Monetary Policy Uncertainty and its impact on the real economy: Empirical Evidence from the Euro area

Quelhas, João

Nova School of Business and Economics

May 2022

Monetary Policy Uncertainty and its impact on the real economy: Empirical Evidence from the Euro area*

João Nuno Quelhas†

May 2022

Abstract

In this paper, we construct a proxy for uncertainty that tracks monetary policy in the Euro area by text-mining thousands of newspaper articles in the press. We calibrate a nonlinear interacted vector autoregression model to study the impact of monetary policy uncertainty on the real economy and on the effectiveness of monetary policy. We find that higher uncertainty leads to a contraction in economic activity, with a higher dampening effect in uncertain times. Uncertainty also influences how strongly movements in the policy rate affect output, investment and consumption as, in uncertain times, average responses are up to three times less powerful than in tranquil times.

Keywords: Monetary Policy, Uncertainty, Euro Area, Textual Analysis, SEIVAR Model

JEL Classification: E32; E40; E50; E52

***Acknowledgment**: I am indebted to João Valle e Azevedo, Pedro Martins, Rui Mota, Tiago Bernardino, Diogo Lima and Diogo Sá for their helpful comments and discussions. I likewise am grateful for the support from Pedro Brinca and João Duarte. I acknowledge funding from Fundação para a Ciência e a Tecnologia (UID ECO/00124/2019, UIDB/00124/2020 and Social Sciences DataLab, PINFRA/22209/2016), POR Lisboa and POR Norte (Social Sciences DataLab, PINFRA/22209/2016). All errors and omissions remain my own.

†Nova School of Business and Economics, Universidade Nova de Lisboa. Rua da Holanda 1, 2775-405 Carcavelos. Email: joao.nuno.quelhas@gmail.com

"Given uncertainty, why build a new plant, or introduce a new product? Better to pause until the smoke clears." — Olivier Blanchard

1 Introduction

Uncertainty has gained much attention from economists in the last decade as it was, arguably, one of the main drivers of the depth and duration of the Great Recession (Bloom, 2014). The European Central Bank (ECB) reported that uncertainty in the Euro area rose substantially during the Great Recession and the Sovereign Debt Crisis, and that these high levels of uncertainty potentially dampened economic activity, notably investment (ECB, 2016). Recently, the European and the world economy have been affected by unprecedented episodes of uncertainty, as shown in Figure 1 by the World Uncertainty Index (WUI).

The most recent event was the Covid-19 pandemic when uncertainty rose to levels never seen before. The unknown consequences of the health crisis made economic agents less certain about their future and, as a result, important decisions have likely been postponed. As Blanchard states[1], uncertainty leads to dramatic collapses in demand, freezing economic activity. To limit the consequences of the recession and prevent instability in the financial system, central banks promptly provided liquidity, limiting the impact of the economic breakdown. The quick decrease in the WUI, shown in the Figure 1, highlights the crucial role of policymakers in events of extreme uncertainty to mitigate that feeling and stabilize the economy.

The contemporaneous occurrence of uncertainty spikes and sharp policy interventions restarted the debate on the impacts of uncertainty on the real economy and on the transmission of monetary policy shocks. Nevertheless, the empirical work on the impact that central banks may have in these events and on how uncertainty constrains the influence of their actions is still limited.

[1]Statement by Olivier Blanchard, in an interview to The Economist, released amid the Great Recession on January 29th, 2009 (www.economist.com/finance-and-economics/2009/01/29).

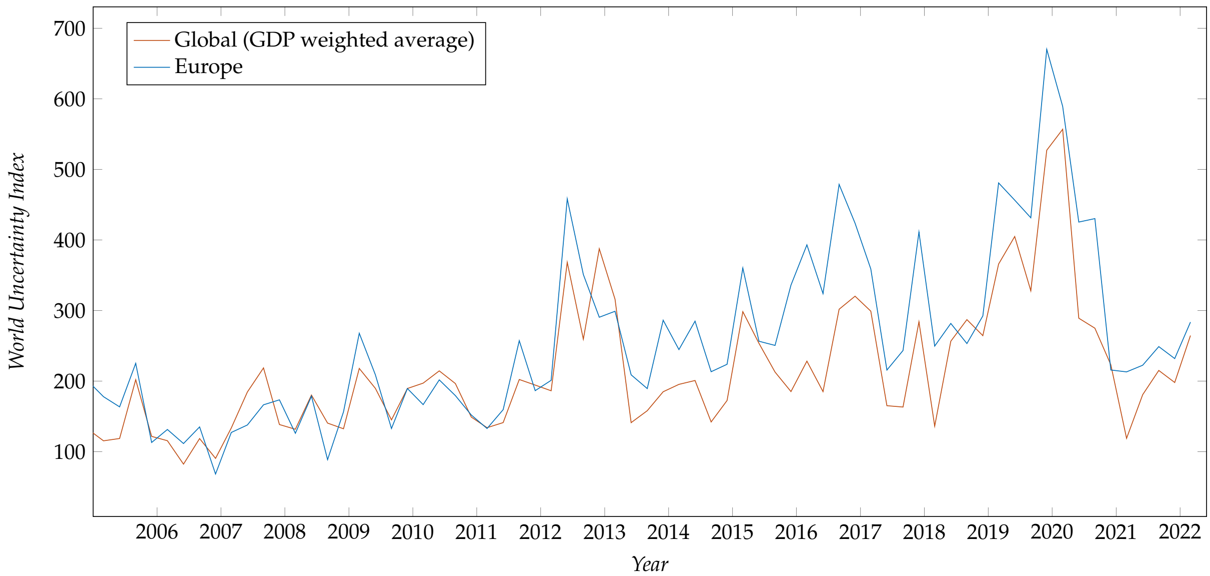

Figure 1. World Uncertainty Index (Global and Europe). Source: Bloom et al. (2018)

This paper contributes to our understanding of these questions. We build a news-based proxy of uncertainty by applying the text-based methodology of Baker et al. (2016). Then, we use the index to investigate the impact of monetary policy uncertainty on real aggregate variables and the effects of monetary policy shocks under different states of uncertainty in the Euro area.

To measure uncertainty, we construct a novel uncertainty index that tracks monetary policy: the Monetary Policy Uncertainty (MPU) index. The index is a high-frequency indicator that uses a semantic search methodology to calculate the frequency of newspaper articles reporting uncertainty about the direction of monetary policy and its consequences on the economy. To construct the index, we use textual analysis techniques to analyze thousands of articles web scrapped from three leading newspapers (Financial Times, The Wall Street Journal and The New York Times) and search for keywords related with central banking. Then, we use our measure of uncertainty to estimate a Self-Exciting Interacted Vector Autoregression (SEIVAR) model, which augments an otherwise standard VAR with an interaction term. This allows us to find the state-dependent responses of real variables to shocks in uncertainty and in monetary policy interest rates.

We find that higher monetary policy uncertainty leads to a contraction in economic activity, with a dampening effect on aggregate variables that is more than double in uncertain times. This uncertainty also influences how strongly movements in the policy rate affect output, investment, and consumption as, in uncertain times, average responses are up to three time less powerful than in tranquil times. This supports the use of nonlinear models where uncertainty is a conditioning variable and can affect policy stimuli. These findings corroborate also others studies that report evidence on the adverse effects of uncertainty.

Related literature. Over the last decade, there has been a surge in research related to uncertainty, which, as Bloom (2014) explains, had several drivers: the jump in uncertainty in 2008 and its influence in shaping the Great Recession, an increase in the availability of proxies for uncertainty and an increase in computing power that allows the study of uncertainty shocks directly in models, making economists go a step further. Our paper is related to two main streams that emerged from the literature about uncertainty: how to accurately proxy it and what are the consequences of elevated uncertainty for the economy.

The intrinsically abstract definition of uncertainty makes it a variable hard to measure. Despite the fact that there is no commonly accepted measure of uncertainty, different authors have proposed several proxies and applied them in the economic literature. These proxies, as reported in ECB (2016), may come from the frequency of articles in newspapers featuring specific keywords, surveys among forecasters, macroeconomic time series, or financial market data. Each proxy measures a specific dimension of uncertainty and empirical studies often applies them to quantify the effects on economic activity.

The pioneering work of Baker et al. (2016) led the way in using text-mining methods in newspaper articles to quantify uncertainty and risk. They developed the Economic Policy Uncertainty (EPU) index, one of the most widely used indicators. For almost 20 countries, the EPU index quantifies policy-related uncertainty by searching the archives of country-level newspapers for articles that contain terms related to EPU. The index shows the evolution of policy uncertainty since 1985 and presents spikes around events and developments associated with a high uncertainty.

To capture uncertainty related to central bank policies, Husted et al. (2020) apply the text-based methodology of Baker et al. (2016) and construct an index of monetary policy uncertainty by tracking the frequency of newspaper articles related to that topic. For the U.S., the MPU index measures the perceived uncertainty surrounding the policy decisions of the Federal Reserve Board and their consequences. The authors assess the accuracy of their construction approach with a human reading of a fraction of the articles selected. The narrow word search used for this MPU index gives rise to an index that isolates MPU relative to the broader word search used for the EPU index, resulting in a more restricted measure of uncertainty. Husted et al. (2020) show that U.S. output and inflation fall and credit costs become tighter following shocks that increase the MPU index. In addition to the U.S. index, Husted et al. (2016) extend the work to Canada, Euro area, Japan, and United Kingdom between 1999 and 2016.[2]

Besides this category of proxies, one can also find survey-based indices. Economic surveys are useful as they give a picture about survey participants' probabilistic assessment of future economic outcomes. There are econometric measures of macroeconomic uncertainty like the one presented by Jurado et al. (2015) that construct an index by extracting the common factors of hundreds individual uncertainty measures. This type of proxies differs from the previous ones as they are obtained with econometric-based methods rather than sentiment-based ones as news or forecasts. Finally, there are also asset-market-based measures computed from instruments traded on the financial markets. One of them is the VSTOXX that measures the 30-day implied volatility of the EuroStoxx50 index options and reflects the financial market investors' sentiment.

The other stream of literature related to our paper focuses on the economic impacts of uncertainty. Back in 1937, Keynes (1937) shed lights about the detrimental impact of uncertainty in real activity by suggesting that investment is a volatile component of aggregate demand because it depends greatly on views

[2]Besides monetary policy, other policy dimensions have been studied (Caldara et al., 2019, 2021; Azzimonti, 2018; Bloom et al., 2018). Recent studies build upon the news-based measures and incorporate machine learning techniques to summarize news coverage. See, for instance, Azqueta-Gavaldon et al. (2020).

about future events, which are subject to uncertainty. More recently, the attention has been reignited by the highly influential paper from Bloom (2009). In a model of investment with fixed adjustment costs, the region of inaction – in which firms find it optimal not to adjust their input levels – varies according to the level of time-varying uncertainty. In periods of high uncertainty, more firms choose to "wait-and-see", voluntarily putting their investments on hold. When uncertainty dissipates, many firms who postponed their factor adjustments find themselves far from their optimal levels and carry out the adjustment required to relieve their pent-up factor demand. Other reasons for a depressing effect of uncertainty include precautionary spending cutbacks by households that directly affect the level of consumer spending in uncertain times (Coibion et al., 2021; Arne and Largent, 2016; Ghirelli et al., 2021).

Moreover, there are also theoretical propositions by Bernanke (1983), Dixit and Pindyck (1994), and Bloom (2014) related with the negative impact of uncertainty on the effectiveness of monetary policy. The hypothesis presented is that elevated uncertainty motivates agents to postpone decisions awaiting better information, and this cautiousness makes them less responsive to changes in interest rates.

Bloom (2009) uses a VAR to identify uncertainty shocks and study their macroeconomic effects. The author estimates that volatility shocks generate a short-run drop in industrial production of 1%, lasting about 6 months, and a longer-run overshoot.[3] Several studies have reached comparable conclusions using several types of proxies to quantify uncertainty.[4] Research on news-based indices supports these findings as it concludes that economic uncertainty has detrimental effects on the economy and asset prices. For example, using firm-level data, researchers have shown that policy uncertainty seems to reduce investment and employment (Baker et al., 2016). Moreover, high levels of the EPU index are expected to lower investment, output, and employment in the

[3] The stock-market volatility indicator is constructed to take a value of 1 for each of the shocks identified by the author between June 1962 and June 2008. The 17 shocks were explicitly chosen as those events when the peak of Hodrick-Prescott detrended volatility level rose significantly above the mean.

[4] See, for instance, Alexopoulos et al. (2009), Caggiano et al. (2014), Nodari et al. (2014) and Leduc et al. (2016).

U.S. (Bachmann et al., 2013). Caggiano et al. (2017) implemented a nonlinear Interacted VAR (IVAR) and conclude that the contractionary effects of uncertainty shocks are statistically more significant when the zero lower bound is binding in the U.S., with differences that are economically important.

Notably, there has been little work on the policy-effectiveness hypothesis. One recent study from Aastveit et al. (2013) considers several measures of U.S. economic uncertainty and estimates their interaction effects with monetary policy shocks as identified through an IVAR methodology. They find that monetary policy shocks have considerably weaker effects on economic activity when uncertainty is high. In the same direction, Pellegrino (2021) assesses whether the real effects of monetary policy shocks depend on the level of uncertainty by estimating a nonlinear IVAR model where uncertainty is modeled endogenously. The author finds that monetary policy shocks are about 50% – 75% more powerful during tranquil than during firm- and macro-level uncertain times in the U.S.. In another study following a similar methodological approach, Pellegrino (2018) reaches the same conclusions when studying whether the effectiveness of monetary policy shocks in the Euro area is influenced by the level of financial uncertainty.

Roadmap. The rest of the article is organized as follows. Section 2 explains how we build our uncertainty measure and why it is relevant to our research question. Section 3 presents the empirical strategy followed. Section 4 describes the main results and robustness checks. Section 5 concludes with final remarks.

2 Measuring Uncertainty

To proxy uncertainty, we construct a novel index of monetary policy uncertainty in the Euro area by text-mining thousands of newspaper articles in the press. We use a semantic search methodology to compute the frequency of articles reporting uncertainty about the direction of monetary policy and its consequences on the economy. With this, we aim to capture uncertainty about what monetary policies will be taken, how they will be put in place and when, and the economic effects of those actions (or inaction). Our measure captures short-term concerns, like whether the ECB will adjust its policy rate, and longer-term worries, such as how the ECB would react if inflation picks up, as reflected in newspaper articles.

To evaluate the sentiment of each article, we use textual analysis techniques and follow the algorithm of Husted et al. (2016). We describe the construction of our MPU index and, then, as our approach may raise potential concerns about newspaper reliability, accuracy, and consistency, we evaluate the contents of the filtered articles and compare the index with several proxies of uncertainty.

2.1 Construction of the Index

The methodology that we follow in constructing the MPU index tracks the frequency of newspaper articles related to uncertainty surrounding central banking policy. Using thousands of articles from three leading newspapers that cover international economic and financial news – Financial Times, The Wall Street Journal, and The New York Times –, we search for articles that contain:

(i) "uncertainty" or "uncertain";

(ii) "monetary policy", "interest rate", "policy rate", "asset purchase" or "EONIA rate";

(iii) "European Central Bank", "ECB" or "Governing Council".

We count the number of articles in each newspaper containing at least one search term for each criterion.[5] We repeat this for 18 years from May 1st of 2005 until April 30th of 2022, as this time frame corresponds to the availability of online articles on the newspapers' websites.

Overall, over 57 000 articles were web scrapped and analyzed for the considered time frame, as detailed in Appendix A.1. To filter the news, we used the automated text-search results from each newspaper and, to collect them, a visual web data extraction software.

[5]Further details about the selection of newspapers and the definition of criteria used are presented in Appendix B.

The distribution of the number of articles filtered shows that the coverage of monetary policy has evolved differently within each newspaper and across them. By visual inspection, we observe that the Financial Times and The Wall Street Journal cover more articles regarding the ECB during the Sovereign Debt Crisis and the Brexit referendum, while The New York Times has a greater number of articles during the Great Recession. The Covid-19 pandemic crisis is reflected in quick but considerable spikes recorded in February and March of 2020.

When constructing the index, we control this changing volume of articles over time and the fact that some newspapers have a higher coverage of monetary policy than others. As such, we compute the ratio, for each day, between the raw count of filtered articles and the total number of articles that only fulfill the third criteria. Then, the share of articles related to monetary policy uncertainty is normalized to have one standard deviation over the entire period. This normalization is pertinent because it allows us to aggregate the individual indices from the three newspapers that mention uncertainty with different frequencies. In the end, the individual indices, presented in Appendix A.2, are aggregated by summing and scaling them to have a mean of 100. We construct the MPU index at monthly and quarterly frequencies from May 2005 until May 2022.[6]

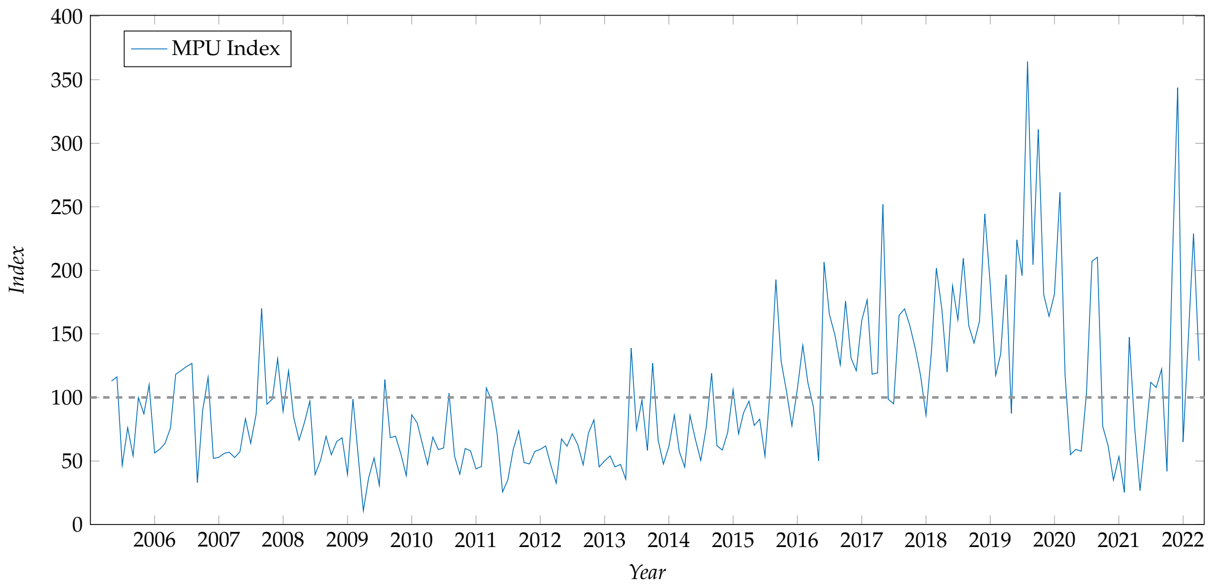

Figure 2. Monetary Policy Uncertainty index for the Euro area. Source: author's calculations.

[6]More information about the construction of the index is presented in Appendix C.

Figure 2 shows the constructed monthly time series for the Euro area. The values above 100 represent higher-than-average uncertainty generated by specific events in which the actions of the ECB and the following consequences for the economy were uncertain. Notably, the index spikes during times of turmoil that affected the economy and, consequently, the direction of monetary policy. The highlighted spikes are indicative of the ability of the index to identify the $ex-ante$ and $ex-post$ uncertainty levels relative to important macroeconomic events.

2.2 Information Content of the Index

A human reading of a sample of the filtered articles identifies how typically the media cite uncertainties related to monetary policies. Firstly, newspapers mention how uncertainty may affect the actions of the ECB. As an example, we have: "Some ECB officials have been hoping that the bank will provide greater clarity about the way ahead by adjusting its forward guidance as soon as at its next meeting in June. But, because of the recent wave of uncertainty, the council could delay any change in the message until July.". Secondly, newspapers usually quote policymakers, economists, political leaders, or industry experts who mention uncertainty concerning monetary policy in their interviews or speeches. For example, we have: "Mario Draghi struck a downbeat tone, warning that the 'persistence of uncertainties' was continuing to weigh on the Eurozone economy and that the governing council stands ready to adjust all of its instruments". Thirdly, the media also discusses the consequences of high uncertainty about the policy of the ECB for the economy and the financial markets. For instance, we retrieved: "Until recently, the only reason long-term inflation expectations looked close enough to the target was because of higher uncertainty, not because the expected future rate was itself close to target". Finally, newspapers also identity uncertainties around the world that may affect the direction of monetary policy, as in this case: "Mr. Constâncio, who sits on the ECB governing council that sets interest rates, did not disclose details as to what the bank could do if the UK's decision triggered a broader wave of uncertainty across Europe.".

The human audit performed suggests that the index is capable of extracting relevant information from a universe of newspaper articles focusing on the perceived uncertainty around monetary policy.

One of the main advantages of news-based uncertainty measures is that they proxy the perception of larger and different population segments compared to other indicators. Husted et al. (2020) explain that news-based approaches assume that newspapers reflect readership, influencing and shaping public opinion, possibly concentrated on educated members, who are likely to be business decision-makers. News-based indices are also more extensive in capturing a broader dimension of uncertainty. They are available for more countries and for periods in which financial market or survey data is not available. Lastly, measuring economic uncertainty based on coverage frequency yields a more precise picture of uncertainty in times of unconventional monetary policy compared to the market-volatility indices, as explained by Baker et al. (2016). As a caveat, we point out that this type of proxies does not distinguish between uncertainty about domestic and external policies, being highly exposed to spillover effects. In addition, even though the selection of newspapers covers the mass-market tabloids, it might not represent the complete media coverage. We conclude that our MPU index sustains a lot of potential in measuring certain dimensions of uncertainty, but its drawbacks should also be considered.

2.3 Benchmark of the Index

We compare the evolution of the index with three related indices, as shown in Appendix A.3. First, we present our MPU index and the one built by Husted et al. (2016) for the Euro area from 1999 until 2016. Even though the methodology behind the construction of the indices is very close, there are two main differences. Husted et al. (2016) uses the historical archives of the same newspapers and can go further in the past while our work is restricted to the online version of them and, thus, we only have data from 2005 onwards. We use different criteria for the selection of articles because instead of "refinancing tender" (which in our analysis yielded a residual amount of articles), we use "asset purchase" (which returned a considerable amount of articles). As expected, they have a significant correlation during the overlapping period, at 0.73. We observe that the critical spikes in uncertainty coincide, and its level is very close for most of the period.

We also compare our indicator with the broader EPU index for the Euro area. This EPU index developed by Baker et al. (2016) captures uncertainty related to general economic policy. It counts the frequency of articles containing the words "uncertain" or "uncertainty" and "economy" or "economics", and one of a number of policy words (like "deficit" or "regulation") in the two leading newspapers from France, Germany, Italy, and Spain. This index, like ours, tends to increase during recession periods, but it also rises sharply ahead of different events like the Brexit referendum in the United Kingdom. The correlation between the two is at 0.42, which means that up to almost half of economic policies uncertainty may be attributed specifically to monetary policies.

Finally, we compare our news-based approach with a metric of financial market uncertainty. The VSTOXX measures the 30-day implied volatility of the EuroStoxx50 index options and reflects the investors' sentiment and overall financial uncertainty. The volatility of financial markets rises steeply during recession periods, as in 2008 and 2012. On the other hand, it remained subdued during unconventional monetary policy periods, especially between 2016 and 2019. This contrasts with our MPU index, which unveils higher uncertainty in the economy when interest rates were at the zero lower bound. The correlation between them is at -0.23, meaning that, as argued, different dimensions of uncertainty are measured by each of them.

The human audit and the comparison with other proxies of uncertainty confirm that our MPU index can provide an appropriate indicator of monetary policy uncertainty given that it is forward-looking and may reflect real-time expectations about the economy transmitted to an influential segment of the population, making it valuable for the purpose of this study.

3 Empirical Strategy

We use the monetary policy uncertainty index in a nonlinear, or self-exciting, interacted VAR (SEIVAR) model and empirically study the impact of monetary policy uncertainty on the real economy and the effectiveness of monetary policy. This strategy allows us to find the response functions of our vector of variables to shocks in uncertainty and in the monetary policy rate.

3.1 Model Specification and Statistical Motivation

The SEIVAR model augments the standard linear VAR with an interaction term, that will comprise two endogenous variables: the monetary policy interest rate and the monetary policy uncertainty index. The latter serves as a conditioning variable, allowing us to understand how the effects of uncertainty differ across different states of the economy. In addition to these, the vector of endogenous variables also considers measures of prices and real activity. Our work relates with the one by Pellegrino (2021) which focuses on the real effects of monetary policy shocks and their dependence on the level of financial uncertainty.

The estimated SEIVAR is the following:

$$\mathbf{Y}_t = \alpha + \gamma\, \mathbf{t} + \sum_{j=1}^{L} \mathbf{A}_j\, \mathbf{Y}_{t\,-j} + \left[\sum_{j=1}^{L} \mathbf{c}_j\, (i_{t\,-j} \;\times unc_{t\,-j}) \right] +\; \mathbf{u}_t \tag{1}$$

$$E\ \left(\mathbf{u}_t\, \mathbf{u}_t'\right) = \Omega, \tag{2}$$

where $\mathbf{Y}_t$ is the (n x 1) vector of endogenous variables, α is the (n x 1) vector of constant terms, γ is the (n x 1) vector of slope coefficients for the linear time trend $\mathbf{t}$, $\mathbf{A}_j$ is the (n x n) matrix of coefficients, and $\mathbf{u}_t$ is the (n x 1) vector of error terms, whose variance-covariance (VCV) matrix is Ω. The interaction term is defined inside the brackets and includes a (n x 1) vector of coefficients $\mathbf{c}_j$, the policy rate, $i_{t\,-j}$, and our measure of uncertainty, $unc_{t\,-j}$.

The model is estimated by Ordinary Least Squares. Following Ivanov and Kilian (2005), we select the number of lags as suggested by the Hannan-Quinn criterion. As a result, we use $L = 1$ in our model, ensuring that the residuals are not serially correlated. To assess whether the inclusion of interaction effects is significant, we test the overall exclusion of the terms in our model. We compute a likelihood-ratio test leading us to reject the null hypothesis of linearity in favor of the alternative, which result motivates the application of our SEIVAR model.

The choice of this model specification is also based on its several advantages and the fact that it matches the purpose of our research question. It directly captures the nonlinearity we are interested in, allowing the interaction between the monetary policy instrument and the uncertainty indicator. Moreover, it does not require identifying thresholds or calibrating transition functions. It is also estimated in the whole sample as it does not need any regime to be imposed prior to estimation, which avoids the problem of lack of freedom to find consistent empirical responses in different states. For these reasons, we found the SEIVAR model adequate for our objectives and with advantages over alternative nonlinear specifications that also employ an observable variable like the Threshold VAR or the Smooth Transition VAR.

3.2 Identification of the Shocks

The identification of shocks from the vector of reduced-form residuals is done by adopting the short-run restrictions that result from the Cholesky decomposition, a conventional strategy used in the related literature.[7]

The vector of endogenous variables is ordered in the following way:

$$\mathbf{Y}_t = [p_t, gdp_t,\ inv_t,\ cons_t,\ i_t,\ unc_t]', \tag{3}$$

where we have, respectively, the price index, GDP, investment, consumption, the policy interest rate, and the uncertainty proxy. While the policy rate is allowed to react to the price index and to the real variables contemporaneously, the inverse does not happen as these variables are not allowed to react on-impact to policy

[7]See, for instance, Pellegrino (2018), Aastveit et al. (2013) and Caldara et al. (2021).

rate changes, according to mainstream literature.[8] We position our uncertainty index in the last place since, by its nature, it is more reasonable to assume it reacts instantaneously to all the variables considered. The degree of endogeneity is, in a sense, maximized in this case, yet the results are robust to modeling uncertainty as the first variable of the vector. The treatment of uncertainty as an endogenous variable in a nonlinear VAR is essential to more appropriately estimate the real effects of monetary policy shocks. Several related studies – Aastveit et al. (2013), Eickmeier et al. (2016), Castelnuovo and Pellegrino (2018) – treat uncertainty as an exogenous regressor. However, Pellegrino (2021) found that monetary policy effectiveness is erroneously found much more powerful in the case of exogenous uncertainty as a result of endogenous uncertainty channels that are not captured by conditionally-linear responses (which are computed by assuming uncertainty to be exogenous, i.e., fixed and constant after the shock).

3.3 Generalized Impulse Response Functions

The inclusion of uncertainty in the vector of endogenous variables is relevant for the computation of the impulse response functions (IRFs) as we are interested in having responses conditional on high and low levels of uncertainty. Also, without accounting for endogenous movements of uncertainty, we could have biased responses as the feedbacks from such movements on the dynamics of the economy would be disregarded. To obtain consistent estimates of the empirical responses from nonlinear models in the presence of an endogenous conditioning variable, we compute Generalized Impulse Response Functions (GIRFs) à la Koop et al. (1996), accounting for an orthogonal structural shock described in Kilian and Vigfusson (2011), as suggested by Pellegrino (2021).

The GIRFs consider that the state of the system is not permanent and will vary endogenously after the shock. As such, they return nonlinear empirical responses that depend on the conditions of the system at the moment of the shock, as well as on the sign and magnitude of this same shock.

[8] See, for instance, Christiano et al. (1999) and Stock and Watson (2001).

In theory, the GIRF at horizon h of the vector Y to a shock in date t, δ_t, computed conditional on an initial history (or initial conditions), $\varpi_{t-1} = \{Y_{t-1}, \ldots, Y_{t-L}\}$, is given by the following difference of conditional expectations between shocked and non-shocked paths of **Y**:

$$GIRF_{Y,t}\Big(h, \delta_t, \varpi_{t-1}\Big) = E\Big[Y_{t+h}|\delta_t, \varpi_{t-1}\Big] - E\Big[Y_{t+h}|\varpi_{t-1}\Big]. \tag{4}$$

We will have as many history-dependent GIRFs referring to a generic initial quarter $t-1$ as quarters in the estimation sample. The corresponding GIRFs will then be averaged, for each horizon, over a particular subset of initial conditions of interest. This means that our state-dependent GIRFs will reflect the average response of the economy to a shock when it is in a given state. Our study considers two different states consistent with the literature, particularly Bloom (2007). We assume that one of the states corresponds to tranquil times and is characterized by initial quarters with uncertainty around the first decile of its empirical distribution. The opposing state corresponds to uncertain times and is linked with initial quarters with uncertainty around its ninth decile. To ensure that we have a significant number of responses in each state, we define a tolerance band of five percentiles centred around the top and bottom deciles.

Theoretically, our state-dependent GIRFs are:

$$GIRF_{Y,t}\Big(h, \delta_t, \Omega_{t-1}^{uncertain\ times}\Big) = E\Big[GIRF_{Y,t}\Big(h, \delta_t, \varpi_{t-1}, \Omega_{t-1}^{uncertain\ times}\Big)\Big], \tag{5}$$

$$GIRF_{Y,t}\left(h, \delta_t, \Omega_{t-1}^{tranquil\ times}\right) = E\left[GIRF_{Y,t}\left(h, \delta_t, \varpi_{t-1}, \Omega_{t-1}^{tranquil\ times}\right)\right], \tag{6}$$

where Ω_{t-1}^{i} denotes the set of histories that we have in each regime.[9]

The algorithm for the simulation of our state-dependent GIRFs was computed resorting to the IVAR Toolbox provided in Pellegrino (2021).[10]

[9]More information about the algorithm used to construct GIRFs is presented in Appendix D.
[10]https://sites.google.com/site/giovannipellegrinopg/home/research

3.4 Macroeconomic Variables

Our vector of observables was chosen to balance between a parsimonious and an informative model, because, on one hand, we are looking to maximize the degrees of freedom of the econometric model in order to reinforce the precision of our impulse responses. On the other hand, we must include a vector of variables that is representative enough to quantify the effects on the real economy.

For these reasons, we built a six-variable SEIVAR model. The variables included are: implicit GDP deflator (*Price*), real gross domestic product (*GDP*); real gross private domestic investment (*Investment*); real personal consumption expenditures (*Consumption*); the EONIA rate and the shadow rate by Wu and Xia (2016) (*Policy Rate*), and the Monetary Policy Uncertainty index (*Uncertainty*). For the robustness checks, we include the EPU index by Baker et al. (2016) (*EPU*) and the Eurostoxx50 implied volatility index (*V2X*). These allow us to ensure that we are analysing the effects of the type of uncertainty we aim to measure.

We estimate the model over the period from the start of the Euro area to the 2^{nd} quarter of 2021 with quarterly data. The variables that track the real activity (i.e., the first four) were transformed by applying a natural logarithm and multiplying by 100.[11] This means that the obtained impulse responses correspond to percent deviations from the trend. The specification of the model in (log-)levels allows for implicit cointegrating relationships in the data (Sims et al., 1990).

Unit root tests suggest that GDP, investment, and consumption are not stationary. The usual procedure to deal with this type of variables is considering it in first differences. Yet, as we are interested in the nature of relationships between variables and not on the specific parameter estimates of each equation, estimating the SEIVAR with variables in non-stationary forms still gives important insights, as suggested by Sims (1980). This methodology is followed by similar literature, such as Pellegrino (2021) and Aastveit et al. (2013). In this application, the possible cointegration between GDP, investment and consumption also advises against a VAR in differences.

[11] More information about variables used and their transformations is shown in Appendix E.

Importantly, we consider the commonly used shadow rate by Wu and Xia (2016) as the indicator of monetary policy stance for the zero lower bound period as it is relevant to have a measure that overcomes the lower bound constraint and incorporates the effects of unconventional measures of the ECB taken in recent years.[12] The shadow rate can proxy unconventional monetary policy at the zero lower bound as shown by the authors and be interpreted as the hypothetical nominal interest rate that would prevail in the absence of the lower bound that leads individuals to replace holding of interest-bearing assets with cash, as Iskrev et al. (2021) explain.[13] Wu and Xia (2016) show that unconventional monetary policy has been more effective, on average, than conventional monetary policy shocks. Thus, using a measure like the EONIA rate for the entire period that would not account for the first type of policies would lead to misleading results.

4 Results

We extract from the estimation the state-conditional response functions of the real variables for the uncertainty and monetary policy shocks. We present the empirical quantification of the average effects in tranquil versus uncertain times and then turn to the statistical difference between them.

4.1 Uncertainty Shock

Figure 3 presents the point estimates for the state-conditional GIRFs of GDP, investment, and consumption after a shock on uncertainty together with the impulse response functions obtained with a linear VAR rooted in our model.

First, we find that an unexpected positive shock of 1 standard deviation in uncertainty leads to significant decreases of the three real variables both when the economy finds itself in states of lower and higher levels of uncertainty. The negative effect, though, is stronger when uncertainty is already high. The

[12] See, for instance, Pellegrino (2021).

[13] The estimates are based on term structure models where the lower bound is imposed through a nonlinearity that could be equivalent to a call option on bonds and use the AAA-government bond yield curve as reference.

effect on real GDP is −0.2% in tranquil times and more than double (−0.55%) in uncertain times. These effects on output result from the response of its components, particularly investment and consumption, which have a similar behavior after the shock. Investment has a more evident response given that it is by nature a more volatile variable than consumption. For this reason, we see that the peak response of investment is two times lower than the peak response of consumption in both states. From the responses over four years, we conclude that the persistence of the effects from this shock is also longer in uncertain times.

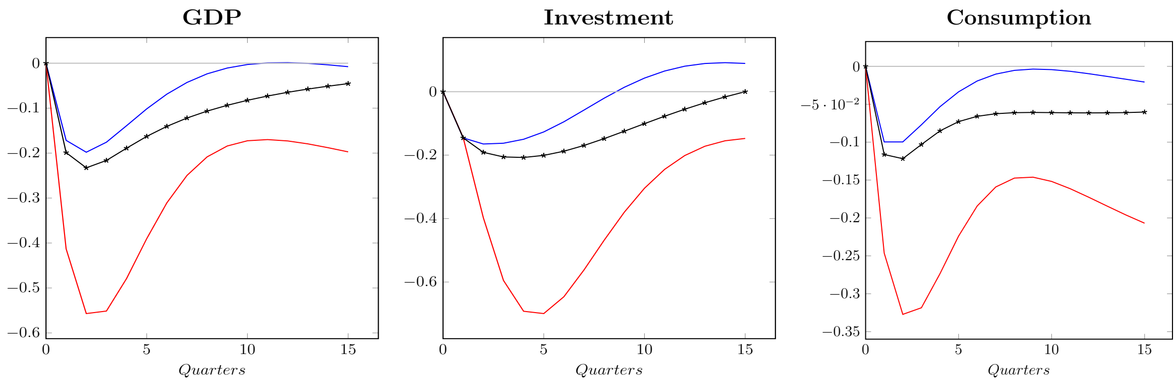

Figure 3. Uncertain vs. tranquil times state-conditional GIRFs for output, investment, and consumption and linear responses, in percentage points (shock: 1 standard deviation unexpected increase in uncertainty). Solid blue (red) line: state-conditional GIRF for tranquil (uncertain) times. Black starred line: IRF from the nested linear VAR.

Second, we observe that the linear responses for the three variables are within the state-conditional GIRFs, meaning that a linear VAR would likely capture the average effect of an uncertainty shock. These responses would underestimate the impact of the shock in uncertain times and overestimate in tranquil times. This confirms the relevance of analyzing nonlinear effects. Appendix A.4 shows the state-dependent evidence for the remaining variables in the model. We highlight that prices decrease in uncertain times, which may be caused by the downturn of economic activity. Moreover, uncertainty leads to expansionary policies as the policy rate decreases after the shock. We see that when uncertainty increases, it mean reverts after three to four quarters.

To examine whether these responses are statistically different between uncertain and tranquil states, we follow a method from Pellegrino (2021) and perform a test.[14] The computation of the test is built on the distribution of the difference between state-conditional responses stemming from the bootstrap procedures and considers the correlation between estimated impulse responses. Figure 4 reports the estimated difference and the corresponding 90% confidence band for the real variables. We can see that the difference is negative and statistically significant for more than two years.

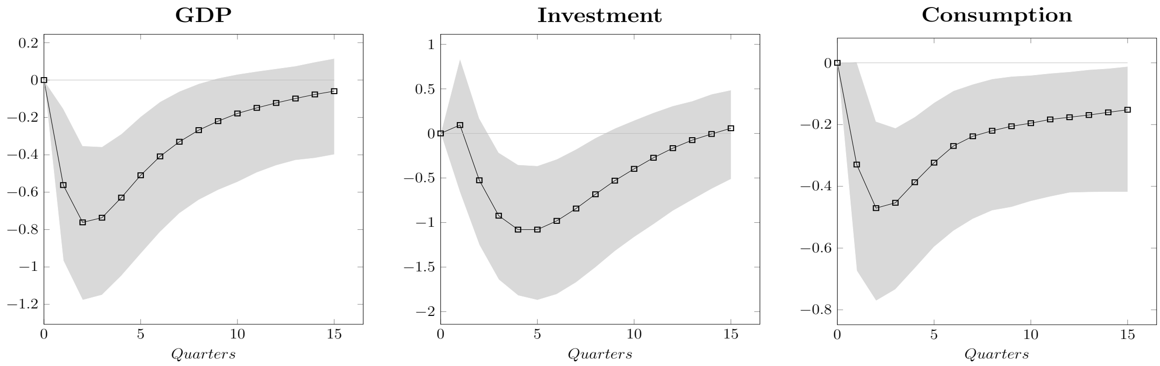

Figure 4. Difference of state-conditional GIRFs between uncertain and tranquil times for a shock in uncertainty, in percentage points. Black squared line: difference between estimated state-conditional GIRFs (uncertain times conditional GIRF minus tranquil times conditional GIRF). Gray area: 90% confidence band.

4.2 Monetary Policy Shock

Figure 5 presents the point estimates for the state-conditional GIRFs of GDP, investment, and consumption after a 25 basis points unexpected decrease in the policy rate together with IRFs obtained with a linear VAR rooted in our model.

The GIRFs suggest that negative monetary policy shocks are, on average, less effective during uncertain times. Focusing on peak reactions, real GDP reacts on average three times more during tranquil times. When the economy goes through the latter, monetary policy is able to boost the output of the economy by 0.27% above the trend, while the same policy would only increase output by 0.11% if uncertainty was on its higher deciles. Second, the persistence of the shock is different between states as, according to the cumulative responses, the increase in real activity is also higher for tranquil times. During the latter, investment and consumption increase by a maximum of around 0.8% and 0.17%, respectively.

[14]The test statistic for the interaction effect, detailed in Appendix F is relevant as the impulse responses for uncertain and tranquil times are correlated, so the confidence bands around each response alone give a distorted impression.

During uncertain times, instead, their maximum reactions are roughly between three-fourths and half of those during tranquil times. These results show that higher uncertainty influences how strongly movements in the policy rate affect the motive to invest and consume, suggesting not only that monetary policy is less effective in economic phases characterized by high uncertainty, but also that it is so in an economically important manner.

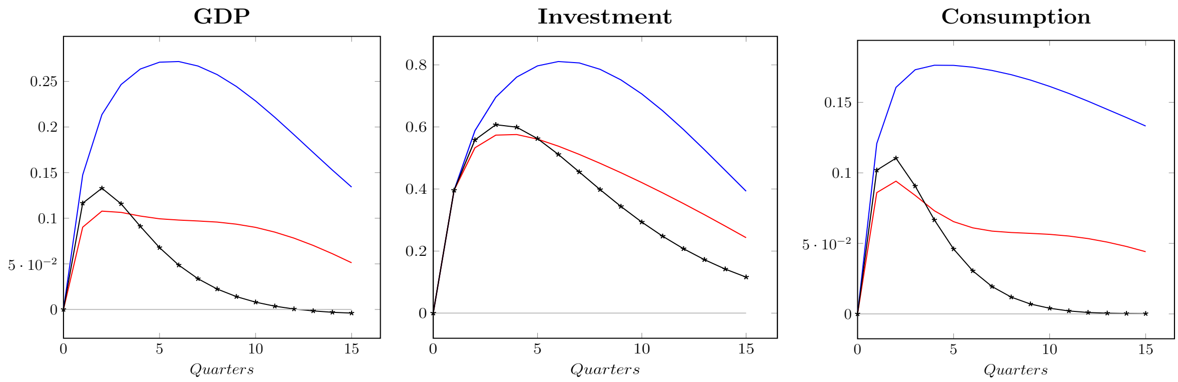

Figure 5. Uncertain vs. tranquil times state-conditional GIRFs for GDP, investment, and consumption and linear responses, in percentage points (shock: 25 basis points unexpected decrease in the policy rate). Solid blue (red) line: state-conditional GIRF for the tranquil (uncertain) times. Black starred line: IRF from the nested linear VAR.

Moreover, we observe that the linear response is within the state-conditional response only for the first five quarters. After this moment, linear IRFs would underestimate the impact of the shock. Extending the analysis to the responses of the remaining endogenous variables, in Appendix A.4, we document a positive reaction of prices. The price response predicts a higher increase in prices following a monetary policy expansion during tranquil times, which goes in line with the conventional effects reported in the literature. In uncertain times, the increase is negligible, meaning that other mechanisms may be in place. Finally, we see that uncertainty increases after a cut of 0.25% in the policy rate. This may be associated with the fact that expansionary policies usually are undertaken as a response to recessions or moments of instability in the economy.

Finally, we examine whether the response of our variables is statistically different between both states after the monetary policy shock in Figure 6. We report again the 90% confidence band for the three variables. We can see that the difference between responses in tranquil and uncertain times is negative.

The confidence bands for real GDP and investment point to statistically different responses between the two conditional states in the medium run, that is, in the period monetary policy exerts the maximum of its power before becoming neutral in the long run.

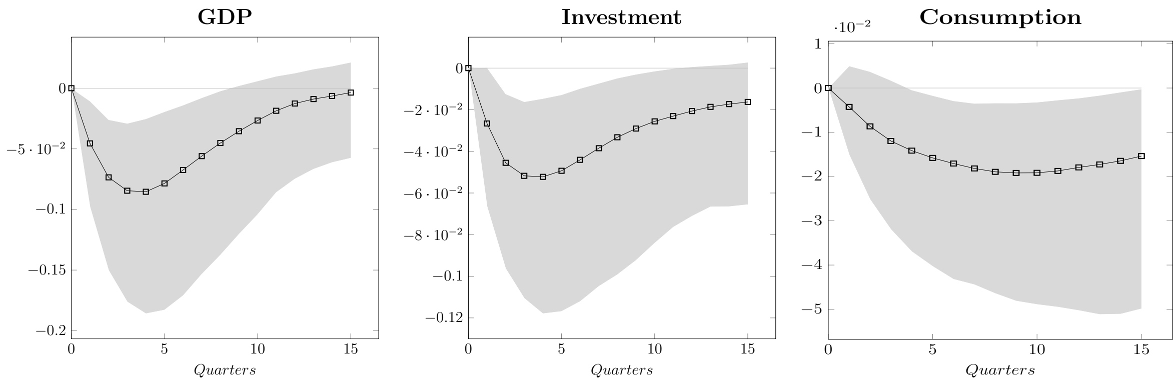

Figure 6. Difference of state-conditional GIRFs between uncertain and tranquil times for a shock in policy rate, in percentage points. Black squared line: difference between estimated state-conditional GIRFs (uncertain times conditional GIRF minus tranquil times conditional GIRF). Gray area: 90% confidence band.

4.3 Robustness Checks

To assess the robustness of our findings, we estimate our SEIVAR model with an extra variable. First, we use the EPU index from Baker et al. (2016) and, then, we employ the Eurostoxx50 implied volatility index, V2X index. Including these variables in our systems allows us to interpret whether our results may be due to other sources of uncertainty: a broader kind of policy uncertainty and financial uncertainty. As such, we want to isolate the residual effect of policy uncertainty that is only specific to monetary policy. For that, in the vector of endogenous variables for each robustness test, we order the new variable after the MPU.

Appendix A.5 presents the point estimates for the state-conditional GIRFs of real GDP, investment, and consumption after a shock on uncertainty and on policy rate, respectively, when we include the EPU index or the V2X index.

The analysis of both estimations leads us to conclude that the results are in line with the ones previously presented. For both cases, the positive shock in uncertainty makes output, investment, and consumption decrease below trend in uncertain times. Similarly, the negative shock in policy rate displays a more powerful impact during tranquil times than in uncertain ones.

5 Conclusion

Starting with the Great Recession and reinforced by the ongoing Covid-19 crisis, uncertainty became one of the focal points of economists and policymakers as it became consensual that it can have important dampening effects on economic activity, even though it is not directly observable. Given this, different proxies to measure uncertainty have been proposed so far.

We construct a novel proxy for uncertainty that tracks monetary policy by text-mining thousands of newspaper articles in the press. From a conceptual point of view, the index reports uncertainty about the direction of monetary policy and its consequences on the economy in the Euro area. It has the advantage that it can be computed at high-frequencies and is directly based on real-time expectations about the economy transmitted to an influential segment of the population. Then, we calibrate a SEIVAR model to explore the impact of monetary policy uncertainty on the real economy.

Higher monetary policy uncertainty leads to contractions in economic activity with a higher dampening effect in uncertain times. We also find that real GDP reacts, on average, three times more to a monetary policy expansion during tranquil times. This supports the use of nonlinear models where uncertainty is a conditioning variable and can affect policy stimuli. The conclusions presented are aligned with other empirical studies and complement the literature that illustrates how uncertainty constrains monetary policy effectiveness.

Our findings have implications for policy as the measure of MPU is a proxy for uncertainty with relevant information and shows a plausible empirical content at the macro level. It could belong to the toolkit of indicators that central banks use to assess the monetary policy stance at each moment in time. Increasing the information set to include economic uncertainty metrics could be beneficial as the economy is constantly evolving, and uncertainty impacts decisions.

We also conclude that monetary policy can be significantly less effective during uncertain times. This suggests that policy could be framed to avoid the "wait-and-see" attitude among economic agents by creating clearer incentives to spend and invest. Our evidence, thus, provides support with empirical evidence to the literature that defends more aggressive policies (Bloom, 2009; Bloom et al., 2018) to mitigate the influence of uncertainty on the effectiveness of monetary policy shocks. Further research may apply machine learning techniques to retrieve richer information from newspaper articles or increase the coverage of the index with country-level newspapers.

References

Aastveit, K. A., G. J. J. Natvik, and S. Sola (2013). Economic uncertainty and the effectiveness of monetary policy. *Journal of International Money and Finance 76*, 50–67.

Alexopoulos, M., J. Cohen, M. Alexopoulos, and J. Cohen (2009). Uncertain times, uncertain measures. *Working Paper*.

Arne, G. and Y. M. Largent (2016). The impact of macroeconomic uncertainty on activity in the euro area. *Review of Economics 67*, 25–52.

Azqueta-Gavaldon, A., D. Hirschbühl, L. Onorante, and L. Saiz (2020). Economic policy uncertainty in the euro area: An unsupervised machine learning approach. *ECB Working Paper Series 2359*.

Azzimonti, M. (2018). Partisan conflict and private investment. *Journal of Monetary Economics 93*, 114–131.

Bachmann, R., S. Elstner, and E. R. Sims (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics 5*, 217–249.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics 131*, 1593–1636.

Bernanke, B. S. (1983). Irreversibility, uncertainty and cyclical investment. *The Quarterly Journal of Economics, Oxford University Press 98*, 85–106.

Bloom, N. (2007). Uncertainty and the dynamics of r&d. *The American Economic Review 97*, 250–255.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica 77*, 623–685.

Bloom, N. (2014). Fluctuations in uncertainty. *The Journal of Economic Perspectives 28*, 153–176.

Bloom, N., D. Furceri, and H. Ahir (2018). The world uncertainty index. *Stanford mimeo*.

Caggiano, G., E. Castelnuovo, and N. Groshenny (2014). Uncertainty shocks and unemployment dynamics in u.s. recessions. *Journal of Monetary Economics 67*, 78–92.

Caggiano, G., E. Castelnuovo, and G. Pellegrino (2017). Estimating the real effects of uncertainty shocks at the zero lower bound. *European Economic Review 100*, 257–272.

Caldara, D., M. Iacoviello, A. Kane, B. Cole-Smith, C. Singer, E. Markiewitz, F. Choudhary, J. Herman, L. Husted, M. Penn, P. Molligo, S. Conlisk, and T. Dhin (2021). Measuring geopolitical risk. *Working Paper*.

Caldara, D., M. Iacoviello, P. Molligo, A. Prestipino, and A. Raffo (2019). The economic effects of trade policy uncertainty. *International Finance Discussion Paper 2019*, 1–49.

Castelnuovo, E. and G. Pellegrino (2018). Uncertainty-dependent effects of monetary policy shocks: A new-keynesian interpretation. *Journal of Economic Dynamics and Control 93*, 277–296.

Christiano, L., M. Eichenbaum, and C. Evans (1999). Monetary policy shocks: What have we learned and to what end? *Journal of Political Economy 113*, 1–45.

Coibion, O., D. Georgarakos, Y. Gorodnichenko, G. Kenny, and M. Weber (2021). Working paper series the effect of macroeconomic uncertainty on household spending. *ECB Working Paper Series*.

Dixit, A. and R. Pindyck (1994). *Investment under Uncertainty*. Princeton University Press.

ECB (2016). The impact of uncertainty on activity in the euro area.

Eickmeier, S., N. Metiu, and E. Prieto (2016). Time-varying volatility, financial intermediation and monetary policy. *CAMA Working Paper 32/2016*.

Ghirelli, C., J. J. Pérez, and A. Urtasun (2021). The spillover effects of economic policy uncertainty in latin america on the spanish economy. *Latin American Journal of Central Banking 2*, 100029.

Husted, L., J. Rogers, and B. Sun (2016). Measuring cross country monetary policy uncertainty. *IFDP Notes, Board of Governors of the Federal Reserve System*.

Husted, L., J. Rogers, and B. Sun (2020). Monetary policy uncertainty. *Journal of Monetary Economics 115*, 20–36.

Iskrev, N., R. Lourenço, and C. Soares (2021). Indicators of monetary policy stance and financial conditions: an overview. *Economic Bulletin and Financial Stability Report Articles and Banco de Portugal Economic Studies*.

Ivanov, V. and L. Kilian (2005). A practitioner's guide to lag order selection for var impulse response analysis. *Studies in Nonlinear Dynamics & Econometrics, De Gruyter 9*, 1–36.

Jurado, K., S. C. Ludvigson, and S. Ng (2015). Measuring uncertainty. *The American Economic Review 105*, 1177–1216.

Keynes, J. M. (1937). The general theory of employment. *Quarterly Journal of Economics 51*, 209–223.

Kilian, L. and R. J. Vigfusson (2011). Are the responses of the u.s. economy asymmetric in energy price increases and decreases? *Quantitative Economics 2*, 419–453.

Koop, G., M. H. Pesaran, and S. M. Potter (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics 74*, 119–147.

Leduc, S., Z. Liu, S. Leduc, and Z. Liu (2016). Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics 82*, 20–35.

Nodari, G., Nodari, and Gabriela (2014). Financial regulation policy uncertainty and credit spreads in the us. *Journal of Macroeconomics 41*, 122–132.

Pellegrino, G. (2018). Uncertainty and the real effects of monetary policy shocks in the euro area. *Economics Letters 162*, 177–181.

Pellegrino, G. (2021). Uncertainty and monetary policy in the us: A journey into nonlinear territory. *Melbourne Institute Working Paper 6*.

Sims, C. A. (1980, 1). Macroeconomics and reality. *Econometrica 48*, 1.

Sims, C. A., J. H. Stock, and M. W. Watson (1990). Inference in linear time series models with some unit roots. *Econometrica 58*, 113–144.

Stock, J. H. and M. W. Watson (2001). Vector autoregression. *Journal of Economic Perspectives 15*, 101–115.

Wu, J. C. and F. D. Xia (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit, and Banking 48*, 253–291.

Appendix

A Additional Figures

A.1 Absolute frequency of newspaper articles collected

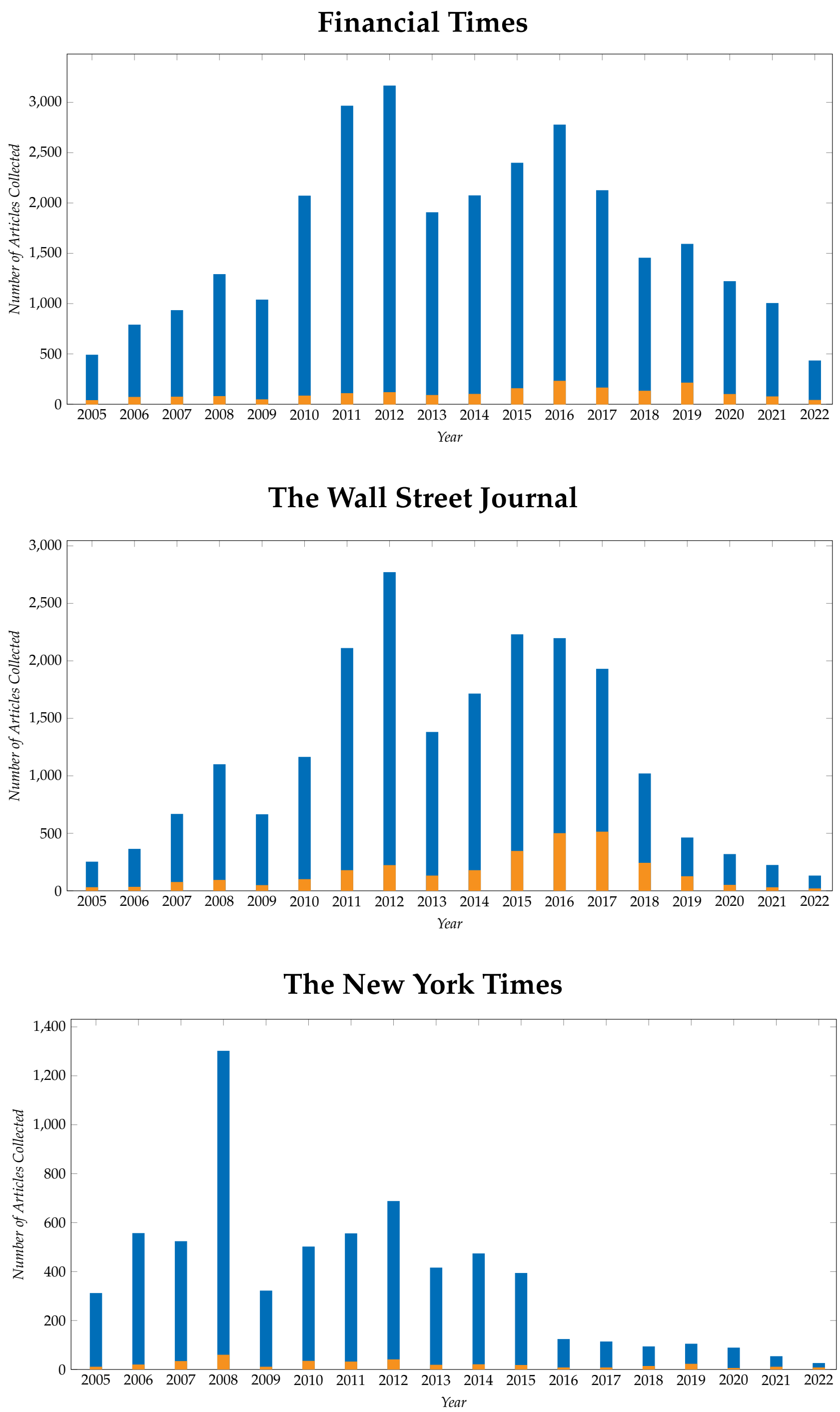

Figure 7. Absolute frequency of newspaper articles collected for each newspaper. Blue bars: number of articles collected each month that fulfill the first criteria. Orange bars: number of articles that fulfill the three criteria each month.

A.2 Individual Monetary Policy Uncertainty indices

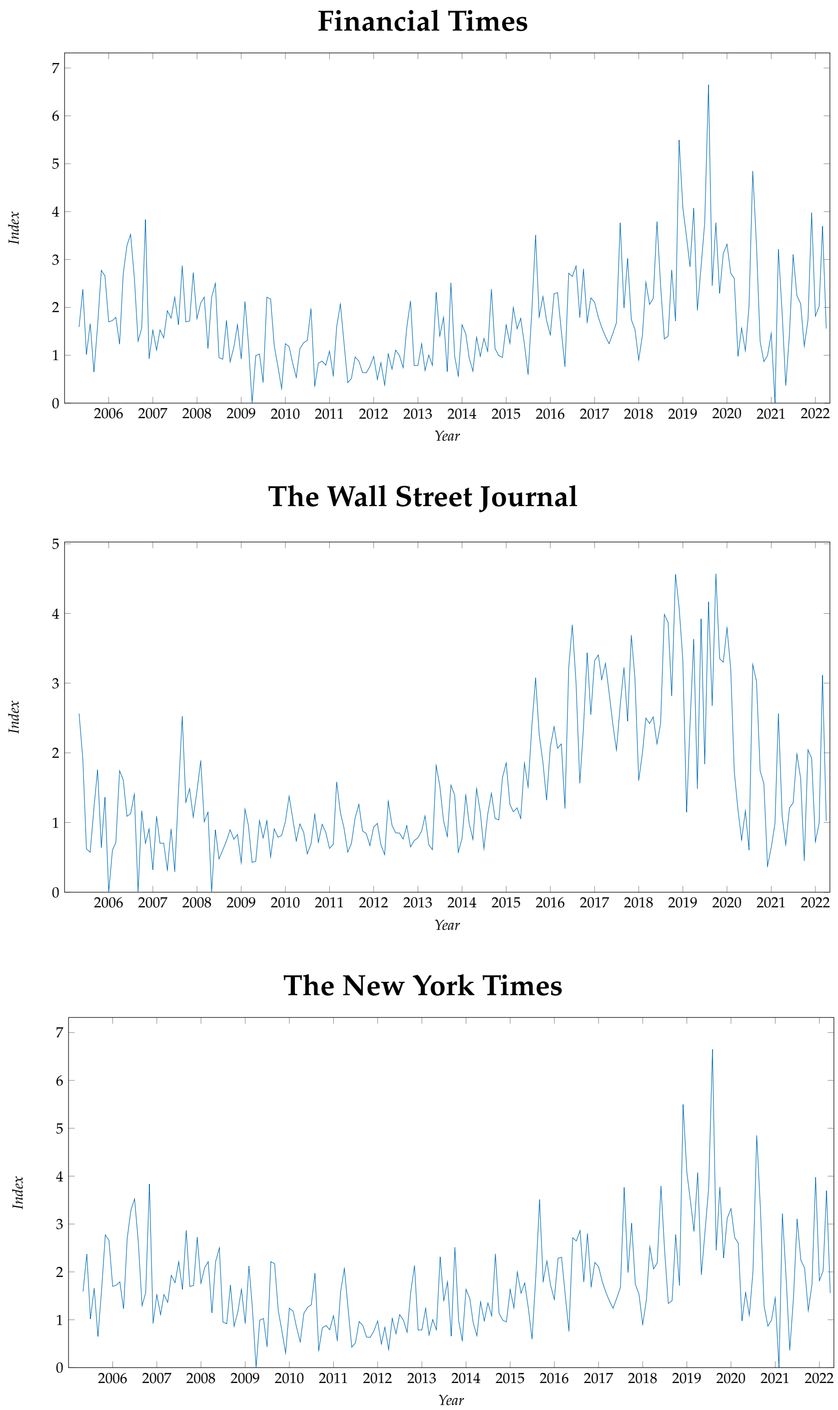

Figure 8. Individual Monetary Policy Uncertainty index for each newspaper.

A.3 Comparison with other uncertainty proxies

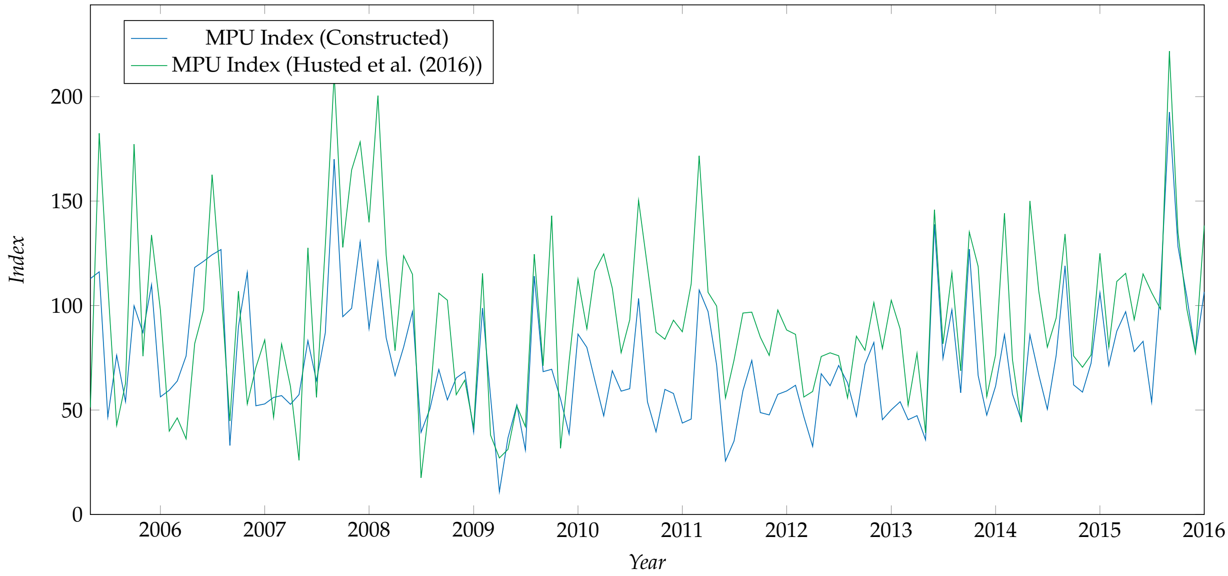

Figure 9. Comparison between the Monetary Policy Uncertainty index and the one by Husted et al. (2016) for the Euro area during the overlapping period (2005 – 2016). Correlation = 73%. Source: author's construction and Husted et al. (2016)

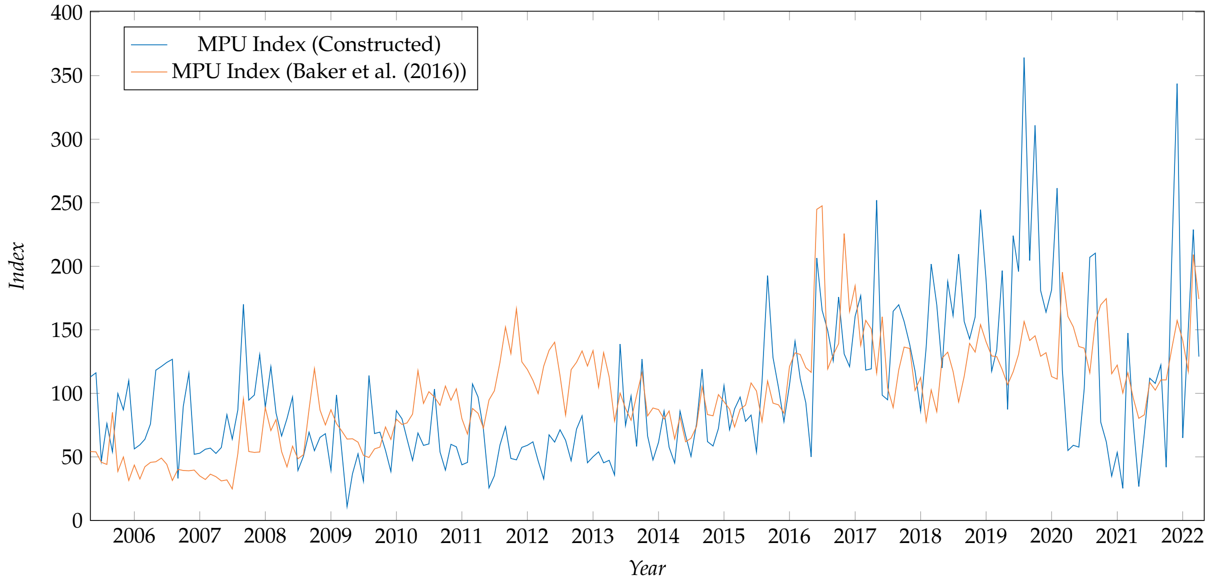

Figure 10. Comparison between the Monetary Policy Uncertainty index and the EPU index built by Baker et al. (2016) for the Euro area during the overlapping period (2005 – 2022). Correlation = 42%. Source: author's construction and Baker et al. (2016)

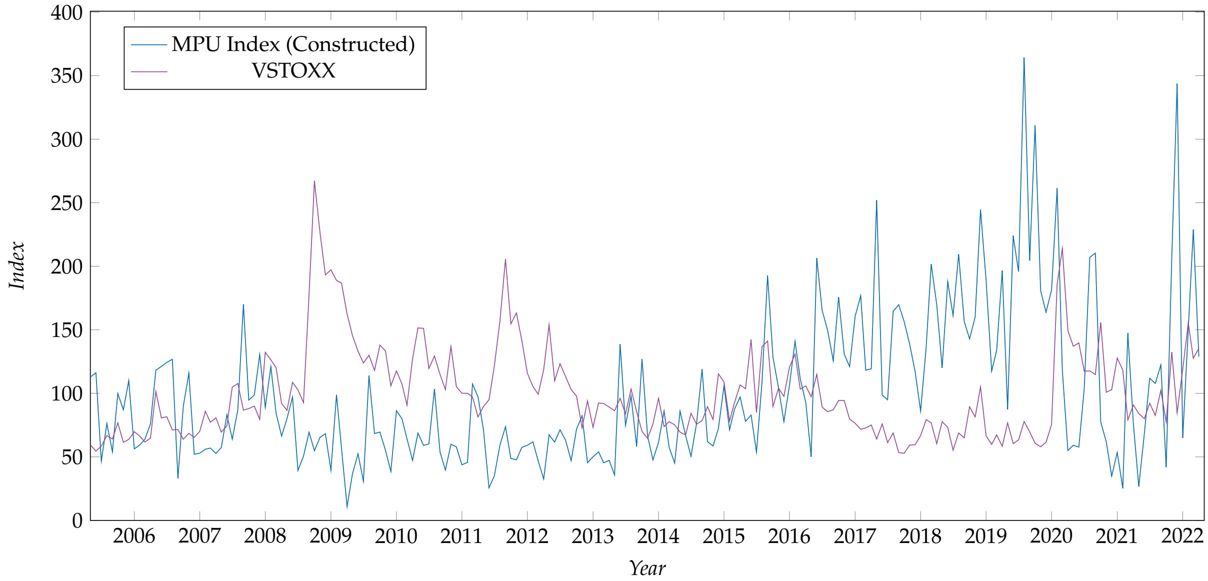

Figure 11. Comparison between the Monetary Policy Uncertainty index and the measure of financial market uncertainty, the VSTOXX during the overlapping period (2005 – 2022). Correlation = – 23%. Source: author's construction and Bloomberg terminal.

A.4 Baseline Results

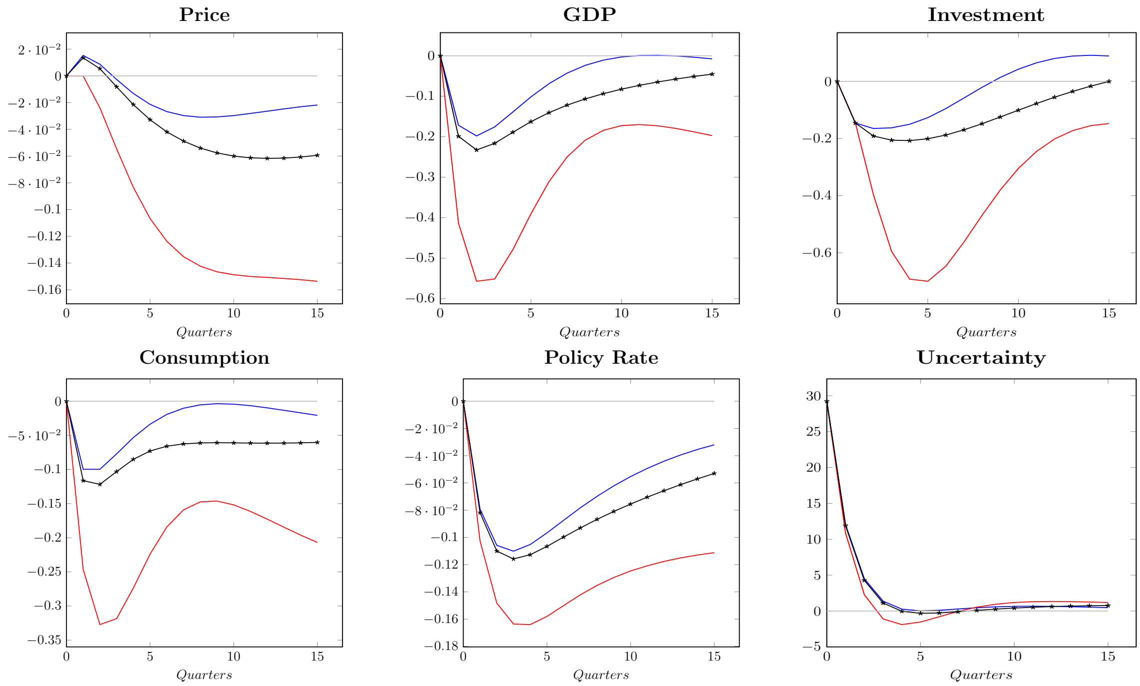

Figure 12. Uncertain vs. tranquil times state-conditional GIRFs for all the variables included and linear responses, in percentage points (shock: 1 standard deviation unexpected increase in uncertainty). Solid blue (red) line: state-conditional GIRF for tranquil (uncertain) times. Black starred line: IRF from the nested linear VAR.

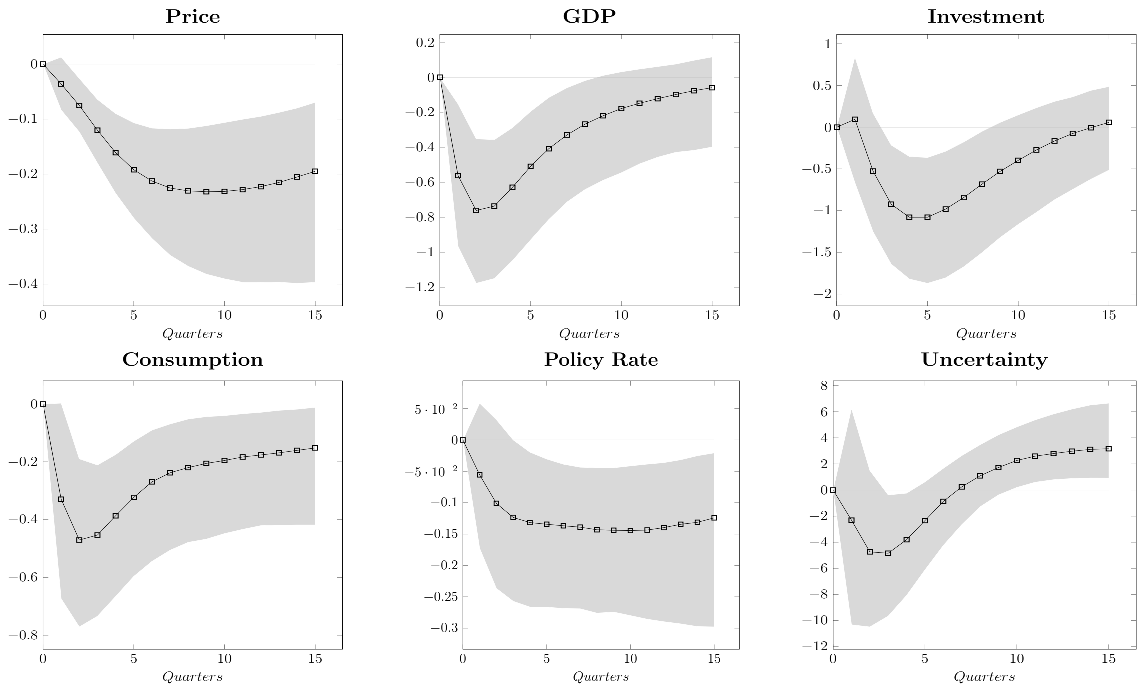

Figure 13. Difference of state-conditional GIRFs between uncertain and tranquil times for a shock in uncertainty, in percentage points. Black squared line: difference between estimated state-conditional GIRFs (uncertain times conditional GIRF minus tranquil times conditional GIRF). Gray area: 90% confidence band.

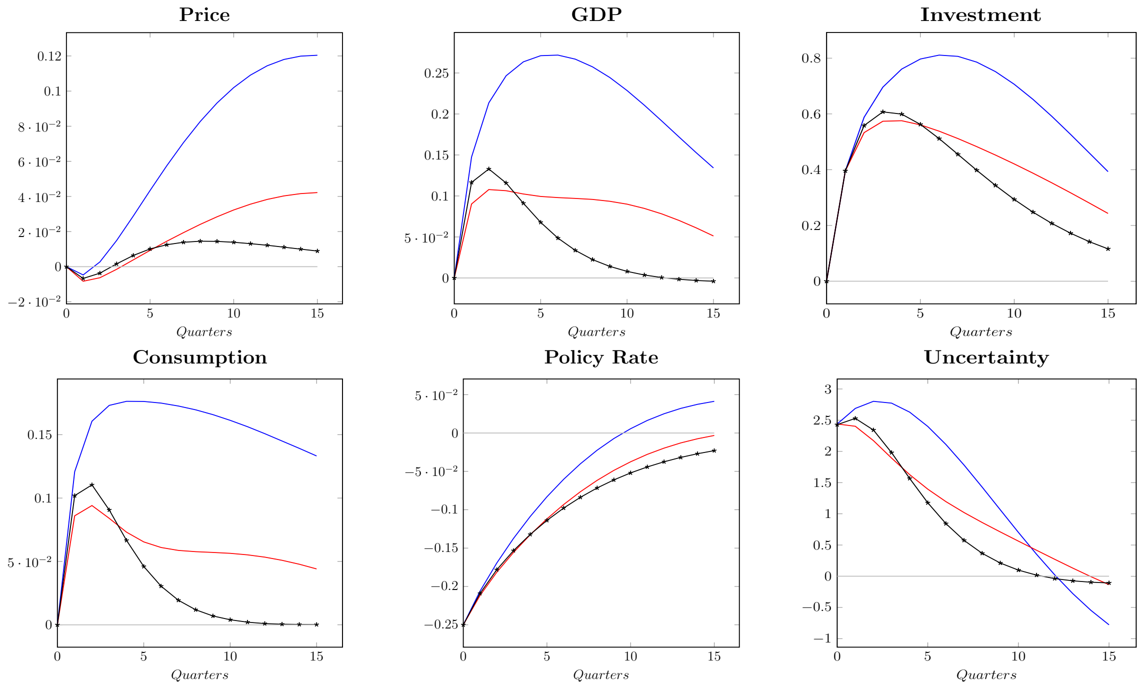

Figure 14. Uncertain vs. tranquil times state-conditional GIRFs for all the variables included and linear responses, in percentage points (shock: 25 basis points unexpected decrease in policy rate). Solid blue (red) line: state-conditional GIRF for tranquil (uncertain) times. Black starred line: IRF from the nested linear VAR.

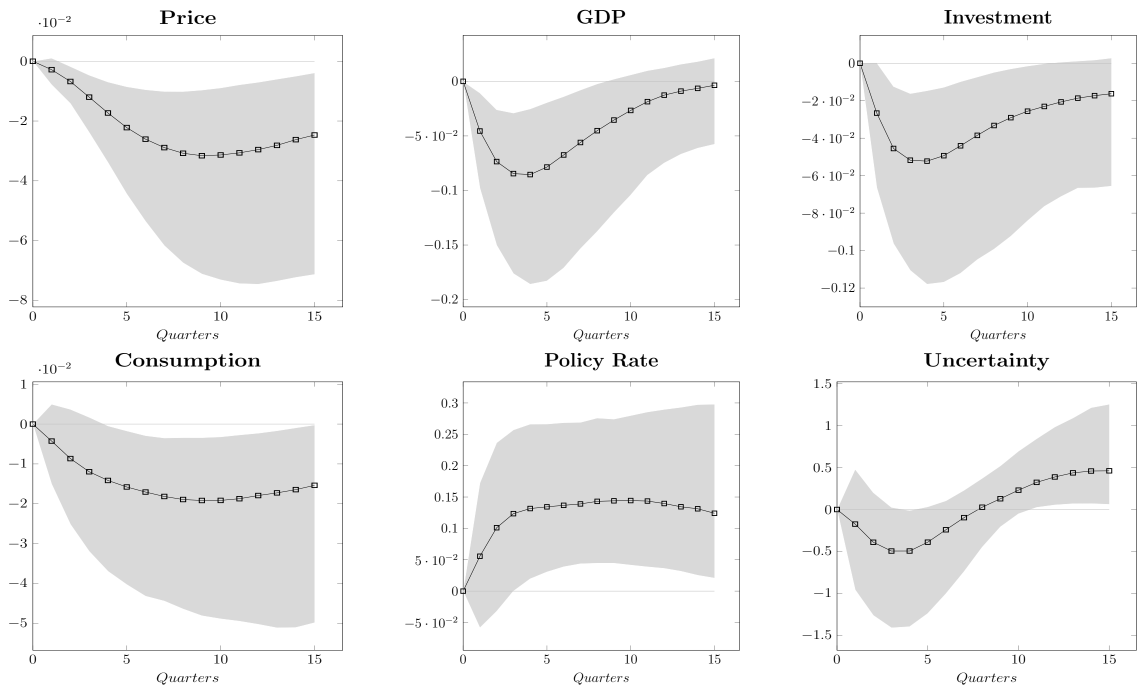

Figure 15. Difference of state-conditional GIRFs between uncertain and tranquil times for a shock in policy rate, in percentage points. Black squared line: difference between estimated state-conditional GIRFs (uncertain times conditional GIRF minus tranquil times conditional GIRF). Gray area: 90% confidence band.

A.5 Robustness Checks

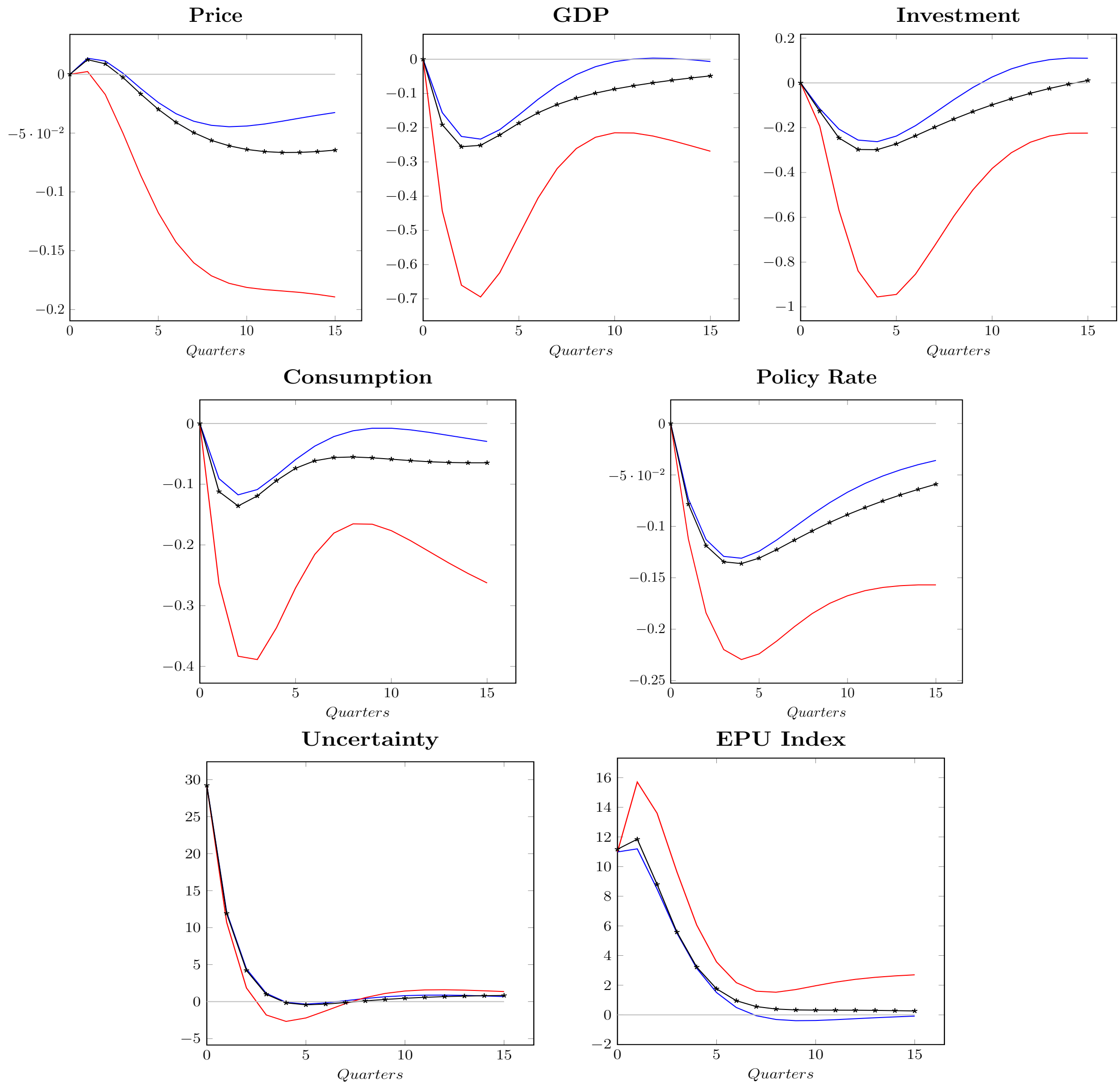

Figure 16. Uncertain vs. tranquil times state-conditional responses for all the variables with the EPU index included and linear responses, in percentage points (shock: 1 standard deviation unexpected increase in uncertainty). Solid blue (red) line: state-conditional GIRF for tranquil (uncertain) times. Black starred line: IRF from the nested linear VAR.

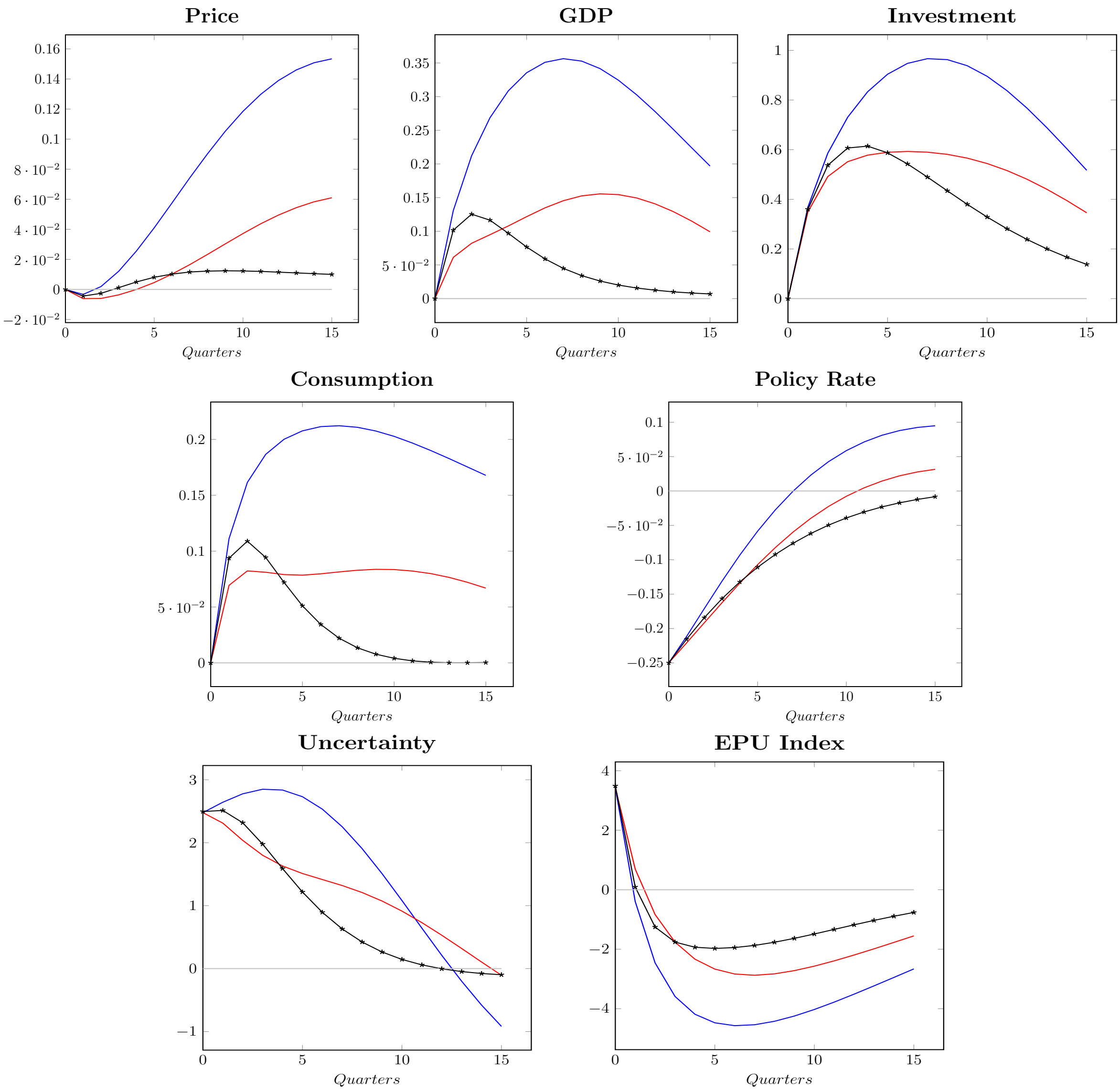

Figure 17. Uncertain vs. tranquil times state-conditional responses for all the variables with the EPU index included and linear responses, in percentage points (shock: 25 basis points unexpected decrease in policy rate). Solid blue (red) line: state-conditional GIRF for tranquil (uncertain) times. Black starred line: IRF from the nested linear VAR.

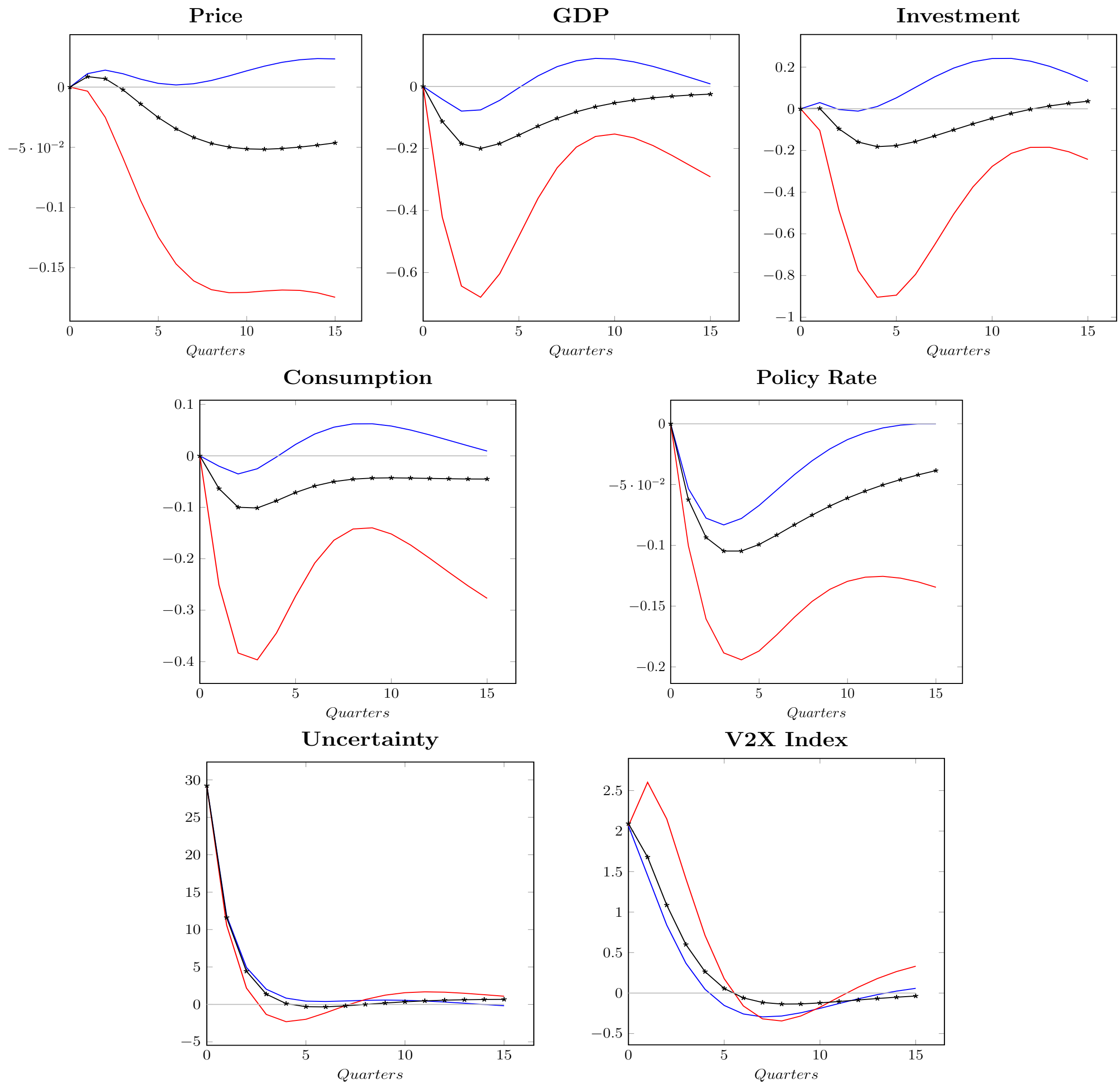

Figure 18. Uncertain vs. tranquil times state-conditional responses for all the variables with the V2X index included and linear responses, in percentage points (shock: 1 standard deviation unexpected increase in uncertainty). Solid blue (red) line: state-conditional GIRF for tranquil (uncertain) times. Black starred line: IRF from the nested linear VAR.

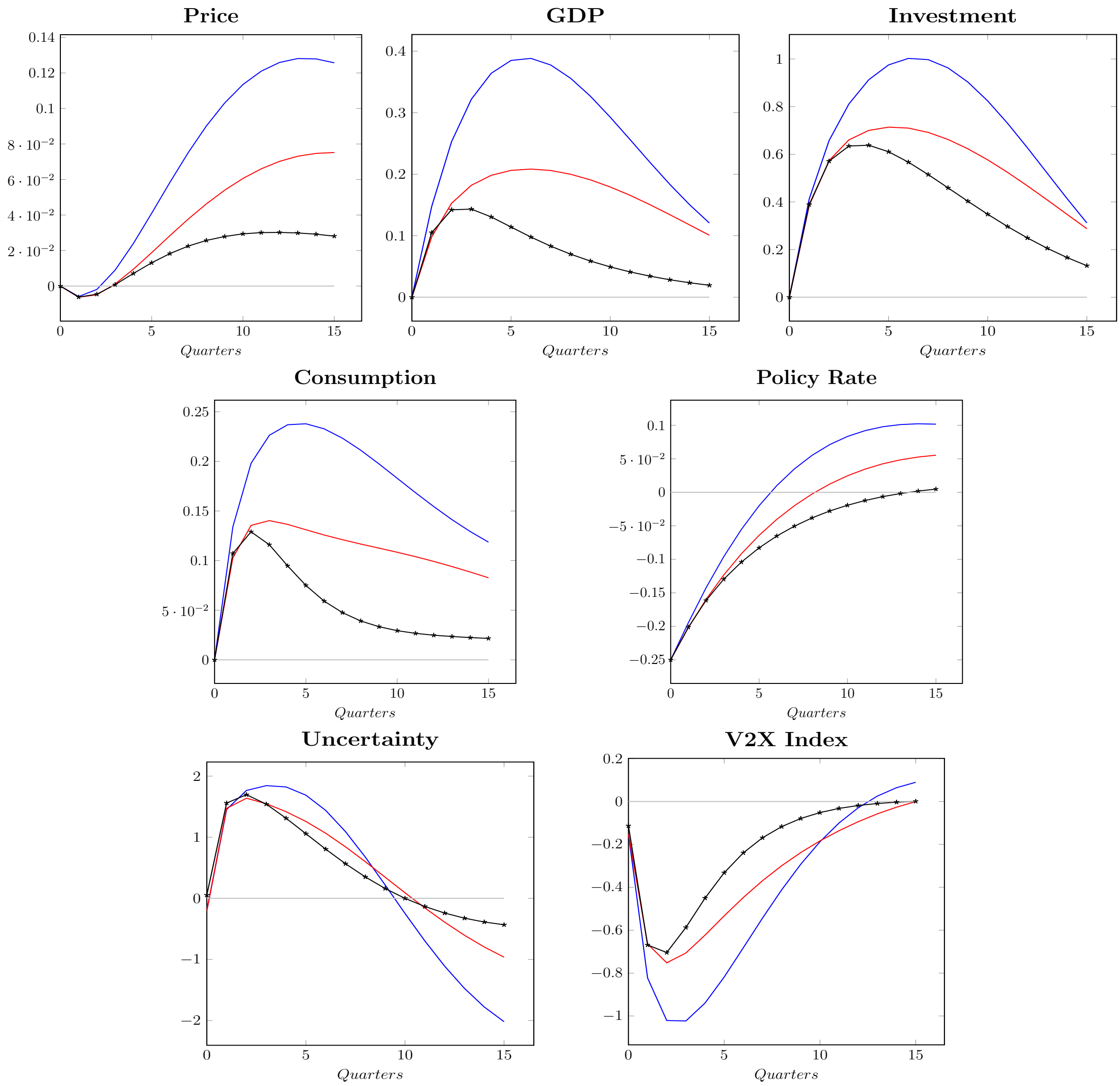

Figure 19. Uncertain vs. tranquil times state-conditional responses for all the variables with the V2X index included and linear responses, in percentage points (shock: 25 basis points unexpected decrease in policy rate). Solid blue (red) line: state-conditional GIRF for tranquil (uncertain) times. Black starred line: IRF from the nested linear VAR.

B Description of the Methodology to Measure Uncertainty

The methodology that we follow in constructing the MPU index tracks the frequency of newspaper articles related to uncertainty surrounding central banking policy. We selected three leading newspapers that cover international economic and financial news: Financial Times, The Wall Street Journal, and the New York Times. The selection of these newspapers is attributed to four main reasons: first, these newspapers are open-source and it is possible to web scrape the title, the link and the date for all of them; second, they have a accessible data until 2005 (not requiring a paid-subscription to access their archives); the website for these newspapers allows to get automated text-search results and, thus, filter only the articles that fulfilled our criteria; finally, these newspapers have a considerable number of readers in all countries of the Euro area, so we consider them representative of, at least, a wide segment of the population.

Using thousands of newspaper articles, we search for articles containing at least one search term for each criteria, presented in Table 1. The criteria was defined following the algorithm of Husted et al. (2016). They follow a exhaustive assessment of their choice of search terms. They iterate through several definitions and try to minimize the error of selection in order to get the most precise picture out of the base data of articles. We adapted their choice to include a "Asset Purchase" in criteria (ii), as this topic is relevant for the monetary policy of the ECB and, when filtering the articles that contained this expression, we got a considerable amount of them. The description of the data collected from each newspaper is detailed in Table 2.

Table 1. Criteria for the filtering of newspaper articles.

	(i)	(ii)	(iii)	**Newspapers**
		Monetary Policy	"European	
	Uncertainty	Interest Rate	Central Bank"	Financial Times
Euro area		Policy Rate	"ECB"	The New York Times
	Uncertain	Asset Purchase	"Governing	The Wall Street Journal
		EONIA Rate	Council"	

Notes: Words in quotes are searched as exact terms. All other words searched allow for plural forms.

Table 2. Details about the data collected from each newspaper.

Newspaper	**Period**	**Base News**	**Filtered News**	**Percentage**
Financial Times	May, 2005 – April, 2022	29 708	1 906	6.4%
The New York Times	May, 2005 – April, 2022	6 635	362	5.5%
The Wall Street Journal	May, 2005 – April, 2022	20 671	2 893	14.0%
Total	May, 2005 – April, 2022	57 014	5 161	9.1%

C Construction of the Monetary Policy Uncertainty Index

To construct the Monetary Policy Uncertainty index, we count, in each newspaper, the number of newspaper articles that contain the search terms defined in Table 1. We repeat this from the May 1^{st} of 2005 until September 30^{th} of 2021, given the availability of online articles on the newspapers' websites. In total, we collected 56 016 news (the ones that fulfill the criteria (iii)), from which 10% check the three criteria, as shown in Table 2.

We control the changing volume of articles over time and the possibility that some newspapers naturally cover monetary policy more than others. As such, we divide, for each day, the raw count of filtered articles by the total number of articles collected. In other words, for each newspaper, we calculate the ratio between filtered articles and the total number of articles citing "European Central Bank" or "ECB" or "Governing Council":

$$n\,(i,t) = \frac{\#mpu\_articles(i,t)}{\#ECB\_articles(i,t)}.$$

The ratio of newspaper articles related to monetary policy uncertainty is then transformed to have a unit standard deviation over the entire period. This normalization is pertinent because it allows us to have aggregate the individual indices from different newspapers that mention uncertainty with different frequencies:

$$nn\,(i,t) = \frac{n\,(i,t)}{stdev\,(n,(i,2005:2021))}.$$

Finally, the individual indices are aggregated by summing and scaling them to have a mean of 100 over the full period. This produces the Monetary Policy Uncertainty index, denoted as MPU:

$$MPU\,(t) = \left[\frac{\sum_i nn\,(i,t)}{avg\,(\sum_i nn\,(i,2005:2021))}\right] * 100.$$

D Computation of the GIRFs

The algorithm employed to compute the GIRFs and their confidence intervals is based on Pellegrino (2021). It reads as follows:

1. Pick an initial condition $\varpi_{t-1} = \{Y_{t-1}, \ldots, Y_{t-L}\}$, i.e., the historical values for the lagged endogenous variables at a particular date $t = L+1, \ldots, T$. Notice that the set includes values for interaction terms;

2. Draw randomly (with repetition) a sequence of (n-dimensional) residuals $\{u_{t+h}\}^s$, $h = 0, 1, \ldots H = 15$, from the empirical distribution $d\left(0, \hat{\Omega}\right)$, where $\hat{\Omega}$ is the estimated VCV matrix. To preserve contemporaneous structural relationships among variables, residuals are assumed to be jointly distributed, so that if date t's residual is drawn, all n residuals for date t are collected;

3. Conditional on ϖ_{t-1} and the estimated model, use the sequence of residuals $\{u_{t+h}\}^s$ to simulate the evolution of the vector of endogenous variables over the following H periods to obtain the path $\{Y_{t+h}\}^s$ for $h = 0, 1, \ldots H$. s denotes the dependence of the path on the particular sequence of residuals used;

4. Conditional on ϖ_{t-1} and the estimated model, use the sequence of residuals $\{u_{t+h}\}^s$ to simulate the evolution of the vector of endogenous variables over the following H periods when a structural shock δ_t is imposed to u_t^s. In particular, we Cholesky-decompose $\hat{\Omega} = CC\prime$, where C is a lower triangular matrix. Then, we recover the structural innovation associated to u_t^s by $\epsilon_t^s = C^{-1}u_t^s$ and add a quantity $\delta < 0$ to the scalar element of ϵ_t^s that refers to the interest rate, i.e., $\epsilon_{t,intrate}^s$. We then move again to the residual associated with the structural shock $u_t^{s,\delta} = C\epsilon_t^{s,\delta}$ to proceed with simulations as in point 3. Call the resulting path $Y_{t+h}^{s,\delta}$;

5. Compute the difference between the previous two paths for each horizon and each variable, i.e.,

$$Y_{t+h}^{s,\delta} - Y_{t+h}^s,$$

for $h = 0, 1, \ldots H$;

6. Repeat steps 2-5 for a number of $S = 500$ different extractions for the residuals and then take the average across s. Notice that in this computation, the starting quarter $t-1$ does not change. In this way, we obtain a consistent point estimate of the GIRF for each given starting quarter in our sample:

$$GI\hat{R}F_{Y,t}\left(\delta_t, \varpi_{t-1}\right) = \left\{\hat{E}\left[Y_{t+h}|\delta_t, \varpi_{t-1}\right] - \hat{E}\left[Y_{t+h}|\varpi_{t-1}\right]\right\}_{h=0}^{15}.$$

   If a given initial condition ϖ_{t-1} brings an explosive response (namely, if this is explosive for most of the sequences of residuals drawn $\{u_{t+h}\}^s$, in the sense that the response of the variable shocked diverges instead of reverting to zero), it is discarded and not considered for the computation of state-conditional responses at the next step.

7. Repeat steps 2-6 to obtain a history-conditional GIRF for each initial condition ϖ_{t-1} of interest. In particular, we select two particular subsets of initial conditions related to the historical level of uncertainty to define two states. An initial condition $\varpi_{t-1} = \{Y_{t-1}, \ldots, Y_{t-L}\}$ is classified to belong to the uncertain times state if unc_{t-1} is within the 5-percentiles tolerance band from the top decile of the uncertainty empirical distribution (i.e., within its 85^{th} and 95^{th} percentiles) and to the tranquil times state if unc_{t-1} is within the same band around the bottom decile of the uncertainty distribution.

8. History-dependent GIRFs obtained in step 7 are then averaged over the state they belong to in order to produce our estimate of the state-dependent GIRFs, i.e.:

$$GIRF_{Y,t}\left(h, \delta_t, \Omega_{t-1}^{uncertain\ times}\right) \;\&\; GIRF_{Y,t}\left(h, \delta_t, \Omega_{t-1}^{tranquil\ times}\right),$$

9. Confidence bands around the point estimates obtained in point 8 are computed through bootstrap. In particular, we simulate $R = 2000$ datasets

statistically equivalent to the actual sample, and for each of them, we construct the corresponding interaction terms coherently with what was done on the actual data. Then, for each dataset, we estimate our IVAR model and implement steps 1-8. In implementing this procedure this time, we have that the starting conditions and the VCV matrix used in the computation depend on the particular dataset r used, i.e., ϖ^r_{t-1} and $\hat{\Omega}^r$. Of the resulting distribution of state-conditional GIRFs, we take the 5^{th} and 95^{th} percentiles to construct the 90% confidence bands.

E Data Sources

We provide more details on the data used for the baseline and robustness analysis, particularly regarding the sources of the series and the transformation they were subject to.

- **Price Index.** The data source is the Eurostat. The exact name of the series is GDP deflator, Price Index (2010 = 100), Seasonally and calendar adjusted. This variable was transformed by applying the natural logarithm and multiplying by 100.

- **Real variables.** The data source is the Eurostat. The precise names of the series we use are the following: Real Gross Domestic Product, Chain Linked Volumes (2010), Million Euro, Quarterly, Seasonally and Calendar Adjusted; Real Gross Private Domestic Investment (Gross Fixed Capital Formation), Chain Linked Volumes (2010), Million Euro, Quarterly, Seasonally and Calendar Adjusted; Real Personal Consumption Expenditures (Households and NPISHs), Chain Linked Volumes (2010), Million Euro, Quarterly, Seasonally and Calendar Adjusted. All the series were transformed to their Annual Rate, then applied the natural logarithm and multiplied by 100.

- **EONIA rate.** The data source is the Statistical Data Warehouse of the European Central Bank. The precise name of the series is Euro Interbank Offered Rate, Percent, Quarterly Frequency, Not Seasonally Adjusted.

- **Shadow rate.** The data source is Cynthia Wu's website.[16] The shadow rates are computed using the method presented in Wu and Xia (2016). We take quarterly averages of the series.

[16] https://sites.google.com/view/jingcynthiawu/shadow-rates

- **Monetary Policy Uncertainty Index.** We use the constructed series presented in Section 2 and extended it until 1999, using the MPU index from Husted et al. (2016). The data source: Board of Governors of the Federal Reserve System's website.[17]

- **Economic Policy Uncertainty Index.** The data source is the Policy Uncertainty website.[18] We use the EPU index constructed by Baker et al. (2016) calculated as the GDP-weighted average of country-specific data for EPU in Germany, France, Italy, and Spain.

- **Stock Market Volatility Index.** The data source is Bloomberg. We use the VSTOXX that measures the 30-day implied volatility of the EuroStoxx50 index options. We take quarterly averages of the series.

[17] https://www.federalreserve.gov/econresdata/notes/ifdp-notes/2016/measuring-cross-country-monetary-policy-uncertainty-20161123.html

[18] https://www.policyuncertainty.com/

F Test Statistic for the Interaction Effect

The test statistic for the interaction effect presented in section 4 is relevant because, as Pellegrino (2021) explains, the impulse responses for tranquil and uncertain times are correlated, so the confidence bands around each response alone give a distorted impression about the statistical significance of their difference. To formally evaluate the difference between the two GIRFs, we compute the test statistic presented in Pellegrino (2021). We use the impulse responses based on draws of the posterior parameters. For each of the 2 000 saved draws, we take the difference between the GIRFs of each variable to a shock for the high and low uncertainty states. This gives a distribution of the difference between responses and allows us to compute the confidence bands. The difference between GIRFs in high and low uncertainty states is statistically significant if the interval between confidence bands lies above or below zero.

In Figures 4 and 6, we present the 90% confidence bands for each variable. Each figure presents the distribution of the difference between the GIRFs under tranquil and uncertain times. For example, a negative value for investment will mean that an expansionary monetary policy shock causes a greater increase in investment when uncertainty is low than when uncertainty is high.