The Impact of Uncertainty on Monetary Transmission

Evidence from the US

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Abstract

This paper investigates the nonlinear interaction of the monetary transmission mechanism and economic uncertainty in the United States. I employ a Threshold VAR model with two states dependent on the level of uncertainty, and identify regime specific shocks using sign-restrictions. Results suggest that the short run contraction induced by the policy shock is larger when uncertainty is high, however, in such times, its impact dissipates more quickly. Comparatively in low uncertainty times, the contraction is smaller with policymakers having a smoother control over the path the economy takes. The short-run larger impact can be leveraged to reduce inflation in a more cost-effective way, however the uncerlying cause of uncertainty needs to be carefully considered.

Keywords: Uncertainty, Monetary transmission, Non-linearity, Sign restriction, Vector-Autoregression

JEL codes: E32, E52, C32

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1 Introduction

The transmission of monetary policy interventions has been a cornerstone of macroeconomic research for academics and policymakers alike, as understanding how monetary policy can affect the real economy has consequential implications for evaluating the right policy strategy. Another field gaining increased attention, especially for empirical macroeconomists, is research on how uncertainty drives business cycles. The literature agrees that uncertainty is an important driver of macroeconomic demand, primarily influencing it through investment decisions. However, the interplay between uncertainty and the monetary transmission mechanism is relatively less investigated. This leads to the purpose of this paper: To extend the existing literature in quantifying how uncertainty - especially uncertainty related to economic policy - affects the transmission mechanism.

Primarily, this paper is a natural followup to Horvath and Atashbar (TBA). The paper establishes how the interest rate channel of monetary transmission in times of elevated global economic uncertainty arising from geoeconomic fragmentation influences economies. The results indicate that in times of high uncertainty, interest rate shocks lead to a larger contraction of macroeconomic demand, primarily reflecting in a larger and longer lasting slump in economic activity.

Earlier works in this field, such as Aastveit et al. (2017) and Aquino et al. (2022), however, find opposing results, suggesting that uncertainty reduces transmission efficacy. The former use an interacted SVAR approach, where the regime indicator is interacted only with interest rates in the equations, and take the very far ends of the uncertainty distribution to define high and low uncertainty regimes. The latter criticizes this and argues for the use of a grid-search algorithm[1] to find the optimal threshold level for the regime switches. Additionally their specification introduces the threshold assumption into the interest rate equation of the SVAR model - implying a state dependent Taylor Rule.

What might drive the key differences?

Firstly, the use of global versus country-specific uncertainty measures. While the two are

[1] Results from this algorithm in the paper suggest the regime switches are at the 57th, 58th and 65th percentile of the historical distribution depending on the index. While it is true, that the correct specification of the threshold value is important for goodness-of-fit, the more ad-hoc definition of high uncertainty at the median and the 70th percentile is kept as in Horvath and Atashbar (TBA) for the sake of simplicity and comparability.

not dissimilar concepts, they could carry different implications. As noted in Ilyina et al. (2023), heightened uncertainty is a channels of geoeconomic fragmentation, which is likely better grasped by the global measures, and thus carry different implications from times of elevated country-specific uncertainty.

Secondly, the application of the threshold assumption. Aastveit et al. (2017) and Aquino et al. (2022) use partial threshold models, whereas in Horvath and Atashbar (TBA) we argue that for correctly measuring the transmission mechanism, it is important to take into account how the entire dynamic system describing the economy changes at the regime switches.

And thirdly, the richness of the datasets used for the estimations. In the global context, more compact, trivariate models were estimated to allow for a wide range of countries to be incorporated. However, relying solely on US data allows for a more rigorous model with additional variables as seen in Aastveit et al. (2017) and Aquino et al. (2022).

This paper intends to fill this knowledge gap, by changing from a birds-eye view to a more microscopic perspective focusing on implications for the United States. I adopt the same Threshold Vector-Autoregression (TVAR) model as well as sign-restriction approach to identify regime specific shocks. To measure the transmission of monetary shocks, I employ a set of quarterly macroeconomic as my core dataset comprising of interest rates, inflation and GDP, and as such, it is possible to measure the transmission of policy shocks to the real economy.

However, relying on US data opens up the possibility to extend the variables (e.g. adding financial stress[2], or checking for the robustness of the results with the Wu and Xia (2016) shadow rate). Additionally, switching from global uncertainty aggregates to the US specific Economic Policy Uncertainty (EPU) index of Baker et al. (2016) allows for a deeper investigation of how the underlying cause of uncertainty impacts the transmission mechanism, as the authors construct category-specific EPU indices (e.g.: indices specific to Monetary Policy, Financial Regulation, or Sovereign debt and currency crises).

Switching from global uncertainty measures to the US-specific EPU might bring up en-

[2]As shown by Li and St-Amant (2010) and Fry-Mckibbin and Zheng (2016), in times of high financial stress, monetary policy can potentially become more effective. As elevated levels of uncertainty are likely associated with higher financial stress, is necessary, as shown later. For this reason, additional to the standard macroeconomic aggregates, the St. Louis Fed Financial Stress Index is considered as a control variable.

dogeneity concerns, as it is not too far-fetched to assume policy shocks driving the policy aspect of the EPU. This is addressed using simple Granger-causality tests, as well as explicitly incorporating the uncertainty index into the model.

Results from an extended TVAR model estimated with a full set of controls indicates that uncertainty inflates the variance of outcomes, exacerbating the impact of shocks in the short run, however in such times the impact of shocks is far less persistent. This can be leveraged by central banks, as the larger shock affects inflation disproportionately more, and as such, a lower short-run sacrifice ratio can be achieved. The source of uncertainty has to carefully be considered, however, as factors such as debt or trade policy concerns can greatly increase the cost of deterring inflation both on the short run, as well as over longer horizons.

The rest of the paper is outlined as follows: Section 2 gives a brief overview of the related literature, Section 3 describes the data used in this paper, Section 4 discusses the methodology, Section 5 showcases the results and their implications and Section 6 concludes.

2 Related literature

Following the seminal works such as Baker et al. (2016) or Caldara and Iacoviello (2022), a vast body of literature has emerged in the field of empirical macroeconomics focusing on economic uncertainty and its implications for economies. The aforementioned papers establish the key implications on the economy. Uncertainty shocks cause a demand-side contraction, the primary channel being uncertainty disincentivizing investments. Moreover (specifically contractive) uncertainty shocks have a more pronounced impact in times of economic turmoil and financial stress.

Caldara et al. (2016) show that financial and uncertainty shocks are pivotal drivers of business cycles, exemplified during events like the Great Recession. Likewise, Bonciani and Ricci (2020) show that global financial uncertainty shocks bear down on economies, particularly in open economies during downturns.

The global importance of uncertainty shocks is further studied in works such as Colombo (2013), Nilavongse et al. (2020) or Biljanovska et al. (2021), showing that uncertainty shocks of large economies - most predominantly shocks in the US - have a considerable spillover effect on economies such as the UK, Euro Area economies, as well as countries of the Western Hemisphere.

Cheng and Chiu (2018) show that geopolitical uncertainty is a significantly influential factor in driving business cycle fluctuations of emerging economies. Works such as Carrière-Swallow and Céspedes (2013), Ahir et al. (2019), Ahir et al. (2022) show that these economies suffer greater downturns as the impact of uncertainty shocks is magnified by credit constraints, albeit there is some dispute in these findings, as Das and Kumar (2018) argue the opposite.

As demonstrated by a number of papers such as Ebeke and Siminitz (2018), Wang et al. (2021), Chen et al. (2021), and William and Fengrong (2022), shocks to uncertainty related to trade policy are shown to exert similar adverse effects on investment by reducing risk appetite; additionally increasing firm markups as well as deterring exports.

On the methodological side of the literature, the use of nonlinear models - such as threshold or smooth-transition techniques - for modeling time series have been steadily rising. TVAR models - as a method of introducing state dependency into multivariate time series models - have seen a wide range of use cases in works such as Baum and Koester (2011) studying the state dependency of fiscal multipliers along the business cycle; Galvão (2006) using such models to predict recession timings; or Alessandri and Mumtaz (2019) showing the state dependency of uncertainty shocks on financial conditions.

Such techniques are used for research on monetary policy as well. Avdjiev and Zeng (2014) show that policy shocks have a larger impact in recession periods, and that monetary policy reacts more aggressively to rising inflation during booms; Schmidt (2020) find evidence for state-dependency on asset prices, with macro-risk and policy risk playing distinct roles for the transmission; while Li and St-Amant (2010) and later Fry-Mckibbin and Zheng (2016) highlight monetary policy efficacy in times of financial stress, emphasizing short-term trade-offs between output and inflation.

The state-dependent nature of uncertainty shocks is further established using nonlinear time series techniques. Schüler (2014) and Colombo et al. (2020) both find that uncertainty shocks have a more significant effect during recessions, also showing the vital role of monetary policy measures - especially balance sheet-based tools - in mitigating such shocks. Nalban and Smădu (2021) also shows that the impact of uncertainty varies with the economic state, amplifying during financial distress but rebounding faster due to monetary policy reactions.

Some additional papers, results shown here are more in line with are Gbohoui (2021) where an increase in investment multipliers is shown in times of high uncertainty, implying larger and longer lasting effects; or Ying and Wang (2022) finding that monetary policy uncertainty moderates the transmission of forward guidance shocks on long-term yields, but not the transmission of Federal Funds Rate or asset price shocks, furthermore, the moderation effect is shown to be a consequence of changes in the term-premium and not through the channel of short rates.

3 Data

3.1 Macroeconomic aggregates

In order to keep the estimation streamlined, I rely on quarterly macroeconomic aggregates from 1985-Q1 to 2023-Q2[3] as the core set of data behind the estimations. The three main aggregates are interest rates, quarterly inflation rates - measured as the first difference of the CPI - and quarterly real GDP growth rates - measured as the first difference of the chain volume index calculated from quarterly real GDP.

Figure 1 below shows three measures of interest rates I consider in different specifications. Primarily, however, I rely on the Federal Funds Rate (FFR) as the policy instrument to estimate interest rate innovations.

In robustness specifications, the 1-Year Treasury Yield and the Wu and Xia (2016) shadow rate are considered as replacements of the FFR in estimating the model. While these three measures show high co-movement, the former - to some extent - may carry some additional information such as market expectations or yield curve dynamics - while the latter shows the implied rate of interest, which significantly differs from headline rates close to the ZLB.

[3]Data for interest rates, inflation and economic activity is available from much earlier, however the sample is restricted to start from 1985-Q1 as it is the earliest available data point for the EPU index. The range of data does change in some specifications, as the Shadow Rate or the St. Louis Fed Financial Stress Index are only available on a shorter period of time.

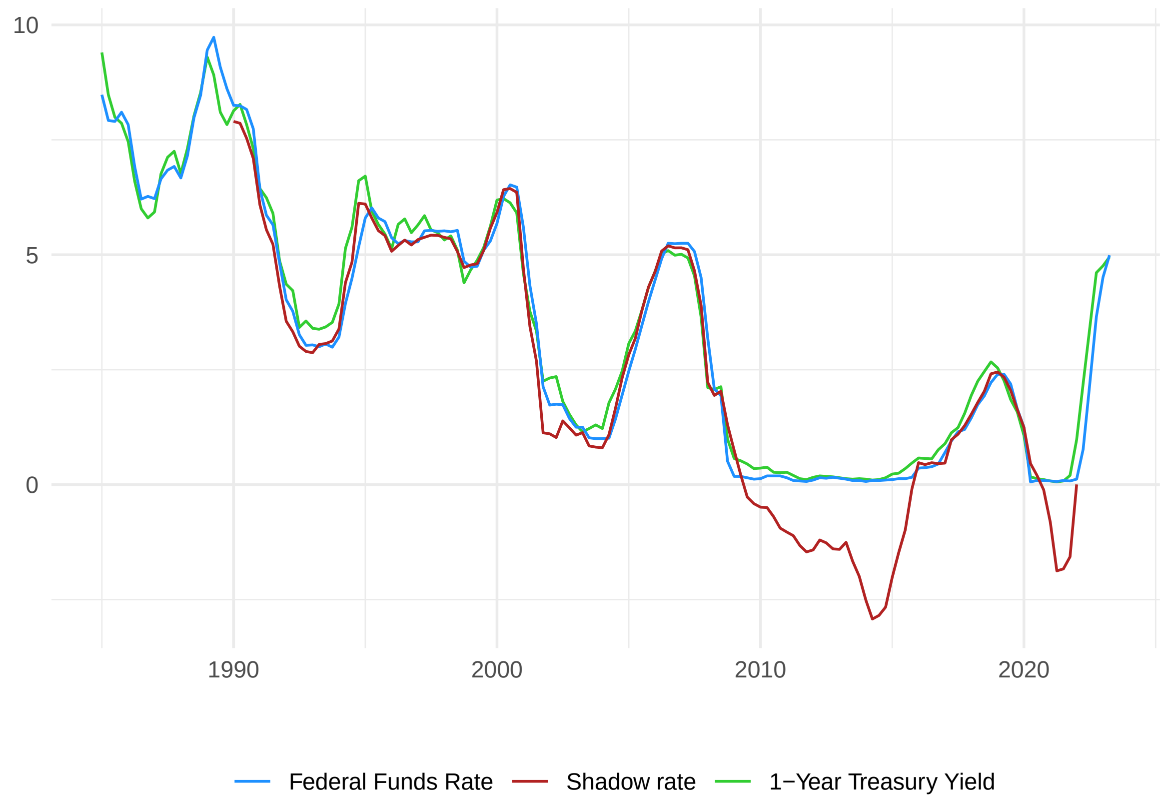

Figure 1: Interest rates

3.2 Measuring uncertainty

In the models outlined, my primary measure of uncertainty is the Baker et al. (2016) EPU index. This measure of uncertainty is constructed from textual data retrieved from articles of influential newspapers in the US. Using the articles, automated text queries are conducted in order to find articles containing terms related to "uncertainty" and either "economic" or "policy."[4]

Why use measures constructed from textual data? A benefit of using the EPU over more standard measures such as the VIX is that it is more tailored to "economic" or "economic policy" related uncertainty, and thus should be more influential on the impact of policy shocks. Additionally, as opposed to being constructed from financial market data, the news articles might be a more suitable source of information to capture expectations of agents in the economy.

In order to define what "high uncertainty" is, I consider two alternatives based on position

[4] The data series of uncertainty measures along with more detailed descriptions of each can be retrieved from policyuncertainty.com.

in the historical distribution of the EPU. In the first case, high uncertainty is defined as values of the EPU above its median, while in the second case, above its 70th percentile. While these are more ad-hoc definitions, for the sake of better conveying the implications of the results, I prefer using such pre-defined levels over an endogenously defined one from a Threshold AR model. The EPU along with the two threshold values can be seen in Figure 2.

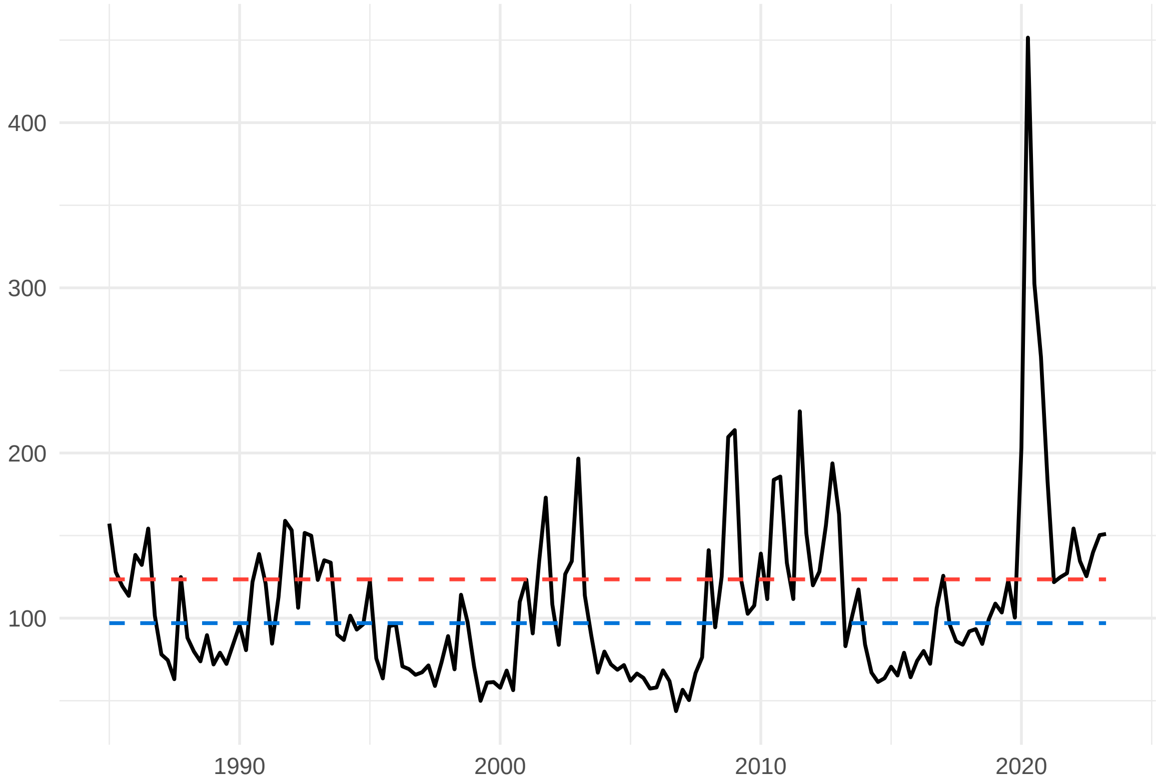

Figure 2: Economic Policy Uncertainty index

Notes: The blue and red lines indicate the median and 70th percentile of the historical distribution respectively.

In Baker et al. (2016), along with the main EPU index, several EPU Categorical indices are also constructed. These indices are more specific to a certain topic within "economic" or "economic policy" such as monetary policy, fiscal policy, or sovereign debt crises. In order to pinpoint the source of uncertainty that might be most influential for the transmission of monetary policy shocks, I repeat the estimations with the EPU Categorical indices in place of the main EPU index. The EPU categorical indices can be seen in Figure 6 of the Appendix.

It is important to mention that there are a number of additional[5] measurements of uncertainty in the literature. Measures such as the VIX Index and the TED spread using market data, as well as the search-term based Equity Market-related Economic Uncertainty Index of Baker et al. (2016) can be used to grasp uncertainty in financial and liquidity markets. Caldara and Iacoviello (2022) and Caldara et al. (2020) use textual data to construct the Geopolitical Risk Index and the Trade Policy Uncertainty index which measure uncertainty around geopolitical and trade tensions. Ahir et al. (2022) use text searches in Country Intelligence Unit reports to construct the World Uncertainty Index, as a broader measure of uncertainty. As this paper focuses on the implications of uncertainty for monetary policy, I use only the EPU and its Categorical indices as they are the most tailored to grasping uncertainty around economic policy.

4 Methodology

4.1 Threshold VAR model

As discussed in the Introduction and Literature sections, TVAR models are suitable for modeling non-linearity problems, such as the one discussed in this paper. For the sake of comparability, I adopt the same baseline setup as in Horvath and Atashbar (TBA), however, in alternative specifications, some other factors are considered. Thus the baseline model can bet written as:

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

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

In this main specification, Y_t consists of the FFR, quarterly CPI inflation and quarterly GDP growth and X_t is the EPU index. To investigate how different sources of economic uncertainty impact the transmission mechanism, the estimation is repeated by replacing plugging in each EPU categorical index into X_t in place of the main EPU index. Two

[5]These measures can be seen in Figure 7 of the Appendix.

different values of μ are considered, the median value as well as the 70th percentile of X_t in each estimation. This allows to check i) how policy shocks affect the economy conditional on the level of economic uncertainty experienced in the same period, ii) to some extent, how much the level of uncertainty matters for the transmission mechanism, and iii) which source of uncertainty is the most influential in altering the transmission channel.

To address some potential issues, a number of robustness checks are conducted. Firstly, I replace the FFR in Y_t with the 1-Year Treasury Yield and the FFR shadow rate. Secondly, I check if the results hold if I change the construction of the regime indicator from X_t to X_{t-1}, making it pre-determined, and thereby eliminating the potential of estimating the impact of two contemporaneous shocks. Thirdly, I incorporate the uncertainty index in its levels as well as a financial stress indicator in order to purge their effects from the aggregates during the estimation.

4.2 Identification

Empirically, an obstacle in estimating impulse responses that show the correct sign associated with monetary shocks is the price puzzle. Estimating a trivariate (interest rates - inflation - GDP) SVAR model yields impulse responses showing a rise in inflation as a consequence of an interest rate shock. This, however goes against standard macroeconomic theory, which states that increasing policy rates should contract macroeconomic demand and thus lead to a decline both in prices as well as output. Numerous authors (among others Hanson (2004), Giordani (2004), Demiralp et al. (2014), Bishop et al. (2017), Cloyne and Hürtgen (2016), Romer and Romer (2004)) investigate the price puzzle, suggesting different explanations or ways of dealing with this phenomenon.

In this paper, I follow a different branch of literature. Pioneered by Uhlig (2005), it is possible to incorporate some prior beliefs into the estimation by imposing sign-restrictions on the impulse responses. His seminal work introduces a (full-Bayesian) rejection as well as a penalty algorithm for estimating SVAR-s as such. The former approach accepts impulse response draws only if they exactly fit the imposed restrictions. The latter accepts draws that violate the sign-restrictions using a goodness-of-fit based penalty score.

At first glance, the penalty approach might seem more desirable due to higher flexibility, however Arias et al. (2018) show some adverse properties of this algorithm. Firstly, the penalty algorithm can artificially impose restrictions on the unrestricted variable, and secondly, the - by design - higher number of accepted responses narrows confidence bands. In a smaller model, such as the trivariate one with a full set of restrictions is no issue, however, if the model is extended with variables on which no restrictions are placed this would be an issue, and the narrower confidence bands would misrepresent the accuracy of the results. Additionally, Rubio-Ramirez et al. (2010) improved on the efficiency of the rejection algorithm of Uhlig (2005), and for these reasons, their iteration of it is used in this paper.

In all estimations, Bayesian models are estimated with 4 lags and a non-informative Wishart prior. For the purposes of this paper, partial identification is sufficient, and as such, sign-restrictions are only imposed on monetary shocks.The sign-restriction is imposed to follow common macroeconomic assumptions, meaning a positive sign on interest rates and negative on inflation and output. The mirror image of the results can be obtained by reversing the sign restrictions, and I assume the impulse responses are independent of the size of the monetary shock. As such, studying sign and size asymmetries is left for future research.

Posterior impulse responses are estimated in a bootstrap simulation with 200 impulse response draws for each 20000 MCMC replication. These are computed separately for both the low and the high uncertainty regime in each case. The accepted posterior impulse responses are aggregated into posterior-medians along with and 84% confidence interval. All computations are done in the R programming language relying on the work of Danne (2015) for the implementation of the sign-restriction algorithms.

5 Results

5.1 Replicating the baseline specification

In the baseline specification, the three equation TVAR is estimated on interest rates, CPI inflation and GDP growth using a four-quarter lag structure. Monetary shocks are measured as innovations of the Federal Funds Rate, and the threshold value μ is calculated as the median of the EPU index. Figure 3 shows the regime specific impulse responses of inflation and economic activity to a 1 percentage point rise in interest rates.

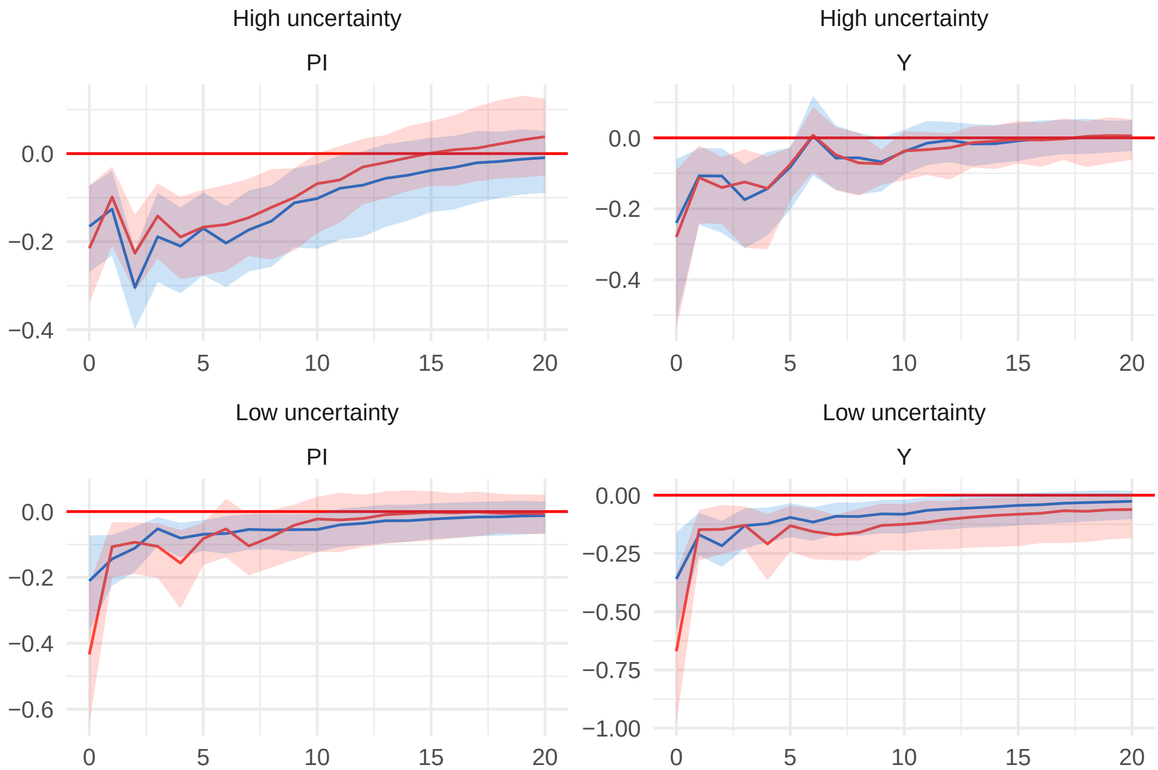

Figure 3: Regime specific impulse responses, original specification.

Notes: The blue solid line represents the posterior median obtaied with the threshold value μ set to the median, the red one with it set to the 70th percentile of the EPU. The shaded areas represent the 84% confidence bands calculated from the posterior impulse response draws.

Results from this estimate suggest that the contemporaneous drop in output is slightly larger in low uncertainty, with the following quarters showing a similar level of contraction. Alongside this, a prolongued disinflation caused by the monetary shock can be observed in the high uncertainty regime. Comparing the two threshold levels, the changes in the impulse responses are close to negligible aside from the change in contemporaneous effects seen in the low regime. Such results are not supported by either of the previous literature. In the following subsections I investigate if other factors could be influential in shaping the impulse responses.

5.2 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. Investigating the potential endogeneity can also guide in selecting the appropriate model specification. Testing for endogeneity is done by running Granger causality tests between the EPU index and the posterior median of the residuals obtained from alternative specifications considered. The results from a select number of these is shown here[6] in Table 1.

	Model	Test 1	Test 2
1	Linear	0.247	0.098
2	Base TVAR, Median	0.86	0.579
3	Base TVAR, 70th perc.	0.034	0.426
4	Full control TVAR, Median	0.962	0.997
5	Full control TVAR, 70th perc.	0.636	0.14
6	Full control TVAR with shadow rate, Median	0.973	0.545
7	Full control TVAR with shadow rate, 70th perc.	0.901	0.179

Table 1: 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. Interpreting the p-values as the likelihood of H_0 to be true, there are a handful of conclusions to draw. The likelihood of policy shocks driving uncertainty stay reasonably low irrespective of specification, however, for the reverse causality case, it varies substantially. Firstly, the likelihood of uncertainty being a driver of policy shocks considerably increases when switching from the median to the 70th percentile threshold. This is likely due to the low number of observations in the regime, and thus an increased likelihood of policy action being taken to mitigate the negative impact of uncertainty. Secondly, using the Shadow rate[7] over the FFR also considerably reduces this likelihood. Given these, the superior

[6] The Linear model is added as a point of comparison for the TVAR models. It is estimated on the FFR, CPI inflation rate and GDP growth rate without further control variables. Full control TVAR represents models estimated with lagged values of the EPU index and the St. Louis FED Financial Stress Indicator added as controls.

[7] Why the Shadow rate might be a more desirable measure is further discussed in the Robustness checks of the Appendix.

specification should be a TVAR with a full set of controls estimated with the threshold level set to the median. The next subsection showcases the impulse responses estimated from this.

5.3 Extended model

Through conducting a number of robustness[8] and endogeneity tests, we arrive at a model that should grasp best how uncertainty influences the transmission of policy shocks. Figure 4 below shows the impulse responses obtained with the new specification after controlling for the level of uncertainty and financial stress.

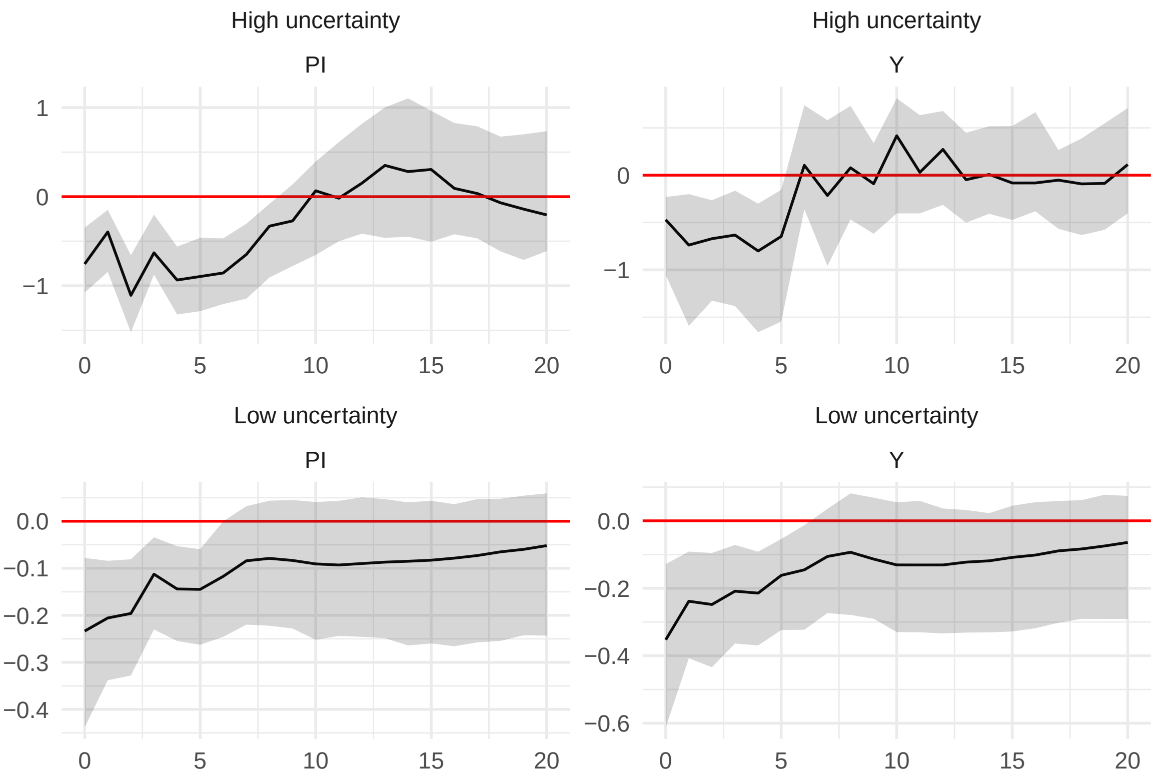

Figure 4: Regime specific impulse responses, extended model.

Notes: In the extended model, interest rates are measured by the FFR, the threshold value is set to the median of the EPU index, lagged values of the EPU and the St. Louis FED Financial Stress Indicator are added as controls.

Partially, the results of the extended model are supported from findings of the previous literature. In low uncertainty times, we see that the policy shock has a comparatively smaller advantage, however, the adjustment is slower, steadier and more persistent over

[8]Discussed in further detail in the Appendix.

the 20 quarter horizon, likely meaning that the central bank has a better control over future expectations. However, in high uncertainty times, the initial contraction in the first few quarters is larger, and dissipates more quickly. Additionally, the estimated impulse responses are much less smooth, and around 12 quarters after the intervention, a rise in inflation can be observed. These could be signs that high uncertainty times cause the variance of future expectations to be larger, in turn causing shocks to have larger impacts on one hand, while on the other causing the less persistent responses.

5.4 Narrative of uncertainty

In Baker et al. (2016), additional to the EPU index, several categorical indices are constructed[9]. To investigate how the underlying cause behind uncertainty interacts with the transmission mechanism, I replicate the estimation with each of these Categorical indices. For this estimation I use the extended model with the threshold set to the median - as seen in the previous subsection - of each Categorical EPU index.

To compare across estimates, I calculate sacrifice ratios as $SacrificeRatio = \frac{\Delta Output}{\Delta Inflation}$ for both uncertainty regimes. In essence, these capture how much output (growth) was forgone at the cost of deterring a percentage point of inflation. These ratios are calculated over a 1-year (4-quarter), 3-year (12-quarter) and 5-year (20-quarter) horizon.

I perform a further round of aggregation, and calculate the relative sacrifice ratio of high uncertainty sacrifice ratios as a fraction of low uncertainty ones. These can be interpreted as how much more (less) the cost is of deterring inflation when uncertainty is high compared to low uncertainty times. The relative sacrifice ratios can be seen below in Figure 5.

For most of these, we can observe that the relative sacrifice ratio is decreasing over time. This is no surprise, given the results seen in Figure 4, seeing as the impact of the policy shock contracts output and prices more persistently in the low regime, and dissipates quicker in the high regime. Additionally, we can observe that for a number of the Categorical EPU indices, the relative sacrifice ratio starts and stays below one, meaning that deterring inflation comes at a lower cost. However, Figure 5 also warns us that the underlying cause behind uncertainty needs to be carefully considered.

[9]Please refer to Figure 6.

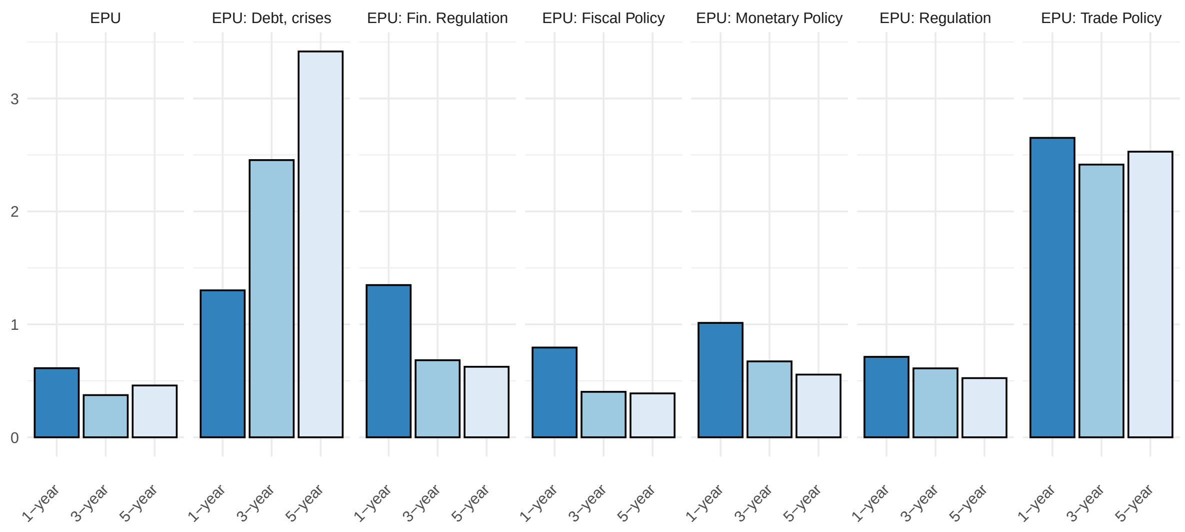

Figure 5: Sacrifice ratios.

Notes: The ratios are calculated from impulse responses obtained using the extended model.

For example, uncertainty related to sovereign debt and currency crises tells a much different story compared to what can be seen from the other indices. Here the high uncertainty sacrifice ratio is larger on the short run and increases over longer horizons. High uncertainty around debt can increase borrowing costs for the government - potentially necessitating austerity measures. An increased demand from governments for debt financing would likely crowd out private investments. A rate hike in such context would add further pressure on government debt schedules and thus enlarge the crowding out effect by either the issuance of new debt or tax increases, carrying over to future periods.

Uncertainty related to trade policy also has a considerable impact on the cost of deterring inflation, albeit this slightly decreases over time. Trade policy uncertainty is directly connected to supply chain disruptions, reflecting in a reduced export demand and higher import costs. Rate hikes can further affect this through the exchange rate channel, as an appreciating exchange rate would further contract exports and mitigate the potential excess import fees.

Uncertainty related to financial regulation also increases the cost of reducing inflation through disrupting financial markets in the short run, however the higher cost dissipates over longer horizons. Counter-intuitively, monetary policy uncertainty does not cause neither short-run, nor long-run excess cost in deterring inflation. However, it is likely an artifact of the high variance of the monetary policy uncertainty categorical index having a high variance over time, making the regime assignment almost random.

6 Conclusion

This paper studies the relationship between uncertainty and the monetary transmission mechanism in the US. A TVAR model is estimated over quarterly interest rates, inflation, and growth, also controlling for the level of uncertainty and financial stress. The EPU and its categorical indices are as threshold variables, and regime specific shocks are identified using sign restrictions. In the short run, high uncertainty is found to inflate the variance of expectations, and enlarge the impact of the interest rate shock. In low uncertainty times policymakers are able to contract demand more moderately, however more smoothly and over a more prolonged period. The narrative behind uncertainty has significant implications. While policymakers might be able to leverage the larger short-run impact through lesser sacrifice ratios, uncertainty related to debt, trade, and financial regulations make it more costly to anchor inflation.

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8 Appendix

8.1 Alternative uncertainty indices

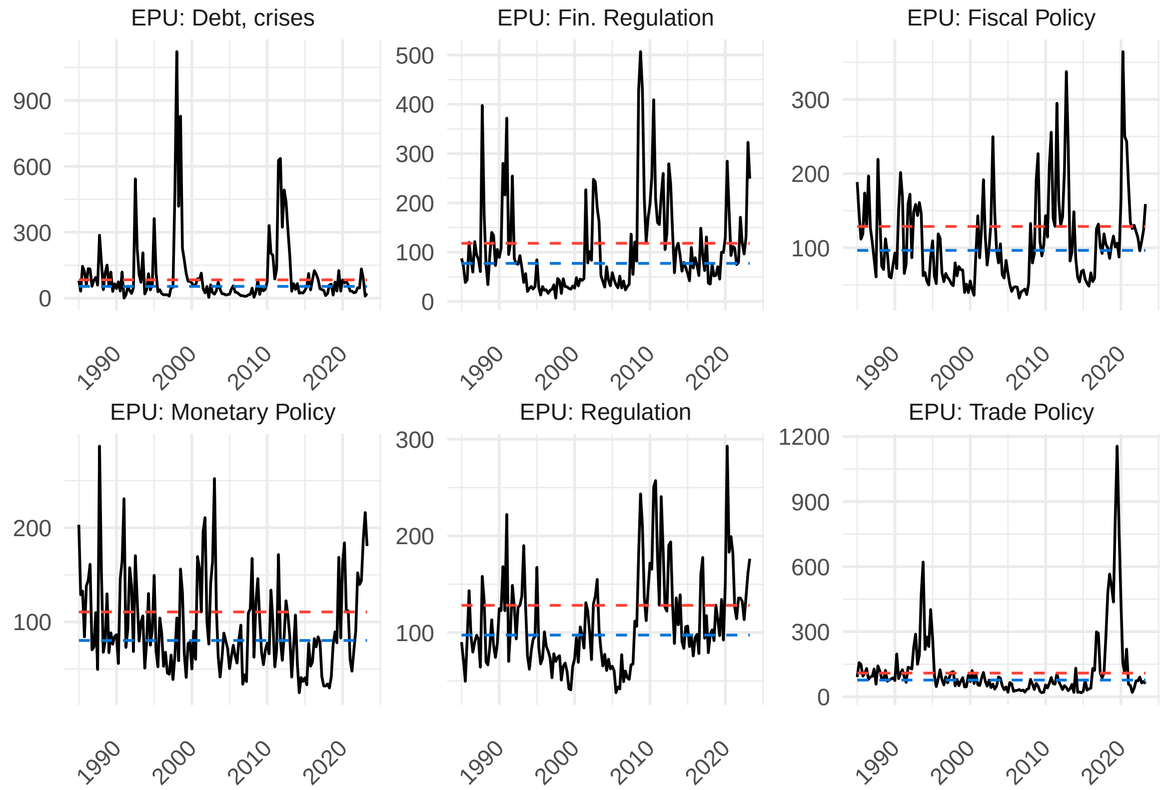

Figure 6: EPU Categorical uncertainty indices

Notes: The blue and red lines indicate the median and 70th percentile of the historical distribution respectively.

8.2 Alternative model specifications

To address robustness concerns, some further specifications are considered. As described in the Methodology section, the first round of robustness checks are done by swapping out the FFR for alternative interest rate aggregates. Additionally, a second check is done by constructing the regime indicator from the $t-1$ level of uncertainty as opposed to the t period level.

In the thrird round of robustness checks, additional variables are considered as controls in the TVAR equation. In one specification, I control for the level of uncertainty explicitly in the model, in another specification the level of financial stress, and finally both.

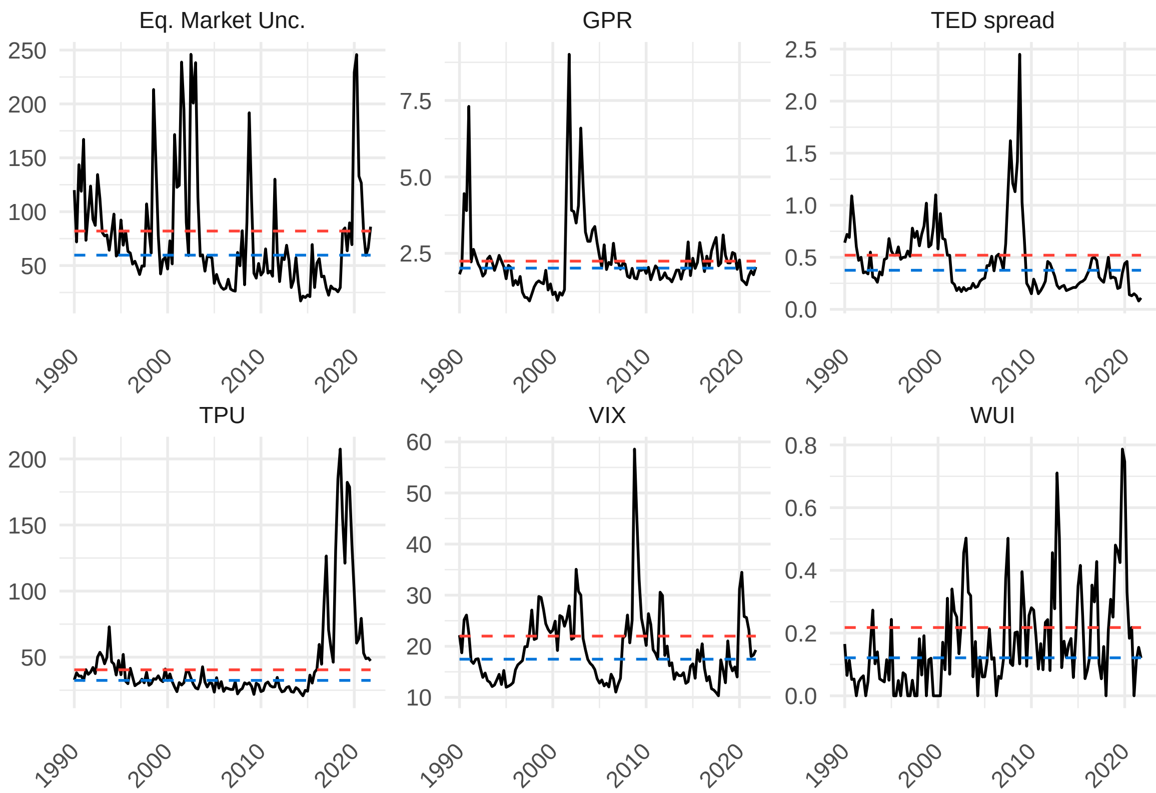

Figure 7: Additional uncertainty measures

Notes: The blue and red lines indicate the median and 70th percentile of the historical distribution respectively.

Respectively, the TVAR equation changed for each of these specifications in order are:

$$Y_t = \sum_{k=1}^{4} \Theta_{high} I(X_t \geq \mu) Y_{t-k} + \sum_{k=1}^{4} \Theta_{low} I(X_t < \mu) Y_{t-k} + \sum_{k=1}^{4} \beta X_{t-k} + \epsilon_t \quad (2)$$

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

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

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.

8.3 Robustness checks

As noted in the the Methodology section, there could be two arguments against the specification used to obtain the results seen above. One of them being using time t values of the EPU to specify the regimes, the other being that the variables should be purged of the share of variance explained by uncertainty. The former is achievable by changing Equation 1 to use X_{t-1} instead of X_t for specifying the regime indicator, while the latter is done as shown in 2. Figure 8 shows that the outcomes obtained from such alternative specifications is largely similar. Two notable differences are i) when uncertainty is controlled for and the $t-1$ value of the index is used for constructing the indicator, the high uncertainty inflation response is slightly dampened; and ii) both inflation and output responses sharpen in high uncertainty when switching from a t to a $t-1$ quarter-based indicator. These however do not cause robustness concerns and indicate that the four-quarter lag of each variable are sufficient controls, as the former of the two differences is relatively minor, while the latter is washed out of the results once the level of uncertainty is also controlled for - yielding results alike to the baseline specification of Equation 1.

As discussed in the Data section of this paper, there are alternative interest rate measures to calculate policy shocks from. Using the 1-Year Treasury Yield over the Federal Funds Rate has the benefit of - to some extent - carrying information about future expectations.

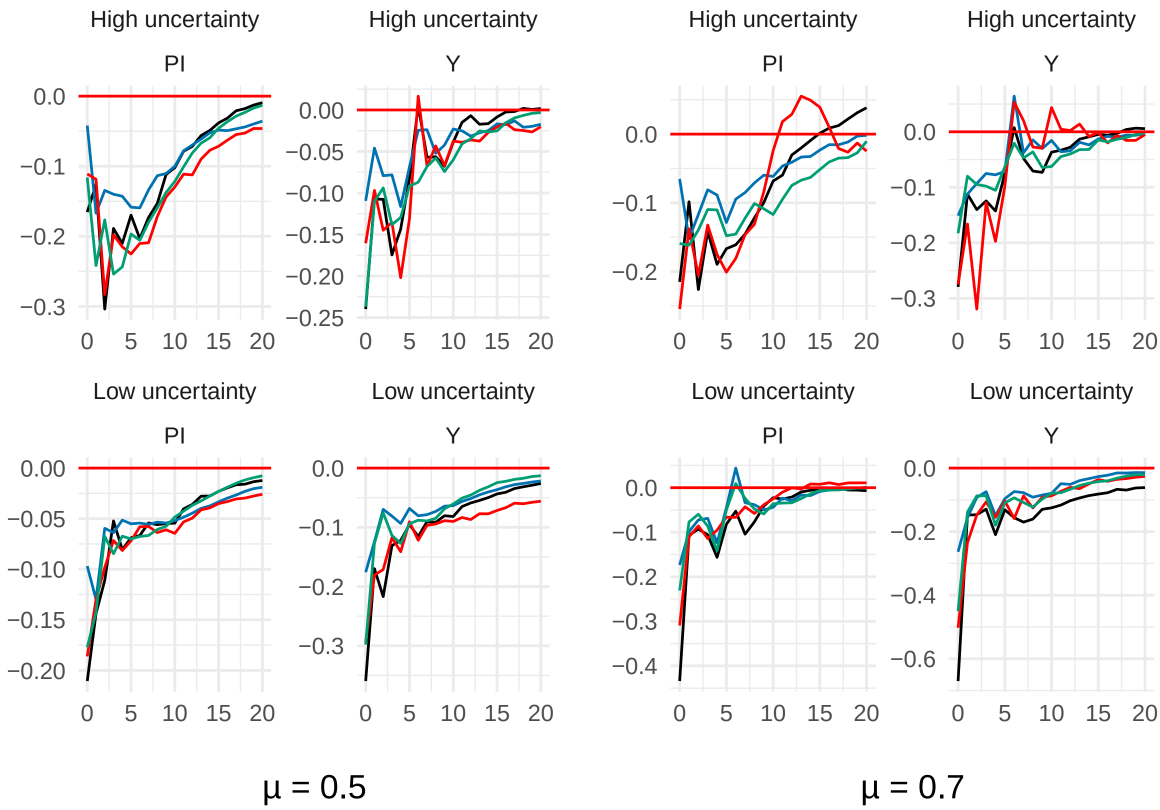

Figure 8: Influence of uncertainty

Notes: The black line shows the base specification, the green, red and blue lines show results obtained with one-quarter lag uncertainty-based regime indicator, uncertainty added as a control variable, and the combination of these two specifications respectively.

The other alternative is the Wu and Xia (2016) Shadow Rate, the added benefit of which is the additional information about implied rates of interest in times when the former two were close to the Zero-Lower-Bound. The data for the Shadow Rate is available in a shorter time span from 1990-Q1 to 2022-Q1, however the exclusion of data from before the 1990s as well as 2022 should not cause concerns.

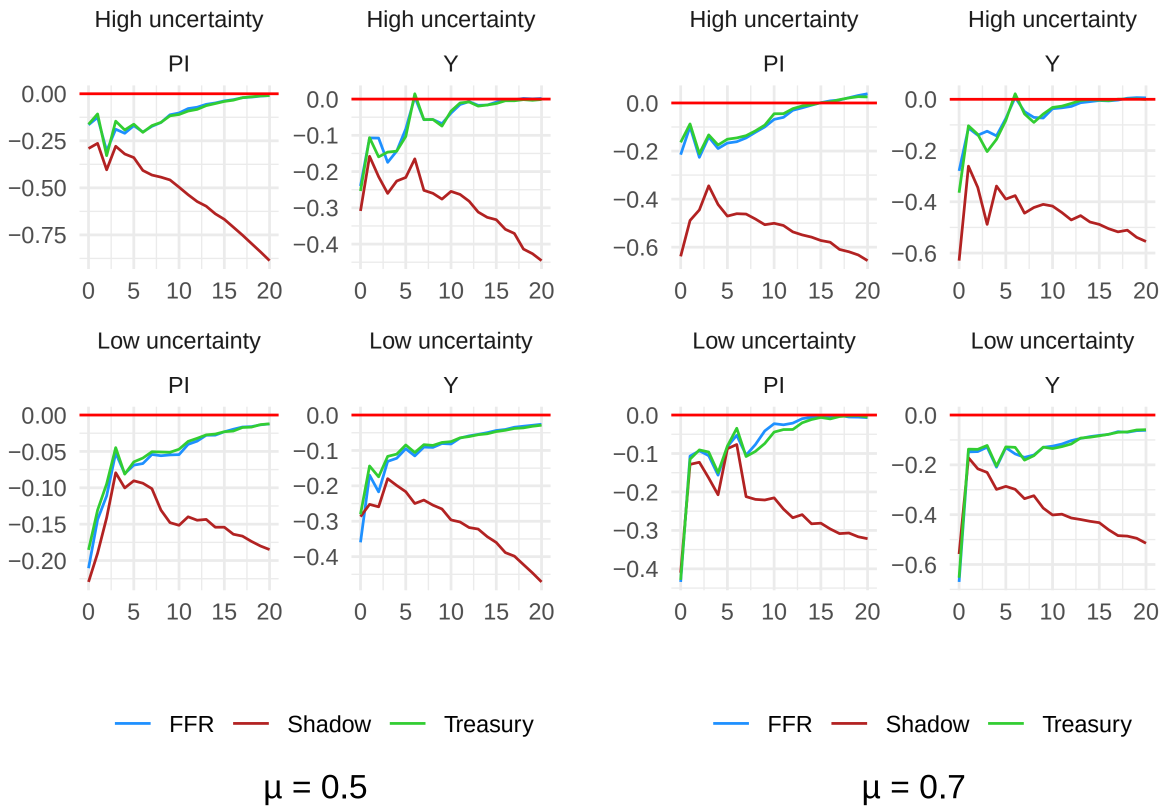

Figure 9: Policy impact calculated with different rates

As seen in Figure 9, the difference between responses obtained when the policy shock is calculated using the FFR and the 1-Year Treasury Yield show little difference, however accounting for implied rates via the Shadow Rate has considerable impact on the results. With the threshold level set to the median, both regimes responses shift downwards, and with the 70th percentile, this is only seen in high uncertainty responses. Such results do support the finding of shocks in high uncertainty times having a larger contractionary effect due to uncertainty causing an increase in volatility.

Purging the effects of financial stress is also a crucial determinant in shaping the results. As seen in Figure 10, after including the financial stress indicator as a control variable, the responses shift downwards drastically, especially in the lower regime. Switching the threshold variable from the median to the 70th percentile, the low uncertainty responses turn almost unaffected, however high regime responses show a drastically increased drop.

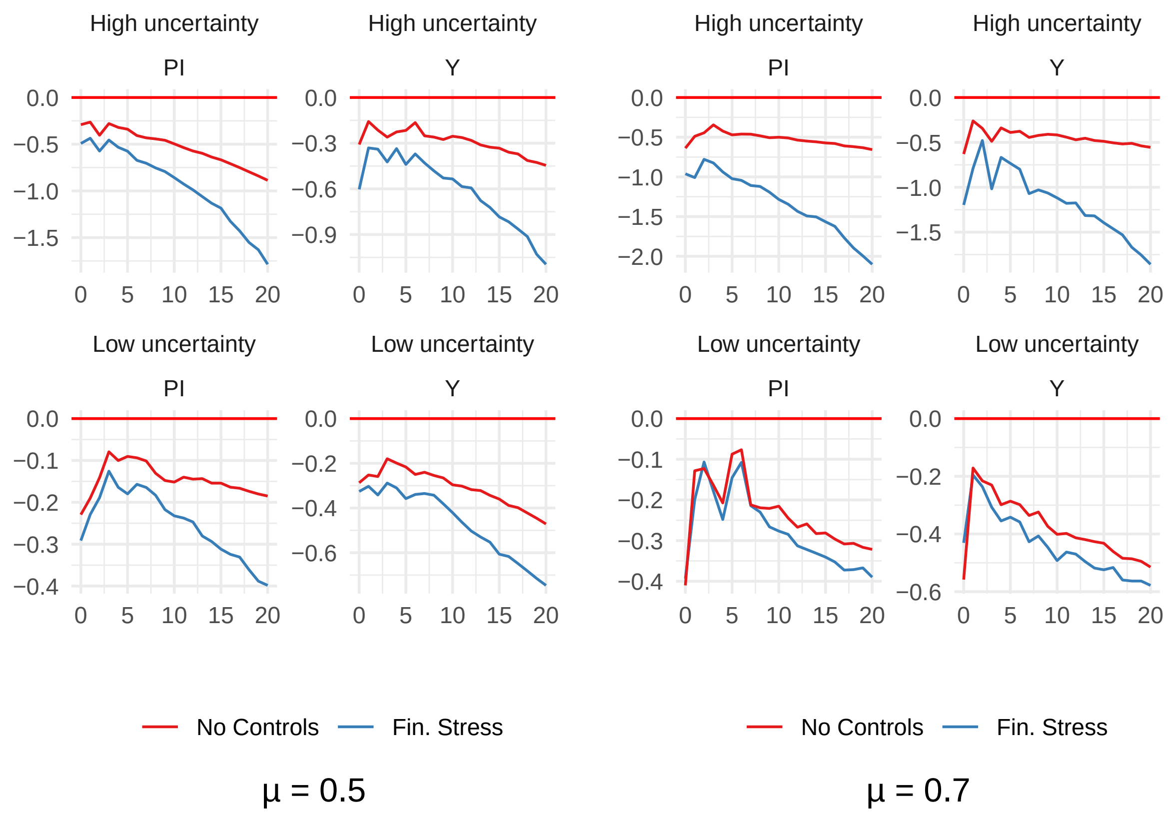

Figure 10: Financial stress versus no controls

Notes: In both the No Controls and the Fin. Stress estimations, the Shadow Rate is used to estimate policy shocks.