Stockholm School of Economics

Department of Economics

5350 Master's Thesis in Economics

Academic Year 2022 - 2023

Navigating Uncertain Waters

A Bayesian Threshold VAR Approach to Understanding the Impact of Commodity Price Shocks on Inflation

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Abstract

The Covid-19 pandemic in early 2020 led to unprecedented uncertainty, reducing the predictability of macroeconomic variables. At the same time, commodity price movements as a contributor to national consumer price inflation continue to surface in debates. Considering these two phenomena, the question arises whether heightened global uncertainty affects the pass-through of international commodity prices to national consumer prices. To our knowledge, this paper is the first to discuss the role of uncertainty in this context. We focus on the effects for a small open economy, i.e. Austria. Methodologically, we rely on a Bayesian Threshold Vector Autoregressive model which endogenously assigns observations to a low and high uncertainty regime. Using monthly Austrian data from 1981 to 2022, we show that the pass-through of commodity price shocks to domestic inflation is larger during high uncertainty. Imposing sign restrictions reveals that these results are driven by underlying demand shocks. Conversely, if commodity price spikes are caused by supply shocks, they do not translate into higher domestic inflation. These findings contribute to the literature by presenting new evidence about the impact of macroeconomic uncertainty on the size and speed of the pass-through of international commodity price shocks to national consumer prices. Prompted by these findings, it is prudent for monetary authorities and policy makers to incorporate macroeconomic uncertainty into their decision making.

Keywords: Austria, Bayesian, Commodity Price Pass-Through, Inflation, Threshold VAR, Uncertainty

JEL: D84, E31, Q02

Supervisor: Rickard Sandberg

Date submitted: May 15, 2023

Date examined: May 26, 2023

Discussants: Giulian Etingin-Frati and Yongjai Lee

Examiner: Karl Wärneryd

Acknowledgments

First of all, we thank our supervisor Rickard Sandberg for being available at all times and providing valuable insights. Furthermore, we wish to express our gratitude to the Austrian Economic Research Institute (WIFO) for hosting Selin as a Junior Fellow and giving indispensable economic insights. In particular, Christian Glocker deserves special thanks for providing us with MATLAB code for the implementation of sign restrictions as well as fruitful discussions. Equal gratitude goes to Stefan Schiman-Vukan for his mentoring during the fellowship. Last but not least, we are indebted to our friends and family for their continuous support of our studies.

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1 Introduction

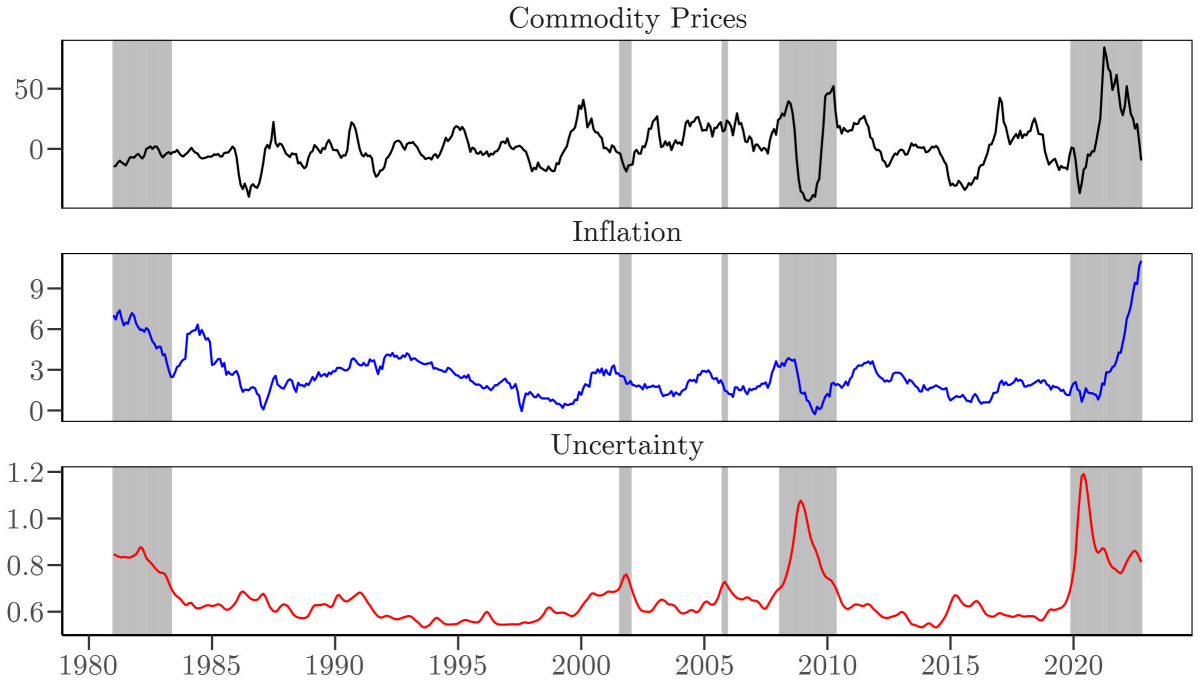
In early 2020, the Covid-19 pandemic catapulted the world into an unprecedented state of macroeconomic uncertainty. The predictability of macroeconomic variables such as output, employment, or inflation decreased rapidly in view of the unparalleled circumstances. The new macroeconomic environment stands in sharp contrast to previous years, where Western economies enjoyed relative stability since the end of the 2007-2008 financial crisis and the subsequent Great Recession. Periods of heightened uncertainty have implications for various dimensions of the economy at large, as evidenced by the considerable interest shown in this topic within the literature. Economic agents adapt their decisions when facing heightened uncertainty, affecting macroeconomic outcomes. The most prominent examples are precautionary savings, financial frictions, and the real options effect (Jurado et al., 2015).

Alongside increasing uncertainty, there has been considerable debate about commodity price spikes and their role in raising national inflation rates. A long-standing topic of discussion in macroeconomic circles, they have received a particularly large amount of public attention in light of skyrocketing commodity prices. These followed Russia's invasion of Ukraine in 2022, which has been associated with heightened global uncertainty. In general, an increase in world commodity prices may not always directly translate to consumer price inflation hikes. Rather, there is a wide range of factors influencing the size and speed of the pass-through including, but not limited to, structural characteristics of the economy, the price-setting behavior of firms, and the market forces driving a shock to commodity prices.

Considering that the intersection between these two topical subjects has remained largely unexplored, we aim to fill this gap by examining the transmission of commodity to consumer prices under varying uncertainty. In essence, we empirically investigate if there is a noticeable difference in the pass-through between periods of low and high uncertainty. Since we are specifically interested in the results for a small open developed economy, we select Austria as the primary object of study. Therefore, the results may be general-

izable to other countries with similar characteristics, which we explore by selecting the Netherlands as a second population of study in Section 6.5.

Figure 1: Commodity Prices, Inflation, and Uncertainty over Time



Notes: The gray bands identifying the periods of elevated uncertainty are an initial result of our estimation. For details, see Section 4. Commodity prices and inflation are reported in year-on-year change while macroeconomic uncertainty is the three-period moving average. For details, see Section 3. *Sources*: International Monetary Fund (2023a, 2023b) and Ludvigson and Ng (2023b).

Given our research question, global commodity prices, domestic headline inflation, and macroeconomic uncertainty emerge as our main variables of interest. To illustrate the differences between low and high uncertainty periods, we plot the selected data in Figure 1. High uncertainty periods are denoted by gray bands and comprise, for instance, the Great Recession as well as the Covid-19 pandemic. These periods are characterized by particularly large swings in commodity prices and consumer price inflation, clearly setting them apart from times of low uncertainty.

Understanding whether the transmission of a commodity price shock to consumer prices changes in face of these seemingly different macroeconomic environments requires an appropriate econometric model. First and foremost, the model must be able to account for the dynamic interlinkages between the macroeconomic time series to appropriately reflect

the economy. An established approach is the Vector Autoregressive model (VAR), used for example in Bakas and Triantafyllou (2018) and Igan et al. (2022). As evidenced in Figure 1, none of the time series appear to be stationary. By relying on a Bayesian approach, we circumvent the necessity for stationarity and hence extensive testing for unit roots. Furthermore, it is essential that the model be sophisticated enough to account for non-linearities, i.e. two different uncertainty regimes. Bayesian VARs are flexible by design and computationally efficient making it straightforward to integrate the determination of a threshold value in the estimation. The resulting Bayesian Threshold Vector Autoregressive model (TVAR) assigns the observations automatically to the respective uncertainty regime based on a threshold value as specified by the model (Blake & Mumtaz, 2015). This facilitates the comparison of the pass-through across uncertainty regimes. Given that the Bayesian TVAR is not sensitive to strict underlying assumptions, the results are generally more robust than those obtained with a frequentist approach. Likewise, the interpretation is more intuitive in the Bayesian context since the uncertainty associated with the results is quantifiable. These properties render the Bayesian TVAR the most suitable approach and enable us to communicate the results of our analysis to policy makers effectively.

Employing the Bayesian TVAR yields insightful results on whether the pass-through of commodity prices changes between periods of low and high uncertainty. In the baseline specification, we assume that commodity price shocks are exogenous and use Cholesky ordering to fully identify the model. We establish a difference in pass-through as our main result. An exogenous shock to international commodity prices of 1% increases Austrian consumer prices by up to 0.026 percentage points (pp) under low versus up to 0.063 pp under high uncertainty. One year after the shock, the rise in consumer prices accumulates to 0.290 pp (0.538 pp) in the low (high) uncertainty regime. The distinct results indicate the necessity to distinguish between low and high periods of uncertainty when examining the commodity price pass-through. Since the baseline model does not account for supply and demand forces underlying commodity prices accurately (Kilian, 2009), we expand our model to include sign restrictions based on Uhlig (2005, 2017). Dissecting the driving forces behind the commodity price spike shows that the pass-through we find can be

traced back to demand shocks induced by increases in global economic activity.

Our thesis primarily contributes to the literature examining varying sizes and speeds of the pass-through under different economic conditions, such as the present inflation regime. To this end, Sekine and Tsuruga (2018) employ a non-linear autoregressive model and find substantial increases in domestic inflation in response to commodity price shocks in countries facing already heightened inflation. Employing non-linear approaches such as a threshold model across developed and developing countries, Abbas and Lan (2020) find a larger pass-through during high inflation and an immediate pass-through during volatile inflation. The former effect is especially pronounced for developed countries and the latter for agricultural commodities. Bems et al. (2021) examine inflation expectations and find that poor anchoring leads to a greater pass-through of commodity terms of trade shocks, i.e. shocks to the relative price of countries' commodity exports compared to imports. The impact of structural country-specific characteristics such as level of economic development, trade openness, or independence of monetary authorities on the transmission of shocks has also been established (De Gregorio, 2012; Furceri et al., 2016; Gelos & Ustyugova, 2017; Roch, 2019). In a wider sense, we contribute to the literature examining the relationship between macroeconomic uncertainty and the economy at large. For instance Huang et al. (2021) and Joëts et al. (2017) have shown how macroeconomic variables react differently in light of uncertainty. To the best of our knowledge, our thesis is the first to link these two areas of research by taking the novel approach of introducing an uncertainty variable into the pass-through mechanism. Through explicitly modeling the impact of uncertainty on the pass-through of commodity price shocks to domestic inflation, we shed light on the non-linearities introduced by uncertainty regimes. This aspect has not been thoroughly examined in the existing literature, making our paper a novel contribution to the field.

The rest of the paper is organized as follows. In Section 2 we outline the pass-through of commodity prices on domestic inflation in general as well as discuss theory and evidence on the potential channels through which uncertainty is a significant factor. Section 3 is dedicated to the data which we use in the estimation of the model. Section 4 outlines the TVAR and identification strategies associated with the different specifications. In Section

5 we discuss and interpret the estimation results. To validate the effects we find, we perform robustness checks with respect to the duration of the sign restrictions as well as the choice of the commodity price and the uncertainty measure. Furthermore, we extend the baseline model to include an interest rate measure and eventually check the results for a similar country, i.e. the Netherlands. These results are discussed in Section 6. Finally, Section 7 elaborates on limitations and policy implications, while Section 8 concludes.

2 Literature Review

Eurozone economies such as Austria are integrated via global value chains and trade. As such, international commodity prices are a principal factor contributing to national consumer price inflation (European Central Bank, 2017). The pass-through of shocks to commodity prices is determined along the pricing chain and influenced by a range of factors. To illustrate how uncertainty can affect this process, we first generally outline the pass-through in absence of uncertainty. Subsequently, we pick a handful of factors involved in the pass-through that have been theoretically and empirically proven to change under uncertainty. These potential channels are suspect to drive a wedge between the pass-through under low and high uncertainty.

2.1 Commodity Price Pass-Through on Inflation

A rise in world commodity prices affects consumer price inflation via the direct and the indirect effect. The subsequent description of these effects follows European Central Bank (2017), Igan et al. (2022), and Sekine and Tsuruga (2018). Consumer price inflation is calculated based on the national consumer price basket and if the component prices, e.g. the coffee price, increase, inflation increases accordingly. In fact, commodities have a dual relevance for consumers since, besides affecting consumers directly, they also serve as intermediate inputs for domestic production processes. Thus, indirect effects emerge as commodity price increases can be passed through to non-commodity goods and services and hence to consumers via the pricing chain. The size and speed of the pass-through

with respect to the indirect effect depend on producers, in particular their production technology and their price setting behavior. They might choose to absorb costs partially if they do not wield enough pricing power.

The heightened inflation caused by direct and indirect effects can give rise to secondary effects, further fueling inflation. For instance, a large pass-through of commodity price shocks to inflation can alter inflation expectations. Since inflation expectations determine the wage and price-setting behavior of workers and firms, they might become self-enforcing (European Central Bank, 2017). As Blanchard (2022) highlights, de-anchored inflation expectations can motivate workers to demand higher nominal wages to be compensated for a decrease in real wages. Higher wages imply higher production costs for firms which they can choose to pass through to consumers. This is seconded by Peersman (2018) who ascribes the rise in inflation partially to inflation expectations and higher nominal wages via the wage bargaining process.

These theoretical considerations are complemented by a large empirical literature aimed at quantifying the size and speed of the pass-through. De Gregorio (2012) and Zoli (2009) find that domestic inflation is especially responsive to food and fuel price movements, giving them a particular importance compared to other commodities. Estimates of the pass-through effect of a 10% shock to commodity prices range between 0.2 and 1.87 pp (Furceri et al., 2016; Gelos & Ustyugova, 2017; Igan et al., 2022; Peersman, 2018; Sekine & Tsuruga, 2018; Zoli, 2009). In particular, Chen (2009) finds that Austrian inflation increases by 0.07% and 1.1% in the short and long run, respectively, following an oil price shock.

The size of the pass-through varies across countries and can be tied to structural country characteristics. On average the pass-through is higher for developing economies compared to developed countries due to a higher share of food in the former's consumption basket (De Gregorio, 2012; Furceri et al., 2016; Gelos & Ustyugova, 2017) and potentially higher energy intensity in their domestic economy (Blanchard & Galí, 2010; Chen, 2009; Gelos & Ustyugova, 2017). Cross-country differences may also be driven by trade openness, ex-

change rate movements, or monetary authorities' independence (Chen, 2009; De Gregorio et al., 2007; Gelos & Ustyugova, 2017).

2.2 Uncertainty and the Pass-Through

While there is substantial research on the role of structural characteristics in the pass-through of commodity to consumer prices, the role of macroeconomic uncertainty is not explicitly accounted for in the literature. However, we identify five streams of literature which indicate that uncertainty can interfere with the propagation of a commodity price shock as described in Section 2.1.

Commodity Price Volatility Commodity prices are determined on international financial markets which are subject to macroeconomic uncertainty. As shown by Bakas and Triantafyllou (2018) and Huang et al. (2021) changes in uncertainty, especially unobservable uncertainty as measured by Jurado et al. (2015), affect the volatility on the commodity market. One should take into account that more volatile commodity price shocks due to heightened uncertainty can lead to higher price responsiveness of firms. Paciello (2012) corroborates this in a theoretical model which examines the price setting behavior of firms under incomplete information. Within his theoretical framework he studies firms' responses to shocks of varying volatility. He finds that firms are more responsive to more volatile shocks. This is due to the fact that they could incur large losses if they fail to respond in sufficient scope and time, which is also highlighted by Sekine and Tsuruga (2018).

Monetary Authorities Central banks are an undisputed force in containing consumer price inflation. Blanchard and Galí (2010) and Chen (2009) argue that active monetary authorities can contribute to reducing the commodity price pass-through. According to the European Central Bank (2017) the varying importance of global factors for domestic inflation over time can be ascribed to monetary policy effectiveness in containing strong commodity price swings. That said, the ability of monetary authorities to affect the actual pass-through depends on various factors, such as macroeconomic uncertainty. Aastveit

et al. (2017) find that monetary policy effectiveness is reduced during periods of high uncertainty. One particular objective of central banks is to align economic agents' inflation expectations with the inflation target. However, the credibility of central banks in achieving their inflation target is reduced during recessive, i.e. highly uncertain, periods (Bodenstein et al., 2012; Dovern & Kenny, 2020), potentially affecting inflation expectations. If firms do not find the central bank's objective believable, inflation expectations become poorly anchored (Beechey et al., 2011). Mishkin (2007) maintains that the declining pass-through of shocks to domestic inflation is the result of improved monetary policy which anchors inflation expectations. Following that logic, inflation will respond more to shocks, including commodity price shocks, when expectations are poorly anchored. Likewise, they can induce secondary effects via the wage bargaining process as discussed in Section 2.2 in which de-anchored inflation expectations reinforce the rise in consumer prices.

Inflation Environment As highlighted by Berger et al. (2017), a hike in global uncertainty is associated with a rise in inflation rates, which in turn can also affect the pass-through. Taylor (2000) establishes a theoretical micro-founded model that explains the price setting behavior of firms depending on the inflation environment. He finds a positive relationship between inflation and its persistence, implying that a low and more stable inflation environment can explain a lower pass-through. Commodity price shocks have a larger effect on inflation during times of already heightened inflation or elevated uncertainty about inflation (Aastveit et al., 2023; Gelos & Ustyugova, 2017; Sekine & Tsuruga, 2018). Abbas and Lan (2020) find a larger pass-through during a high inflation regime and an immediate pass-through during a volatile inflation regime, especially for agricultural commodities. For instance, for a small open developed economy, in this case Sweden, they find a statistically insignificant increase of 0.023% in response to a 1% agricultural commodity price shock during times of low inflation. However given high inflation the short-run response increases to 0.043% and turns statistically significant. This pattern is common among developed countries, thus heightened or more volatile inflation during periods of high uncertainty may increase the pass-through.

Financial Frictions As explained in Section 2.2, firms pass through increased production costs to consumers. Gilchrist et al. (2014) develop a theoretical model to show how movements in uncertainty impact investment dynamics and firms' financing costs in a setting with financial frictions. Their simulation results indicate that fluctuations in volatility are a key driver of credit spreads thereby affecting the economy at large. Moreover, they provide both micro and macro evidence that credit spreads widen in response to higher uncertainty. These financial frictions increase the marginal cost of firms by driving up the working capital cost (Christiano et al., 2015). When firms operate in such an environment, they tend to increase prices more in response to shocks since their ability to rely on outside capital is reduced (Gilchrist et al., 2017). Hence, due to a rise in credit spreads, the pass-through of increased commodity prices can be higher during periods of elevated uncertainty.

Real Options Theory A high uncertainty environment is likewise characterized by an increased option value to wait since, under the irreversibility of investments, firms reap higher returns from waiting for information in an uncertain compared to a predictable environment. Pioneered by Bernanke (1983), this so-called *Real Options Theory* posits that firms and consumers consider uncertainty as a key factor before making decisions. For one, firms may delay investments and capacity expansions when facing elevated uncertainty. For another, the theory of precautionary savings suggests that consumers react to uncertainty in a similar fashion by postponing consumption decisions.[1] In response to a commodity price shock amidst high uncertainty, firms and consumers may thus delay their production and consumption choices. Consequently, quantities will be slow to adjust in response to the shock, amplifying the price adjustment and thereby the size of the pass-through (Van Robays, 2016).

[1]For empirical evidence on this, see for example Coibion et al. (2021).

3 Variable Selection and Data

Exploring the aforementioned theoretical considerations necessitates an adequate data set. We rely on extensive monthly time series data from January 1981 to October 2022, resulting in 502 observations, depicted in Table 1. The data set consists of three types of variables: domestic, i.e. Austrian, and global macroeconomic variables as well as macroeconomic uncertainty, all of which are presented and described in detail below and plotted in Figure 7 in Appendix A.[2]

Table 1: Variable Selection

Variable	**Description**	**Transformation**	**Time**	**Source**
COM	Commodity Price Index	Year-on-Year Percentage Change	1981:M1-2022:M10	IMF
USDEUR	US-Dollar Euro unadjusted nominal exchange rate	-	1981:M1-2022:M10	BIS
CPI*	Consumer Price Index	Year-on-Year Percentage Change	1981:M1-2022:M10	IMF
IP*	Industrial Production Index	Year-on-Year Percentage Change	1981:M1-2022:M10	IMF
OECD IP*	OECD countries Industrial Production Index	Year-on-Year Percentage Change	1981:M1-2022:M10	OECD
MU	Macroeconomic Uncertainty	3 period Moving Average	1981:M1-2022:M10	Sydney Ludvigson

Note: Variables denoted with * were obtained already transformed. BIS and OECD refer to Bank for International Settlements (2023) and Organization for Economic Co-operation and Development (2023), respectively. COM is obtained from International Monetary Fund (2023a). In the case of CPI and IP, IMF refers to International Monetary Fund (2023b). MU is obtained from Ludvigson and Ng (2023b).

As mentioned in the Section 1, relying on a Bayesian approach entails advantages related to data handling. Enders (2015, p.195, p. 291) discusses how non-stationary time series are problematic in a frequentist context since common tools such as the t-test and F-test are not applicable. Therefore, extensive stationarity testing is required before applying a VAR. He acknowledges that differencing is widely used to transform non-stationary series.

[2]Note that we do not include interest rate measures in the baseline specification, as is common when examining the commodity price pass-through. For relevant literature, see for instance Abbas and Lan (2020) and Sekine and Tsuruga (2018). However, we include an interest rate measure, i.e. the policy rate, in our sensitivity analysis, see Section 6.4.

However, valuable variation in the variables is discarded through this transformation. The Bayesian approach circumvents all these issues since it does not rely on asymptotic theory.

3.1 Domestic Macroeconomic Variables

To investigate the impact of commodity price shocks on end consumers, we rely on headline inflation, measured by the monthly Consumer Price Index (CPI). The index takes into account the prices of all goods and services purchased by a representative household in the country.[3] In addition, we include Industrial Production (IP) to measure domestic economic activity, which is preferable to Gross Domestic Product (GDP) in light of commodity price shocks. Input price changes directly affect producers, whereas GDP includes services that are less susceptible to commodity price shocks. In service economies such as Austria, IP is more reactive to commodity price shocks than GDP.[4] Moreover, it is also available at higher frequency than GDP.

Both domestic variables are considered as the percentage change relative to the same month in the previous year. This data modification fulfills two purposes: Firstly, both variables are indices and transforming them into percentage changes facilitates the interpretability of the results. Secondly, taking the year-on-year change accounts for seasonality in the variables. To keep the data sources transparent and comparable across countries, we use data from the International Financial Statistics as published by International Monetary Fund (2023b).

3.2 Global Macroeconomic Variables

The main global variables of interest are commodity prices which are determined on international markets. In economic research some commodities such as oil have enjoyed particular attention due to their special geopolitical role, see e.g. Kilian (2009) and Van Robays (2016). We choose to take on a broad perspective by considering a Commodity

[3]One could also focus on narrower definitions of inflation such as core, energy, or food price inflation or on different stages of the pass-through, e.g. import price or producer price inflation. However, for our purposes, we choose headline inflation following Gelos and Ustyugova (2017) and Sekine and Tsuruga (2018).

[4]Services contribute with 62.4% to Austria's GDP (World Bank, 2023).

Price Index (COM) that builds on a wide range of commodities such as energy, industrial raw materials, and food. The Commodity Terms of Trade database as compiled by Gruss and Kebhaj (2019) and published by the IMF gives access to six monthly country-specific commodity price indices for 182 countries starting in 1980. Out of the six indices the *Import Price Index* is relevant for the research question at hand. To construct the index, Gruss and Kebhaj (2019) take into account 45 commodities and their corresponding real, i.e. deflated, world prices in US Dollars (USD). Next, the authors weight the log difference of each respective commodity's real world price and calculate the total of all sub-components. The weights are given as the share of the commodity in the overall imports of the specific country. The World Bank and the Hamburg Institute of International Economics also provide commodity price indices which are constructed in a similar manner. However, only Gruss and Kebhaj (2019) use country-specific weights which we prefer since they reflect countries' trading patterns more accurately.

For modeling the supply and demand movements underlying international price movements, the identification via sign restrictions requires a measure of global economic activity. A detailed explanation of why this is the case is provided in Section 4.3.2. Following Van Robays (2016) we rely on OECD Industrial Production (OECD IP) which covers over two thirds of world output (World Bank, 2023). In line with the reasoning in the previous section, we transform the global variables as their year-on-year change in percent.

Last but not least, we include the exchange rate as it is another relevant macroeconomic variable shaping CPI. While prices on global markets are set in USD, a country's domestic inflation is calculated based on the local currency. Thereby, the pass-through of a COM increase can also be affected by the exchange rate. To account for exchange rate fluctuations, we include the unadjusted, nominal exchange rate (USDEUR) as published by Bank for International Settlements (2023).

3.3 Uncertainty Measure

In general, uncertainty can be defined as "the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents on their decision making" (Jurado et al., 2015, p. 1177). We consider uncertainty as a variable in order to capture its influence on the decision making of economic agents and the resulting implications for the macroeconomy.

Uncertainty is inherently difficult to account for in a model since there exist no objective measures or well-suited proxies. In their seminal paper Jurado et al. (2015) address this issue by creating their own measure of Macroeconomic Uncertainty (MU) which we rely on. Their approach differs from others in that they focus on identifying "whether the economy has become more or less predictable" (Jurado et al., 2015, p. 1178). Firstly, instead of measuring realized volatility of one particular time series, Jurado et al. (2015) consider various economic indicators, reflecting uncertainty in multiple dimensions of the economy such as markets, geographic regions, firms, and sectors. Jurado et al. (2015) base their calculations on 132 economic indicators such as consumer spending, price indexes, labor costs, or real income. Secondly, their approach removes the forecastable component of the series before calculating conditional volatility. This is to ensure that greater dispersion in the data does not automatically imply higher uncertainty, as forecastable variations should not increase uncertainty in the economy. These two distinct features render MU as defined by Jurado et al. (2015) superior to other measures such as realized volatility of the stock market or the economic policy uncertainty index (a newspaper-based measure) introduced by Baker et al. (2016). MU has become a widely established measure and was used by, for example, Joëts et al. (2017). The development of MU over time is visualized in Figure 7 in Appendix A and seems to rise during major recessive periods.

4 Methodology

To draw conclusions on our research question, we rely on a Bayesian TVAR and the resulting impulse response functions (IRFs). Since this approach combines several statistical

concepts, we illustrate the methodology by starting with describing the basic Bayesian VAR in Section 4.1 and subsequently augmenting it. In Section 4.2, we introduce the threshold to the VAR, discuss the choice of priors and make the algorithm underlying the estimation explicit. We choose IRFs as the main tool for analyzing the pass-through from international commodity prices to national consumer prices because they are particularly well-suited for visualizing complex interdependencies. Therefore, Section 4.3 is dedicated to the two identification schemes underlying the IRFs used, first a Cholesky decomposition and sign restrictions thereafter.

4.1 Bayesian VAR

VARs were first introduced by Sims (1980). His contribution led to a paradigm shift in macroeconomics as it pointed to VARs as an alternative to analyze economic relationships that was less restrictive than traditional structural models. Following Sims (1980) a VAR generalizes the univariate autoregressive model by regressing each variable on its own lagged values as well as the lagged values of other variables in a system. Consequently, every variable in the system is allowed to influence itself and all others. According to Sims (1980), the main appeal of VARs compared to other macroeconometric models is that there is no need to impose restrictive theoretical assumptions. Since Sims (1980), a large literature on VARs has emerged and they have become an integral part of standard macroeconomic analysis. Following many other researchers, e.g. Kilian (2009), Peersman (2018) and Igan et al. (2022), we opt for a VAR to analyze the interlinkages between world prices and national macroeconomic variables. The IRFs associated with a VAR provide an intuitive way to answer the research question since they visualize the impact of a shock in one variable on all other variables in the system. In Section 4.3, we elaborate in detail on IRFs since they are our main tool to conduct inference on the data.

We follow Chan (2020) in defining the general structure of a Bayesian VAR (p) for $t = 1, ..., T$. It is given by

$$Y_t = c_0 + \sum_{l=1}^{p} B_l Y_{t-l} + u_t, \tag{1}$$

where Y_t is a $j \times 1$ vector of j endogenous time series variables, c_0 is a $j \times 1$ fixed vector of intercepts, p is the lag length, B_l is a $j \times j$ fixed coefficient matrix, and u_t is a $j \times 1$ vector of disturbances. Following standard assumptions u_t is normally distributed with zero mean and variance covariance matrix Σ. For conciseness we define $b = (c_0, B_1, ..., B_p)'$ and $x = (Y_1, Y_2, ..., Y_T)'$. VAR (p) is a multi-equation regression with j equations. Each variable is expressed in one equation with $k = jp + 1$ regressors.

To elaborate on the Bayesian estimation of the VAR (p), we need to introduce the basics of a Bayesian framework first since the approach differs fundamentally from the frequentist one. Subsequent remarks are largely based on Robert (2007, pp. 9-10). The main distinction between Bayesian and frequentist statistics is the view on the nature of the parameters. In frequentist estimation, parameters are assumed to be fixed but unknown, while Bayesians treat parameters as random variables that follow a distribution. Unlike frequentist estimation, the use of a Bayesian model allows for the integration of available information on parameter values during the estimation process. Bayesians choose a prior distribution $\pi(\theta)$ where the parameter vector $\theta = [b; \Sigma]$, with b being the coefficient and Σ the variance covariance matrix. This represents subjective beliefs about parameters which are then updated with information obtained from the data (x). The result of the Bayesian estimation is the updated distribution, called posterior distribution, encompassing all available information on the parameters θ. Via the posterior distribution, the uncertainty associated with the parameter is fully captured which is not possible when following a frequentist approach. The posterior distribution contains all the information necessary to conduct inference. Commonly one measure is chosen as the point estimate to summarize the extensive information. Possible estimators include but are not limited to the posterior mean, median, mode, or variance (Robert, 2007, p. 165).

The following equation specifies the posterior distribution $\pi(\theta \mid x)$ based on Robert (2007, p. 165):

$$\pi(\theta \mid x) = \frac{f(x \mid \theta)\pi(\theta)}{\int f(x \mid \theta)\pi(\theta)d\theta}. \tag{2}$$

$\pi(\theta)$ is the prior distribution on the parameters which we discuss in detail in Section 4.2.2. $\int f(x \mid \theta)\ \pi(\theta)\ d\theta$ is the normalizing constant needed to ensure that the posterior probability distribution integrates to 1. The likelihood function $f(x \mid \theta)$ for a VAR (p) is introduced in Equation 4 following Chan (2020).

For better readability, we introduce the matrix notation corresponding to the VAR (p) as outlined by Chan (2020):

$$Y = Xb + U. \tag{3}$$

Note that Y is a $T \times j$ matrix with Y_t' as rows, X is a $T \times k$ matrix where rows are given by X_t' with $X_t' = (1, Y_{t-1}', ..., Y_{t-p}')$. As defined above, $b = (c_0, B_1, ..., B_p)'$.

U is a $T \times j$ innovation matrix with u_t' as rows and $vec(U)$ follows a normal distribution: $vec(U) \sim N(0, \Sigma \otimes I_T)$. Based on the matrix representation of the VAR (p), we can derive the corresponding likelihood function:[5]

$$f(Y \mid b, \Sigma) = (2\pi)^{-\frac{Tj}{2}} |\Sigma|^{-\frac{T}{2}} \mathrm{e}^{-\frac{1}{2}\,\mathrm{tr}\left(\Sigma^{-1}(Y-Xb)'(Y-Xb)\right)}. \tag{4}$$

To obtain the posterior distribution, one needs to multiply the likelihood by the prior distribution (Chan, 2020). To obtain analytical, i.e. closed form results a natural conjugate prior is required. If one chooses an alternative prior, other methods must be deployed to derive the posterior distribution (Chan, 2020). As highlighted above, the choice of priors is an essential step when working with a Bayesian framework. We follow Blake and Mumtaz (2015) and opt for priors based on dummy observations which we elaborate on in Section 4.2.2.

[5]For details on the mathematical derivation see Chan (2020).

4.2 Threshold VAR

4.2.1 Model Specification

Accounting for non-linearities pushes the limits of a standard Bayesian VAR. Given that we are interested in the heterogeneous effects of the pass-through of COM to CPI, we need to extend the standard VAR. Numerous models such as Markov-switching, Time-Varying Parameter (TVP), or threshold models have been proposed in this context. As remarked by Van Robays (2016) other models can pose difficulties for the interpretation of the results. For example, she highlights that TVP models skip the fundamental question of why the parameters are changing over time in the first place. Thus, they provide no insights concerning the driving forces behind the parameter change. Van Robays (2016) claims that when estimating Markov-switching models, the same issue arises since the transition variable is latent. Given that we are interested in the role uncertainty plays in establishing non-linearities, we need to be able to explicitly account for uncertainty as the driver behind the variation in the estimated parameters. To investigate asymmetric responses to shocks in different uncertainty regimes the TVAR, developed by Tong (1978), emerges as the most suitable model.[6]

Moreover, to specify our model as realistically as possible, we need to include the threshold variable uncertainty as an endogenous variable. Van Robays (2016) points out that it would be ignorant to assume that international price shocks do not feed back into MU. Strict exogeneity of MU with respect to the macroeconomy is unrealistic. The TVAR is well-suited to tackle this issue by considering uncertainty as part of the endogenous vector of variables (Van Robays, 2016).

Relying on a TVAR makes it necessary to tackle potential endogeneity bias which can arise due to the fact that the threshold variable endogenously responds to other variables in the system (Van Robays, 2016). Thus, we need to ensure that the regime switch is not solely triggered by shocks to the main variable of interest, i.e. COM. If this were the case, any difference in the effects of COM shocks on CPI could be driven by the

[6]The TVAR has since been employed in various economic applications, see Hansen (2011) for an overview.

difference in commodity shock sizes not by uncertainty (Van Robays, 2016). To prevent this pitfall of the TVAR, we follow the approach by Joëts et al. (2017) and Van Robays (2016): Firstly, we choose the one period lagged value of MU as the threshold variable to ensure that we only consider COM shocks that occur within the regime. Secondly, we use the three-period moving average of the uncertainty measure to guarantee that regime switching occurs only if elevated MU shows some persistence.

We extend the basic Bayesian VAR from Section 4.1 to implement the TVAR. The following description of the TVAR in this section is based on Blake and Mumtaz (2015, pp. 145-150). They specify the TVAR as follows:[7]

$$\begin{aligned} Y_t &= c_1 + \sum_{l=1}^{p} B_1 Y_{l,t-l} + u_t, \text{Var}\left(u_t\right) = \Sigma_1 \text{ if } S_t \leq Y^*, \\ Y_t &= c_2 + \sum_{l=1}^{p} B_2 Y_{l,t-l} + u_t, \text{Var}\left(u_t\right) = \Sigma_2 \text{ if } S_t > Y^*. \end{aligned} \tag{5}$$

While t is the time index, Y_t is a $j \times 1$ matrix which encompasses the macroeconomic variables and the uncertainty measure described in Section 3. The exact order of the variables depends on the identification strategy which is discussed in Section 4.3.

S_t is the threshold variable which is a lagged value of MU. The delay parameter d, which is determined prior to the estimation, is set to 1 meaning that we choose the one time lagged value of MU as the threshold variable as done by Joëts et al. (2017). Y^* indicates the threshold level for MU and is determined endogenously with a Metropolis Hastings algorithm. Thus, there is no need to set the threshold beforehand. If S_t is less than or equal to Y^*, the observation at time t is assigned to the low uncertainty regime. If S_t is greater than Y^*, the observation at time t is attributed to the high uncertainty regime.

The TVAR allows for the estimation of a VAR specific to each regime. Each regime has its respective constant (c_1 and c_2), coefficients (B_1 and B_2), as well as variance covariance

[7]Note that Blake and Mumtaz (2015) use a more general notation than in Equation 1, as $Y_{l,t-l}$ allows for different coefficients depending on the lag.

matrix of the error term (Σ_1 and Σ_2).

To determine the optimal lag length of the model (p), we apply the Ljung-Box test which checks for autocorrelation in the residuals of each variable (Enders, 2015, p. 72). In the spirit of parsimony, we choose the model with the fewest lags for which we fail to reject the null hypothesis of no autocorrelation among the residuals.

4.2.2 Choice of Priors

We implement a Gibbs Sampler with a Metropolis Hastings step to estimate the Bayesian TVAR. As is common in Bayesian Econometrics, we set priors beforehand and follow the approach outlined in Blake and Mumtaz (2015, pp. 48-52) on which we base the subsequent explanation in this section. More specifically, we choose natural conjugate priors for the parameters which are based on dummy observations for both regimes. To implement this specific type of prior, artificial data Y_D and X_D need to be created based on realized observations. The weights assigned to the artificial data in the estimation process determine the tightness of the prior. This can be fine-tuned via hyperparameters which are essential in the creation of these so-called dummy observations. The tighter each hyperparameter, the more weight is assigned to the artificial data compared to the actual observations.[8] In our estimation we rely on the standard hyperparameter specification applied by Blake and Mumtaz (2015, pp. 145-150). Having generated dummy observations based on the existing data and pre-determined hyperparameters, we define the prior mean of the VAR coefficients as

$$b_0 = \left(X_D' X_D\right)^{-1} \left(X_D' Y_D\right) \tag{6}$$

and the prior scale matrix for the variance covariance matrix as

$$S = \left(Y_D - X_D b_0\right)' \left(Y_D - X_D b_0\right). \tag{7}$$

The definition in Equation (6) is the result of a Ordinary Least Squares (OLS) regression of Y_D on X_D while the prior scale matrix for the error covariance matrix in Equation (7)

[8] For more details on the creation of dummy observations see Blake and Mumtaz (2015, pp. 49-50).

is based on S, the Sum of Squared Residuals from this regression. Given these definitions we specify the normal inverse Wishart prior, which is the natural conjugate prior, for the VAR coefficients as

$$p(b \mid \Sigma) \sim N\left(\tilde{b}_0, \Sigma \otimes \left(X_D' X_D\right)^{-1}\right) \tag{8}$$

and for Σ as

$$p(\Sigma) \sim IW\left(S, T_D - K\right), \tag{9}$$

where $\tilde{b}_0 = vec\left(b_0\right)$, T_D is the number of dummy observations and K is the number of regressors per equation. The conditional posterior distributions of the VAR parameters are obtained applying a Gibbs sampler. The sampler is used thanks to its computational efficiency and is described in detail in Section 4.2.3.

To identify the threshold endogenously in a Bayesian context, we also need to set a prior for Y^*. Following the standard for the TVAR, the prior is specified as follows:

$$p(Y^*) \sim N\left(\bar{Y^*}, \sigma_{Y^*}\right). \tag{10}$$

The threshold prior follows a normal distribution with mean Y^* and variance σ_{Y^*}. To specify the prior distribution, $\bar{Y^*}$ is given by the arithmetic mean of Y_t, while the variance σ_{Y^*} is set to 10. We follow Blake and Mumtaz (2015, pp. 145-150) in choosing this standard distribution for the threshold prior. As described in Section 4.2.3, the threshold is then sampled using a Metropolis Hastings step.

4.2.3 Gibbs Sampling Algorithm

The steps of the Gibbs sampler based on Blake and Mumtaz (2015, pp. 145-150) and the associated code are as follows:

Step 1: The data are split into two different samples. The mean of the data is taken as the initial value for Y^*. In line with the above, those observations in which the threshold variable S_t falls below Y^* are allocated to the first regime $Y_{1,t}$ (low uncertainty), and those in which S_t exceeds Y^* to the second regime $Y_{2,t}$ (high uncertainty), respectively.

Step 2: Then, the algorithm samples the VAR parameters $b_i = c_i, B_i$ and Σ_i in both regimes $i = 1, 2$. With X as the right hand side variables of the VAR, the conditional distribution is

$$H\left(b_i \mid \Sigma_i, Y_t, Y^*\right) \sim N\left(vec\left(\beta_i^*\right), \Sigma_i \otimes \left(X_i^{*\prime} X_i^*\right)^{-1}\right)$$
$$H\left(\Sigma_i \mid b_i, Y_t, Y^*\right) \sim IW\left(S_i^*, T_i^*\right)$$

with

$$\beta_i^* = \left(X_i^{*\prime} X_i^*\right)^{-1}\left(X_i^{*\prime} y_i^*\right)$$
$$S_i^* = \left(y_i^* - X_i^* b\right)'\left(y_i^* - X_i^* b_i\right).$$

y_i^* is given by $[Y_{i,t}; Y_D]$. As explained above, the natural conjugate priors are based on dummy observations for both regimes. Y_D are the dummy observations that are relevant for the prior of the left-hand side of the VAR. X_i^* is $[X_{i,t}; X_D]$ with X_D being the dummy observations that define the prior for the right-hand side of the VAR. This illustrates clearly how the dummy observations are considered in the estimation process.

Step 3: Since the threshold Y^* is unknown, we employ a Metropolis Hastings step to sample it. This is achieved by drawing a new value from the random walk $Y_{new}^* = Y_{old}^* + e, e \sim N(0, \Omega)$. Its acceptance probability is defined as

$$\alpha = \frac{F\left(Y \mid b_i, \Sigma_i, Y_{\text{new}}^*\right) p\left(Y_{\text{new}}^*\right)}{F\left(Y \mid b_i, \Sigma_i, Y_{\text{old}}^*\right) p\left(Y_{\text{old}}^*\right)},$$

where the function F represents the likelihood of the VAR which consists of the likelihood of both regimes. If the corresponding acceptance probability is larger than a draw

from the uniform distribution U(0,1), then Y^*_{new} is the new threshold value. Otherwise, Y^*_{old} is kept.

Step 4: If the pre-defined burn-in period is surpassed, IRFs are estimated for each regime in accordance with the selected identification strategy. More details on this step are provided in Section 4.3.

4.3 IRFs and Identification

Having set up the TVAR, we want to gain an economically meaningful understanding of its estimation results. As alluded to previously, a common way to deduce conclusions from a VAR is to construct IRFs. As explained by Lütkepohl (2005, pp. 51-66, p. 357), they visually represent the response of one variable to an exogenous shock in another variable. He emphasizes that in a reduced form VAR, the interpretation of impulse responses is problematic since error terms of variables can be correlated. Without further assumptions it is not possible to clearly isolate the shock and assign it to one variable. In order to achieve a sound economic interpretation, structural restrictions need to be imposed on the model parameters of the reduced form VAR. Lütkepohl (2005, pp. 51-66, p. 357) argues that the restrictions depend on the prior economic reasoning and the identification strategy chosen by the researcher. To pin down the pass-through of commodity prices, we rely on a baseline model identified by the Cholesky decomposition. However, to gain insights into the underlying market movements driving the price shocks, we need to turn to another identification strategy, i.e. sign restrictions.

4.3.1 Cholesky Decomposition

Following one strand of literature, that is Gelos and Ustyugova (2017) and Gubler and Hertweck (2013), we initially do not account for driving forces behind commodity price movements. In our baseline TVAR world price shocks are taken as exogenous to the national macroeconomy and we disregard OECD IP for the time being. Consequently, the demand- and supply-induced changes in international commodity prices cannot be clearly isolated and the impulse responses represent an average effect (Gubler & Hertweck,

2013). The exogeneity assumption is reasonable in our cases given that Austria is a small open economy that cannot influence world market prices.[9] Considering price shocks as exogenous makes it reasonable to rely on the Cholesky decomposition as an identification scheme, which we will briefly describe below.

We base the following on Uhlig (2005). Firstly, note that the error term u_t of Equation (1) can be deconstructed in a linear combination of the matrix A and an innovation term v_t. In general, the vector v contains all j fundamental innovations which are assumed to be mutually independent with $\mathrm{E}[vv'] = I_j$. This is a standard assumption in the VAR literature which is necessary to ensure that there is no unexplained causal connection between shocks. A violation of the independence assumption would imply that we cannot clearly attribute a shock to one variable. The matrix A represents the instantaneous impact on all variables. The ith column of A shows the impact of the ith fundamental innovation on all others. Following Uhlig (2005), the variance covariance matrix Σ is subsequently defined as

$$\mathrm{E}[u_t u_t'] = A\mathrm{E}[v_t v_t']\, A' = AA'. \tag{11}$$

As highlighted by Lütkepohl (2005, pp. 51-66, p. 357), to achieve full identification of the innovations we need further restrictions on A, that is, a recursive ordering of the variables. In particular, the Cholesky decomposition prescribes a specific causal order of the variables based on economic concepts. Each variable can contemporaneously affect only itself and the subsequent variables in the ordering. Since a different ordering can lead to different implications of the IRFs, the ordering of the variables is critical to the interpretation of the results (Lütkepohl, 2005, pp. 51-66, p. 357). Given the small open economy assumption, we order COM first. Moreover, MU comes last in the ordering as suggested by Jurado et al. (2015) and Joëts et al. (2017). This implies that shocks to other variables transmit to uncertainty within the same month whereas shocks to uncertainty take time to materialize. As mentioned by Alessandri and Mumtaz (2017) the assumption that prices and output respond sluggishly to exogenous impacts is quite

[9]The small open economy assumption holds for most countries as argued by Gruss and Kebhaj (2019).

common. Macroeconomic variables are ordered in between as USDEUR, CPI, and IP. Formally:

$$Y_t = (COM_t, USDEUR_t, CPI_t, IP_t, MU_t)'.$$

The results of the baseline specification with the Cholesky decomposition are discussed in Section 5.2.

4.3.2 Sign Restrictions

The exogeneity assumption with respect to international commodity prices abstracts from the underlying dynamics that move prices initially. Differentiating between demand and supply shocks enables us to add another dimension to the economic interpretation of the TVAR. To identify these two types of shocks, we turn to sign restrictions. First introduced by the seminal paper Uhlig (2005), we base the description of the underlying theory in the following paragraph on Uhlig (2017).

At the core of sign restrictions lie basic assumptions on the slopes of the supply and demand curves. For the supply curve, we impose that it slopes upward, whereas the demand curve slopes downward. For both curves, we assume that a positive shift results in higher quantity produced and the error term associated with each curve is normally distributed with mean zero and variance one. These assumptions are standard in economics and widely accepted.[10] Moreover, we assume that the error terms of the demand and supply curves are mutually independent, otherwise we cannot disentangle the effect of the different shocks. Accepting these assumptions implies distinct signs for the responses of price and quantity to a supply or demand shock as discussed subsequently for our specific case.

We focus on commodity supply shocks as well as commodity demand shocks driven by economic activity.[11] Kilian (2009) and Van Robays (2016) describe the mechanisms underlying the shocks as follows: On the one hand supply disruptions in commodity markets lead to an exogenous shift in the supply curve increasing world commodity prices. Thus,

[10] For a complete mathematical specification of the supply and demand curves, see Uhlig (2017).

[11] In the oil price literature, e.g. Kilian (2009) and Van Robays (2016), it is common to distinguish between oil supply shocks, oil demand shocks driven by economic activity and oil-specific demand shocks. Given the breadth and generality of COM, identifying specific shocks is not feasible.

global economic activity approximated by OECD IP is impeded due to the difficulty to access inputs and their price increase. On the other hand increased global demand for goods fuels demand for commodities as input in industrial production. Consequently, world commodity prices increase. These are the two types of shocks we identify and refer to in their abbreviated form as supply and demand shock. We restrict the signs of the price variable COM and the quantity measure OECD IP to react in the direction specified in Table 2.

Table 2: Shock Types

Shock Type	COM	OECD IP
Demand shock driven by global economic activity	+	+
Supply shock	+	-

In the implementation of sign restrictions we follow Uhlig (2005) on which we base the subsequent explanations in this section. For the sake of readability, we only describe how sign restrictions are implemented in the low uncertainty regime, since it is analogous for the high uncertainty regime. Moreover, we focus on a demand shock as the identification of supply and demand shocks are identical except for the signs imposed on the direction of the shock.

While we rely on imposing a recursive ordering on the variables in Section 4.3.1, this is not necessary when applying sign restrictions. Identifying a demand shock only requires finding the innovations in line with the aforementioned shock. Therefore, we pin down a single column $a \in R^j$ of A which is called an impulse vector. The demand shock impulse vector a, we are interested in, is characterized by positive impulse responses to COM and OECD IP for one quarter after the shock.

To generate a candidate matrix A, which we can then check for an impulse response vector that fulfills the sign restrictions, we first compute a Cholesky decomposition of Σ. Let $\tilde{A}$ be a Cholesky factor of Σ, and as a consequence $\tilde{A}\tilde{A}' = \Sigma$. This four-dimensional Cholesky decomposition matrix has the following dimensions: $j = 6$ variables, $i = 6$ shocks, $k = 36$ horizons and the number of draws = 2000. Element $(1, 1, 1, 1)$ of $\tilde{A}$ thus

relates to the response of the first variable, i.e. OECD IP, to a shock to itself in the first horizon period in the first draw. Next, we multiply $\tilde{A}$ with a random orthonormal matrix (called rotation matrix) Q (i.e. $QQ' = I$), such that

$$A = \tilde{A}Q, \tag{12}$$

to ensure random draws from all possible responses. Based on the candidate responses in matrix A, we then evaluate the resulting impulse responses. If they comply with the imposed restrictions, they are saved. Otherwise, we disregard them and evaluate the next candidate impulse response as given by A. There is no consensus in literature on the number of horizons for which sign restrictions are imposed. We choose to restrict the signs for one quarter post-impact to ensure some persistence in the response of the variables. As a consequence, shocks that cause COM and OECD IP to increase instantaneously but lead to OECD IP decreasing one month later would not be classified as demand shocks. This assumption is discussed in Section 6.1, where we evaluate alternative horizons.

Given horizon k, matrix of VAR coefficients b and variance covariance matrix Σ, we obtain a set of all demand shock impulse vectors, $O = \{k, b, \Sigma\}$. The set of admissible impulse vectors is generated using inequality restrictions since we only check for the direction of the response. Consequently, O typically contains many vectors. In contrast to the Cholesky decomposition, sign restrictions are not an exact form of identification and do not lead to one single solution for the impulse response vector. To report results, we rely on the median, 16th and the 84th percentile for the sample of impulse responses at each horizon, as is common in the literature (Baumeister & Hamilton, 2020).

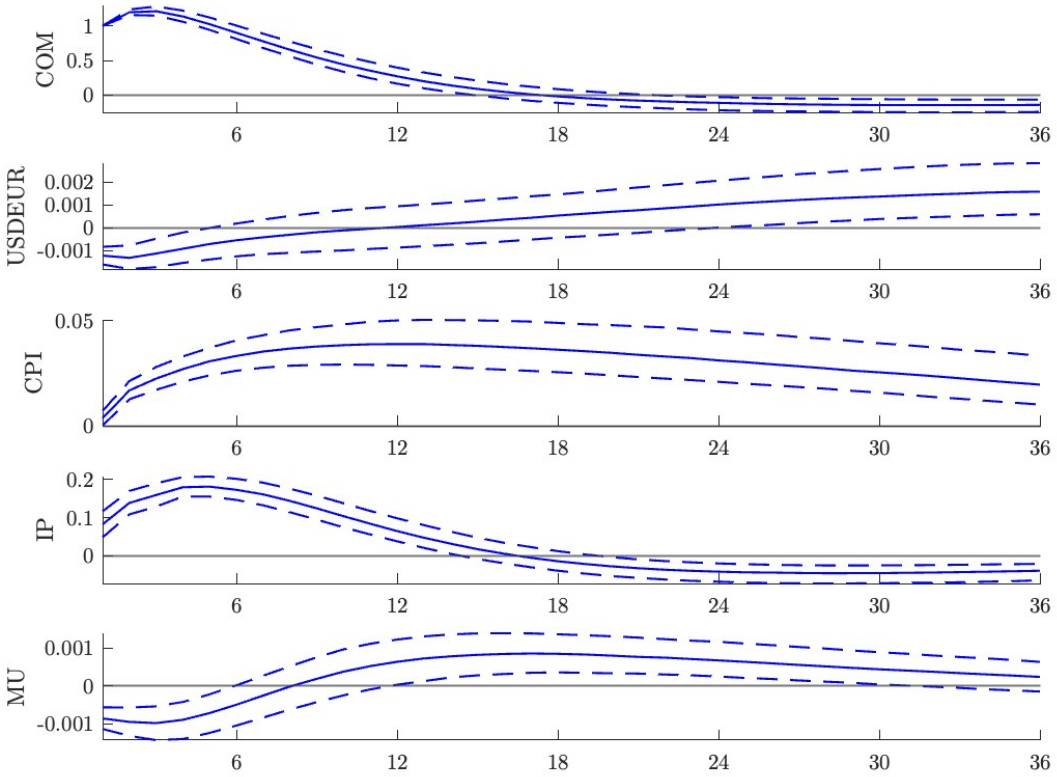
The advantage of using sign restriction is that they are agnostic compared to the Cholesky decomposition. Sign restrictions do not require us to impose explicit restrictions on the main variable of interest, i.e. CPI. The identification is based on sound economic theory concerning the slopes of the demand and supply curves and does not necessitate relying on a causal ordering.

5 Results and Interpretation

In the following section we report and interpret three model specifications. Firstly, we present a Bayesian VAR without a threshold which serves as a benchmark in Section 5.1. To understand the importance of each uncertainty regime in driving these first results, we further establish our baseline model – the TVAR identified via Cholesky ordering – in Section 5.2. Eventually, to disentangle the demand and supply movements underlying the commodity price shock, we apply a TVAR with sign restrictions in Section 5.3.

5.1 Bayesian VAR without a Threshold

Figure 2: Austria - IRFs, no Threshold



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

To establish a point of reference, we first run a standard Bayesian VAR without differentiating between states of uncertainty. That is, we estimate a VAR with five variables:

COM, USDEUR, CPI, IP, and MU. The lag length is set at three lags and kept throughout all subsequent analyses, based on the results of the Ljung-Box test as explained in Section 4.2.1.

We rely on IRFs to evaluate the response of the domestic macroeconomy to a COM shock. The reactions to a one unit shock to COM are depicted in Figure 2. A one unit shock corresponds to a 1% increase in the year-on-year COM. Note that since we are conducting a Bayesian analysis, the graphs show the median as well as the 16th and the 84th percentile of the IRF. We rely on the median as a point estimate of the posterior distribution of the impulse response. The 16th and the 84th percentiles mark the boundaries of the confidence region which includes the parameter θ with 68% probability. Indicating confidence regions is common practice and of major importance to thoroughly understand the results by visualizing the uncertainty related to the point estimate. Frequentist and Bayesian inference largely diverge on this topic. The following definitions are based on Robert (2007, pp. 259-260). Generally speaking, Bayesian credibility intervals indicate the given probability that a parameter θ is part of a fixed confidence region. The frequentist counterpart to the credibility intervals are confidence intervals, which represent a random region that, over repeated sampling, will contain the true value of the parameter θ with a given probability. The Bayesian interpretation comes more naturally and enables us to claim that the impulse response lies within the dashed lines with a probability of 68%.

The main variable of interest for answering the research question is CPI. A 1% shock to COM translates to a median increase in Austrian CPI which peaks around 0.04 pp after one year and subsequently decreases to 0.02 pp over the next two years. The effect we find fits in with those found by the literature ranging between 0.2 and 1.87 pp in response to a 10% shock for various commodities (Chen, 2009; Furceri et al., 2016; Gelos & Ustyugova, 2017; Igan et al., 2022; Peersman, 2018; Sekine & Tsuruga, 2018; Zoli, 2009).

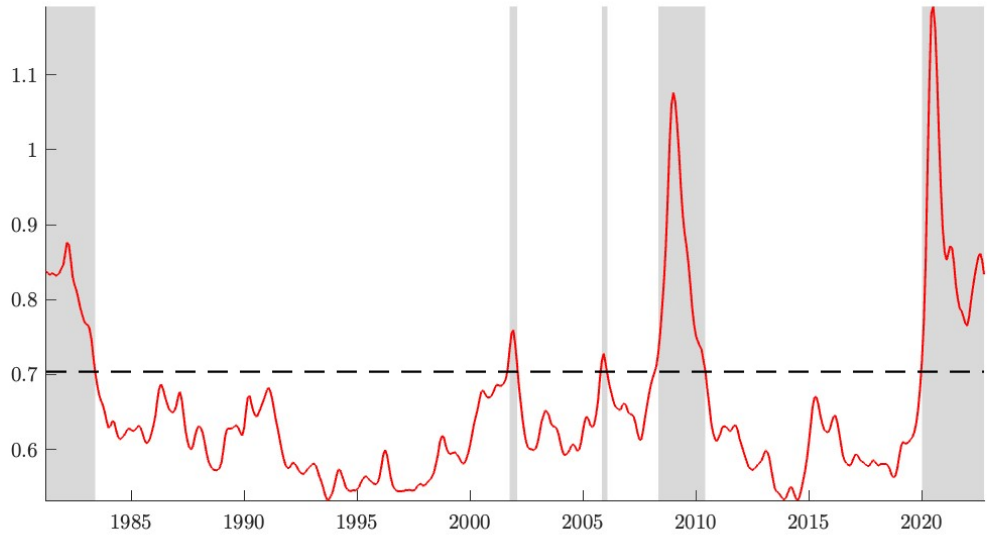
The response patterns of other variables are also sound. By construction, COM increases contemporaneously by 1% but the effect fades away within about a year. The effect on

USDEUR is confined to a relatively small range. In contrast, IP increases substantially in response to the COM shock peaking after five months at 0.2 pp in the median. After 18 months, the effect on IP turns slightly negative. To thoroughly examine the response of IP, we need to look into the demand and supply forces driving the shock, see Section 5.3. The median response of MU decreases slightly during the first six months after the shock. Afterwards, it remains elevated for another 22 months before returning to its initial level. The decrease in MU could be due to market participants' doubts about size and direction of commodity market movements which are alleviated by a realization of the shock, at least in the short-run.

5.2 Bayesian VAR with a Threshold

Threshold Results The preliminary results mentioned in Section 5.1 illustrate an average effect across low and high uncertainty periods. To properly address the research question, we turn to the TVAR which divides the data into two regimes: low and high uncertainty.

Figure 3: Periods of High Macroeconomic Uncertainty

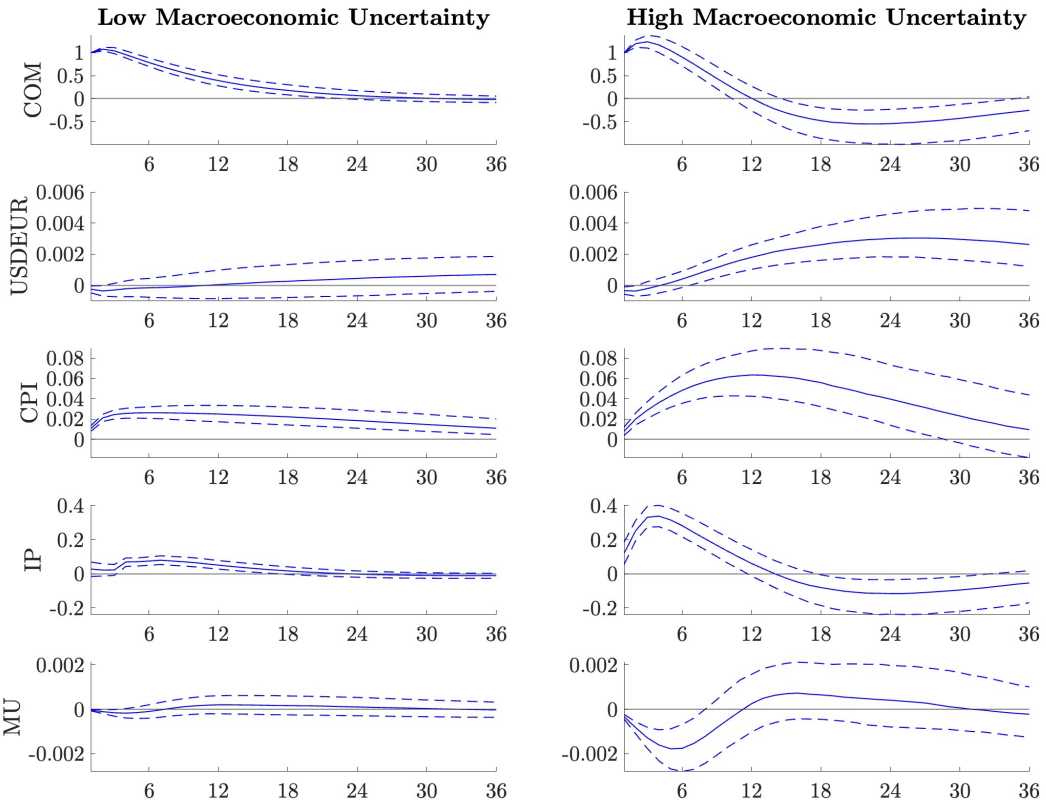


The first result of our estimation is the threshold value. It is endogenously determined at 0.7047, which is visualized in Figure 3. The red line illustrates the development of MU

over time, while the dashed black line indicates the threshold value. This implies that any observation associated with MU above this value is included in the high uncertainty regime. Out of 502 observations, 403 and 99 observations are considered in the low and high uncertainty regime, respectively. The sample split is made explicit by the gray bands in Figure 3 which represent periods of high MU. These include the 1981-1982 recession, the bursting of the DotCom Bubble, the financial crisis and associated recession between 2007 and 2010, as well as the periods after 2019 linked to the Covid-19 pandemic and Russian invasion of Ukraine. This result is unsurprising since recessions go hand-in-hand with a significant decline in economic activity raising uncertainty for businesses and consumers.

CPI Results Next, we turn to the IRFs, of which there are now two sets for every variable. The left panel in Figure 4 shows the credibility intervals of the responses in case of a COM shock during low uncertainty periods while those for high uncertainty times are in the right panel. Note that the credibility intervals are widened in the high uncertainty regime. This is unsurprising since they are more exposed to fluctuations by definition. The different responses of CPI to a 1% shock in the low versus the high uncertainty regime are visualized in the third row in Figure 4. The median response of CPI increases in both regimes but the peak effect more than doubles in the high uncertainty regime. We report the explicit values at each horizon in Table 3. During low uncertainty, the effect peaks at 0.026 pp after 5 months while during high uncertainty, the effect peaks at 0.063 pp after one year. Based on the fact that the credibility intervals of the two regimes do not overlap for about a year after the shock, it can be inferred that the responses for CPI are notably different.

Figure 4: Austria - IRFs with Threshold



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

Table 3: CPI Median IRFs to COM Shocks

Low Uncertainty			High Uncertainty		
1-12	13-24	25-36	1-12	13-24	25-36
0.011	0.025	0.018	0.008	0.062	0.037
0.021	0.024	0.017	0.020	0.062	0.034
0.025	0.024	0.017	0.029	0.061	0.031
0.026	0.023	0.016	0.036	0.059	0.028
0.026	0.023	0.015	0.043	0.058	0.026
0.026	0.022	0.015	0.048	0.056	0.024
0.026	0.022	0.014	0.053	0.053	0.021
0.026	0.021	0.013	0.056	0.051	0.019
0.026	0.020	0.013	0.059	0.048	0.016
0.026	0.020	0.012	0.061	0.045	0.014
0.025	0.019	0.012	0.062	0.042	0.013
0.025	0.019	0.011	0.063	0.040	0.010

Note: Columns represent the periods after impact.

To holistically depict the effect of a COM shock on CPI, we complement our analysis with cumulative IRFs. The corresponding graphs can be found in Figure 9 in Appendix B and illustrate the total change in each variable, as the responses until each time horizon are added up. We also establish a difference in the median accumulated response of CPI one year after the shock: CPI rises by 0.290 pp in the low uncertainty regime compared to 0.538 pp in the high uncertainty regime. Moreover, Figure 9 in Appendix B demonstrates that the effect of a COM shock does not cancel out over time but accumulates in either regime. This finding underlines the importance of our results for monetary authorities and policy makers.

The difference in CPI responses to a COM shock depending on the uncertainty regime is the major insight of this thesis. The relevant literature which was examined in Section 2.2 provides several theoretical and empirically tested channels to explain the divergence. For instance, the implications of the *Real Options Theory* can be seen in Figure 4. Pioneered

by Bernanke (1983), it posits that firms and consumers prefer to postpone economic decisions in light of uncertainty. During highly uncertain times, we see a reduction in MU following a realized COM shock. Economic agents are therefore incentivized to change their behavior and act on economic decisions. Thus, the responses of quantities and prices, e.g. CPI and IP, are larger in response to a shock.

Remaining Variables The remaining variables respond as expected. By construction, COM increases, since it is the variable that experiences the shock. Initially, this effect is quite similar across both regimes. However, after one year, the effect is still faintly positive in the low uncertainty regime while it is negative in the high uncertainty regime. This might be related to higher volatility of COM given high uncertainty.

With respect to the other variables in the TVAR, we observe muted responses in the low uncertainty regime compared to the high uncertainty regime. This supports the hypothesis that some average effects seen in Figure 2 are largely fueled by the economy's responses during high uncertainty. In particular, the exchange rate appreciates more strongly in the high uncertainty regime. In general, a COM shock will induce the USD to appreciate relative to the Euro (EUR) since a price increase in USD-traded commodities will drive up demand for USD. This effect is amplified in periods of high uncertainty since the USD is a safe-haven currency. Conversely, during low uncertainty, the credibility interval covers zero over the entire horizon.

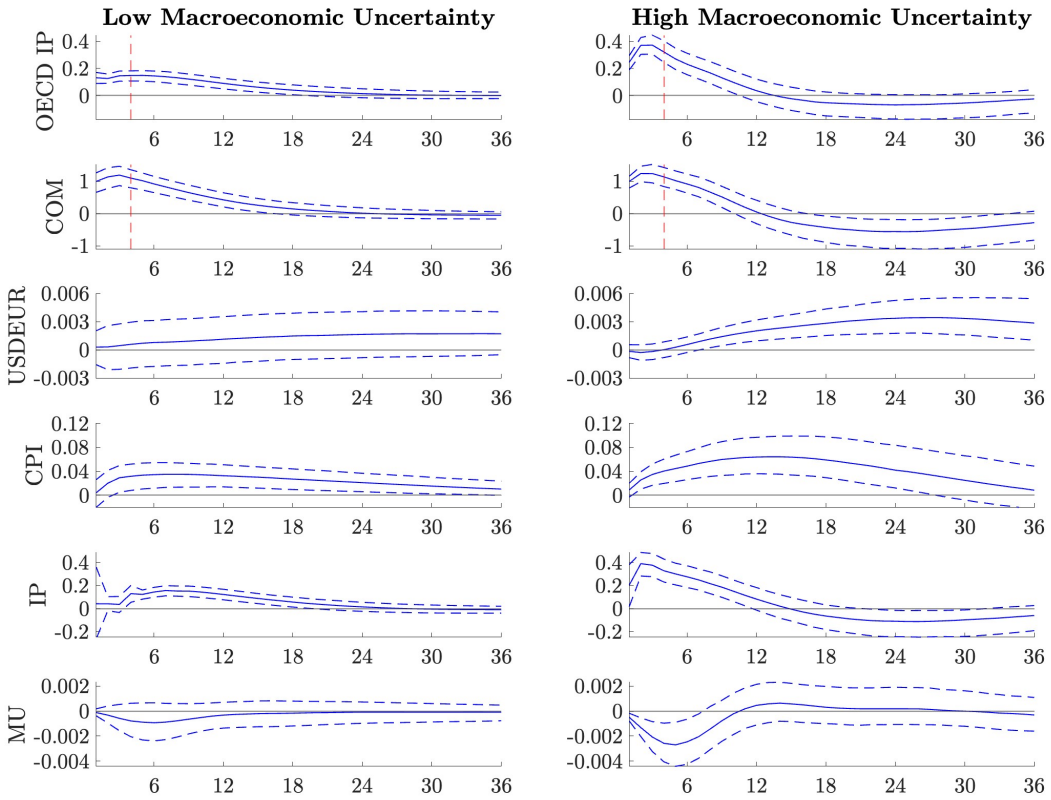
IP rises in both regimes but even more so given high uncertainty. During low uncertainty, IP's median increase is relatively small, i.e. roughly 0.05 pp, six to twelve months after the shock. In the high uncertainty regime, the median increase peaks after three months at approximately 0.25 pp. After a year and a half, the effect turns slightly negative. The response of IP is closely tied to the underlying supply and demand movements, which we discuss in Section 5.3.

Moreover, the initial drop in MU that emerged in the standard Bayesian VAR in Section 5.1 can be solely attributed to the high uncertainty regime. While periods of low uncertainty always contain zero in the credibility interval, periods of high uncertainty show a

decline in MU during the first eight months after a COM shock. This can be attributed to a COM shock alleviating part of the prevailing macroeconomic uncertainty during highly uncertain periods. However, this mechanism does not apply to stable times.

5.3 Bayesian VAR with a Threshold and Sign Restrictions

Figure 5: Austria - IRFs Demand Shock



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM demand shock driven by economic activity. The red line indicates the horizon imposed on sign restrictions.

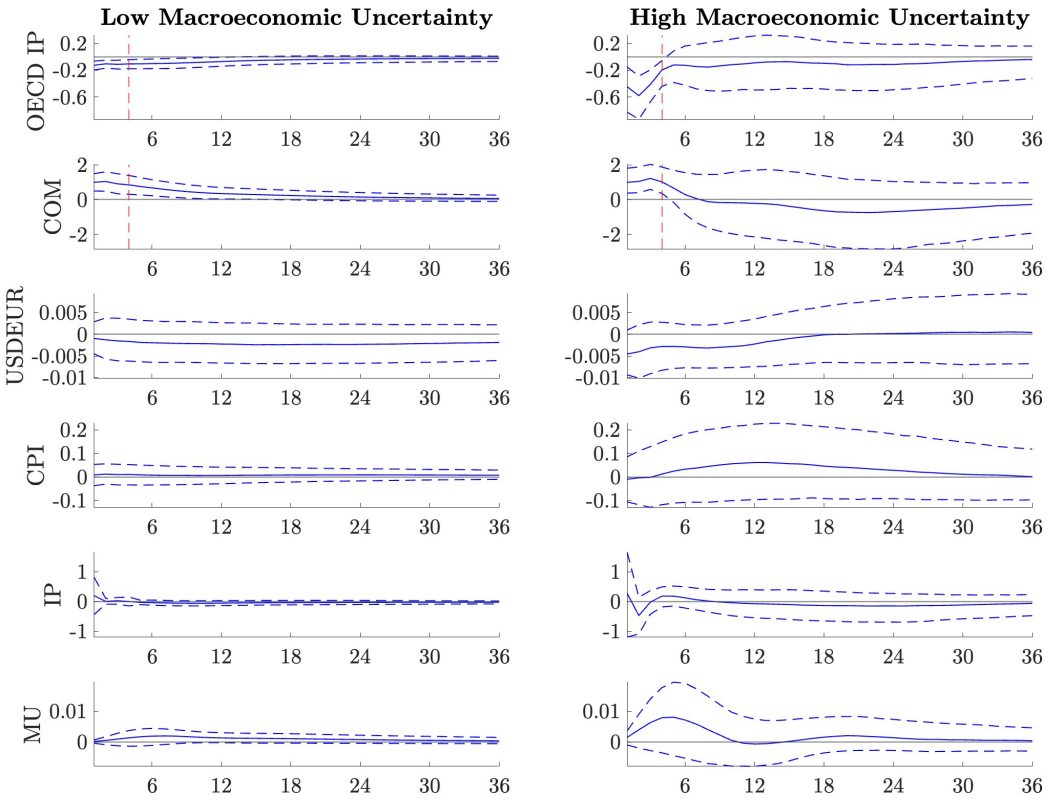
Next, we employ sign restrictions in order to precisely pin down the origins of the price movements. The different identification approach does not affect neither the lag selection nor the threshold estimation. Thus, the model still selects three lags and endogenously identifies 0.7047 to be the threshold value and applies the same classification of observations as in Section 5.2. Therefore, the implied IRFs are directly comparable to the ones obtained in the previous section.

As explained in Section 4.3.2, we restrict the signs of the impulse responses of global economic activity proxied by OECD IP and COM to move in the same direction. That is, they either both react positively or negatively, mirroring the movements of a global demand shock. The resulting impulse responses are depicted in Figure 5. Each regime is scaled so as to represent a 1% shock specific to the regime. To complement the demand shock, we also specify a supply shock, restricting the signs of OECD IP and COM to react in opposite directions. The resulting impulse responses are visualized in Figure 6.

The similarity between the responses to an exogenous COM shock and a demand shock is striking. The impulse responses of CPI follow the same patterns but differ slightly in the effect size. For demand shocks, the median peak response (cumulative effect after one year) under low uncertainty increases to 0.035 pp (0.361 pp) from 0.026 pp (0.290 pp) in the baseline. Similarly, the CPI response under high uncertainty rises to 0.069 pp (0.630 pp) from 0.063 pp (0.538 pp) at baseline.

Moreover, the credibility intervals increase when sign restrictions are used for identification. This is due to the nature of the identification approach. The use of a random-number generator in determining the rotation matrix introduces another layer of uncertainty to the estimates. This step is not present in the Cholesky decomposition. The median impulse response of CPI in the high uncertainty regime is still more pronounced than in the low uncertainty regime but the difference is attenuated due to the larger credibility intervals. The use of sign restrictions can also be seen as a robustness check of the ordering imposed in the baseline model. As emphasized by Uhlig (2005), the choice of a different Cholesky decomposition does not impact the IRFs identified via sign restrictions.

Figure 6: Austria - IRFs Supply Shock



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM supply shock. The red line indicates the horizon imposed on sign restrictions.

The role of supply shocks in shaping CPI diverges from that of demand shocks. Considering only the median impulse responses, COM shocks raise national prices which illustrates that in the median supply shocks tend to be rather inflationary than deflationary. However, the 68% credibility interval includes zero over the entire forecast horizon following the shock. This means that for supply shocks, we cannot exclude the possibility of a pass-through effect different from zero. Considering these IRFs suggests that the effect on CPI seen in the TVAR in Figure 4 is almost exclusively driven by demand shocks. This insight is in line with the findings of many other authors, such as Kilian (2009). In his seminal paper, he employs a structural VAR differentiating between demand and supply shocks to examine the impact of oil price shocks on the US economy. One of the main insights is that US consumer price inflation rises significantly in response to a demand shock driven

by global economic activity but does not react significantly to an oil price shock caused by supply disruptions. Recent estimates by Igan et al. (2022) further corroborate this finding. Using a cross-country structural vector autoregression model, they fail to find an effect of supply shocks on CPI.

Regarding the responses of other variables to COM shocks, we are particularly interested in Austrian IP. In response to a demand shock, we find a median increase in IP during the first year in both regimes. While during low uncertainty, IP returns to its original level 18 months after the shock, during high uncertainty IP turns negative after 14 months. Our results partially mirror the patterns described by Kilian (2009). He finds that demand shocks lead to an insignificant increase in US real GDP in the first year, followed by a significant decline in the second and third year which eventually turns negative. He attributes this development to the adverse effect of high input prices on the industry dominating the initial stimulus stemming from increased global economic activity. As a result the recessionary effects of the shock become effective with a delay. Concerning the impact of a supply shock, the median IRF in the low uncertainty regime indicates a small initial increase in IP which wears out quickly. During high uncertainty periods, there is a transitory drop in IP. However, as with CPI, we fail to exclude the possibility of a pass-through effect different from zero as the 68% credibility interval includes zero over the entire horizon following the shock. In contrast to our results, Kilian (2009) finds that US real GDP experiences a transitory decrease due to oil supply disruptions. The differences are likely to arise due to the different choice of sample, time, and commodities.

With respect to MU, we observe the same pattern as with the baseline model but only in the case of a demand shock. In the case of a supply shock there is no reduction in MU in the high uncertainty regime. The intuitive explanation for this observation is that a global demand shock reduces MU as surging demand is usually a sign of economic upturn. The positive sentiment feeds back into IP as the option value to wait of consumers and firms is reduced and they stop postponing decisions in light of uncertainty. Consumers act on their buying decisions and firms invest. Thus, IP is pushed further and shows a distinctly stronger response in the high uncertainty than in the low uncertainty regime. The larger

boost in IP is then also reflected in the larger effect on consumer prices as higher demand pushes up prices. In contrast to that supply shocks tend to stir uncertainty rather than alleviate it given that supply disruptions are another source of uncertainty and are usually unforeseen. Hence, it is unsurprising that we do not observe a similar effect for supply shocks.

6 Sensitivity Analysis

In this section we explore how the IRFs obtained for the commodity price pass-through may be affected by different variables and assumptions used in the analysis so far. More precisely, we seek to explore the robustness of the estimates to changes in the duration of the sign restrictions, the commodity price variable, the uncertainty variable, the inclusion of an interest rate measure as well as to taking Austria as the small open economy of choice.

6.1 Horizon of Sign Restrictions

Given the discussion of the horizon on which sign restrictions are imposed in Uhlig (2005), we acknowledge that the chosen horizon can affect the results. Uhlig (2005) imposes different horizons on his monetary policy shock and finds that changing the horizon causes IRFs and their credibility intervals to move. Primarily, we observe that the differences in the pass-through of commodity prices to inflation are fueled by demand shocks. To ensure that this result is not only specific to a single horizon, we repeat the analysis with another plausible horizon. Canova and Paustian (2011) advocate strongly for imposing sign restrictions only on impact to avoid misspecification. Van Robays (2016) follows this approach in her analysis of oil market dynamics under varying uncertainty. Thus, we include a model which restricts only the first month in Appendix C.1, yielding results that are very similar to the main results obtained when restrictions hold beyond impact. In the low uncertainty regime the median peak increase in response to a demand-induced shock is 0.035 pp, which is only slightly higher with sign restrictions imposed on impact

(0.036 pp). The effect for the high uncertainty regime is identical with 0.069 pp. Supply shocks do not seem to contribute to the wedge between low and high uncertainty regimes in either specification as the credibility intervals always contain zero.

6.2 Exchange Rate

Exchange rate movements can moderate the pass-through of price shocks (De Gregorio et al., 2007; European Central Bank, 2017; Sekine & Tsuruga, 2018). Commodities are priced in USD, whereas the calculation of national inflation rates is based on the domestic currency. Evidently, commodity imports involve currency exchange. If a COM shock is accompanied by an appreciation of the USD, the import price increase is amplified via the exchange rate. Conversely, if the USD depreciates, the exchange rate mitigates the impact of price shocks for the domestic macroeconomy.

To ensure that the effects which we find are not mainly driven by exchange rate movements, we conduct a robustness check. Instead of the USD-based COM from the IMF, we use the EUR-based commodity price index provided by the Hamburg Institute of International Economics (2023) which we abbreviate as HWWI. The two indices are very similar in their construction. The HWWI considers 31 commodities which are weighted by the share of the respective commodity in OECD commodity imports.

The figures in Appendix C.2 show that the main result remains unchanged when replacing the USD-based data with the EUR-based HWWI: the pass-through to domestic inflation is higher during the high uncertainty regime in the baseline specification. The patterns of response look similar across all variables except for the exchange rate in the low uncertainty regime. However, as evidenced by Figure 12 and Figure 13, the response of CPI is dampened when using the HWWI compared to the IMF's index as the shock variable. In the low uncertainty regime, the median peak response is strongly reduced, from 0.026 pp to 0.017 pp. Considering the high uncertainty regime, we find a median pass-through of 0.038 pp instead of 0.063 pp at peak. This indicates that exchange rate movements play a role in determining the CPI. However, the distinctive wedge between low and high

uncertainty regimes remains robust. Figures 14 and 15 reinforce that these observations are driven by demand shocks.

6.3 Financial Uncertainty

As discussed in Section 3.3 there is no consensus in the literature on a single measure of uncertainty. To investigate if the pass-through is sensitive to other types of uncertainty, we examine if heightened uncertainty in financial markets produces the same effect as MU. Analogously to MU and based on 148 financial time series, Jurado et al. (2015) compute a measure of Financial Uncertainty (FU) which is made available by Ludvigson and Ng (2023b).

The time series used in the computation are linked to asset returns and financial indicators not covered by MU (Ludvigson & Ng, 2023a). Figure 8 in Appendix A depicts FU over the past four decades and shows that it peaked in the mid-1980s, around the time of the DotCom bubble at the turn of the 21st century and during the financial crisis and associated recession between 2007 and 2010. It spiked again at the beginning of the Covid-19 crisis. Considering FU as the threshold variable results in the threshold being endogenously determined at 0.9848, thereby changing the observations included in each regime (see Figure 16 in Appendix C.3). However, as evidenced in Figure 18, this does not change the main insight of a higher pass-through under high uncertainty. The difference is even more pronounced than in the main specification: During low uncertainty the median peak response is 0.020 pp (previously 0.026 pp), compared to 0.068 pp in the high uncertainty regime (previously 0.063 pp). Moreover, Figure 19 and Figure 20 indicate that the results seem to be attributable to demand rather than supply shocks, which is in accordance with our original results.

6.4 Interest Rate

Further extending our analysis, we include an interest rate measure, specifically the policy rate (POLICY) set by the central bank. Thereby, we are able to proxy for monetary policy and gauge the response of monetary authorities to a COM shock in the model. Following

Alessandri and Mumtaz (2017), we include the policy rate second to last in the Cholesky ordering.[12]

As illustrated in Appendix C.4, explicitly modeling monetary policy does not change our main findings while providing some additional results. For instance, Figure 22 in Appendix C.4 reveals that in response to a 1% COM shock, POLICY increases in the median up to 0.05 pp in the high uncertainty regime. Conversely, the left panel shows that it is almost unresponsive in the low uncertainty regime. This result indicates that during periods of high uncertainty, monetary authorities notably raise POLICY in response to a COM shock. Furthermore, our results with respect to CPI remain largely robust compared to the main model. While the median peak increase in the low uncertainty regime does not change (0.026 pp), it is attenuated slightly in the high uncertainty regime (0.057 pp instead of 0.063 pp), indicating some success of the monetary policy intervention. However, the wedge between low and high uncertainty periods remains and is driven by demand shocks. Observing that during heightened uncertainty CPI increases more, despite a stronger monetary policy response, may indicate weakened monetary policy effectiveness during uncertain periods as described in Section 2.2 and shown by Aastveit et al. (2017).

6.5 Netherlands

The main study object of the thesis is Austria. As an additional robustness check, we run all specifications for the Netherlands. As mentioned in Section 2.1, structural characteristics can influence the pass-through and hence lead to cross-country differences. Austria and the Netherlands are very similar in key characteristics such as level of development, size of the economy, and membership in the European Union. Moreover, both countries belong to the Eurozone and thus, their monetary policy authority is shared between the European Central Bank (ECB) and the respective national central bank. Hence, it is reasonable to assume that the independence of monetary authorities is similar, too. Taken

[12]Note that we need to take into account the change in the policy rate regime when the Euro was introduced in Austria in 1999, as provided in the calculations by the Austrian Economic Research Institute (European Central Bank, 2023).

collectively, these factors give reason to expect little differences in the pass-through across these two countries.

Our baseline specification and its results are reported in Figure 26 along with further specifications in Appendix C.5. The main result, that is, a stronger pass-through of COM shocks to domestic inflation in high uncertainty, is confirmed for the Netherlands. The effect size is similar in magnitude as well. During high uncertainty the median peak response of the Netherlands and Austria is basically the same (0.062 pp and 0.063 pp). In the low uncertainty regime the median peak response is halved for the Netherlands (0.013 pp compared to 0.026 pp) indicating a better containment of inflation in response to a COM shock. For IP, the effect is roughly halved for the Netherlands. With respect to demand and supply shocks, Dutch data proves to have similar patterns to Austrian data, implying that the effects are mainly driven by demand shocks in commodity markets.

7 Discussion

This section is intended to discuss the findings of this thesis. To this end we want to bring attention to possible limitations of our approach which have not been addressed in the sensitivity analysis. Taking into account the limits of this thesis, we proceed to outline possible applications and extensions of the model in a policy-relevant context as well as its implications for policy makers.

7.1 Validity and Limitations

Like every statistical model, the Bayesian TVAR has its shortcomings. As highlighted in Section 4.3, inference for VARs is based on the identification approach. One of our approaches is the implementation of sign restrictions in Section 4.3.2, which is subject to criticism by Baumeister and Hamilton (2020) and Kilian and Murphy (2012). They highlight the fact that sign restricted identification does not lead to a unique solution but instead proposes a set of impulse response vectors which are all consistent with the restrictions imposed. Given that all responses are admissible, it is challenging to report

these due to their large number. We rely on the common approach to report the median IRF (Baumeister & Hamilton, 2020). In place of this, Kilian and Murphy (2012) prefer to extend sign restrictions with size restrictions to narrow down the set of admissible IRFs. For example, Van Robays (2016) augments standard sign with boundary restrictions on price elasticities. However, this technical extension surpasses the scope of this thesis.

Apart from methodological restrictions associated with the Bayesian TVAR, we also wish to point out the limits of our results. While we find a different pass-through in low and high uncertainty regimes, the model is not designed to pin down the reasons for the divergence. Even though we identify potential channels for the differing pass-through based on established economic theory and vast literature in Section 2, the empirical testing of these channels in the given context requires different model specifications and possibly even different econometric techniques. Thus, exactly identifying the role of each channel in driving the wedge in pass-through raises a new question which we leave to future research.

Moreover, we wish to highlight that the external validity of the results is limited since we focus on the Austrian economy. As we have seen in Section 6.5 the results are robust when studying another small open developed economy, but we lack results for economies with differing structural characteristics. A panel VAR or a global VAR could help to attain a more general understanding of the impact of uncertainty on the pass-through.

7.2 Policy Implications

Keeping the aforementioned limitations in mind, the central message of this thesis is that global commodity price shocks affect CPI in Austria, and more so during periods of high uncertainty. This has direct policy implications. Firstly, governments need to take the general level of uncertainty into account when setting appropriate policies. To start, governments might need to implement fiscal policies to mitigate the impacts of commodity price shocks. For instance, the Austrian government could subsidize investments, which would make the Austrian economy less dependent on importing commodities. When designing such policies, considering that a large part of the effects on the national economy

is driven by commodity price shocks during highly uncertain times is essential. Following our results, times of uncertainty render the domestic economy more vulnerable to international developments. Governments are hence encouraged to include an uncertainty variable in macroeconomic computations underlying their decision-taking process. Secondly, due to a higher pass-through during high uncertainty, risk management practices are crucial to dampen the impacts during highly uncertain periods. Besides generally diversifying the economy away from commodity dependence, governments could build up reserves to be accessed during especially volatile and uncertain periods so as to alleviate inflationary pressures from expensive imports. Thirdly, as commodities affect the world market, governments need to collaborate in their effort to ensure that both global uncertainty and global commodity prices do not deviate substantially from their long-run trend too much or for too prolonged a time.

Apart from governments, monetary authorities have an inherent interest in understanding the pass-through of international commodity prices to domestic inflation. In light of our results, we also encourage forecasters and analysts working for monetary authorities to take into account uncertainty in macroeconomic computations. Including uncertainty measures and potentially classifying the observations based on the level of uncertainty provides valuable insights on the composition of the average effect. Besides the general level of uncertainty, our results highlight that central banks need to consider commodity price movements when designing their monetary policy to conduct inflation targeting. Due to the inflationary pressures from commodity price increases, interest rates might need to be adapted. In the case of Austria, this competence lies with the ECB.

Lastly, the model presented in this thesis could be employed and extended by governments and monetary authorities alike to gain deeper insights into the effects of commodity price shocks. For instance, one could apply this methodology to analyze the pass-through on not only headline but also core inflation to capture the more persistent effects. This application would be especially relevant for policy makers. By splitting the inflation variable into sectors, i.e. into energy, food, industrial goods, and services, direct and indirect effects could be identified. Another interesting dimension worth exploring could be cross-

country differences and the driving forces behind them. This could be complemented by introducing country-specific uncertainty indexes, provided such are available.

8 Conclusion

In this thesis, we have investigated the impact of commodity price shocks in a small open economy based on varying levels of uncertainty. To our knowledge, we are the first to investigate how commodity price pass-through dynamics and global macroeconomic uncertainty are linked. The Bayesian TVAR identifies periods of high uncertainty and clearly demonstrates that the pass-through of commodity prices on Austrian inflation is larger during these periods. During times of low uncertainty, domestic inflation reaches a peak median increase of 0.026 pp, and a cumulative increase of 0.290 pp after one year compared to 0.063 pp and 0.538 pp during high uncertainty. Expanding our model to include sign restrictions, we are able to derive that the observed effects are brought about by demand shocks. These results are robust with respect to different measures of uncertainty and commodity prices, the inclusion of the policy rate and hold for the Netherlands, too.

The distinct responses observed between the two regimes support the notion that uncertainty should be accounted for and explicitly incorporated in macroeconomic models. These valuable insights are particularly relevant for monetary authorities and policy makers. This is due to the fact that average results observed for the Austrian economy can be decomposed into two notably different responses that necessitate different policy measures. For example, an uncertain environment makes the economy more vulnerable to commodity price shocks. Therefore, governing bodies should consider the prevailing macroeconomic uncertainty when gauging potential impacts of global shocks on the economy and deciding on appropriate monetary and fiscal responses.

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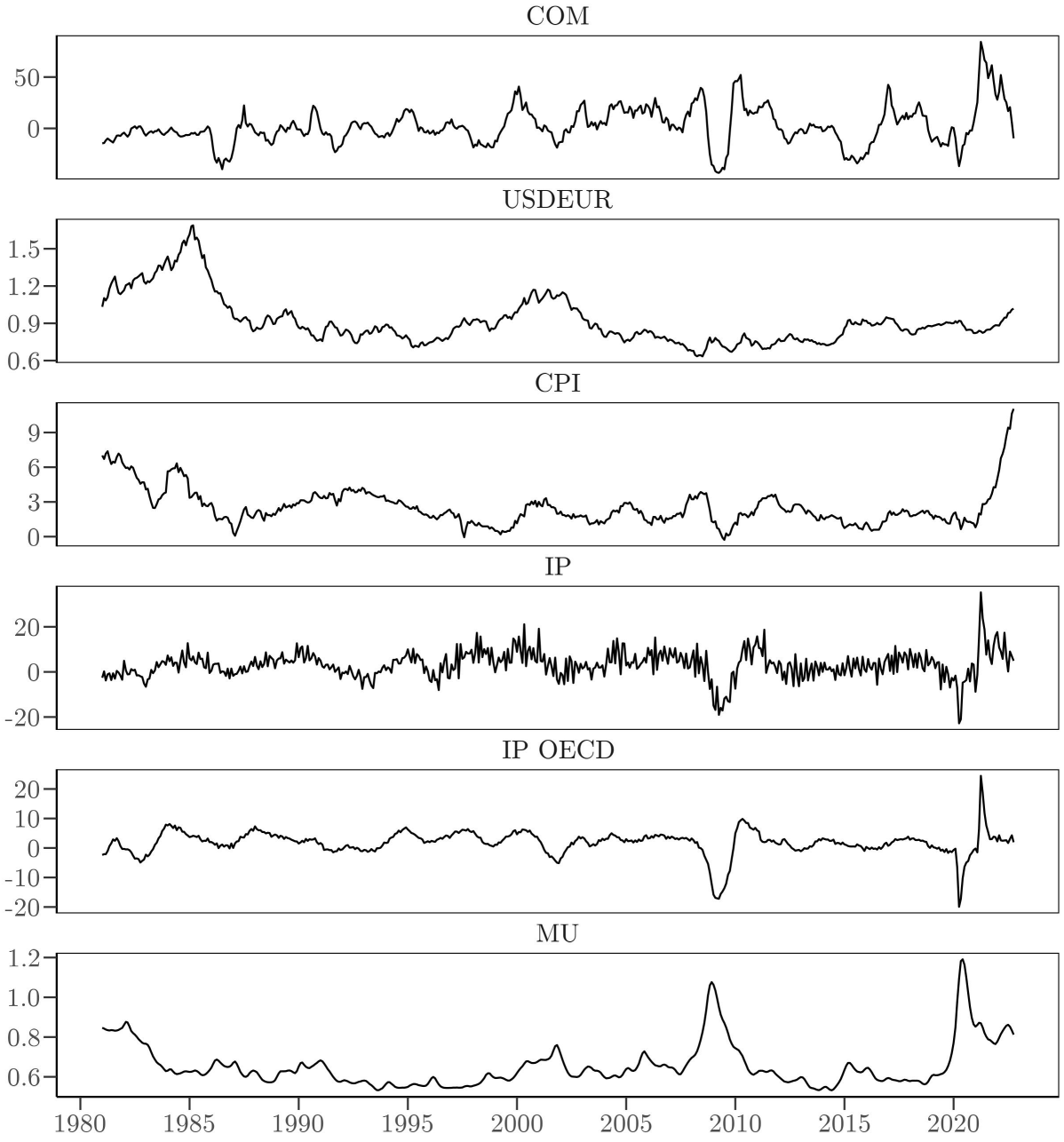
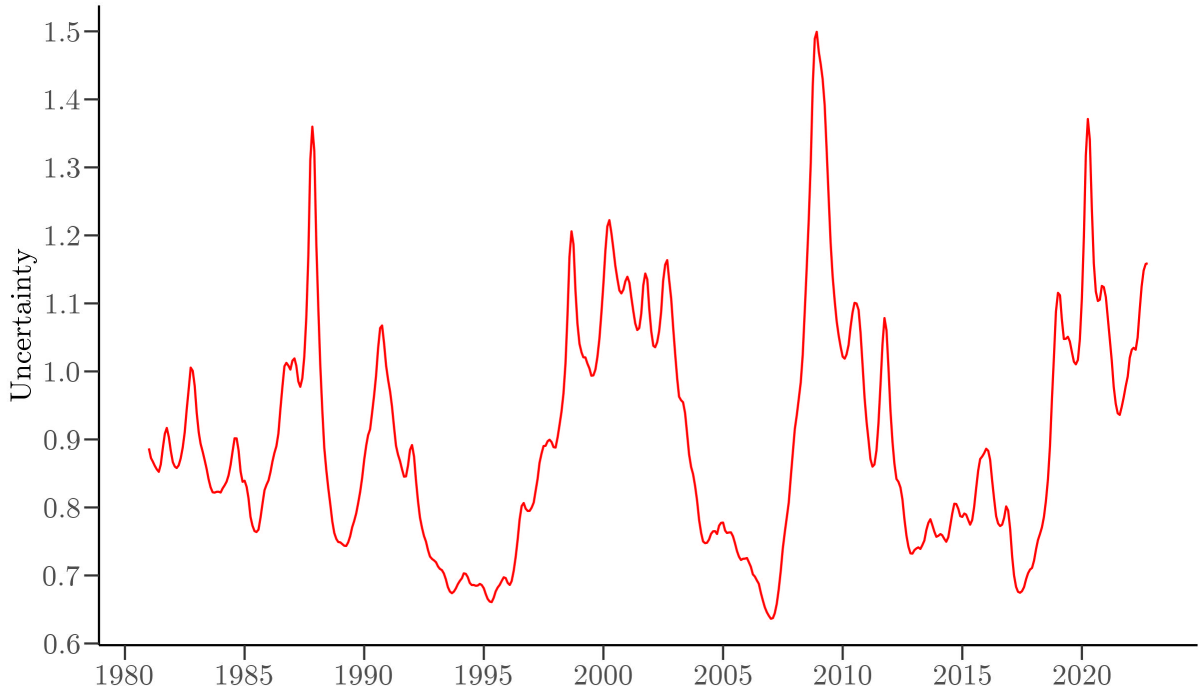
A Data plots

Figure 7: Main Variables



Notes: COM, CPI, IP and IP OECD are year-on-year growth in %. MU is the three-period moving average of one-month ahead macroeconomic uncertainty. USDEUR is the unadjusted, nominal exchange rate. *Sources*: Bank for International Settlements (2023), International Monetary Fund (2023a, 2023b), Ludvigson and Ng (2023b), and Organization for Economic Co-operation and Development (2023).

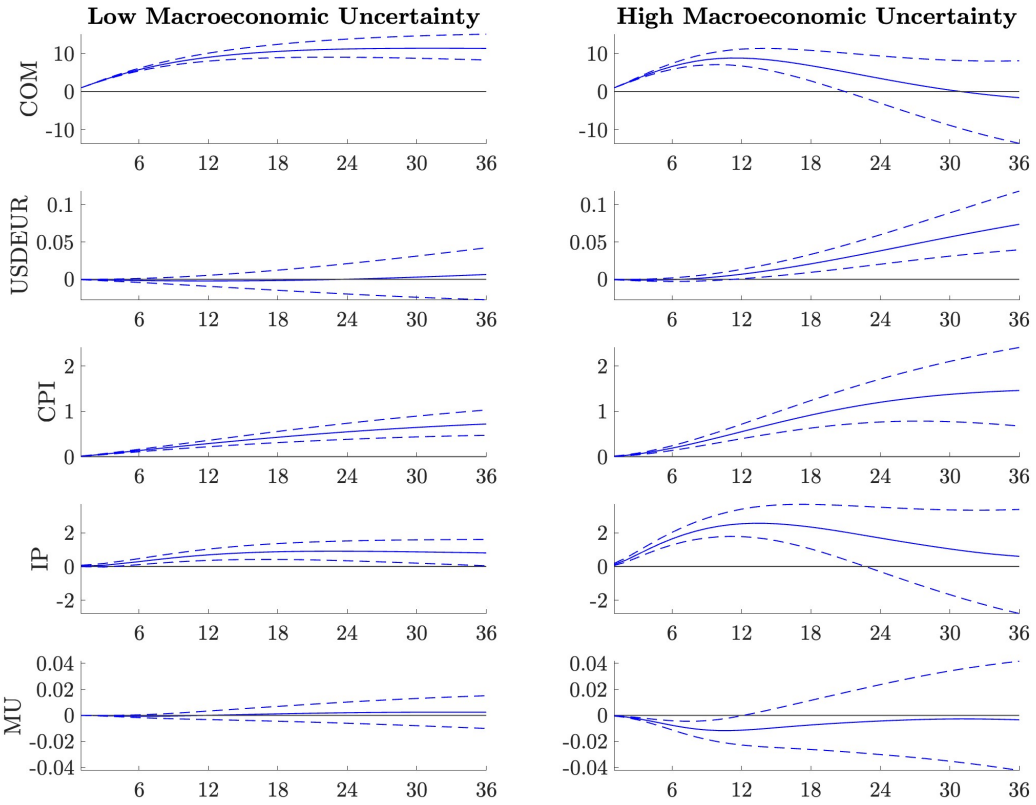
Figure 8: Financial Uncertainty



Notes: Three-period moving average of one-month ahead financial uncertainty. *Sources*: Ludvigson and Ng (2023b).

B Cumulative IRFs

Figure 9: Austria - Cumulative IRFs

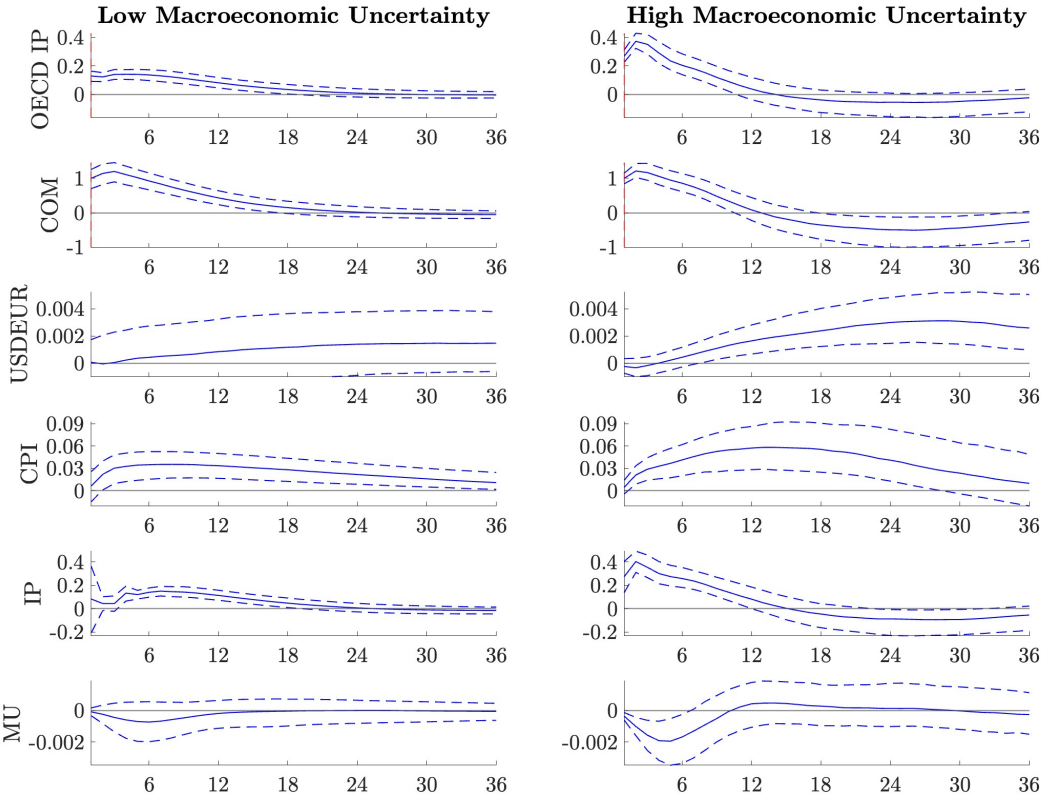


Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

C Sensitivity Analysis

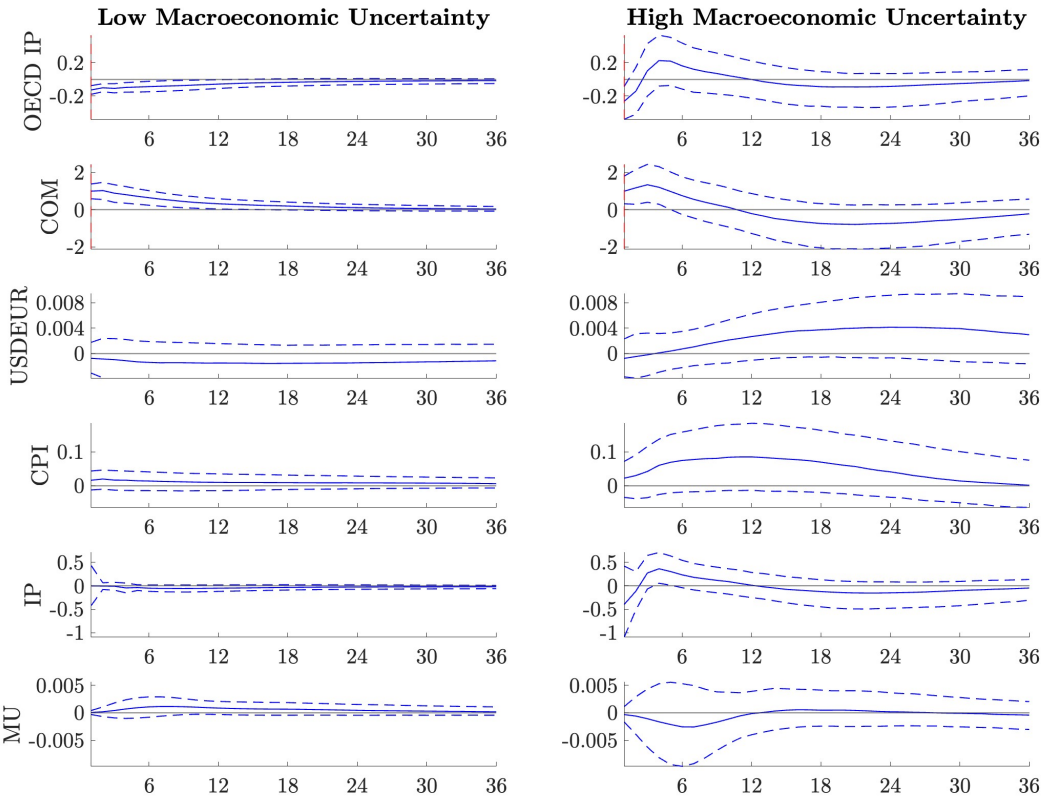
C.1 Horizon of Sign Restrictions

Figure 10: Austria - IRFs Demand Shock, Sign Restrictions on Impact



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM demand shock driven by economic activity. The red line indicates the horizon imposed on sign restrictions.

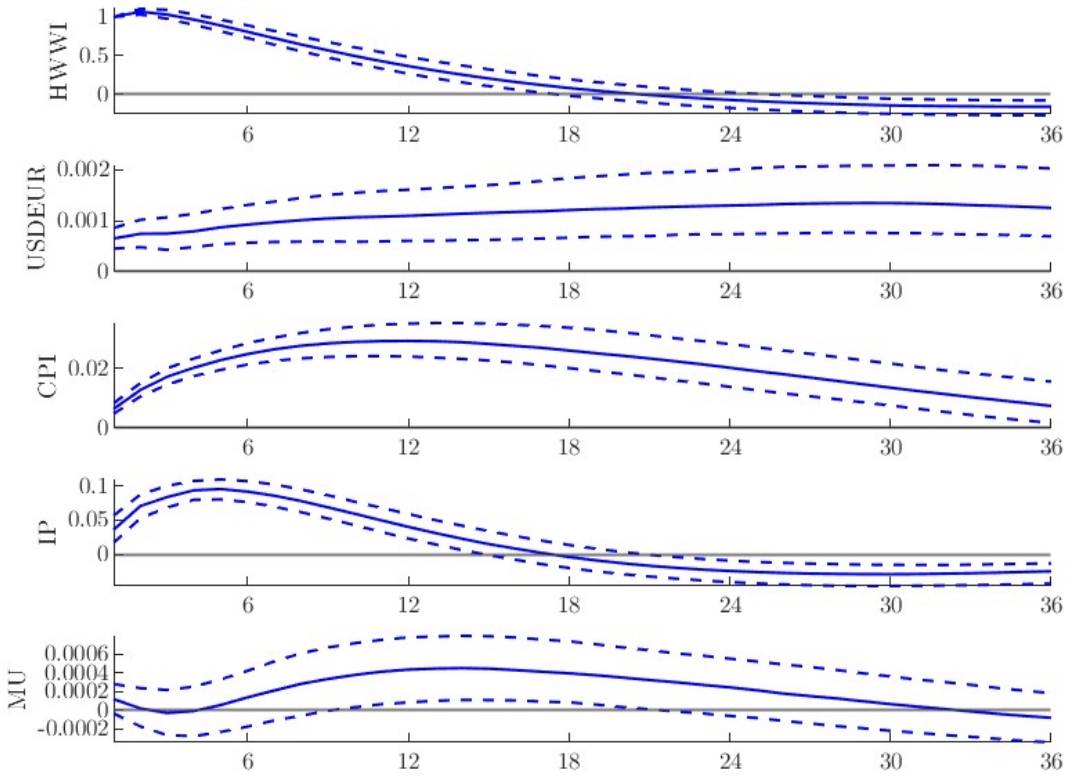
Figure 11: Austria - IRFs Supply Shock, Sign Restrictions on Impact



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM supply shock. The red line indicates the horizon imposed on sign restrictions.

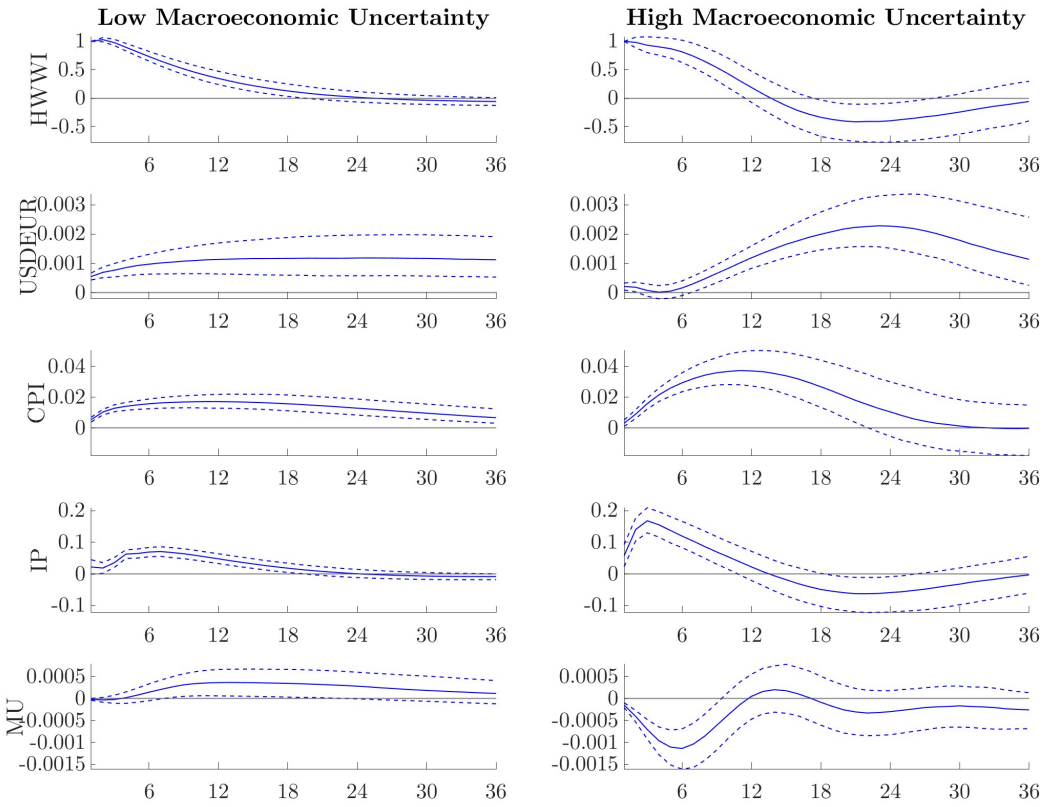
C.2 Exchange Rate

Figure 12: Austria - IRFs, no Threshold, HWWI



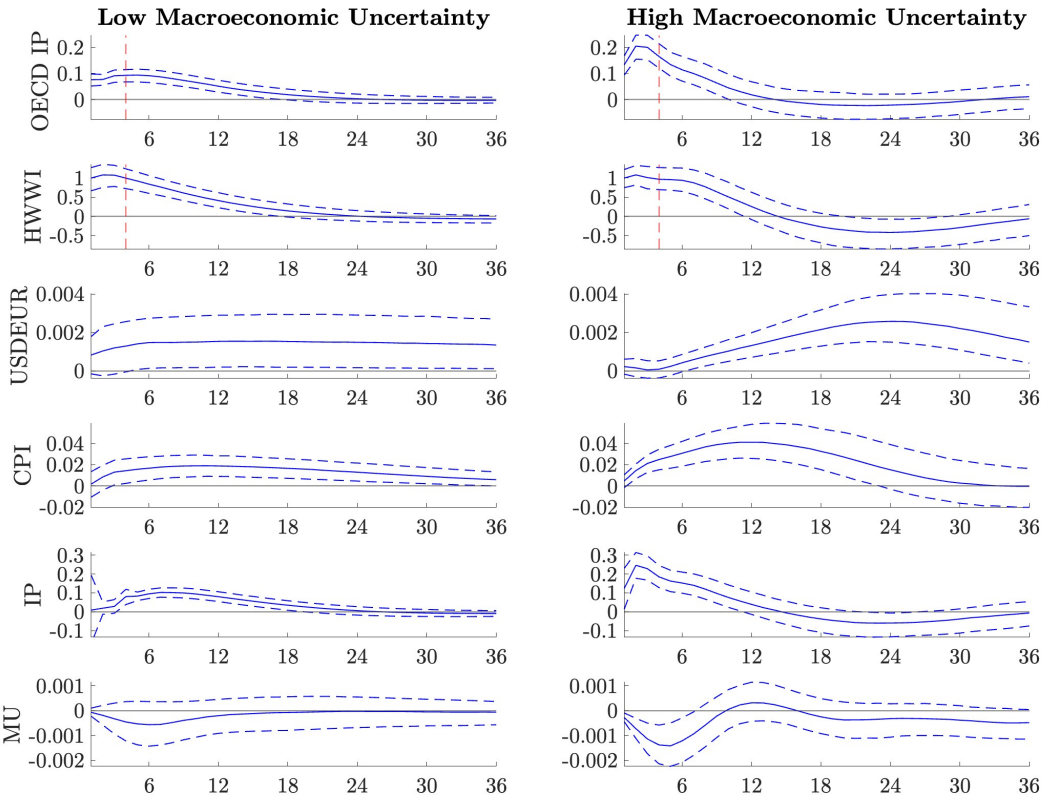
Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

Figure 13: Austria - IRFs with Threshold, HWWI



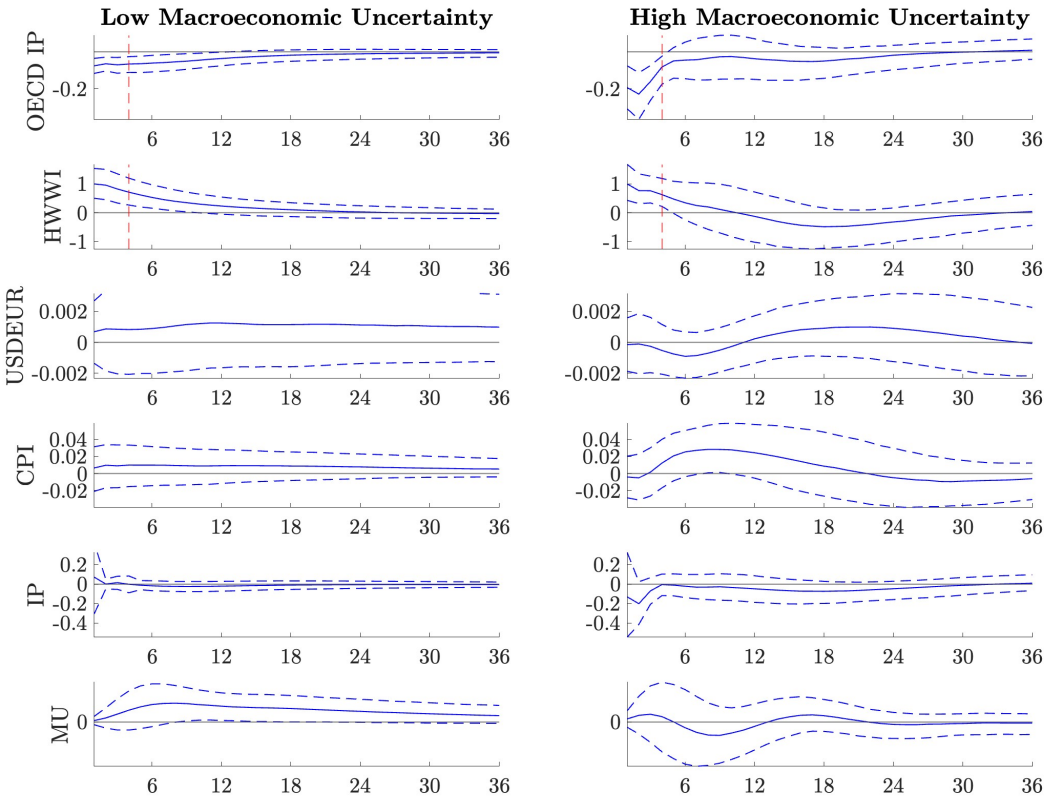
Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

Figure 14: Austria - IRFs Demand Shock, HWWI



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM demand shock driven by economic activity. The red line indicates the horizon imposed on sign restrictions.

Figure 15: Austria - IRFs Supply Shock, HWWI



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM supply shock. The red line indicates the horizon imposed on sign restrictions.

C.3 Financial Uncertainty

Figure 16: Periods of High Financial Uncertainty

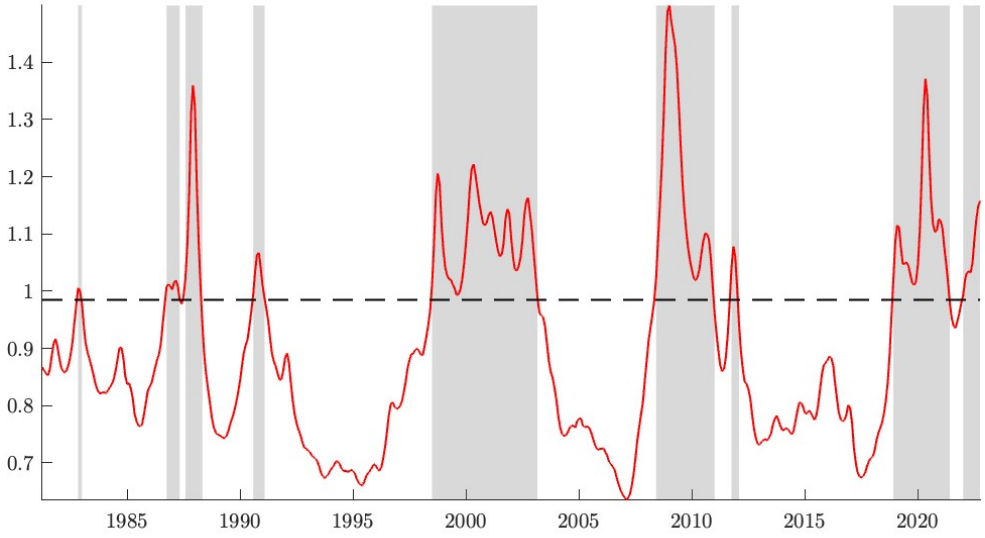
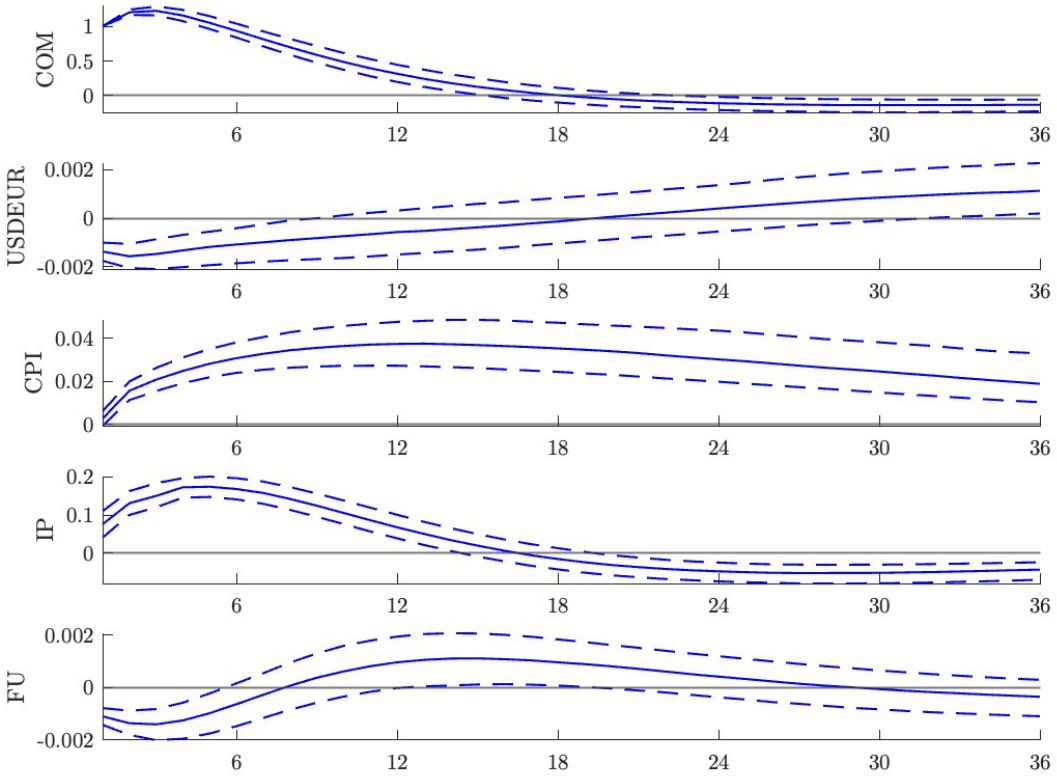
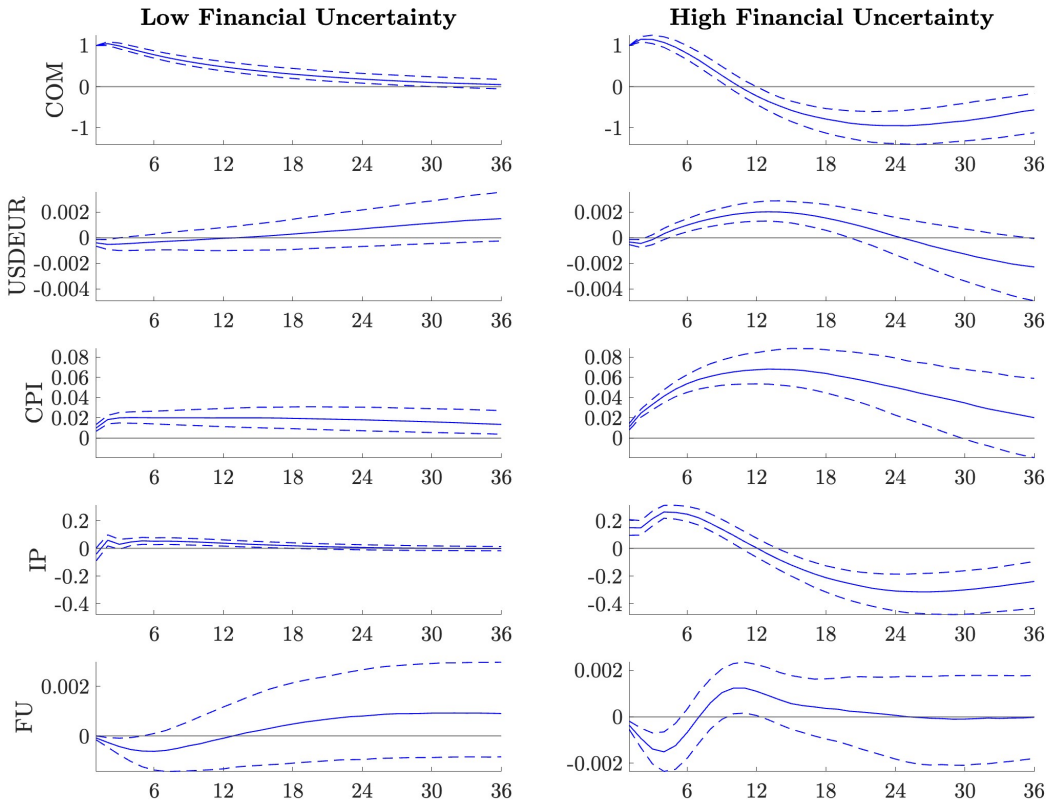


Figure 17: Austria - IRFs, no Threshold, Financial Uncertainty



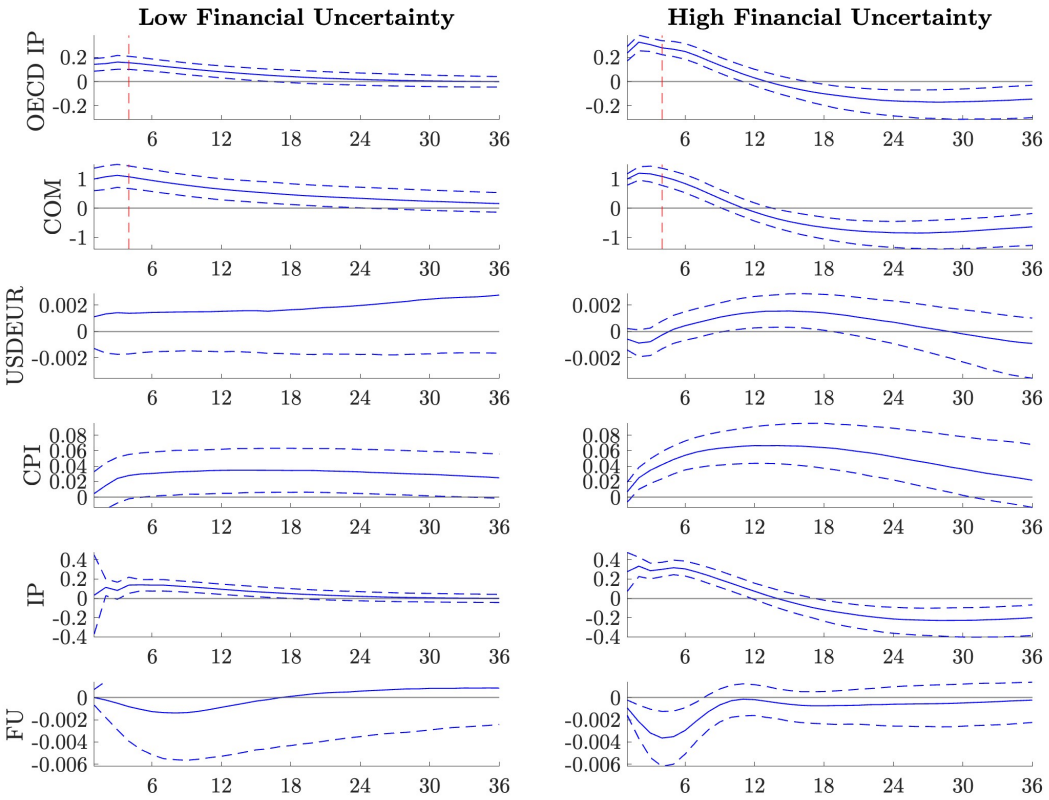
Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

Figure 18: Austria - IRFs with Threshold, Financial Uncertainty



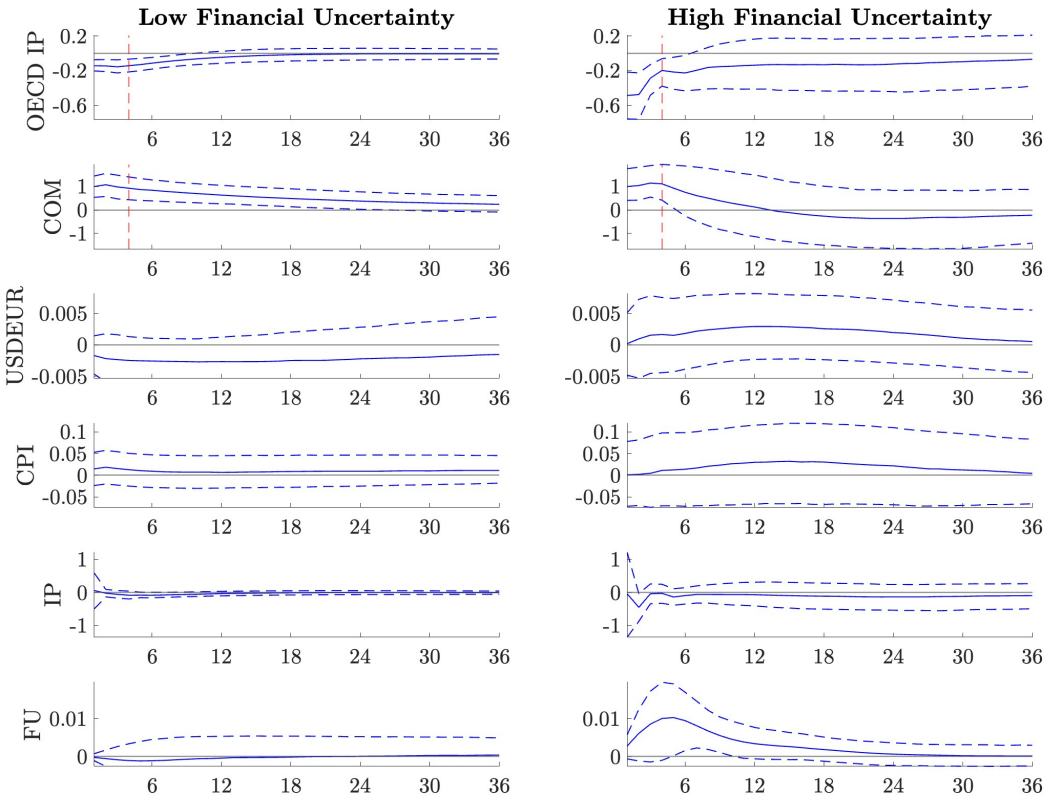
Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

Figure 19: Austria - IRFs Demand Shock, Financial Uncertainty



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM demand shock driven by economic activity. The red line indicates the horizon imposed on sign restrictions.

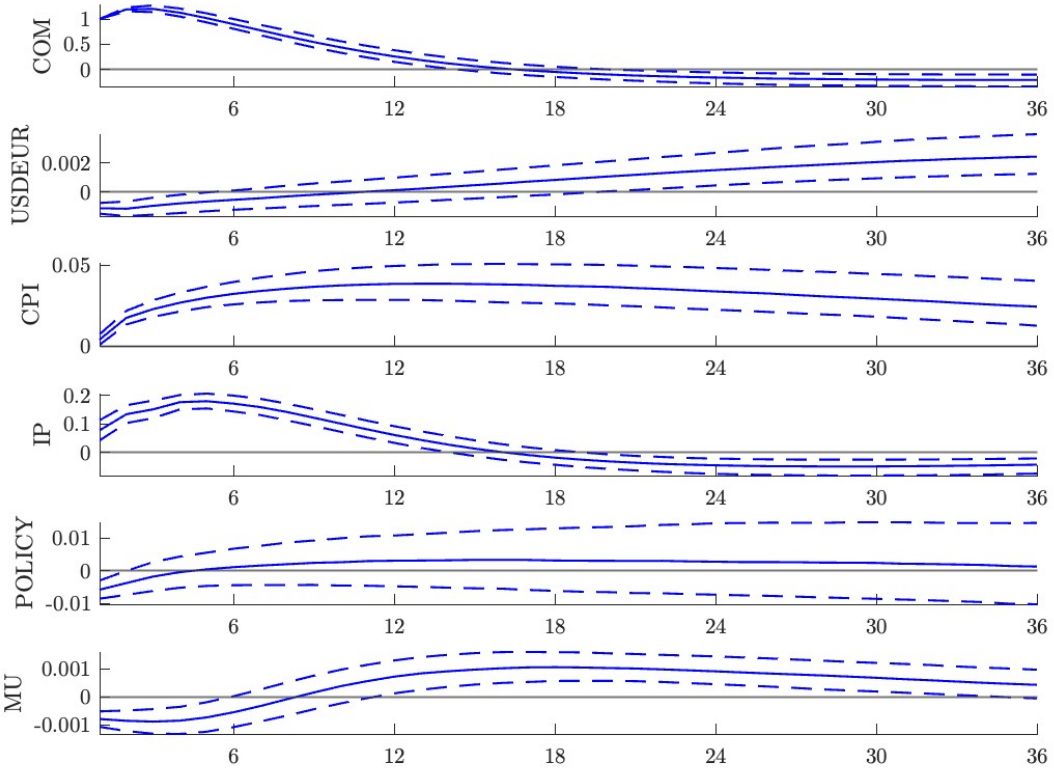
Figure 20: Austria - IRFs Supply Shock, Financial Uncertainty



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM supply shock. The red line indicates the horizon imposed on sign restrictions.

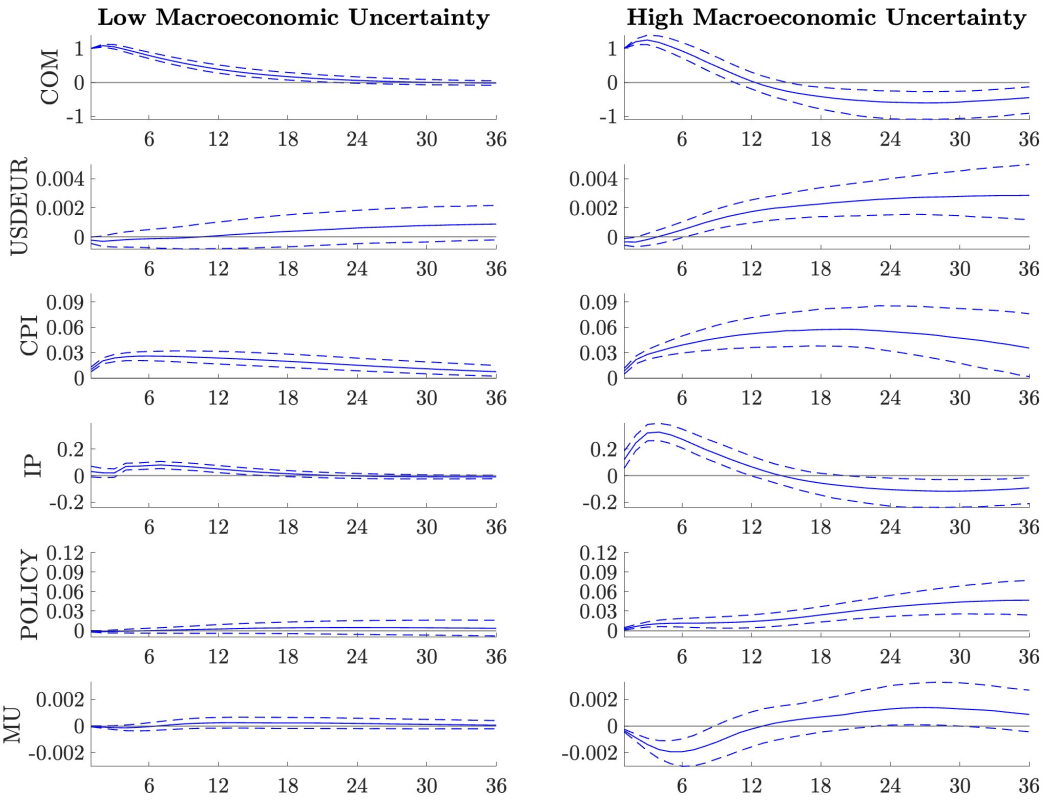
C.4 Interest Rate

Figure 21: Austria - IRFs, no Threshold, Policy Rate



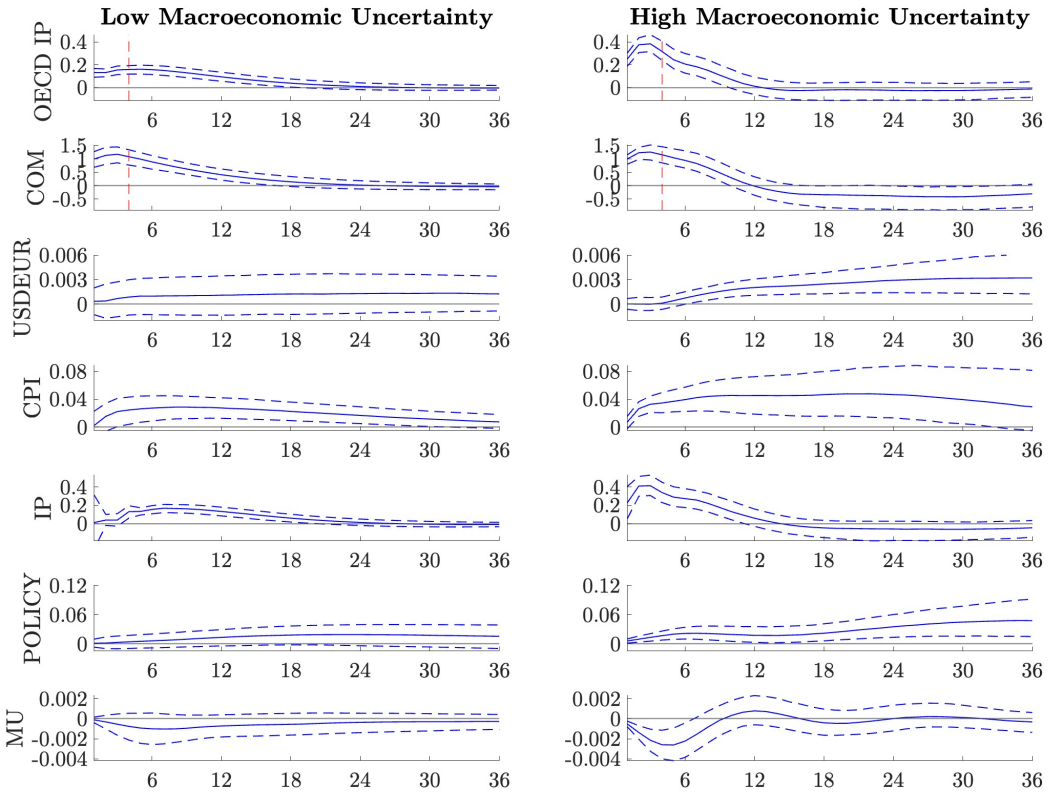
Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

Figure 22: Austria - IRFs with Threshold, Policy Rate



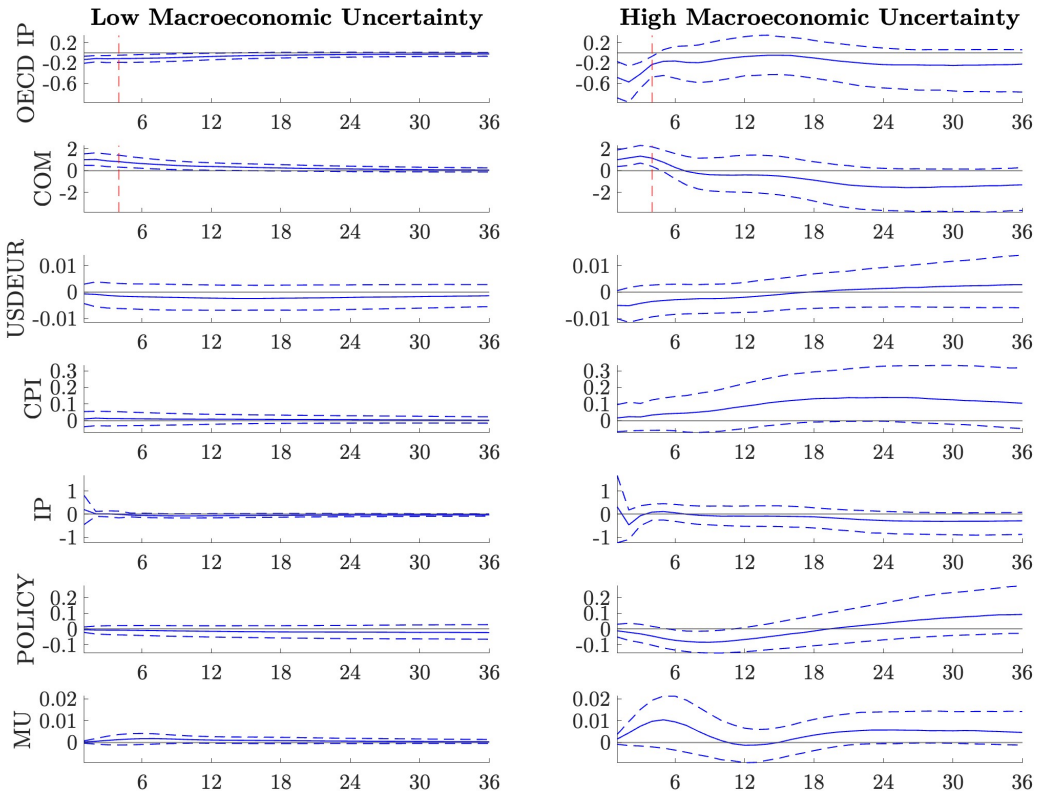
Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

Figure 23: Austria - IRFs Demand Shock, Policy Rate



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

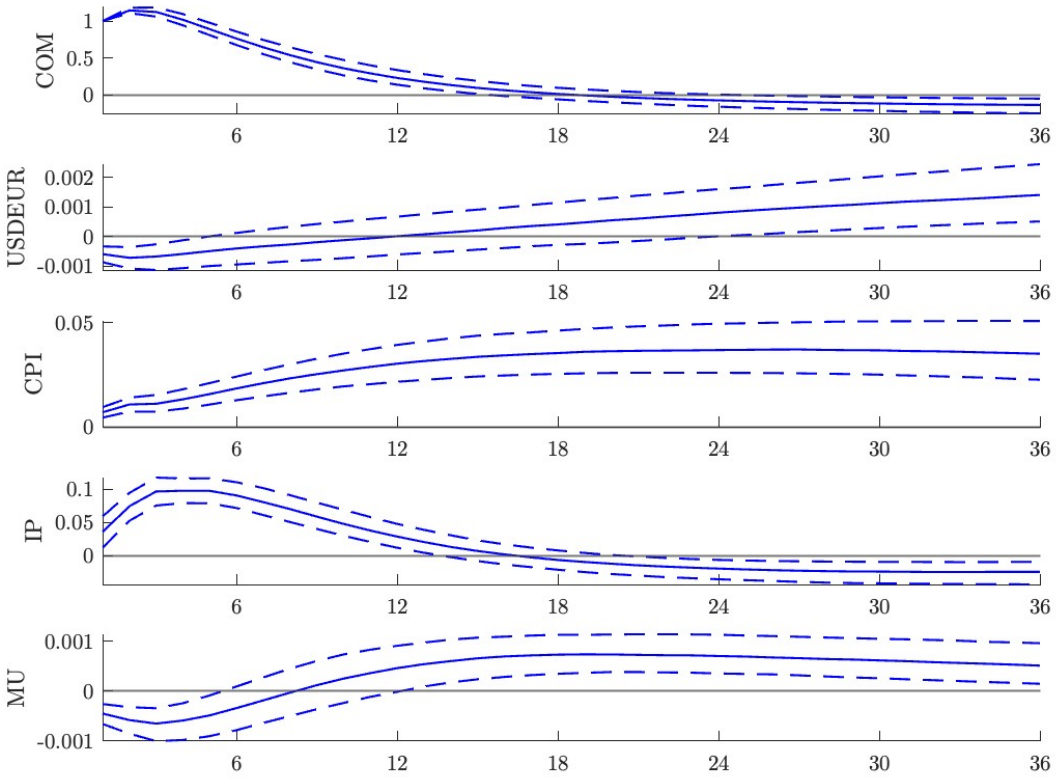
Figure 24: Austria - IRFs Supply Shock, Policy Rate



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

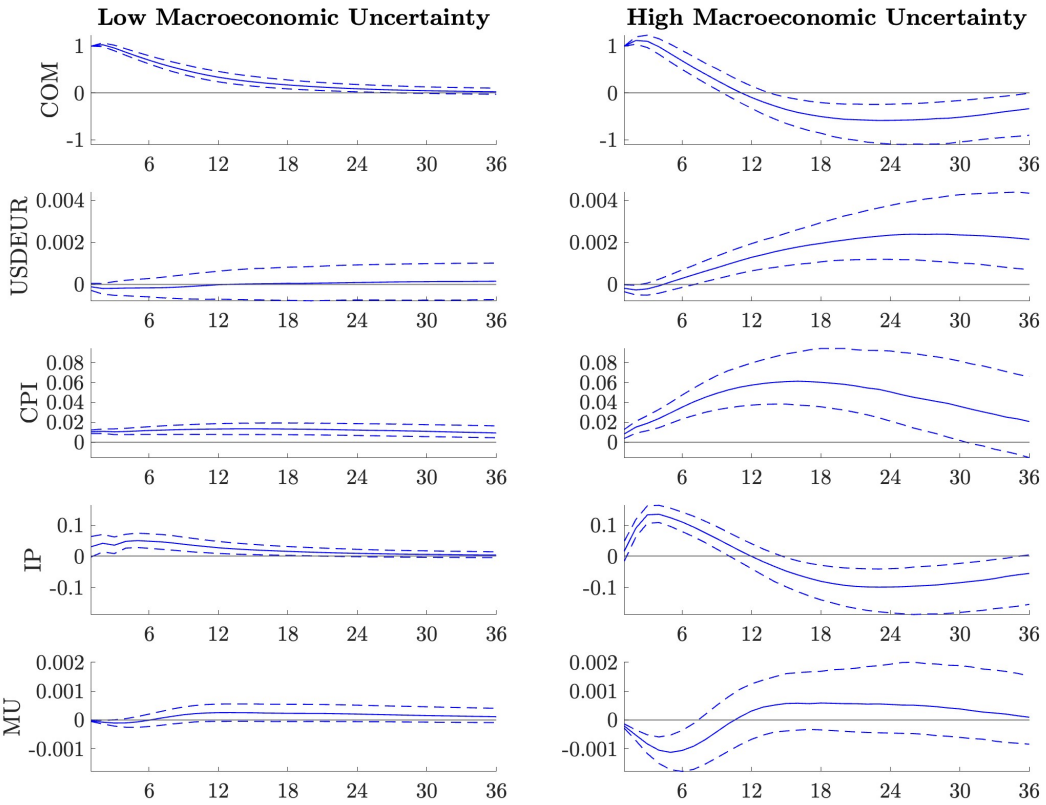
C.5 Netherlands

Figure 25: Netherlands - IRFs, no Threshold



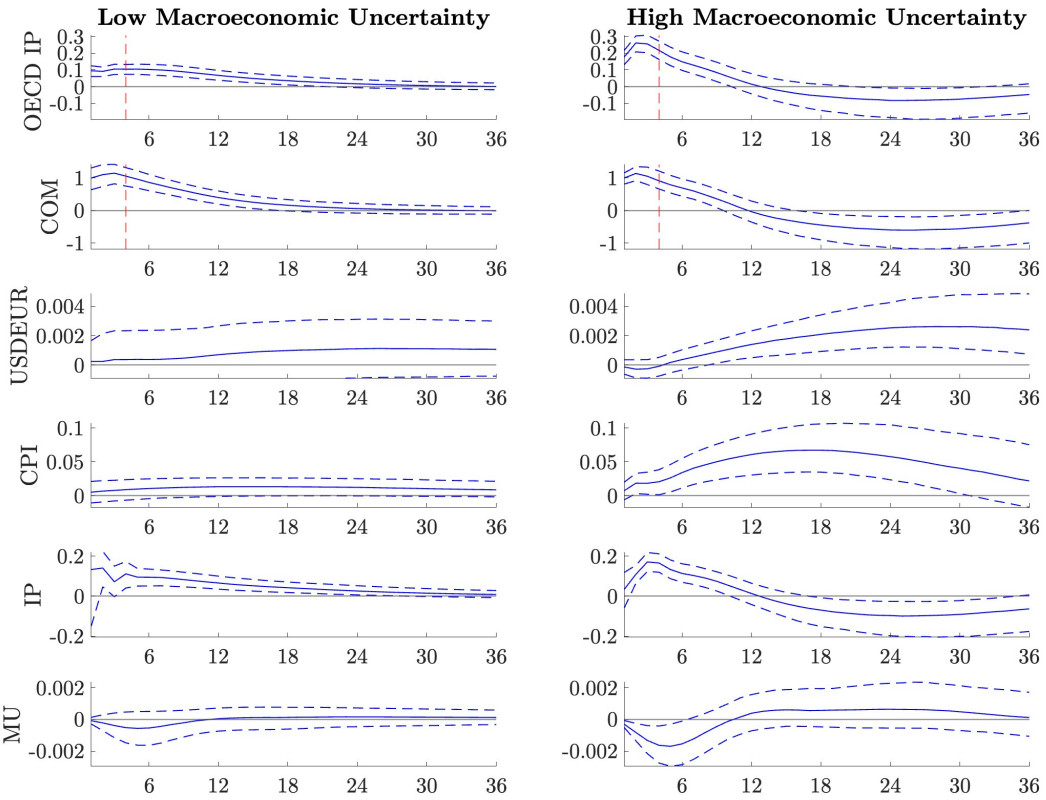
Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

Figure 26: Netherlands - IRFs with Threshold



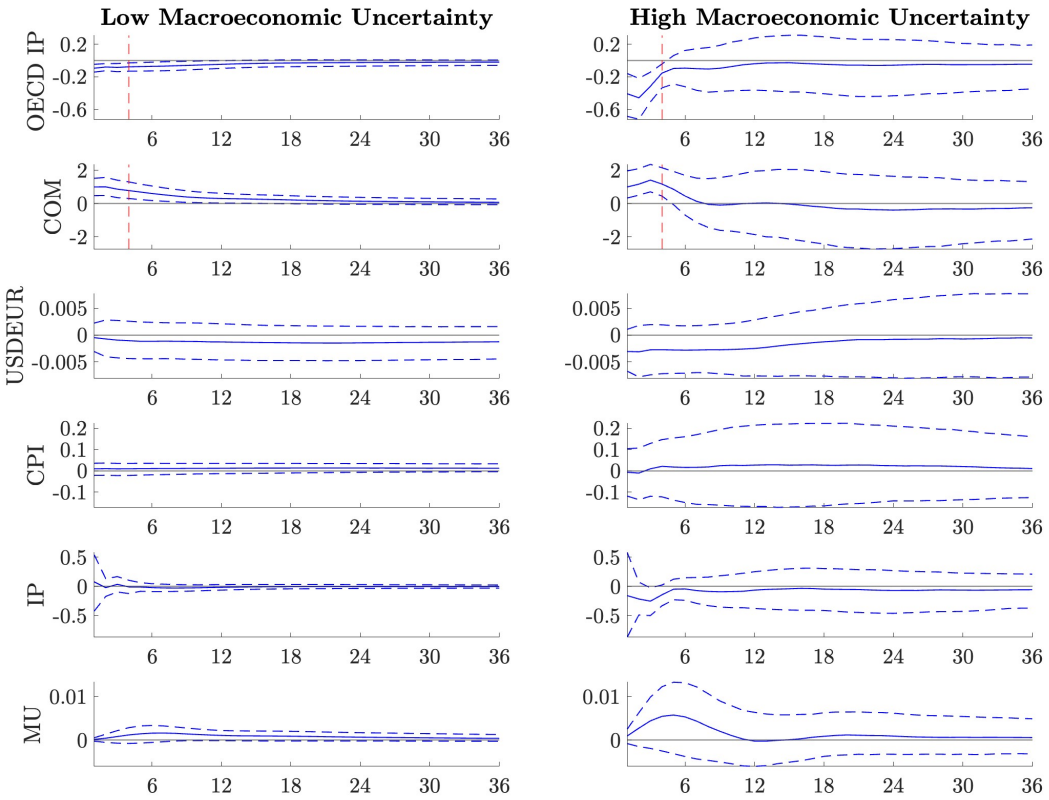
Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM shock.

Figure 27: Netherlands - IRFs Demand Shock



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM demand shock driven by economic activity. The red line indicates the horizon imposed on sign restrictions.

Figure 28: Netherlands - IRFs Supply Shock



Notes: The bands represent the 68% credibility interval of the estimated IRFs to a 1% COM supply shock. The red line indicates the horizon imposed on sign restrictions.