	-0.008	0.042	-0.051	0.031
DT(-6)	-0.008	0.034	-0.042	0.027
NDT(-1)	0.669	0.050	0.616	0.717
NDT(-2)	0.005	0.041	-0.035	0.046
NDT(-3)	-0.017	0.030	-0.047	0.012
NDT(-4)	-0.019	0.023	-0.044	0.004
NDT(-5)	0.005	0.019	-0.013	0.023
NDT(-6)	0.004	0.016	-0.013	0.019
W(-1)	-0.011	0.166	-0.190	0.147
W(-2)	-0.021	0.094	-0.120	0.067
W(-3)	0.001	0.065	-0.064	0.066
W(-4)	-0.012	0.050	-0.061	0.036
W(-5)	0.008	0.039	-0.032	0.046
W(-6)	-0.001	0.034	-0.034	0.034
H(-1)	-0.839	0.457	-1.317	-0.380
H(-2)	-0.023	0.278	-0.299	0.238
H(-3)	-0.060	0.192	-0.251	0.126
H(-4)	-0.006	0.141	-0.145	0.137
H(-5)	-0.011	0.117	-0.122	0.112
H(-6)	-0.017	0.097	-0.117	0.079
PI(-1)	0.342	0.183	0.150	0.523
PI(-2)	-0.009	0.128	-0.140	0.119
PI(-3)	-0.013	0.088	-0.100	0.076
PI(-4)	-0.005	0.068	-0.072	0.062
PI(-5)	-0.001	0.054	-0.054	0.053
PI(-6)	0.005	0.045	-0.038	0.052
PE(-1)	-0.019	0.058	-0.078	0.041
PE(-2)	-0.039	0.035	-0.074	-0.002
PE(-3)	-0.001	0.025	-0.027	0.023
PE(-4)	0.003	0.018	-0.016	0.022
PE(-5)	-0.002	0.015	-0.018	0.012
PE(-6)	-0.000	0.012	-0.012	0.012
Constant	-1.044	2.488	-3.492	1.478

Sum of squared residuals: 185012.27
R-squared: 0.561
adj. R-squared: 0.463

Table 5: Non-domestic turnover VAR coefficients

Endogenous: H

	Median	St.dev	Low.bound	Upp.bound
DT(-1)	0.012	0.013	-0.001	0.024
DT(-2)	-0.002	0.008	-0.010	0.007
DT(-3)	0.002	0.006	-0.004	0.007
DT(-4)	0.002	0.004	-0.003	0.006
DT(-5)	-0.000	0.004	-0.004	0.004
DT(-6)	0.001	0.003	-0.002	0.004
NDT(-1)	-0.001	0.003	-0.004	0.002
NDT(-2)	0.000	0.002	-0.002	0.002
NDT(-3)	0.000	0.001	-0.001	0.002
NDT(-4)	0.000	0.001	-0.001	0.001
NDT(-5)	0.000	0.001	-0.001	0.001
NDT(-6)	0.000	0.001	-0.001	0.001
W(-1)	0.000	0.014	-0.013	0.014
W(-2)	0.004	0.008	-0.005	0.012
W(-3)	0.003	0.006	-0.003	0.009
W(-4)	0.000	0.005	-0.004	0.005
W(-5)	-0.001	0.003	-0.004	0.003
W(-6)	0.000	0.003	-0.003	0.003
H(-1)	0.430	0.055	0.373	0.483
H(-2)	0.070	0.040	0.031	0.110
H(-3)	0.030	0.030	0.001	0.063
H(-4)	0.013	0.024	-0.011	0.037
H(-5)	0.008	0.019	-0.012	0.026
H(-6)	0.002	0.016	-0.013	0.018
PI(-1)	-0.025	0.016	-0.041	-0.009
PI(-2)	-0.005	0.011	-0.015	0.006
PI(-3)	-0.001	0.008	-0.009	0.006
PI(-4)	-0.001	0.006	-0.007	0.004
PI(-5)	-0.001	0.005	-0.005	0.004
PI(-6)	-0.001	0.004	-0.005	0.003
PE(-1)	0.010	0.005	0.005	0.015
PE(-2)	0.001	0.003	-0.002	0.004
PE(-3)	0.000	0.002	-0.002	0.002
PE(-4)	0.000	0.002	-0.001	0.002
PE(-5)	0.000	0.001	-0.001	0.001
PE(-6)	-0.000	0.001	-0.001	0.001
Constant	-0.733	0.233	-0.960	-0.503

Sum of squared residuals: 1386.25
R-squared: 0.261
adj. R-squared: 0.096

Endogenous: PI

	Median	St.dev	Low.bound	Upp.bound
DT(-1)	0.031	0.030	0.002	0.061
DT(-2)	-0.008	0.017	-0.025	0.008
DT(-3)	-0.005	0.013	-0.017	0.008
DT(-4)	-0.003	0.009	-0.011	0.006
DT(-5)	0.000	0.007	-0.007	0.008
DT(-6)	0.000	0.006	-0.006	0.006
NDT(-1)	0.005	0.007	-0.001	0.012
NDT(-2)	-0.001	0.004	-0.005	0.003
NDT(-3)	-0.000	0.003	-0.003	0.003
NDT(-4)	-0.000	0.002	-0.002	0.002
NDT(-5)	0.000	0.002	-0.002	0.002
NDT(-6)	0.000	0.001	-0.001	0.002
W(-1)	-0.022	0.030	-0.051	0.006
W(-2)	0.005	0.018	-0.013	0.022
W(-3)	-0.002	0.012	-0.014	0.011
W(-4)	-0.000	0.009	-0.010	0.009
W(-5)	-0.000	0.007	-0.008	0.007
W(-6)	-0.001	0.006	-0.007	0.005
H(-1)	-0.014	0.085	-0.101	0.070
H(-2)	-0.007	0.051	-0.056	0.046
H(-3)	-0.006	0.034	-0.038	0.029
H(-4)	-0.003	0.027	-0.030	0.025
H(-5)	-0.000	0.021	-0.022	0.021
H(-6)	0.001	0.017	-0.015	0.018
PI(-1)	0.938	0.050	0.891	0.987
PI(-2)	-0.022	0.044	-0.065	0.022
PI(-3)	0.003	0.030	-0.027	0.032
PI(-4)	0.003	0.023	-0.020	0.025
PI(-5)	0.002	0.019	-0.018	0.021
PI(-6)	0.002	0.016	-0.014	0.017
PE(-1)	-0.005	0.011	-0.015	0.006
PE(-2)	-0.003	0.006	-0.009	0.003
PE(-3)	-0.001	0.004	-0.006	0.003
PE(-4)	-0.001	0.003	-0.004	0.003
PE(-5)	-0.000	0.003	-0.003	0.002
PE(-6)	-0.000	0.002	-0.002	0.002
Constant	0.429	0.480	-0.037	0.923

Sum of squared residuals: 6627.49
R-squared: 0.862
adj. R-squared: 0.831

Endogenous: PE

	Median	St.dev	Low.bound	Upp.bound
DT(-1)	0.041	0.104	-0.058	0.147
DT(-2)	0.035	0.066	-0.028	0.102
DT(-3)	0.001	0.046	-0.044	0.047
DT(-4)	0.007	0.035	-0.028	0.041
DT(-5)	0.010	0.028	-0.017	0.039
DT(-6)	0.003	0.023	-0.018	0.026
NDT(-1)	0.011	0.025	-0.015	0.035
NDT(-2)	0.011	0.016	-0.004	0.026
NDT(-3)	0.002	0.011	-0.009	0.012
NDT(-4)	-0.003	0.008	-0.011	0.006
NDT(-5)	-0.001	0.007	-0.008	0.005
NDT(-6)	0.001	0.006	-0.004	0.007
W(-1)	-0.050	0.114	-0.164	0.062
W(-2)	-0.009	0.065	-0.073	0.061
W(-3)	-0.002	0.044	-0.046	0.045
W(-4)	-0.003	0.034	-0.039	0.029
W(-5)	0.001	0.027	-0.026	0.028
W(-6)	0.003	0.023	-0.020	0.025
H(-1)	-0.376	0.312	-0.699	-0.082
H(-2)	-0.119	0.184	-0.305	0.066
H(-3)	-0.007	0.128	-0.143	0.116
H(-4)	0.016	0.095	-0.077	0.105
H(-5)	-0.016	0.078	-0.090	0.061
H(-6)	0.007	0.065	-0.058	0.069
PI(-1)	0.249	0.124	0.128	0.375
PI(-2)	0.066	0.086	-0.020	0.152
PI(-3)	0.037	0.060	-0.018	0.099
PI(-4)	0.026	0.045	-0.021	0.069
PI(-5)	0.019	0.037	-0.018	0.054
PI(-6)	0.014	0.031	-0.017	0.044
PE(-1)	0.660	0.053	0.608	0.714
PE(-2)	-0.078	0.039	-0.117	-0.040
PE(-3)	0.026	0.029	-0.003	0.055
PE(-4)	0.008	0.024	-0.016	0.033
PE(-5)	-0.013	0.018	-0.031	0.005
PE(-6)	0.007	0.016	-0.009	0.023
Constant	-2.823	1.671	-4.478	-1.115

Sum of squared residuals: 82924.35
R-squared: 0.600
adj. R-squared: 0.511