Monetary transmission in a fragmented, uncertain world

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Abstract

In this paper, we investigate the nonlinear relationship between economic uncertainty and the monetary transmission mechanism. We use a Threshold Vector Autoregression model and impose sign-restrictions on quarterly interest rates, GDP growth, and CPI inflation across a broad range of countries. Our findings suggest that during periods of elevated uncertainty, monetary shocks lead to more profound economic contractions, followed by sluggish output adjustments. The effectiveness in curbing inflation exhibits mixed results contingent on the underlying uncertainty narrative. Nonetheless, the overarching trend in our results tends to support the notion that heightened uncertainty acts as a channel for propagating shocks, thereby amplifying their influence. Consequently, our implications for policymakers emphasize that while heightened uncertainty does not inherently hinder the transmission mechanism, it does disrupt monetary policy by escalating the costs associated with reducing inflation.

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1 Introduction

The transmission mechanism of monetary policy and its effects on the economy have long interested academics and policymakers. However, understanding the dynamics of monetary transmission has become even more crucial in an era characterized by heightened uncertainty and geoeconomic fragmentation. Uncertainty, stemming from factors such as geopolitical events or policy shifts can impede monetary policy's effectiveness in influencing key aggregates. Likewise, economic fragmentation, characterized by regional disparities or structural differences within economic blocks may further complicate monetary transmission channels.

Recent global developments added an additional layer of complexity to modern day economics by introducing the concept of geoeconomic fragmentation. As pointed out by Ilyina et al. (2023), heightened uncertainty levels can result from and contribute to the increasingly fragmented geoeconomic landscape. The fragmentation would bear its mark on uncertainty surrounding economic policy, geopolitical tensions, as well as trade; all for which measurements exist thanks to developments in measuring uncertainty.

Given the extensive body of literature on uncertainty, and the general consensus derived from uncertainty shocks, the implications of heightened uncertainty are well-defined. These implications should provide insights to shape our methodologies and draw informed conclusions. However, the interaction between uncertainty and the transmission of monetary policy remains relatively underexplored. This knowledge gap prompts the inquiry: Does uncertainty indeed hold significance for the transmission mechanism, and if it does, what ramifications does this bear for monetary policy?

With that being said, it's important to note that there exist studies that delve into the interplay between uncertainty and monetary policy. Aastveit et al. (2017) or more lately Aquino et al. (2022) have specifically explored this question. The findings from their research point to a noteworthy conclusion: in periods characterized by heightened uncertainty, the efficacy of monetary policy diminishes.

Why results showing ineffectiveness of monetary policy might make sense? On one hand, the existing literature broadly agrees on how uncertainty shocks impact the economy - a demand-dampening effect which is primarily achieved through decreased investment as a result of elevated precautionary savings. In this context, the rationalization aligns with standard economic theory that interest rate shifts would naturally be less impactful when investment levels are already diminished. Another argument can come from following the definition of Knight (1921). We can think of economic uncertainty as a sign of unforeseen fluctuations affecting the economy. In this context, it is plausible that the efficacy of policy interventions diminishes, as uncertainty erodes the clarity behind economic beliefs.

What might be counterarguments to the above? Firstly, literature indicates that in periods of heightened financial stress or recession, monetary policy might be more effective. Although uncertainty and recessions are distinct concepts, they do share certain similarities such as reduced investment and decreased risk appetite. Secondly, the idea that uncertainty could contribute to increased volatility, thereby acting as a conduit for magnifying the impact of shocks is not without precedent in the literature. These would suggest contrary to the previous viewpoint, that elevated levels of uncertainty would rather amplify the impact of shocks - including the impact of monetary shocks. Additionally, should uncertainty indeed be a confounding factor would not necessarily imply that policy efficacy is reduced. Instead, it emphasizes that accounting for economic uncertainty is important for policy decisions.

Aastveit et al. (2017) employ an interacted SVAR approach, where uncertainty is interacted only with the interest rate, and consider 10th and 90th percentiles of uncertainty distributions to characterize periods of high and low uncertainty. Aquino et al. (2022) imposes the threshold assumption to the interest rate equation of their SVAR model only. As opposed to setting the threshold levels in an ad-hoc manner, they employ a grid search approach to find the threshold value for regime switches. By doing so, they address the issue of using only observations from the two extreme tails of the distribution - the low number of observations widening confidence bands and thus giving us misleading results on why monetary policy may lose its effectiveness.

While we do acknowledge the arguments of Aastveit et al. (2017) on the concern of having to estimate multitude of parameters in a model where uncertainty is interacted with all lagged variables, we believe that having a more comprehensive model where the interaction between uncertainty and all other variables - as opposed to merely the interest rates (or only applying the threshold assumption as proposed in Aquino et al. (2022)) - is paramount for uncovering how monetary shocks under each uncertainty regime impact the economy.

Additionally, we acknowledge the importance of correctly specifying the threshold value for the regime switches as outlined in Aquino et al. (2022), we argue for setting it to a specific position within the uncertainty distribution should be better at conveying the implications. Given their grid search method placing the threshold for regime switches to the 57th, 58th and 65th percentile of uncertainty levels with various uncertainty measures, our ad-hoc definitions of high uncertainty being above the median in the main, and above the 70th percentile in an alternative setting should not raise the concerns on the number of observations delegated to each regime misleading our results.

Considering the above arguments, we aim to develop a parsimonious econometric model to assess this relationship. We employ a two-regime Threshold Vector Autoregression (TVAR) model to assess how economic dynamics may differ under the two uncertainty regimes. In order to reduce the number of parameters that need to be estimated, we rely on a smaller-scale model, only incorporating interest rates, GDP growth and CPI inflation rate as endogenous variables. To identify monetary shocks, we adopt the sign-restriction methods proposed by Uhlig (2005), Rubio-Ramirez et al. (2010) and Arias et al. (2018) identifying only interest rate shocks. We repeat this estimation exercise across a diverse spectrum of countries, encompassing both advanced and emerging market economies. By doing so, we aim to provide a comprehensive overview of the interaction between uncertainty and the monetary transmission mechanism.

In terms of reducing inflation our results are somewhat ambiguous, as responses of inflation vary across uncertainty indices. Comparing our results with the two threshold values however, we are more likely to believe that in times of high uncertainty, the drop in inflation is also slightly amplified.

In contrast to the outcomes presented in Aastveit et al. (2017) and Aquino et al. (2022), our own estimations reveal noteworthy disparities. The primary difference arises in the response of output to contractionary policy shocks during periods of elevated uncertainty. Our findings suggest that interest rate shocks, when occurring in times of heightened uncertainty, lead to a more pronounced and prolonged contraction compared to times of low uncertainty. This pattern holds consistently across various uncertainty indices and different threshold values. In terms of the impact of policy shocks on inflation, our results suggest a degree of ambiguity, as response patterns vary across uncertainty indices. As opposed to a lack of robustness we attribute this to the narrative behind the employed uncertainty index. However, comparing our results with the two threshold values, a we find uncertainty acting as a conduit of amplifying shocks a more fitting explanation.

To conclude on the preview of our results, the primary implications from the interaction of heightened uncertainty and monetary shocks is as follows: We do not believe that high uncertainty directly hinders the efficacy of the transmission mechanism, however our results strongly suggests that it is disruptive for policy-making in the sense that it increases the cost of cracking down on inflation.

The rest of the paper is outlined as follows. The next section gives a brief overview of previous literature related to our research. Section three describes the data employed in our estimations, with an additional emphasis in describing measures of uncertainty. Section four gives a brief overview of our methods employed in this paper, including the estimation setup as well as further calculations. Section five discusses the results in detail and section six concludes.

2 Literature review

Due to having a large pool of literature on related topics, such as uncertainty shocks or the effects of fragmentation, we decided to map out key concepts and implications from previous literature in a compactly summarized format. Below is a table containing such findings and some highlighted papers connected to them:

Highligh or main findings	**Highlight of related papers**
New uncertainty measures can be derived from textual data.	Baker et al. (2016), Caldara et al. (2020), Caldara and Iacoviello (2022), Ahir et al. (2022)
Uncertainty shocks cause a contraction similar to negative demand shocks. The primary channel is through investments; high uncertainty leads to precautionary savings.	Bloom (2009), Bloom (2014), Caldara et al. (2016), Cheng and Chiu (2018), Bonciani and Ricci (2020), Nilavongse et al. (2020)
Geoeconomic fragmentation is shown to have a severe negative impact on economies.	Eppinger et al. (2021), Felbermayr et al. (2021), Andriantomanga et al. (2022), Bolhuis et al. (2023)
The IMF Staff Discussion Note points to heightened uncertainty as one channel through which geoeconomic fragmentation affects economies.	Ilyina et al. (2023)
Trade policy uncertainty—a concept tailored to fragmentation—is shown to reduce investment and export incentives, thereby dampening economic activity.	Sudsawasd and Moore (2006), Osnago et al. (2015), Ebeke and Siminitz (2018), Chen et al. (2021), Wang et al. (2021)
Nonlinear time-series models for causal analysis and forecasting reveal that shock impacts are enhanced in recessions, with monetary and fiscal multipliers exhibiting state dependency.	Avdjiev and Zeng (2014), Schüler (2014), Fry-Mckibbin and Zheng (2016), Colombo et al. (2020), Gbohoui (2021), Schmidt (2020)

2.1 Literature on economic uncertainty

Research on uncertainty shocks has already accumulated a substantial body of literature. The interest in this field saw a significant upswing following influential advancements in text-based uncertainty measurements [1] such as Baker et al. (2016) or Caldara and Iacoviello (2022). Several, including classic and novel papers such as Abel (1983), Bernanke (1983), Rodrik (1991), Bloom et al. (2007), Bloom (2009), Gilchrist et al. (2014), Bloom

[1] We give a more thorough insight into such indices, and papers that describe how they are constructed in the Data section of this paper.

(2014), Bloom et al. (2018) have yielded findings that align with the aforementioned studies. The prevailing common finding is that the primary channel through which uncertainty impacts the economy is by reducing investments, as heightened uncertainty incentivizes an accumulation of precautionary savings.

Baker et al. (2016) show that increased levels of policy uncertainty lead to a contraction in economic activity, as it dampens firms' investment and hiring decisions, as well as causing a downturn in stock returns. It is also shown that policy uncertainty has an amplified negative impact during economic downturns. Moreover, the asymmetric nature of uncertainty shocks is shown, as a negative shock's impact is notably more pronounced than that of an equally sized positive shock.

Caldara and Iacoviello (2022) present similar findings with respect to geopolitical risks. They establish a connection between elevated geopolitical risk and various adverse outcomes, including reduced stock returns, heightened market volatility, and a decrease in business investment—ultimately leading to economic contraction. The impact of geopolitical risk is further heightened during times of high uncertainty and financial stress. Furthermore, global financial channels, such as disruptions in trade and capital flows play a crucial role in the impact of geopolitical risk.

Caldara et al. (2016) highlight the importance of financial and uncertainty shocks as drivers of business cycle fluctuations, and suggest that the Great Recession was likely caused by the interaction of such shocks. Bonciani and Ricci (2020) use local projections to estimate the impact of global financial uncertainty on small open economies. Global financial uncertainty shocks are shown to have a contractionary impact on the economies, and furthermore, this is enhanced by higher openness, and economic downturns.

Colombo (2013) shows that uncertainty shocks in the US have a considerable spillover effect on the Euro area business cycle, with the the spillover effect having a higher contribution than Euro area uncertainty shocks. Nilavongse et al. (2020) estimate a SVAR model of the UK economy with domestic and US policy uncertainty and show that US uncertainty shocks lead to a decline in economic output, while domestic shocks are more prominent in explaining exchange rate variations. Biljanovska et al. (2021) show that spillovers can account for approximately two thirds of the contraction induced by uncertainty shocks, additionally economic policy uncertainty shocks in the US, Europe and

China have the largest impact on Europe and the Western Hemisphere.

Carrière-Swallow and Céspedes (2013) show that uncertainty shocks have considerably more influence in emerging economies due to credit constrains. This is confirmed also by Ahir et al. (2019) and Ahir et al. (2022), albeit there is some disagreement on these results, as Das and Kumar (2018) argue the opposite. Cheng and Chiu (2018) estimate the impact of geopolitical risk shocks on emerging economies, and find that these are important drivers of their business cycles, as global geopolitical risk movements can explain a significant proportion of output variation. Jung et al. (2021) show using data from Korea that geopolitical risk incur a sharp reduction in stock prices, which is especially seen in firms that are large, primarily domestically owned or have high fixed assets.

2.2 Literature on economic fragmentation

Recent developments - such as the Covid-19 pandemic or the war in Ukraine - added an additional layer to economic uncertainty through geoeconomic fragmentation or deglobalization, a process not widely seen in modern times, bringing more uncertainty to the table regarding economic outlooks. Although though geoeconomic fragmentation is a more novel concept, Global Value Chains (GVCs) and trade restrictions have been widely researched, predominantly using general equilibrium models.

Some of the latest research points to fragmentation inducing considerable losses in output as well as increased inflationary pressure. Bolhuis et al. (2023) build a novel dataset and highlight the importance of granularity in correctly estimating how harmful fragmentation can be in terms of reduction of output. Andriantomanga et al. (2022) supply chain disruptions have a sizable impact on inflation. Implications for monetary policy indicate that monitoring supply chains and adjusting policy stance accordingly can help mitigate the harmful effects of disruptions on inflation.

There seems to be a general agreement GVCs are beneficial, as decoupling would lead to welfare losses. Felbermayr et al. (2021) shed light on the substantial real income cost of Europe decoupling from China and non-European trade partners, which could be further increased in case of a trade war. Heiland et al. (2020) study a hypothetical disintegration of the EU and find such an event would cause severe welfare losses. Dixon et al. (2021) model financial decoupling between the US and China, and find that a one-sided limitation of flows from US to China would boost domestic investments and thus GDP and cause a decline in China. Conversely, the same is established for China, however if both limit flows to the other country the impact on the US is more severely negative. Felbermayr et al. (2023) find adverse effects of doubling non-tariff barriers (as a proxy of decoupling) for both the imposing and the targeted country as welfare decreases in all countries involved. Using firm level data, Banh et al. (2020) and Karpowicz and Suphaphiphat (2020) show that participating in GVCs increases productivity and innovation.

Further studies on trade restriction measures back these results. Amiti et al. (2019) and Fajgelbaum et al. (2020) evaluate the impact of protectionist trade policies them adverse effects for the US in the short run after introduction. Amiti et al. (2019) find similar results for other countries as well. Bown and Crowley (2007) find evidence for anti-dumping policies of the US to be effective at deflecting and depressing exports. Crozet and Hinz (2020) discover a "friendly fire" type effect of sanctions from Western exporters stemming primarily on excess country risk on international transactions with Russia.

However there is some research that indicates a lack of benefit from globalization in certain instances. Prasad et al. (2007) argue that globalization is not always growth inducing in developing countries, as certain characteristics, such as good institutions or flexible exchange rate regimes are are important for realizing the benefits of globalization. Bergin et al. (2023) find evidence for capital account openness does not always promote growth, as capital controls paired with reserve accumulations can lead to higher GDP growth particularly in emerging economies.

Conclusions with respect to volatility exposure are unclear as for example Eppinger et al. (2021) argues that decoupling does reduce exposure to foreign shocks on average, however the welfare losses exceed the benefits of lower exposure. On the contrary, D'Aguanno et al. (2021) argue for the lack of a 'double-edged sword' effect of GVCs, as they find no evidence for increased volatility, only increased production. Moreover, re-shoring measures are found to have increased volatility, whereas an increased diversity of GVCs lowers volatility by proportionally lowering exposure to single countries.

2.3 Connection between uncertainty and fragmentation

While we can see that a number of authors have addressed the issue of geoeconomic fragmentation, the literature revolves primarily around general equilibrium models, as opposed to more empirical research such as using time series methods. A potential link between measuring uncertainty and geoeconomic fragmentation - and additionally a link between research on fragmentation and time series econometric methods - can be captured using trade uncertainty. Caldara et al. (2020) and Ahir et al. (2022) both construct measures for capturing trade policy uncertainty and examine its impact on the real economy. In line with previous findings, a number of papers (e.g.: Sudsawasd and Moore (2006), Osnago et al. (2015), Ebeke and Siminitz (2018), Wang et al. (2021), Chen et al. (2021), William and Fengrong (2022)) find that trade policy uncertainty diminishes investment incentives, as well as some findings suggest an increase in firm markup, lower risk appetite, or a reduction of exports. The argument can be made that geopolitical risks, such as Caldara and Iacoviello (2022) can be a good measurement also, as it captures events that generally disrupt global relations. With that being said, we do not consider these de facto measurements of geoeconomic fragmentation, however these should be the closest proxies available at our disposal.

2.4 Literature on nonlinear time series methods

Another area of research that has been gaining increasing popularity in empirical macroeconomics is the utilization of nonlinear time series models. While standard linear models such as SVAR-s have traditionally dominated the field, researchers are now recognizing the limitations of them in capturing more complex dynamics and addressing issues like state dependency or asymmetries. Nonlinear models offer a more novel approach, allowing for a more nuanced understanding of how variables interact and evolve over time.

Schüler (2014) proposes a quantile SVAR approach to model how uncertainty impacts the economy across the business cycle and finds that uncertainty shocks have a sharper impact in recession periods. Furthermore, the financial system plays an important role in the transmission of uncertainty shocks during recessions, as a bad state of the financial system leads to uncertainty shocks pushing the economy in a deeper recession. Colombo et al. (2020) use a smooth transition VAR approach to uncover that uncertainty shocks are significantly more severe in recessionary periods versus normal times. They highlight the importance of monetary policy in response to uncertainty shocks, as balance sheet based monetary policy is effective at mitigating the impact of uncertainty shocks. Nalban and Smădu (2021) show on Euro Area data that the impact of uncertainty is state dependent. More specifically, times of financial distress amplify uncertainty shocks, however the rebound in such times is accelerated which is a result of monetary policy reaction. Gbohoui (2021) use a smooth transition panel local projections approach to show that in times of high uncertainty public investment multipliers are larger, and thus investment shocks have a larger, longer lasting effect.

Some papers focus on the potentially state dependent nature of monetary policy as well. Kakes et al. (1998) uses a Markov-Switching approach to model the state dependency of monetary policy and finds strong evidence for state dependency in the US and Germany, some evidence for the UK and Belgium, and finds that irrespective of state, monetary policy is rather ineffective. For the US and Germany, it is shown that monetary policy is more effective in recessionary periods. Güney (2018) models the policy functions of the central bank in Turkey and finds asymmetric preferences. The central bank has a more aggressive reaction to inflation gap in recession times compared to expansions while the reaction to growth and inflation uncertainty is higher during expansions. Lin (2020) examines the asymmetric effects of monetary policy with the results suggesting that GDP and investments react asymmetrically to interest rate innovations.

A relatively straight-forward way of introducing state dependency in multivariate time series analysis is to use Threshold Vector Autoregression (TVAR). The majority of the literature employs a single threshold (two regimes), such as recessions versus booms, times of high and low financial stress, with some limited use of three regime models. Some use cases are: Baum and Koester (2011), who show that fiscal multipliers are highly state dependent on business cycle position; Galvão (2006) who incorporate additional structural breaks to predict recession timings; Alessandri and Mumtaz (2019) show that uncertainty shocks are state dependent on financial conditions - in normal times uncertainty is inflationary, while during times of financial distress it is deflationary and has considerably larger effect on output.

TVARs appear in literature related to monetary policy as well. Schmidt (2020) shows that monetary shocks have state dependent effect on assets, with macro-risk being most prominent for risky assets, while policy risk is more defining for corporate bonds. Avdjiev and Zeng (2014) show that in times of low growth the impact of most shocks (including monetary policy shocks) is heightened, additionally, the reaction of monetary policy is more aggressive during booms. Over the more frequent two-state model, they employ three regimes, as it is supported by statistical tests. Fry-Mckibbin and Zheng (2016) compare monetary policy in times of high and low financial stress. Results indicate that monetary expansions are effective in times of high stress, with large expansions being likely to move the economy to a low stress state. Results also indicate a short-run tradeoff between output and inflation. Li and St-Amant (2010) have previously drawn similar conclusions on Canadian data.

As evidenced in this section, the realm of literature concerning economic uncertainty is extensive, encompassing various studies exploring the intersection of uncertainty and nonlinear dynamics. Additionally, recent research focusing on monetary policy suggests the potential for state dependency in both the execution of monetary policy and outcomes of monetary shocks. Much of this literature is interconnected with the position withing business cycle or with episodes financial stress - noting that the latter is aligned with the concept of uncertainty - the investigation into state-dependent effects originating from uncertainty within monetary policy related research remains relatively unexplored [2]. The objective of this paper is to address this gap in knowledge, by exploring how uncertainty changes the outcome of monetary shocks, exploring various measures (of difference sources of) uncertainty on a global scale, as well as extending the research to a number of economies across the world.

3 Data

3.1 Macroeconomic aggregates

To ensure the simplicity of our estimations, we focus on three key macroeconomic indicators: interest rates, GDP, and CPI. The data is based on a quarterly frequency. Interest rates are considered in their absolute levels, while GDP and CPI are entered into the esti-

[2]See the Introduction section for a more details on addressing papers with similar research questions and methods.

mation as first differences, representing quarterly growth rates and inflation, respectively. We gather quarterly data for a wide range of economies, encompassing both advanced and emerging economies. This broad inclusion permits a more comprehensive exploration of the fundamental relationship between uncertainty and the monetary transmission mechanism. It facilitates cross-country comparisons, enabling us to consider specific details such as economic size and developmental stage.

Relying on a relatively concise set of macroeconomic indicators provides flexibility in experimenting with more complex models - we leave this open for future research. This approach however offers dual advantages. Firstly, by utilizing just three variables instead of an extensive array, we substantially reduce the number of parameters that need to be estimated. This is necessary for being able to parsimoniously estimate the TVAR models, as by design, such models have an increased number of coefficients. Secondly, given the widespread availability of these variables, this allows us to incorporate the most amount of economies into our analysis. Data is incorporated from the earliest available observation to the latest, taking into account the earliest and latest availability of each uncertainty index.

3.2 Measures of uncertainty

Besides macroeconomic aggregates, a key data series our estimation requires is a measure of uncertainty. Measuring the level of economic uncertainty is by no means trivial, and there are multiple approaches of doing so. Historically, uncertainty can be quantified through the lens of financial market data. Notably, indices such as the VIX, which monitors stock market volatility, or the TED spread - indicating the disparity between short-term treasury bill returns and LIBOR - as a measure of credit risk or financial strain, stand out as instruments capable of tracking macroeconomic uncertainty. In recent years, alternative approaches have emerged as uncertainty measurements, which can be considered "text-based" indices as they predominantly rely on extracting information from newspaper coverage or reports. Figure 1 showcases the uncertainty indices used in this paper. Data for uncertainty indices was recovered from policyuncertainty.com.

Baker et al. (2016) construct the Economic Policy Uncertainty (EPU) index by combining three components: newspaper coverage, tax code-related provisions that generate uncertainty, and disagreement among economic forecasters. The newspaper coverage component captures the frequency of news articles mentioning keywords related to economic policy uncertainty. The tax code-related provisions component focuses on provisions that generate uncertainty, such as expiring tax laws or temporary tax provisions. The forecaster disagreement component measures the dispersion of economic forecasts. The index is predominantly driven by the newspaper coverage component, as it has the highest weight in the aggregation. By combining these components, the authors construct the EPU index on a monthly frequency for the United States from 1985 onward. They find that the EPU index exhibits substantial variation over time and spikes during periods of significant policy-related events, such as elections, geopolitical tensions, and major policy changes. Davis (2016) later extends the index on a global level, as well as several authors contributing to the EPU literature by constructing country specific EPU indices (Baker et al. (2013), Kroese et al. (2015), Zalla (2016), Cerda et al. (2016), Arbatli et al. (2017), Armelius et al. (2017), Gil and Silva (2018), Hardouvelis et al. (2018), Davis et al. (2019), Ghirelli et al. (2019)).

Caldara and Iacoviello (2022) propose a newspaper coverage approach to measuring geopolitical risks, the Geopolitical Risk Index (GPR). The main index uses 10 newspapers, and - similarly to the EPU - tracks geopolitical risks from 1985, however the authors also construct a Historical GPR available from 1900 based on 3 newspapers, as well as country specific GPR indices for 44 different countries. The GPR index can also be broken down into 8 subcategories: War Threats, Peace Threats, Military Buildups, Nuclear Threats, Terror Threats, Beginning of War, Escalation of War, Terror Acts. For better accuracy, the authors also employ the use of unigrams, bigrams and boolean operators, as opposed to previous index construction methods, such that as of the EPU.

Ahir et al. (2022) construct a quarterly World Uncertainty Index (WUI), using Economist Intelligence Unit reports. The index measures the frequency of the word "uncertainty" and its variants in the EIU reports. Several versions of the WUI are available including country specific indices for 143 countries, a global average, and country-group specific aggregates (based on region and development). The global WUI is effective at tracking uncertainty, with the index spiking around key policy shifts and geopolitical events such as the 9/11 attacks, Euro debt crisis or the Brexit referendum. The authors also construct the World Trade Uncertainty Index, and World Uncertainty Spillover Indices similarly on a country-specific and broad aggregate level. The WTUI tracks the relative frequency of "uncertainty" and variants being mentioned in proximity to keywords related to trade, while the WSUI "uncertainty" and its variants being mentioned in proximity to country specific keywords (such as keywords specific to the US, UK or G7 + China).

Caldara et al. (2020) construct three indices that track trade related uncertainty. Their main index uses earnings calls to construct a firm-level Trade Policy Uncertainty index using search terms such as "tariff", "import duty", "import barrier". The two supplementary indices constructed are a news based index (closely following the construction of the EPU index), and a Tariff Volatility retrieved from a Bayesian stochastic volatility model. Results from their estimations indicate that firm level shocks to trade policy uncertainty leads to a decline in firm level capital, which is backed by results with aggregate measures, as they show a contraction in private investments. In this paper we use the news based Trade Policy Uncertainty (TPU) as it is publicly available and spans from the 1960s up to 2023.

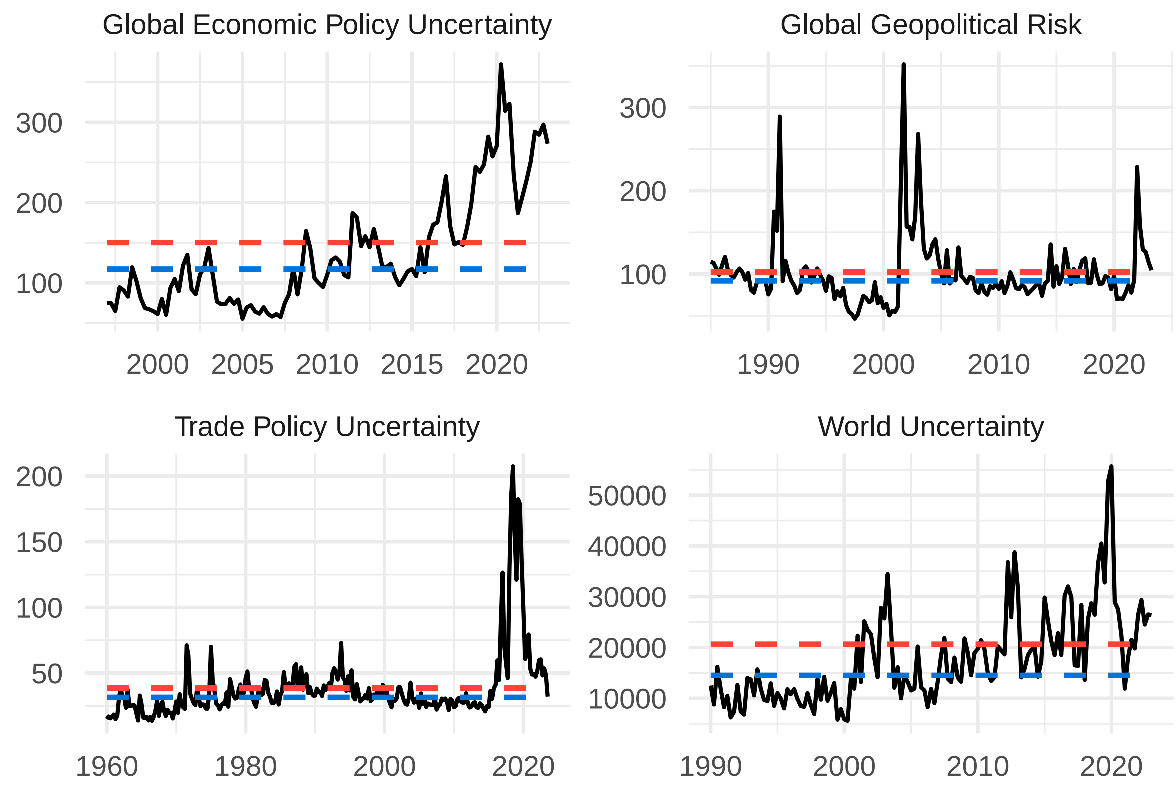

Figure 1: Historical data of uncertainty measures.

Notes: The blue line indicates the median, while the red line indicates the 70th percentile of the respective index.

To summarize, we use 4 distinct uncertainty measures as threshold variables for the TVAR estimation. The WUI can be considered as the broadest measure of uncertainty, and the only non-news-based index in our roster - and thus will serve as the baseline for our estimates. The EPU encapsulates economic policy related uncertainty, while the GPR and the TPU are the closest measurements we have to encapsulate uncertainty more tailored to geoeconomic fragmentation, as their search terms are primarily related to geopolitical and trade related risks.

4 Methodology

4.1 The price puzzle and the use of sign-restrictions

An empirical challenge for this analysis is coercing macroeconomic aggregates to behave the way it is written in all macroeconomics textbooks, i.e. to solve the price puzzle. There have already been numerous papers on solving the price puzzle (e.g.: Hanson (2004), Giordani (2004), Demiralp et al. (2014), Bishop et al. (2017), Cloyne and Hürtgen (2016), Romer and Romer (2004)). As discussed in the data section, we decided to streamline the data used for the estimations in order to reduce the amount of parameters. In a linear context, an alternative would have been to expand on our set of variables and include commodity prices, monetary aggregates or financial frictions, as control variables. With this in mind, our best choice for identification is to use sign-restrictions, as it allows for incorporating our prior beliefs about the direction of responses - such as an increase in interest rates should lead to a decline in output and prices - without having to incorporate additional controls.

A frequently cited paper in sign-restriction literature is the work of Uhlig (2005), introducing a penalty and a rejection algorithm approach. Comparing the two approaches, the rejection algorithm only accepts impulse responses that exactly fit the sign restriction criteria. On the other hand, the penalty algorithm assigns penalty scores to ones that do not exactly fit the sign restriction criteria, and accepts the ones with the lowest penalty scores. While this flexibility at first might seem favorable, it has some “hidden features” as pointed out by Arias et al. (2018). In our case - as we are working with a full set of restrictions - the artificial introduction of additional (unwanted) restrictions is no issue, however the penalty approach artificially narrows confidence intervals for the estimates, thus giving us a false sense of robustness in the results. For this reason, we implement the full Bayesian rejection algorithm. Rubio-Ramirez et al. (2010) improved upon the efficiency of the estimation process and thus their version of the algorithm is implemented. In all cases, the Bayesian models are estimated with 4 lags - given that we use quarterly data - and a non-informative inverse Wishart prior.

4.2 The Threshold VAR approach with sign-restrictions

We introduce non-linearity by using each uncertainty index to create an indicator function, taking the interactions of the indicator with each variable, then estimating the VAR model. In essence this means that we assume uncertainty changes the dynamics of the economy. We explore two different threshold levels as indicated in 1, the median and the 70th percentile for each respective index. We acknowledge the fact that a grid-search approach for an optimal threshold level is possible to use in threshold models, however the lack of economic interpretation behind the measurement units of uncertainty indices leads us to instead use threshold levels that refer to positions within their historical distribution.

A generalized mathematical representation of the model would be as follows:

$$Y_t = \sum_{k=1}^{4} \Theta_{high} I(X_t \geq \mu) Y_{t-k} + \sum_{k=1}^{4} \Theta_{low} I(X_t < \mu) Y_{t-k} + u_t \tag{1}$$

where Y_t is the vector of endogenous variables, Θ_{low} and Θ_{high} are the coefficient matrices for each regime, $I(.)$ is the regime indicator function, X_t is threshold variable, μ is the threshold value and u_t is the error term.

We would like to note that using contemporaneous values of the threshold variable is unorthodox in the literature of threshold models, as the indicator is most often created based on lagged values. One could argue against our approach that this introduces a confounding bias type effect, as results from the high regime could be interpreted as two shocks impacting the economy simultaneously. However, running the model with changing the specification of equation (1) above from X_t to X_{t-1} yielded no substantial change in the impulse responses. As the focus of our research is to investigate if interest rate shocks taking place in high uncertainty times have a different impact on the economy compared to low uncertainty times; as well as the results being robust to the changed specification; we believe our approach should be more suited for the purposes of this research.

The vector of endogenous variables Y_t is defined as

$$Y_t = \begin{Bmatrix} r_t \\ \pi_t \\ y_t \end{Bmatrix} \tag{2}$$

where r_t is the interest rate, π_t is the quarterly inflation rate and y_t is the quarterly GDP growth. Shocks are identified with a full set of sign-restrictions for the interest rate shock. We use standard assumptions of a positive monetary policy shock raising interest rates and this subsequently leads to a decline in prices as well as output. As we are only interested in monetary policy shocks, partial identification is sufficient, thus no more restrictions are needed to be specified and only interest rate shocks need to be estimated.

The estimation procedure is done using Markov Chain Monte Carlo (MCMC) simulation with 20000 sampling replications. Impulse responses are constructed following Rubio-Ramirez et al. (2010)[3]. We begin by drawing reduced form coefficients Θ_i and residuals u_t from the posterior draws. We compute the Cholesky factor P of the resiudal covariance matrix Σ_u, draw a random orthogonal rotation Q and form $P^* = PQ$ and check whether responses implied by (Θ, P^*) satisfy the sign restrictions on horizons $h = [1, 6]$ repeating procedure up to 200 times per per posterior draw. We continue drawing from the posterior until we either reach 1000 accepted impulse responses or all posterior draws have been exhausted. [4]

The above procedure is repeated for each regime, ensuring not only that we have different economic dynamics dependent on the uncertainty regime, but also that the contemporaneous effect of the interest rate shock is allowed to be regime specific. The large simulation is necessary in order to find a sufficient number of impulse responses that exactly fit the sign-restrictions in each regime. The estimation of the model and shocks is repeated for all countries in the sample and with all uncertainty measurements as indicators.

[3]The computations are done in R using the "VARsignR" package created by Danne (2015).

[4]We have no "exact science" reasoning for the choice of 20000 MCMC draws and 200 (sub)draws per MCMC replication. Our goal was to use a number that is large enough to yield a sufficient number of responses that fit the sign-restriction criteria, while ensuring that the estimation time would not be so long that it hinders the writing of this paper.

We would like to acknowledge some limitations of the outlined methodology. Firstly, the setup described above is computationally extensive, necessitating a considerable amount of time to run with every possible specification on every country in our dataset. Secondly, given the large amount of parameters, a number of countries have to be excluded due to an insufficient number of data points; for the remainder of the countries, in a number of cases the algorithm would not find a set of impulse responses that fit the sign restriction criteria; and for a number of countries the simulated impulse responses would be diverging[5] leading us to exclude them from our final results as well. Initially, we consider 111 countries, however due to the outlined difficulties, we have 36 to 54 countries with valid sets of impulse responses depending on the uncertainty index and threshold level used.

An additional disadvantage of threshold models is their "binary" nature. Although our results demonstrate that higher levels of uncertainty have a drastic effect on how the economy responds to an interest rate shock, our ability to draw conclusions on how the transmission of monetary policy changes over small increments of uncertainty is limited.

5 Results

5.1 Implications from our estimates with the WUI

Having the impulse responses obtained, we proceed to compute the posterior median and an 84% confidence interval for each country-regime combination. Considering the large number of countries under examination, we perform another round of aggregation to derive global aggregates, along with several distinct country-group aggregates. These represent the point-by-point medians of the previously calculated posterior median impulse responses and their respective confidence bands. Certain key impulse responses are presented here in the results section, while additional ones are provided in the Annex section of this paper. In all impulse response graphs, we depict a 1 percentage point shock to interest rates for the sake of easier comparability. Our main bases of comparisons are the

[5] In each case we consider impulse responses on a 20 quarter horizon. We disregard all estimates where it would be suggested that the effect of the monetary shock by the end of the 20-quarter horizon that exceed a certain limit. We are inclined to discount findings that imply that a unit increase in interest rates would result in a deviation from the steady state of any variable by over 5 percentage points five years post impact. While this is a "rule of thumb" approach, it helps us eliminate diverging outcomes, as well as to make sure we do not overshoot the impact of the shock.

initial impacts, as well as response patterns across variables, regimes and country groups.

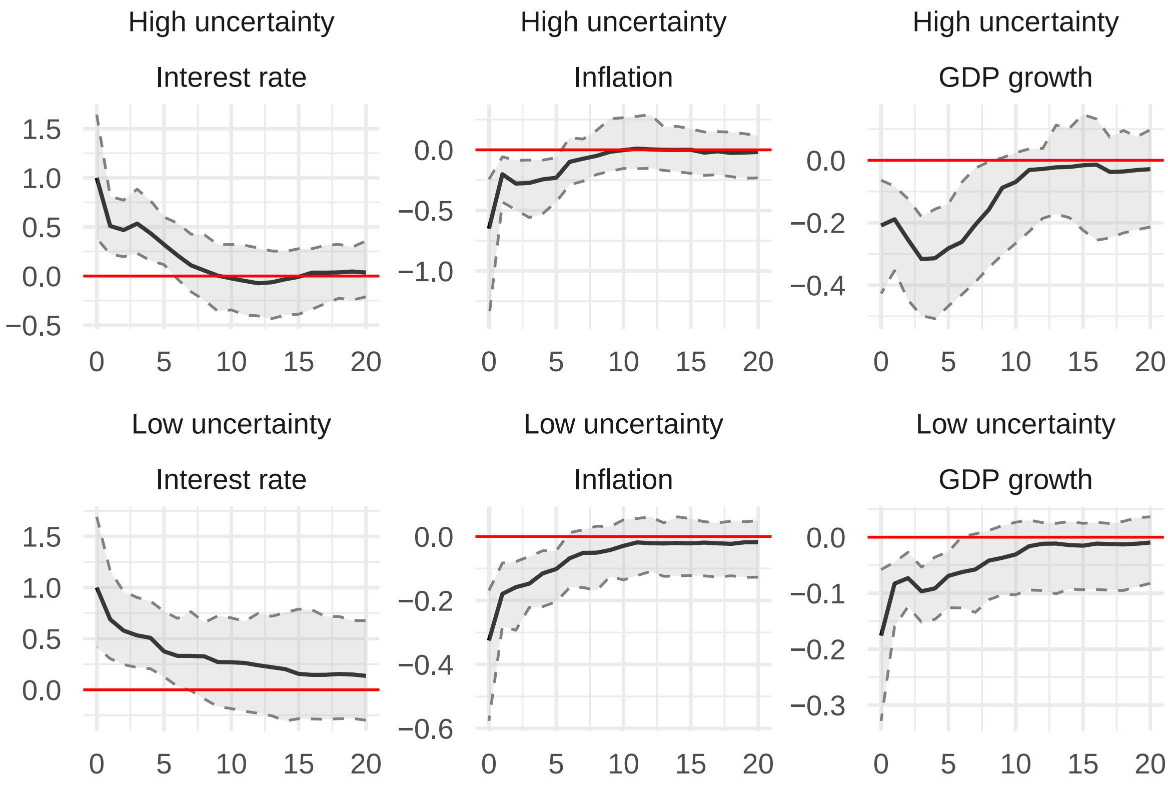

Figure 2: Global IRFs with the WUI and median threshold.

Notes: Point-by-point median impulse responses aggregating over all countries with valid impulse responses. The World Uncertainty Index is used as the threshold variable with the threshold level set to the median. The confidence intervals are the 68% confidence level.

Firstly, the aggregation of data across all countries provides insights into the overall implications of elevated uncertainty for interest rate shocks. In Figure 2, we show a graphical representation of a 1 percentage point increase in interest rates under each regime, employing the WUI as the threshold variable. Analyzing the responses of inflation, it seems that the belief of interest rate shocks being less effective in anchoring inflation is not supported. The response pattern and persistence of inflation remain quite similar irrespective of the regime, and in fact, the initial impact seems more pronounced during periods of high uncertainty.

When we examine the responses of GDP growth, we can observe that the shock induces deeper recessions with a more sluggish adjustments in economic activity. At first glance, one might conclude that these findings align with the notion of monetary policy being more effective during recessionary periods. However, such a conclusion would be flawed due to several reasons. Firstly, the enhancement in reducing inflation during high uncertainty times is not as apparent. Secondly, it is essential to recognize that high uncertainty times and recessionary periods are not synonymous. Additionally, while the inflation anchoring capability remains relatively similar, the deeper contraction triggered by monetary shocks is an indication of stronger transmission, but altogether this does not necessarily an indicate that policy is more effective.

5.2 Addressing different uncertainty measures

From aggregating across all countries, it is not readily apparent, however the responses obtained from the estimation show significant heterogeneity, suggesting that country-specific characteristics play an important role in shaping how economies react to monetary shocks during periods of higher uncertainty compared to times of lower uncertainty[6]. Additionally, Figure 2 only showcases the difference in responses when using the WUI as threshold variable, however results from the estimation also suggest that the source of uncertainty matters also. This does not mean that our results are not robust to the alternative uncertainty indices - as similar differences in contemporaneous effects and response patterns can be observed - we only imply that the narrative behind uncertainty matters. In Figure 3 we address this by reporting impulse responses across all indices, as well as comparing the responses of Small and Large Economies. [7]

Comparing across different indices, as well as Large and Small Economies, we can again observe that the most major difference is in the response patterns of output. We can again conclude that high uncertainty leads monetary shocks to cause a more pronounced recession with a more sluggish recovery. The recovery seems to be more long lasting in Large Economies, while (with 3 of the 4 indices) the lowest point of the recession being larger in Small Economies. The size of the gap between high and low uncertainty responses

[6] We explored if the obtained results show any correlation with country specific measures such as economic or export diversity, institutional quality, or financial development. However we did not find any evidence of such characteristics driving either the initial or the 20-quarter accumulated impact of the shock on inflation or growth. Moreover such characteristics do not seem to drive interest rate innovations in the high uncertainty regime, which provides some further belief in the credibility of our results.

[7] To further investigate, we repeat the aggregation by replacing the country groups with Advanced Economies and Emerging Economies in place of Large and Small Economies, as it can be seen in Figure 7 in the Annex. The key implications do not change, however the difference between the country groups is less apparent. This leads us to believe that the size of the country matters more than its level of development.

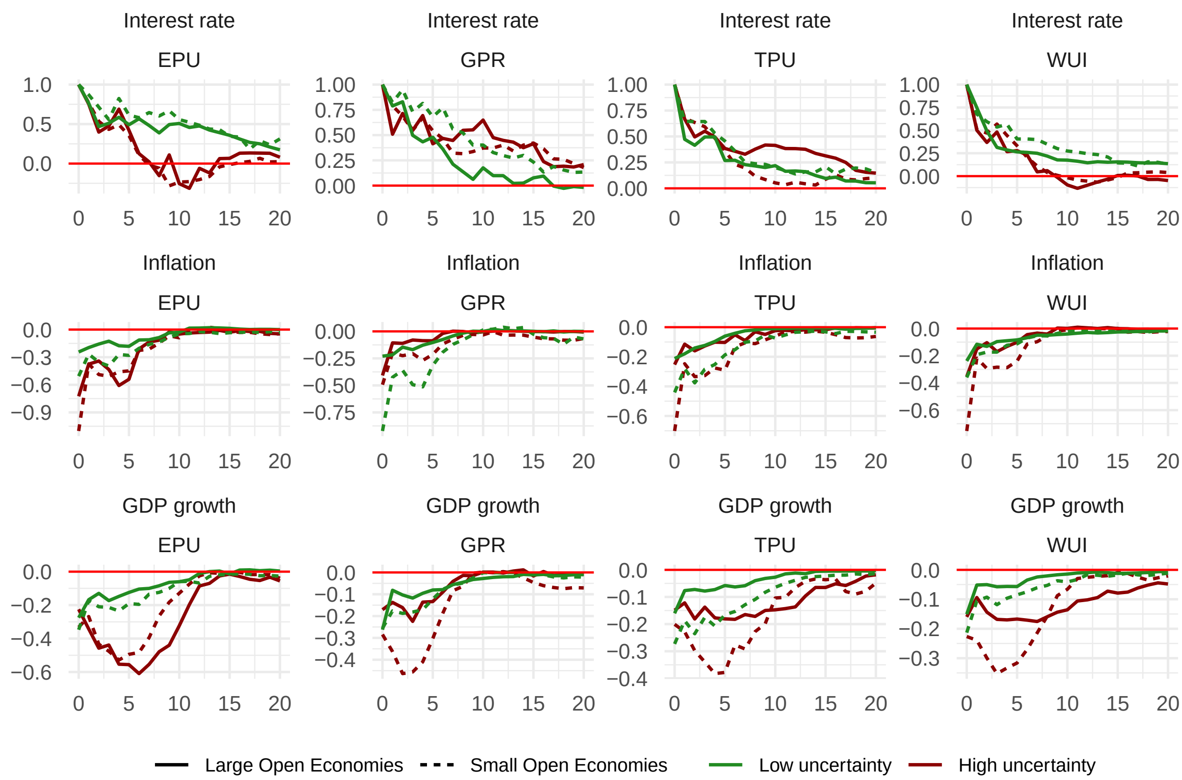

Figure 3: Small and Large Economy IRFs, median threshold.

Notes: Point-by-point median impulse responses comparing Small and Large Economies with valid impulse responses. The threshold value for each uncertainty index is set to its median.

is consistent with between the TPU and the WUI. Responses of output obtained with the GPR show the smallest gap between responses for Large Economies, and the largest gap for Small Economies, suggesting that Large Economies are more resilient to geopolitical shocks. Additionally the rapidest recovery from a shock in the high uncertainty regime is observed with the GPR. The only exception in high uncertainty is with the EPU, where Large Economies face a slightly deeper and longer lasting drop in output than Small Economies. Responses in the low regime across all indices indicate a milder but long lasting effect, which is elevated in Small Economies.

Implications for inflation are less clear. In Large Economies and the WUI, the initial drop in inflation is slightly larger in times of high uncertainty, while the transmission is longer lasting in the low regime, but the difference in the responses is small. Similar observations can be made with respect to Small Economies, the only difference being that inflation remains more persistently lower between the 2nd and 8th quarters after the shock in the high regime. Responses with the TPU show in essence no difference between the two regimes, while the GPR (being the only index to do so) indicates that high uncertainty hinders the ability of monetary shocks to anchor inflation. This possibly indicating that fragmentation is disruptive for monetary policy in the sense that with the drop in inflation does not change much, only the drop in output is elevated - thus increasing the trade-off between reducing prices and promoting growth. The EPU index however indicates a gap in the opposite direction - meaning the drop in inflation is larger in high uncertainty.

Response patterns of interest rates differs across indices also. With the WUI and the EPU, the adjustment of interest rates is more sluggish in times of low uncertainty in both country groups. Responses with the GPR and the TPU indicates that Large Economies tend to keep interest rates high longer when uncertainty is high, while the opposite is more apparent in Small Economies. To some extent, these make sense narratively, as the former two indices indicated the reduction of inflation to be smaller in the low uncertainty regime. With the GPR and the TPU, aiming to keep interest rates persistently higher makes sense given the responses of the inflation rate, while there is also credibility behind the faster adjustment of interest rates in Small Economies, given that the drop in output is more severe.

What could be behind results with the EPU slightly differing from other indices? A potential argument for that could be endogeneity. If we compare search terms of the indices, the EPU differs from the others in the sense that it picks up on articles that specifically cover policy related terms (such as “federal reserve” or “legislation”). This means, that the index should take higher values around times of policy interventions - albeit irrespective of whether it is contractionary or expansionary. High policy uncertainty is thus more likely to be associated with policy shocks, and thus lead to an exaggerated impact. To what extent it is possible that policy shocks and a global uncertainty have an endogenous relationship is hard to say, however it is more likely to exist in Large Economies than Small Economies. This reasoning would be backed by the gap between high and low uncertainty responses of Large Economies. However, this reasoning is by no means conclusive, and further research could examine the potential endogeneity between policy uncertainty and policy shocks.

5.3 Addressing the level of uncertainty

How much does the level of uncertainty matter? While the threshold model cannot precisely quantify how a unit increase in uncertainty affects transmission efficacy, we can experiment with different threshold values to try and approximate the answer. In an alternative specification, we raise the threshold value from the median level of uncertainty to the 70th percentile and conduct the estimation again. What to expect from this exercise is not readily apparent. To clarify, let us use the responses of output as an illustration on what we expect to change from increasing the threshold level. On one hand, the high regime response should shift downwards as higher uncertainty should lead to a deeper recession induced by the shock. On the other hand, moving observations previously labelled as high uncertainty times into the low uncertainty regime should also mean that the low uncertainty output responses shift downwards as well.

The comparison between the two threshold levels using the WUI as the threshold variable and aggregating globally can be seen in Figure 4. As we can see, impulse responses of output followed the outlined example, and in the low regime the response pattern turned more similar to what we previously saw with high uncertainty responses in the high regime. The responses of inflation also shifted downwards in both regimes, which should also solidify previous findings that the level of uncertainty serves as a conduit for shocks, and thus higher uncertainty leads to more pronounced shocks. Even with this in mind,

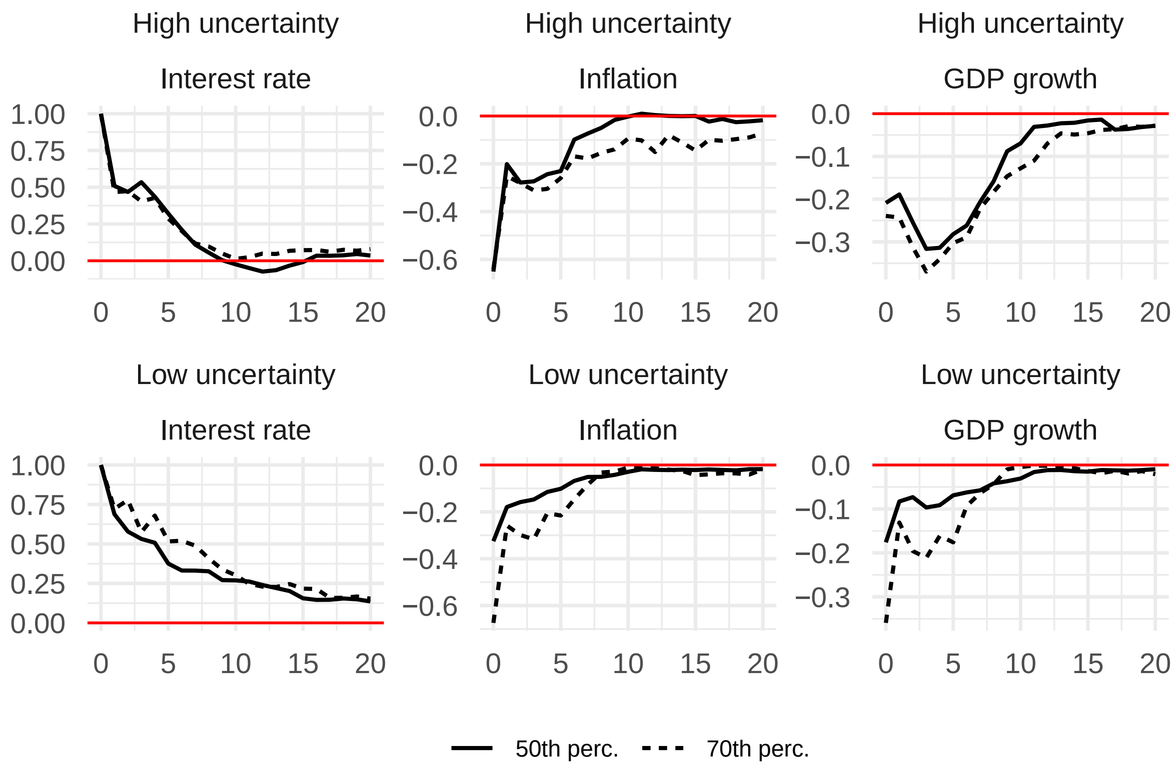

Figure 4: Global IRFs with the WUI, median and 70th perc. thresholds.

Notes: Point-by-point median impulse responses comparing threshold levels at the 50th and 70th percentiles in the whole sample with valid impulse responses. The World Uncertainty Index is used as the threshold variable.

our conclusions from these findings remain unchanged, higher uncertainty is "disruptive" for monetary policy in the sense that it disproportionately increases the cost of reducing inflation.

To further investigate, we consider the previous aggregations (Large and Small Economies as seen in Figures 8 and 9 ; and Advanced and Emerging Economies as seen in Figures 10 and 11) and compare results obtained with the threshold value set to 70th percentile and the previously seen median responses. The degree to which low uncertainty results change as a result of including above-median data points to their pool, and high uncertainty responses change as a result of considering a more extreme subset of the observations varies across aggregation and measure of uncertainty. The change in responses however is consistent across the board with one exception being results obtained with the GPR index, where it is implied that higher geopolitical risk directly shrinks the transmission of the shock both to GDP and Inflation.

5.4 Implications for policymakers and researchers

To sum up the results, whether or not uncertainty directly disrupts the ability of monetary policy to anchor inflation is ambiguous, as the implications vary based on the index. Not accounting for the initial drop, the responses of inflation exhibit a small difference between the two regimes. The implications for output are clear and robust to all indices, monetary shocks cause a sharper and more elongated drop in times of high uncertainty. The sluggish adjustment is more pronounced in Large Economies, while the sharper drop in Small Economies.

To some extent, our results also suggest that higher uncertainty leads to a larger impact of the shock. While as stated before, these results are contradictory to some previous literature, there are some convincing theories as to why our results could be credible. Uncertainty can exert its effect on the economy through either distorting future expectations, or through inflating the variance of present outcomes. The latter reinforces our results, as through higher variance of outcomes, contractionary shocks leading to a larger drop in demand.

This reinforces the idea that uncertainty inflates the variance associated to the time period, and by doing so, serving as a conduit that enlarges the impact of macroeconomic shocks.

In this sense, high uncertainty does not definitively disrupt the transmission mechanism itself, however it puts policy makers into more difficult position, where reducing inflation comes at a higher cost in terms of output losses. Recognizing this might guide central banks in navigating the heightened uncertainty and inflationary pressure faced in the early 2020s by being more cautious with policy actions. Alternatively - while our research does not directly address this - these results highlight the importance of alternative policy tools. More specifically, managing expectations through forward guidance measures can be a potential tool for cutting through the fog of uncertainty and ensuring that the cost of reducing inflation is minimized by reducing economic uncertainty in the first place.

Some research questions in this field however still remain unanswered. Although repeating the estimations with a higher threshold value provided some proof of robustness on the results, we could only conclude that the level of uncertainty matters, not how much it matters. It might be possible to address this question by using three regimes as opposed to two, this however would considerably increase the number of parameters that need to be estimated. Alternatively, using a smooth-transition, or a time-varying-parameter VAR might be better suited for this role. Furthermore, the framework we established does not differentiate between expansionary and contractionary shocks, however some previous literature indicates the possibility of sign-asymmetry of monetary shocks. Additionally, our paper relied on the global variant of the uncertainty indices used, (excluding the TPU) they are calculated on a country specific basis for a number of countries. This proposes the additional question of whether or local or global uncertainty matters more for the policy makers in certain countries or country groups. Moreover, the bulk of research on uncertainty focuses on short run dynamics, but not on long run implications of uncertainty. Given the results from numerous papers in the field of uncertainty, as well as ours, long run implications of uncertainty might be worth investigating as well.

6 Conclusion

In this study, we examine the relationship between uncertainty and the effectiveness of the monetary transmission mechanism employing TVARs and sign-restriction identification for monetary shocks. Our findings regarding the inflation anchoring capability of monetary authorities across different uncertainty regimes have shown mixed results, which varies depending on the chosen measure of uncertainty. Confirmed by our estimation with an elevated threshold level, what is more likely is that in times of high uncertainty, contractionary shocks have an even larger effect. Nevertheless, a robust result emerges, indicating that (positive) monetary shocks, when combined with high uncertainty, can lead to deeper and longer lasting fall in output. This indicates that uncertainty is disruptive for policymakers, rather than the transmission mechanism itself, as the cost of reducing inflation increases.

Our results indicate that Small Economies experience a sharper drop in output, however their rebound is also much hastier compared to Large Economies. Such a distinction is less apparent when comparing Advanced and Emerging Economies, indicating that the resilience to uncertainty has less to do with development, but more with the size of the economy. Comparing across the narratives of uncertainty indices, Trade Policy Uncertainty seems to be the most disruptive for monetary policy, as responses of inflation are relatively similar in the two regimes, while the heightened contraction of output is just as apparent as with any other index. As for results with the Economic Policy Uncertainty Index, we are somewhat concerned for potential endogeneity between policy shocks and the index - especially in more influential economies - however further investigation of this is left for future research.

Additional future research might investigate questions such as global or local uncertainty is more influential for monetary transmission; how exactly do small increments in uncertainty change the responses of macroeconomic aggregates to shocks; or whether or not uncertainty increases the asymmetry between positive and negative monetary shocks.

In conclusion, our study contributes valuable insights into the complex interactions between uncertainty and the impact of monetary policy on the economy. For policymakers, our results highlight that heightened uncertainty calls for treading lightly in terms of policy actions, as the cost of reducing inflation might be severely increased. It also brings light to the importance of combating uncertainty itself, with steady, transparent policy-making, as well as perhaps via managing expectations.

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8 Annex

8.1 Annex A - Further evidence from US data

This section of the Annex intends to further our investigation, by changing from a birds-eye view to a more microscopic perspective focusing on implications for the United States. This allows us to carry out more meaningful robustness checks, as a richer set of data is available fore the US. Specifically, in this section we are testing for three things: i) does adding extra controls - the uncertainty index and a financial stress measure - change the results?; ii) alternative interest rates for estimating the policy shock - this allows us to use the Wu and Xia (2016) Shadow Rate to check if the presence of a Zero-Lower-Bound biases or results; and iii) we check if there are any endogeneity concerns between the estimated policy shock series and the uncertainty index. To keep this section concise, we only report results obtained with the Baker et al. (2016) EPU index as the threshold variable.

Controlling for uncertainty and financial stress: In our original setup, we considered a parsimonious 3-equation TVAR model with interest rates, inflation and GDP growth, using an exogenous threshold variable. While this setup is effective in investigating our research question - does economic uncertainty change the monetary transmission mechanism - it leaves some questions unanswered. In Baker et al. (2016) (and subsequent additions to the literature) it was shown that economic uncertainty is an important driver of business cycles. Naturally, this raises the question: does not accounting for uncertainty introduce some omitted variable bias that substantially changes our results?

Moreover, economic uncertainty is often associated with high financial stress. Li and St-Amant (2010) and Fry-Mckibbin and Zheng (2016) show that financial stress interferes with the transmission of monetary policy, and interventions in times of high stress can often be more effective. Could this be behind our results? To check the robustness of our results to a potential omitted variable bias, we consider three more model specifications:

$$Y_t = \sum_{k=1}^{4} \Theta_{high} I(X_t \geq \mu) Y_{t-k} + \sum_{k=1}^{4} \Theta_{low} I(X_t < \mu) Y_{t-k} + \sum_{k=1}^{4} \beta X_{t-k} + \epsilon_t \quad (3)$$

$$Y_t = \sum_{k=1}^{4} \Theta_{high} I(X_t \geq \mu) Y_{t-k} + \sum_{k=1}^{4} \Theta_{low} I(X_t < \mu) Y_{t-k} + \sum_{k=1}^{4} \gamma Z_{t-k} + \epsilon_t \quad (4)$$

$$Y_t = \sum_{k=1}^{4} \Theta_{high} I(X_t \geq \mu) Y_{t-k} + \sum_{k=1}^{4} \Theta_{low} I(X_t < \mu) Y_{t-k} + + \sum_{k=1}^{4} \beta X_{t-k} + \sum_{k=1}^{4} \gamma Z_{t-k} + \epsilon_t \quad (5)$$

where X_{t-k} represents the inclusion of four lags of the uncertainty indicator, and Z_{t-k} represent the inclusion of four lags of the St. Louis Fed Financial Stress Index. The graph below reports results obtained with these specifications along with the results of our baseline estimate for the US.

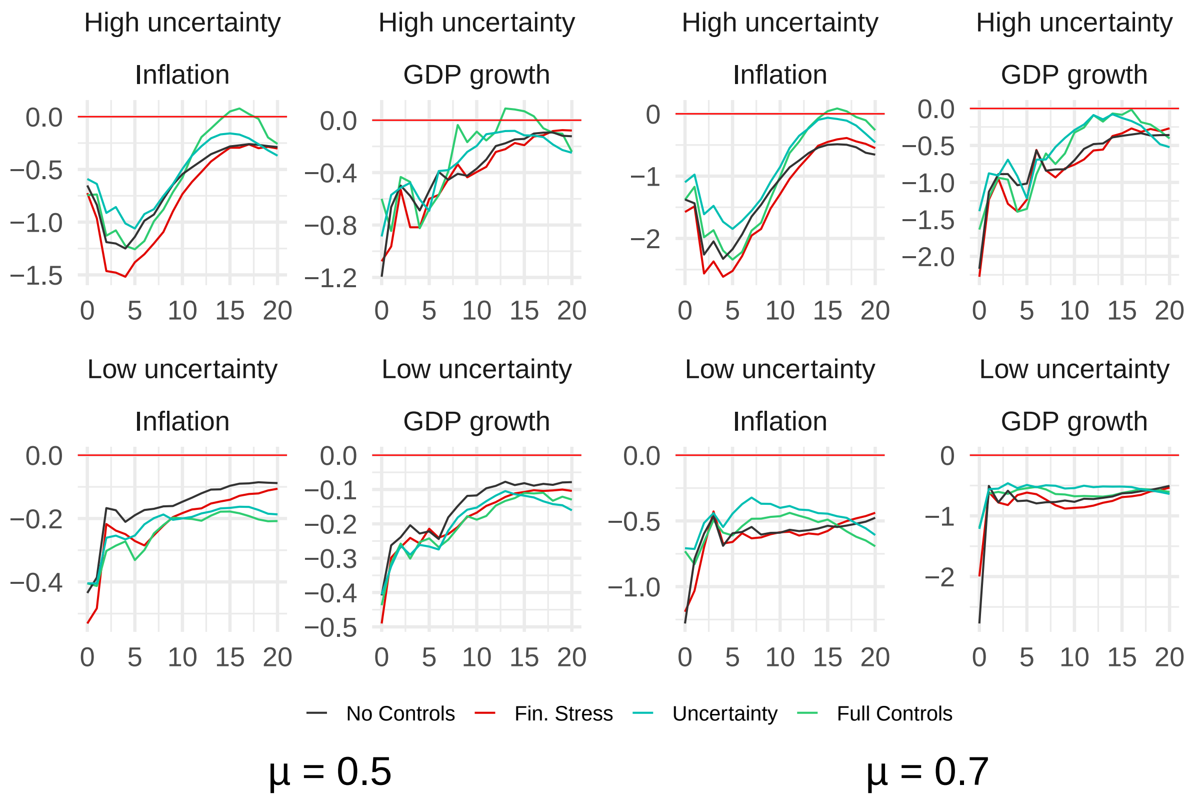

Figure 5: Robustness check across different control variable structures using US data.

Through visual inspection of the graphs, we can draw the following conclusions. Responses aside from high uncertainty inflation stay relatively similar across either specification.

When controlling for uncertainty, the transmission of policy shocks becomes slightly more muted. This should be in line with the uncertainty literature, as economic uncertainty can be a significant driver of fluctuations. On the other hand, when controlling for financial stress, the responses slightly sharpen. This again would be in line with literature, as policy shocks during high uncertainty times can calm the markets, thus here we are accounting for another transmission channel. Accounting for both, makes the responses essentially makes the responses indistinguishable from the baseline model for the first 10 quarters following the shock. Overall, the differences are relatively minor, and the same implications can be drawn irrespective of which model specification we consider. While this exercise did uncover some evidence for an omitted variable bias, this should not be too concerning.

Robustness across different interest rates: When investigating the efficacy of monetary policy shocks in post-GFC times, academics and policymakers alike tend to question if the ZLB interferes with results obtained with an empirical model. Without an appropriate measure to track implied interest rates, this question can be difficult to tackle. When focusing on the US alone, however, the Wu and Xia (2016) Shadow Rate can serve as an appropriate measure to overcome this difficulty. In order to check if the ZLB interferes with our results, we estimate the baseline model again, replacing the Fed Funds Rate with the Shadow Rate between early 2009 through 2016 and 2020 through 2022. Additionally, we estimate the model another time, using the return on 1-year Treasury Bills, as longer yields are also less susceptible to the ZLB.

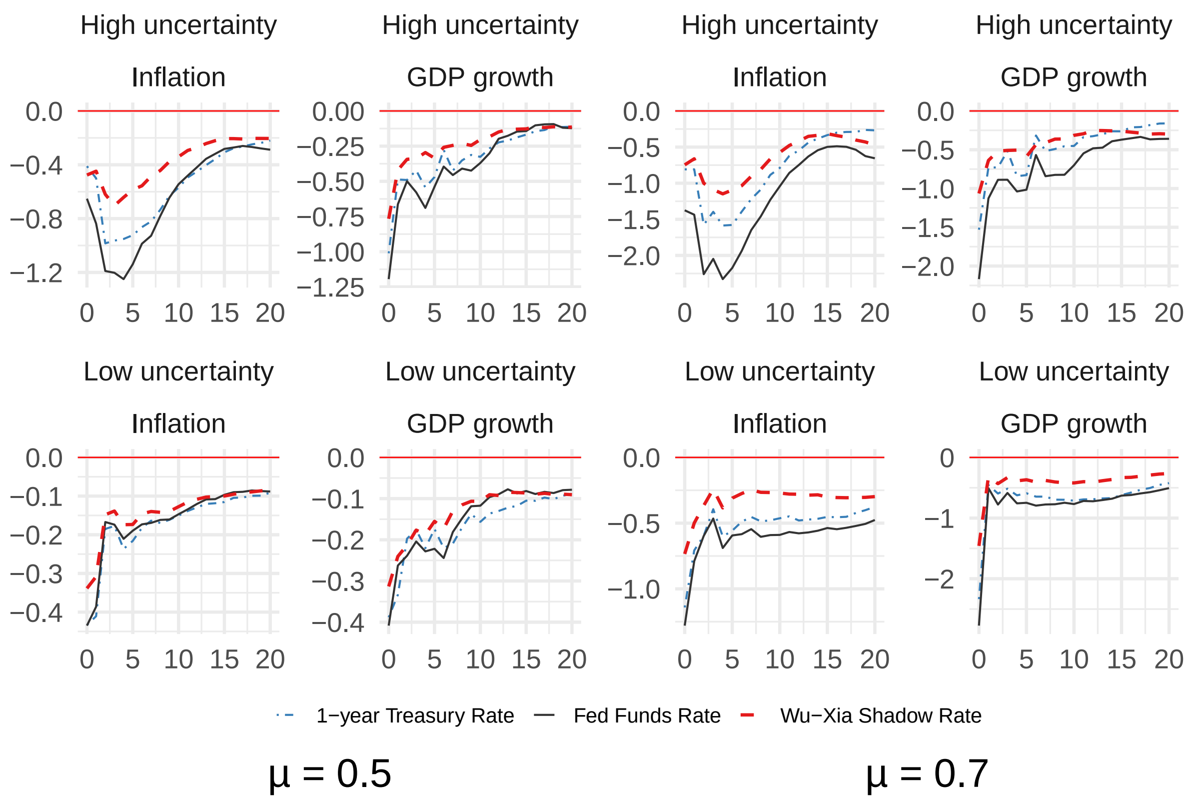

Figure 6: Robustness check across different interest rates using US data.

When using the Shadow Rate, aside from low uncertainty responses with $\mu = 0.5$ (i.e. the threshold value set to the median), the IRFs shift noticeably upward. This points to the fact that indeed the correct specification should be one that properly accounts for the existence of the ZLB. Nevertheless, regardless of whether or not we use an interest rate that is adjusted for the ZLB or not, we arrive at the same conclusions. Additionally, on a broader scale, a number of less advanced economies in our sample did not face a ZLB period, making this slightly less of a severe concern. Additionally, the Shadow Rate is seldom available for countries, responses obtained with a slightly longer yield fail to properly account for the ZLB, and the above mentioned reasons, we are not too concerned by this with respect to the robustness of our results.

Endogeneity: Studying the relationship between policy shocks and (policy) uncertainty naturally raises the question of whether or not the uncertainty index is endogenous to policy innovations. To test for this, we run Granger causality tests between the EPU index and the posterior median of the residuals obtained from various model specifications. We summarize a select few of these here in Table 2.

	Model	Test 1	Test 2
1	Linear	0.4	0.055
2	Base TVAR, Median	0.705	0.246
3	Base TVAR, 70th perc.	0.917	0.621
4	Full control TVAR, Median	0.813	0.288
5	Full control TVAR, 70th perc.	0.978	0.32
6	Full control TVAR with shadow rate, Median	0.484	0.362
7	Full control TVAR with shadow rate, 70th perc.	0.98	0.325

Table 2: Granger causality tests with alternative model specifications

Notes:

Test 1: H_0: Shock does not cause uncertainty

Test 2: H_0: Uncertainty does not cause shock

The results of these tests suggests that in most cases we fail to reject the null, and thus policy shocks do not drive uncertainty, neither the other way around. In fact, all non-linear specifications outperform the standard linear SVAR. Interpreting the p-values as the likelihood of H_0 to be true, in a linear setting, there is a high likelihood of uncertainty Granger-causing the monetary shock. As the p-values of the test stay relatively similar across specifications, we are not concerned that endogeneity between the policy shock series and policy uncertainty would exist. Furthermore, this exercise reinforces our belief that the threshold specification is superior in this context.

8.2 Annex B - Additional graphs referenced in the paper

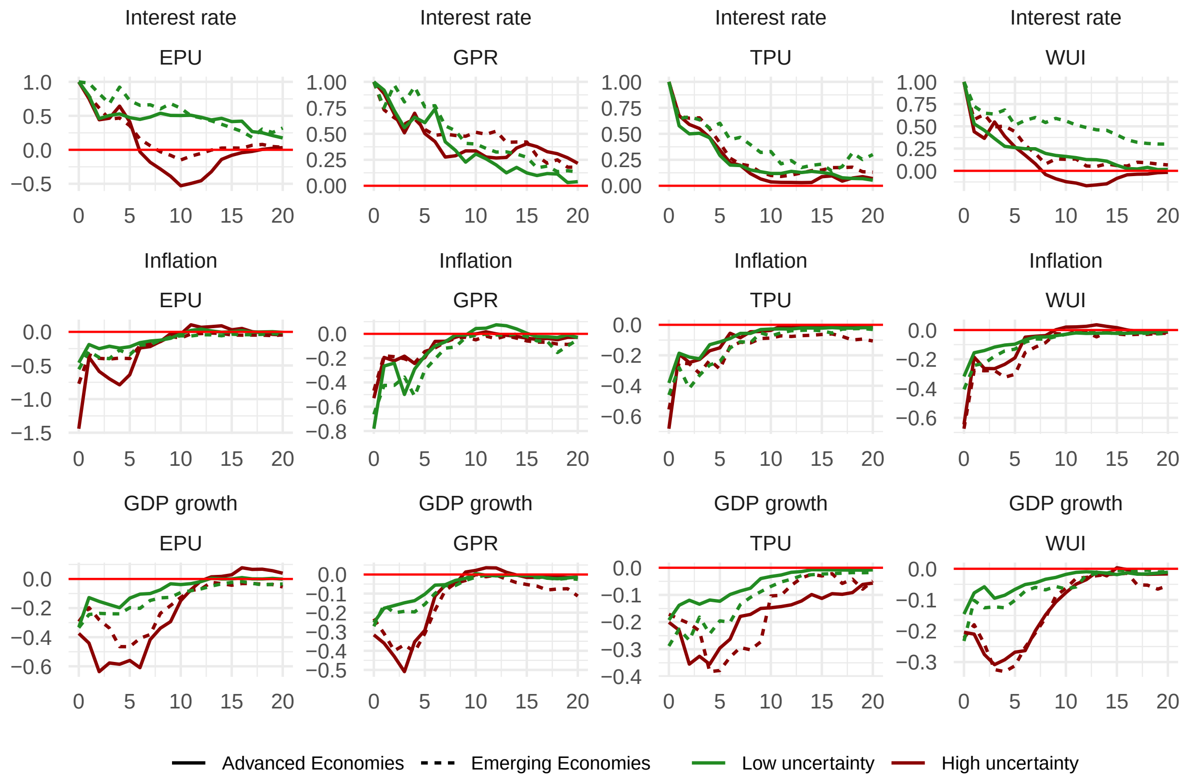

Figure 7: Advanced and Emerging Economy IRFs, median threshold.

Notes: Point-by-point median impulse responses comparing Advanced and Emerging with valid impulse responses. The threshold value for each uncertainty index is set to its median.

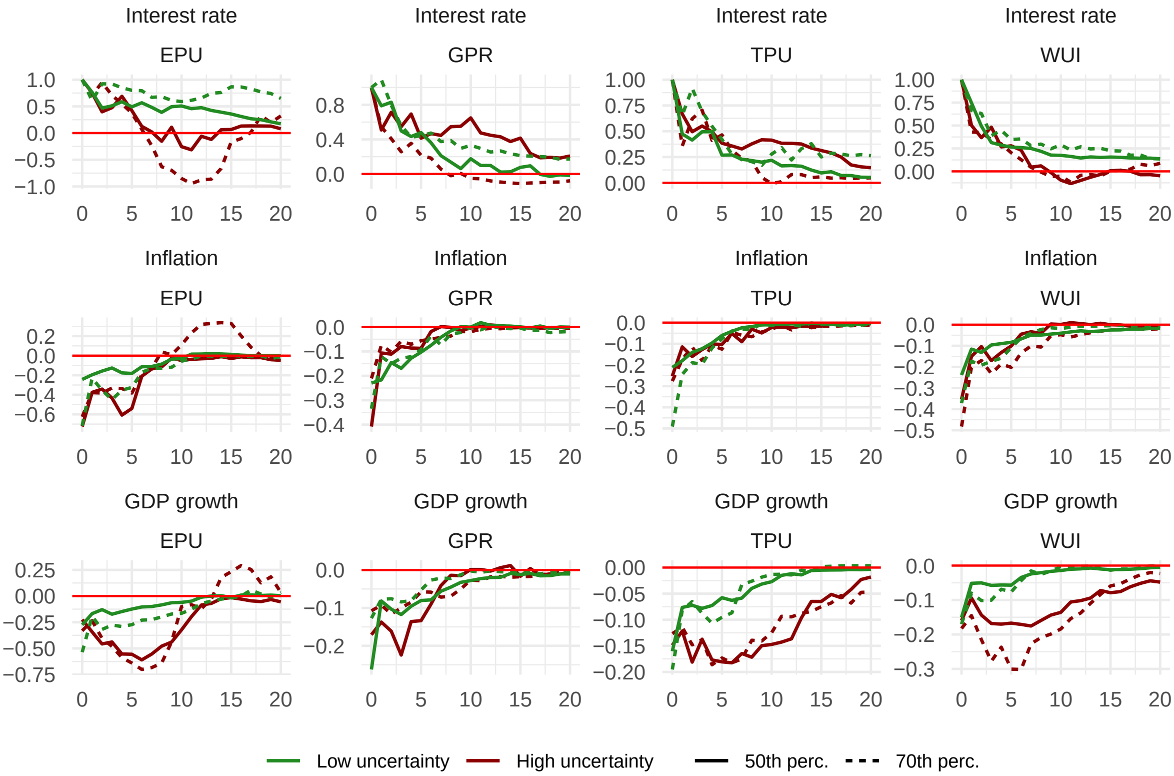

Figure 8: Large Economy IRFs, median and 70th perc. thresholds.

Notes: Point-by-point median impulse responses comparing threshold levels at the 50th and 70th percentiles in Large Open Economies with valid impulse responses.

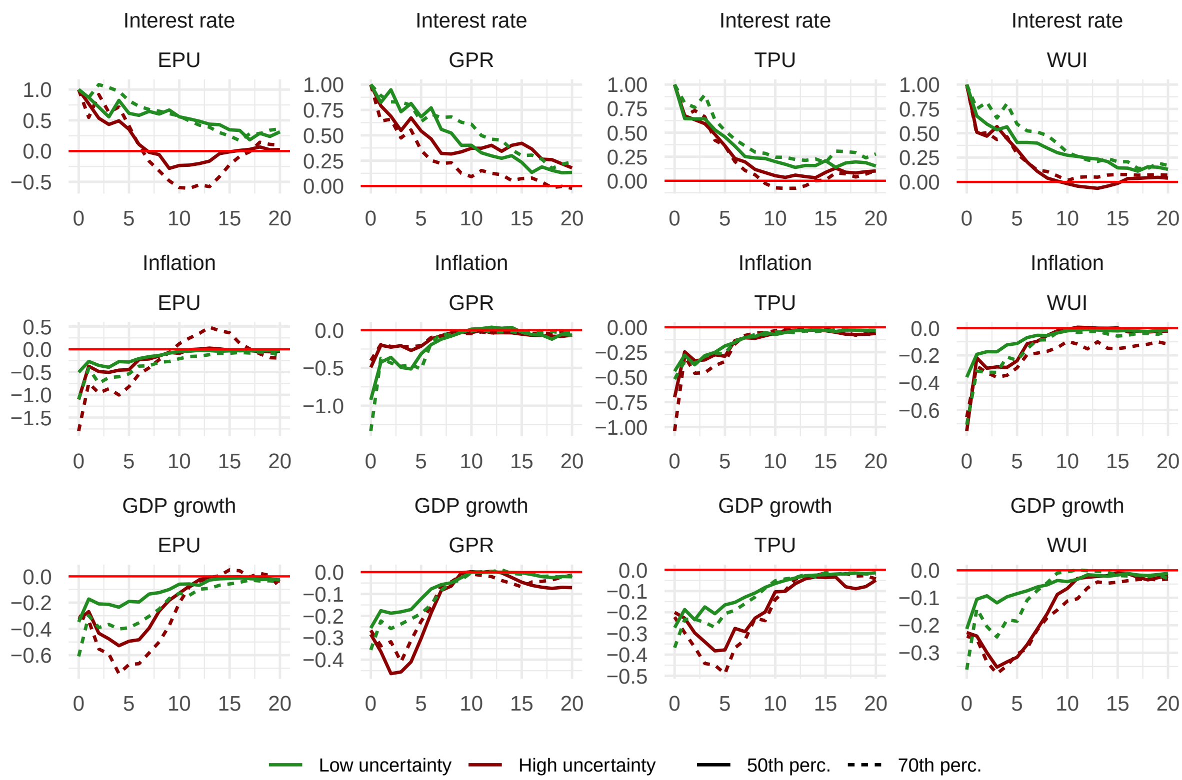

Figure 9: Small Economy IRFs, median and 70th perc. thresholds.

Notes: Point-by-point median impulse responses comparing threshold levels at the 50th and 70th percentiles in Small Open Economies with valid impulse responses.

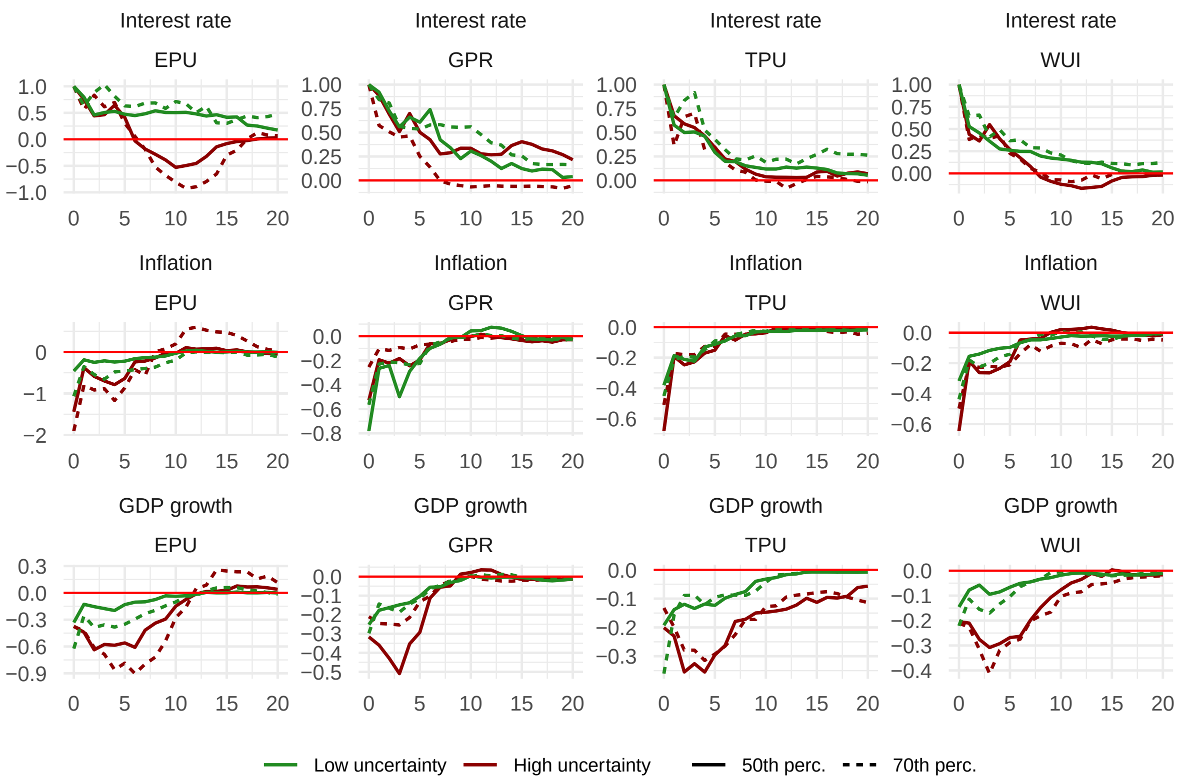

Figure 10: Advanced Economy IRFs, median and 70th perc. thresholds.

Notes: Point-by-point median impulse responses comparing threshold levels at the 50th and 70th percentiles in Advanced Economies with valid impulse responses.

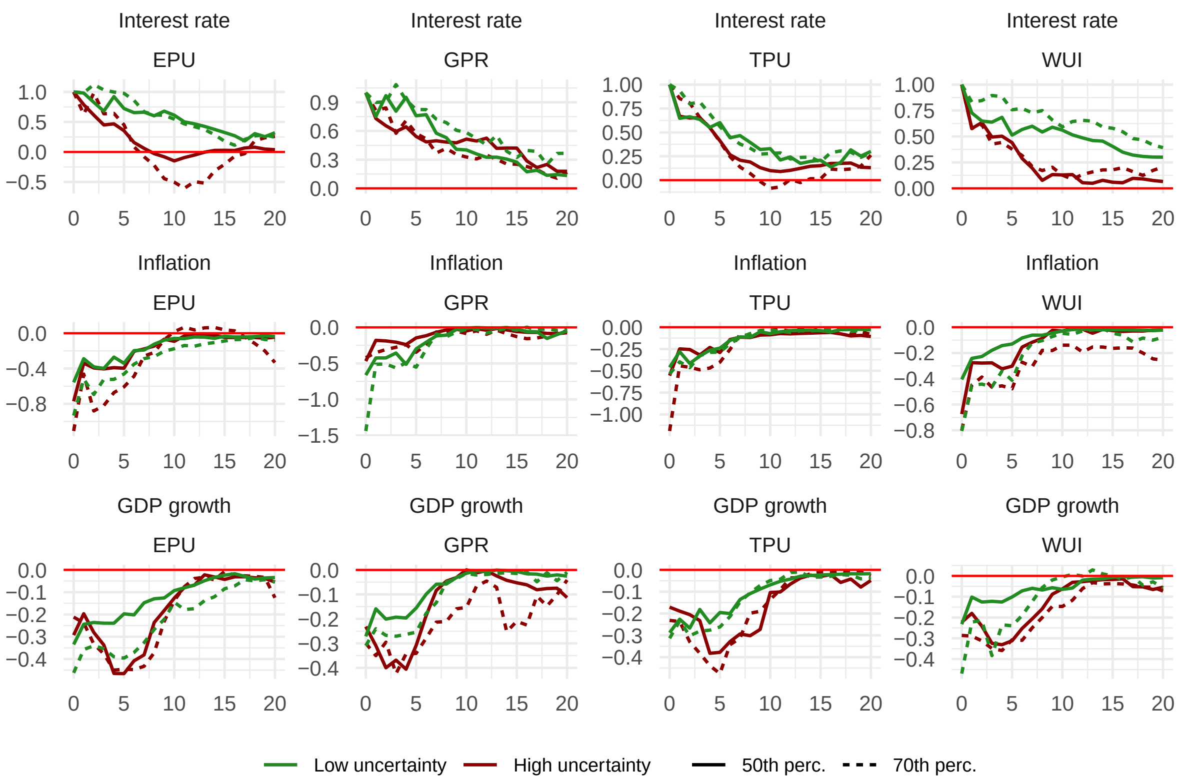

Figure 11: Emerging Economy IRFs, median and 70th perc. thresholds.

Notes: Point-by-point median impulse responses comparing threshold levels at the 50th and 70th percentiles in Emerging Economies with valid impulse responses.

8.3 Annex C - Variants of Figures 2 and 4

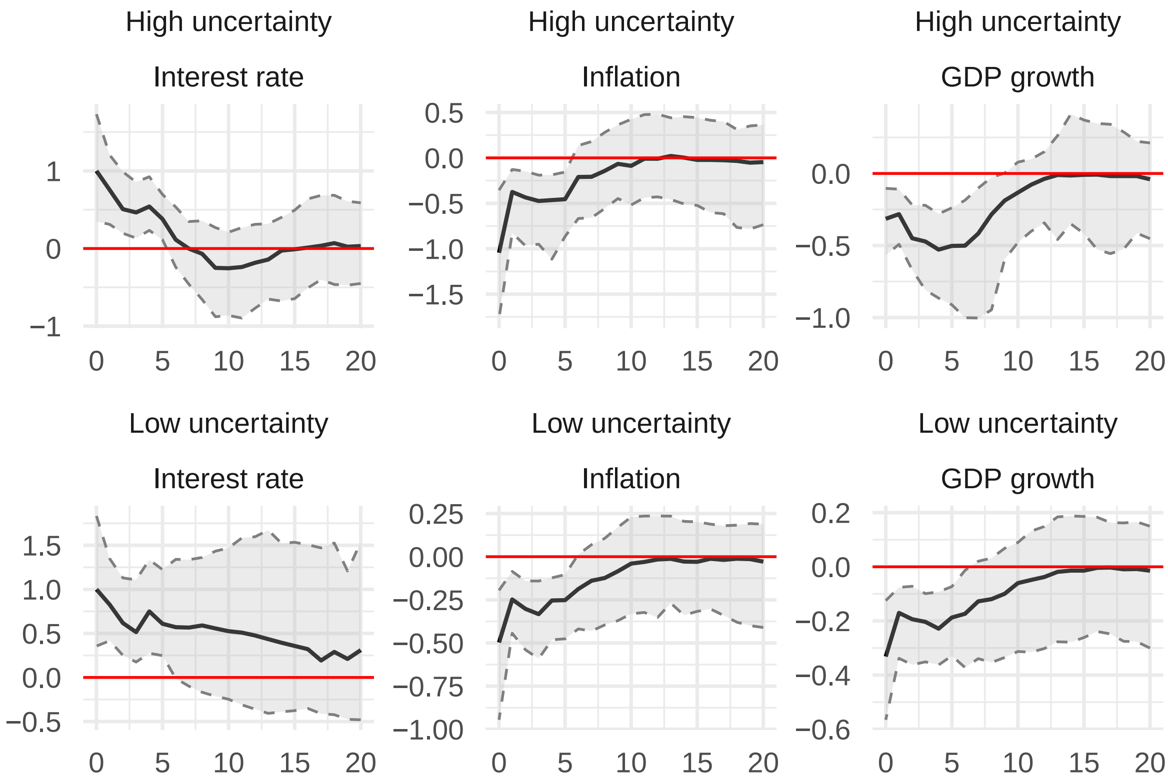

Figure 12: Global IRFs with the EPU and median threshold.

Notes: Point-by-point median impulse responses aggregating over all countries with valid impulse responses. The Economic Policy Uncertainty Index is used as the threshold variable with the threshold level set to the median. The confidence intervals are the 68% confidence level.

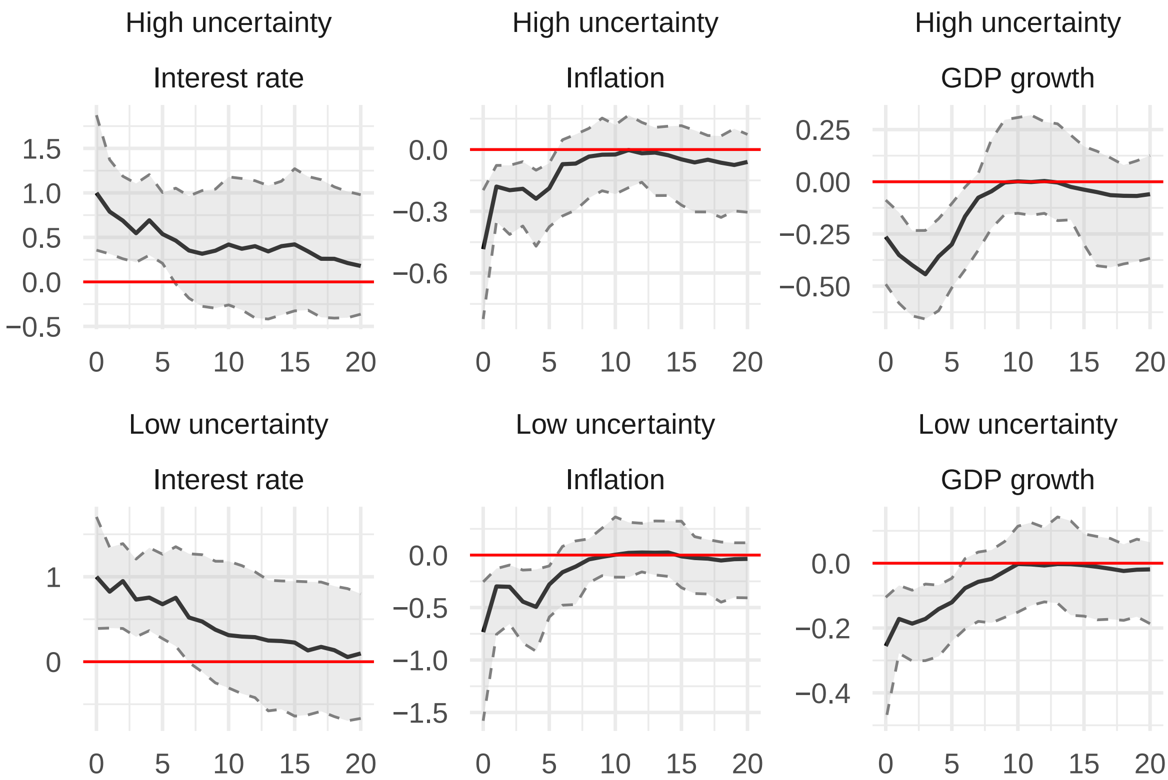

Figure 13: Global IRFs with the GPR and median threshold.

Notes: Point-by-point median impulse responses aggregating over all countries with valid impulse responses. The Geopolitical Risk Index is used as the threshold variable with the threshold level set to the median. The confidence intervals are the 68% confidence level.

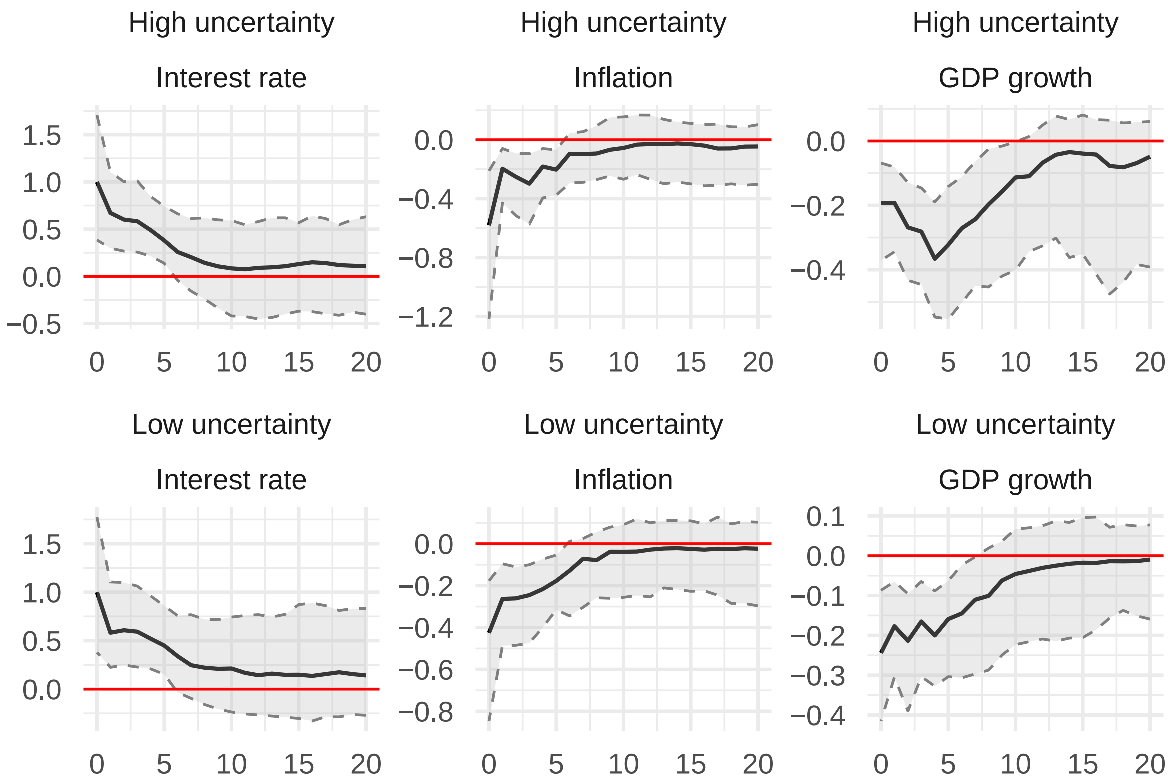

Figure 14: Global IRFs with the TPU and median threshold.

Notes: Point-by-point median impulse responses aggregating over all countries with valid impulse responses. The Trade Policy Uncertainty Index is used as the threshold variable with the threshold level set to the median. The confidence intervals are the 68% confidence level.

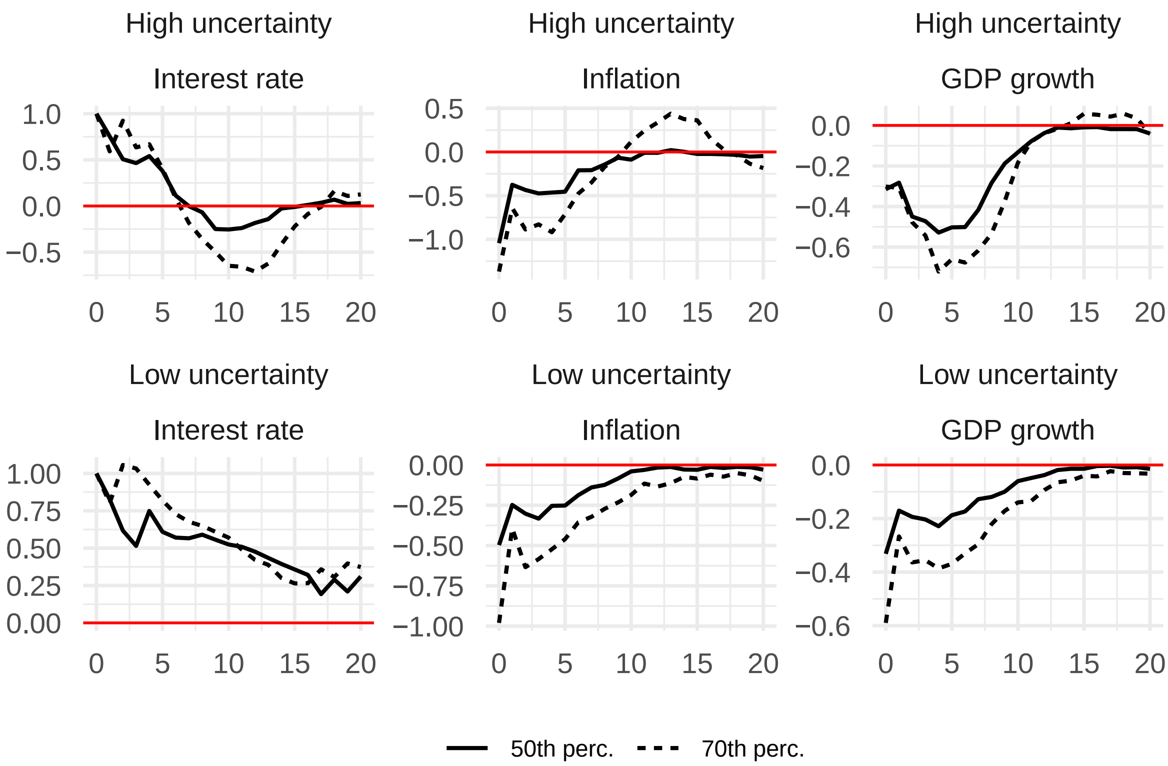

Figure 15: Global IRFs with the EPU, median and 70th perc. thresholds.

Notes: Point-by-point median impulse responses comparing threshold levels at the 50th and 70th percentiles in the whole sample with valid impulse responses. The Economic Policy Uncertainty Index is used as the threshold variable.

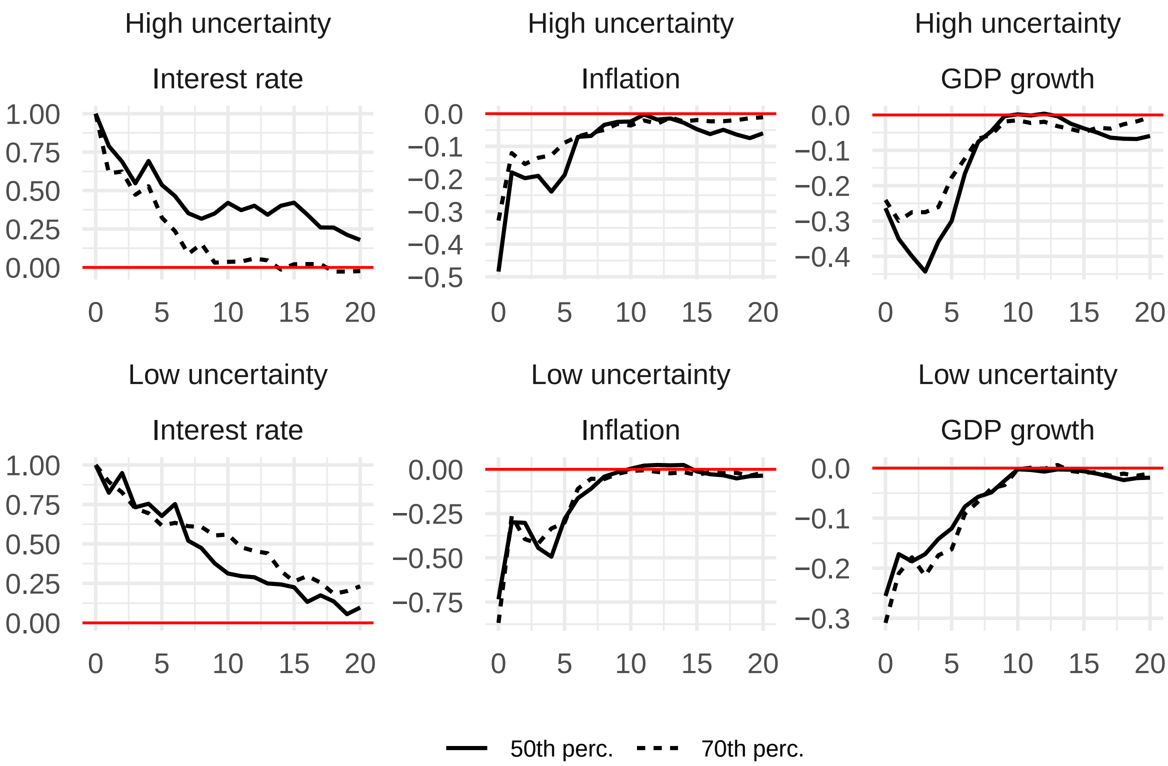

Figure 16: Global IRFs with the GPR, median and 70th perc. thresholds.

Notes: Point-by-point median impulse responses comparing threshold levels at the 50th and 70th percentiles in the whole sample with valid impulse responses. The Geopolitical Risk Index is used as the threshold variable.

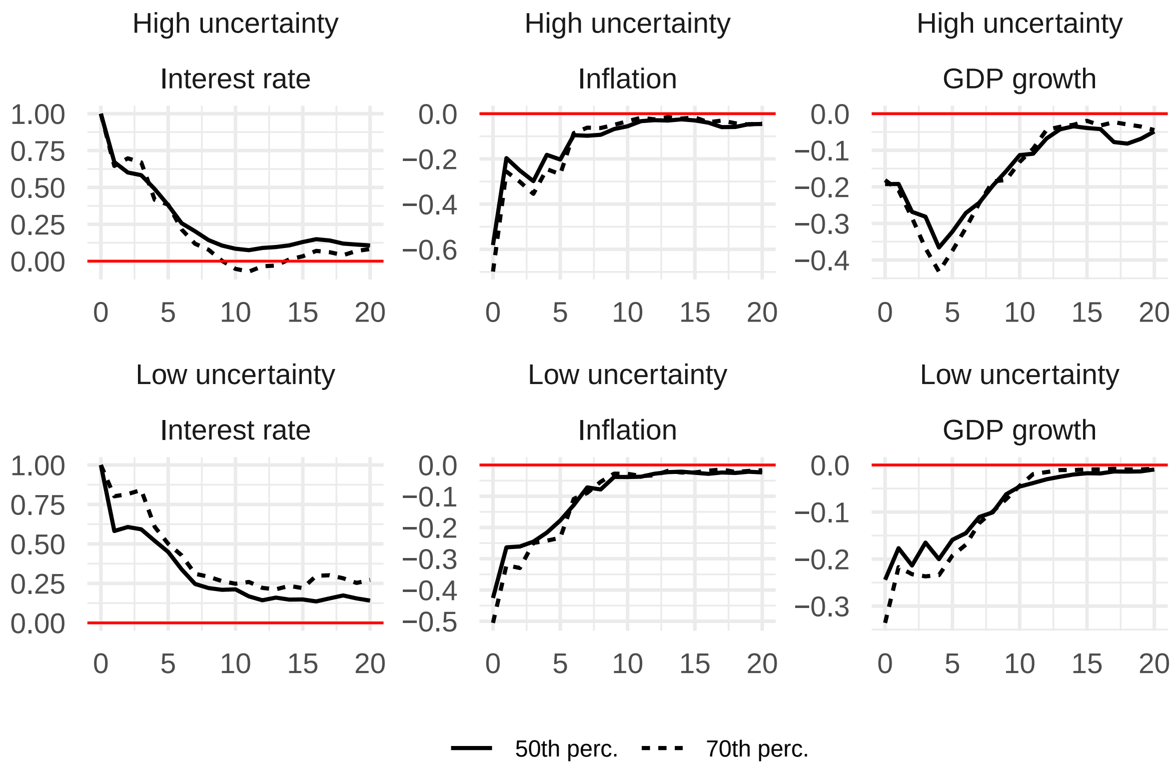

Figure 17: Global IRFs with the TPU, median and 70th perc. thresholds.

Notes: Point-by-point median impulse responses comparing threshold levels at the 50th and 70th percentiles in the whole sample with valid impulse responses. The Trade Policy Uncertainty Index is used as the threshold variable.