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Abstract

This paper estimates a non-linear Interacted VAR model to assess whether the real effects of monetary policy shocks are milder during times of high uncertainty. Crucially, uncertainty, i.e. the conditioning indicator discriminating "high" and "low" uncertainty states, is modeled endogenously in the VAR and is found to significantly decrease after an unanticipated monetary easing. Generalized Impulse Response Functions à la Koop, Pesaran and Potter (1996), which take into account the effect of this decrease, reveal that monetary policy shocks are significantly less powerful during uncertain times, the peak reactions of a battery of real variables being about two-thirds milder than those during tranquil times. The endogenous decrease in uncertainty is shown to be key to estimate precisely the effects of monetary policy shocks.

JEL classification: C32, E32, E52

Keywords: Monetary policy shocks, Non-Linear Structural Vector Auto-Regressions, Interacted VAR, Generalized Impulse Response Functions, Endogenous Uncertainty

"[T]he reduction in risk associated with an easing of monetary policy and the resulting reduction in precautionary saving may amplify the short-run impact of policy [...]. Likewise, reduced risk and volatility may provide an extra kick to capital expenditure in the short run, as firms are more likely to undertake investments in new structures or equipment in a more stable macroeconomic environment."

Governor Ben S. Bernanke
Remarks at the London School of Economics Public Lecture
London, England, October 9, 2003

1 Introduction

The recent experience of the Great Recession in the US, which was accompanied by a large spike in many proxies of uncertainty, has renewed interest and sparked debate about the effects of uncertainty on macroeconomic outcomes. As documented by a number of studies, when an unexpected increase in uncertainty hits the economy, a contractionary effect on real aggregate variables generally follows.[1] More recently, the empirical literature has begun to question whether uncertainty shocks might have a state-conditional impact, namely whether their real effects might depend on a particular phase experienced by the economy.[2] However, there has still been limited empirical research on the role that uncertainty might play in influencing the effectiveness of unexpected policy stimuli. The earliest works along this dimension are Aastveit, Natvik, and Sola (2017) and Ricco, Callegari, and Cimadomo (2016), who employ non-linear Structural VAR models to respectively show that monetary policy shocks and fiscal policy shocks are less powerful in a context of high uncertainty.

This work sheds new light on the uncertainty-dependent effects of monetary policy shocks and shows that taking into account the endogenous response of uncertainty to monetary shocks is key in order not to disregard important transmission channels and hence to correctly estimate the effects of an unexpected monetary stimulus. Recently,

[1] A non-exhaustive list of such works includes Bloom (2009), Mumtaz and Theodoridis (2015b), Baker, Bloom, and Davis (2016), Gilchrist, Sim, and Zakrajšek (2014), Bachmann, Elstner, and Sims (2013), Leduc and Liu (2016), Colombo (2013), Mumtaz and Zanetti (2013), Nodari (2014), Jurado, Ludvigson, and Ng (2015) and Carriero, Mumtaz, Theodoridis, and Theophilopoulou (2015).

[2] See, among others, Nodari (2014), Caggiano, Castelnuovo, and Groshenny (2014), Caggiano, Castelnuovo, and Nodari (2017), and Caggiano, Castelnuovo, and Figueres (2017), who employ non-linear Structural VAR techniques to enquire whether recessionary vs. non-recessionary phases are important in determining the impact of uncertainty shocks; Alessandri and Mumtaz (2018), who investigate whether good vs. bad financial regimes are important for the quantification of the real effects of uncertainty shocks; and Caggiano, Castelnuovo, and Pellegrino (2017), who study the interaction between uncertainty and the Zero Lower Bound (ZLB).

it has been empirically documented that uncertainty is mitigated by monetary policy easings (Bekaert, Hoerova, and Lo Duca (2013)). According to Bernanke's quote above, this associated reduction of uncertainty may temporarily amplify policy effectiveness by reducing precautionary savings and by providing an extra kick to investment via a "more stable macroeconomic environment". In principle, such consequences may be economically relevant provided that precautionary savings play a significant role in consumption fluctuations (Caballero (1990) and Parker and Preston (2005)), and that a less uncertain environment makes it significantly less valuable for firms to "wait and see" before to invest (Bernanke (1983), Bertola and Caballero (1994), Dixit and Pindyck (1994), Bloom, Bond, and Reenen (2007), Bloom (2009)).[3] However, the literature is still silent on the importance of the Bernanke's "endogenous uncertainty" mechanism for the quantification of the uncertainty-dependent effects of monetary policy shocks.[4]

We investigate this issue by proposing a Self-Exciting Interacted VAR (SEIVAR) model which we estimate with quarterly post-WWII US data. This non-linear Interacted VAR augments an otherwise standard VAR with an interaction term including two variables, i.e., the variable used to identify the monetary policy shock (the policy rate) and the conditioning variable that identifies the "uncertain times" and "tranquil times" states (the proxy for uncertainty). This framework is particularly appealing to address our research question in that it enables us to model the interaction between monetary policy and uncertainty in a parsimonious manner and yet to precisely estimate the economy's response conditional on very high/low uncertainty. Importantly, we model both interaction variables endogenously, which is key to acknowledge not only the fact that uncertainty may influence the effectiveness of monetary shocks, but also that monetary shocks themselves may dynamically influence uncertainty. The latter possibility creates, de facto, a feedback effect which makes the model Self-Exiting (or "fully" non-linear) in the iteration after a monetary policy shock.[5]

In order to correctly take this feedback effect into account we compute fully non-linear Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran, and Potter

[3] In this study, we follow most of the empirical literature and do not distinguish between risk and uncertainty although they are technically two different concepts (see Bloom (2014, p. 154)). Uncertainty is proxied with measures of volatility, though we acknowledge these may consist in a mixture of risk and uncertainty.

[4] We review some of the other mechanisms why the monetary policy transmission mechanism may be affected by uncertainty in the next Section.

[5] The term "Self-Exciting" is borrowed from the time series literature (see, e.g., the SETAR model) and here reflects the fact that the "state" and the iteration of the system over time are determined by the values of the endogenous conditioning variable.

(1996). This modeling strategy contributes to the literature in two respects. Methodologically, it represents a novel and more general framework in the IVAR literature that allows to endogenize conditioning variables.[6] Application-wise, it contrasts with the strategy employed by recent VAR analyses on the uncertainty-dependent effectiveness of monetary policy shocks – e.g., Aastveit, Natvik, and Sola (2017), Eickmeier, Metiu, and Prieto (2016) and Castelnuovo and Pellegrino (2018) –, which work with nonlinear VAR models featuring an exogenous conditioning variable and therefore compute conditionally-linear IRFs for a fixed value of the uncertainty proxy. Our strategy enables us to consider both the possibly endogenous reaction of uncertainty (our conditioning indicator) to the policy shock and its feedbacks on the dynamics of the system. In this way, we capture both the effects of an endogenous decrease in uncertainty on precautionary savings and firms' willingness to invest and their state-dependent consequences. One of the results of this paper is exactly that of showing the far-from-negligible quantitative differences that arise when modeling uncertainty as exogenous vs. endogenous. Furthermore, our econometric strategy has the additional advantage of allowing temporal initial conditions to play a meaningful role (Koop, Pesaran, and Potter (1996)), which is important if one wants to gain further insights on the effects of monetary policy shocks from a historical perspective.

Our main results can be summarized as follows. First, we find that the historical effectiveness of monetary policy shocks is inversely correlated with the level of uncertainty at the time of the shock, a finding robust also to unconventional monetary shocks during the ZLB period.

Second, we find that, even after endogenizing uncertainty, there is still clear and robust statistical evidence of weaker real effects of monetary policy shocks during uncertain times relatively to tranquil times. More specifically, the peak reaction of real activity, in particular GDP, is approximately two-thirds weaker when the shock occurs in uncertain times than when it occurs in tranquil ones, an economically important difference. We also find that uncertainty decreases after an expansionary monetary policy shock in both states, therefore validating our modeling choice.

Third, when analyzing the role of endogenous uncertainty through counterfactuals

[6] Contributions that have recently employed IVARs are Towbin and Weber (2013), Sá, Towbin, and Wieladek (2014), Lanau and Wieladek (2012) and Aastveit, Natvik, and Sola (2017). Unlike the present study, they use a fixed conditioning variable in computing empirical responses. One exception is Caggiano, Castelnuovo, and Pellegrino (2017), who employ a fully nonlinear IVAR model similar to ours and compute GIRFs to enquire whether the real effects of uncertainty shocks are magnified at the zero lower bound.

exercises, we find that its decrease has a non-negligible quantitative effect on the estimated state-conditional responses. The difference between the state-dependent effects of monetary policy gets halved when uncertainty is treated as an endogenous variable versus when it is not. We argue this difference is driven by the interaction of two "endogenous uncertainty channels" at work which cannot be captured by conditionally-linear responses (which are computed by assuming uncertainty to be exogenous) and whose strength is state-dependent. On the one hand, there is the indirect uncertainty channel that Bernanke refers to in his statement, which is the channel that works via the reduction of uncertainty after a monetary policy easing. Such channel, *ceteris paribus*, works as an amplifier of the effects of monetary policy shocks. On the other hand, there is the compensating effect of this amplification that works by making the policy intervention less persistent since the economy is doing better than if uncertainty did not decrease. Our findings imply that the general equilibrium results of these two channels is that of making monetary policy less uncertainty-dependent with respect to what we would have found by assuming uncertainty as exogenous to monetary policy.

Our findings are relevant both from a policy and from a modeling standpoint. From a policy perspective, we lend support to theoretical studies that recommend more aggressive stimuli in uncertain times (see, e.g., Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)). While we find that, due to the mitigating power of unexpected policy easings on uncertainty, monetary policy gains some effectiveness when it is most needed, i.e., during uncertain times, we still find that during these times monetary policy is way less effective than during tranquil times. This suggests that policy makers should use fully nonlinear empirical models when it comes to quantifying the real effects of monetary shocks. From a theoretical perspective, our analysis suggests that modeling the endogenous reaction of uncertainty to policies, rather than considering it as an exogenous process, is crucial to correctly assessing alternative policies in environments characterized by uncertainty.[7]

The present paper is organized as follows. Section 2 reviews the related literature starting from close empirical papers. Section 3 describes our empirical methodology and the data employed. The main results on the effectiveness of monetary policy shocks in tranquil vs. uncertain times are presented in Section 4,. Section 5 focuses on the role of endogenous uncertainty. Section 6 concludes. An online Appendix details the

[7] To the best of our knowledge, the only work we are aware of that takes into account the endogenous uncertainty reaction to a monetary policy shock in the context of a structural model is Mumtaz and Theodoridis (2015a).

algorithm at the basis of the computation of GIRFs, presents extra results and discusses robustness checks on the main results.

2 Related literature

The work closest to ours is Aastveit, Natvik, and Sola (2017). They estimate Bayesian IVAR models for the US to investigate whether monetary policy is less effective when uncertainty is high. Compared to their study, our work crucially endogenizes uncertainty in a SEIVAR model and consistently computes fully nonlinear GIRFs. Hence, we deal with a more general framework which allows us to dig deeper on the uncertainty-dependent effects of monetary policy shocks. First, we show that uncertainty is mitigated by monetary policy shocks no matter what the state of the economy is. Second, we show that taking into account this endogenous uncertainty mechanism halves the difference between state-conditional responses although such difference remains still statistically and economically different. Third, we use our framework to perform an historical analysis of the effects of monetary policy shocks, something which cannot be done in a IVAR framework with exogenous conditioning variables.

Other related recent empirical works are Eickmeier, Metiu, and Prieto (2016), Castelnuovo and Pellegrino (2018) and Caggiano, Castelnuovo, and Nodari (2017). The aim of the first two studies is to investigate more structurally through the New-Keynesian framework how uncertainty influences the effectiveness of monetary policy shocks. They establish facts with nonlinear VAR models and interpret these facts via, respectively, a state-dependent calibration or estimation of a New-Keynesian DSGE model. With respect to their conditionally-linear Threshold VAR frameworks, this study endogenizes uncertainty and shows how important it is for the estimation of the effects of monetary policy shocks. Caggiano, Castelnuovo, and Nodari (2017) estimate a Smooth-Transition VAR model to investigate the stabilizing role of systematic monetary policy in presence of heightened uncertainty during recessions and expansions. Our work is complementary to theirs, in that it focuses on the effects of monetary policy *shocks* conditional on different levels of uncertainty.

Further connected empirical works are Weise (1999), Mumtaz and Surico (2015) and Tenreyro and Thwaites (2015), who investigate the transmission mechanism of monetary policy in good and bad economic circumstances. Their results suggest that monetary policy shocks are less effective during bad times. Unlike these studies, ours explicitly focuses on the relevance of uncertainty in the transmission of monetary policy shocks.

This is important for two reasons. First, to empirically test the predictions of the theoretical papers reviewed below which suggest uncertainty-related explanations for a state-conditional impact of monetary policy shocks. Second, conditioning on recessions could lead to spurious results since recessions can have a range of causes – financial distress, oil shocks, policy switches, and so on – and uncertainty is just one of these.[8] Empirically, the fact that periods of high uncertainty levels and recessionary periods, and vice versa, have not always coincided in the recent US history allows us to focus on the role of uncertainty by explicitly using uncertainty as our "conditioning" variable.[9]

On the theoretical side, several explanations point to a lower effectiveness of monetary policy shocks when uncertainty is high. First, the presence of some form of fixed costs or partial irreversibilities in the investment or hiring processes could give uncertainty a role. In these cases, heightened uncertainty can increase firms' option value of waiting to hire and invest, thus making the real economy less sensitive to any policy stimulus (Bloom (2009)). Bloom, Bond, and Reenen (2007) propose a model that displays a "cautionary effect" in firms' investment decisions when uncertainty is high and provide empirical evidence at the firm level for this effect as regards firms' demand shocks. Aastveit et al.'s (2017) work includes a stylized theoretical model that makes explicit how the investment response to interest rate moves can depend on the level of uncertainty due to a "caution effect" at play in a world with non-convex adjustment costs and irreversible investment. Bloom et al. (2018) simulate their general equilibrium model featuring time-varying volatility, non-convex adjustment costs in both capital and labor, and firm-level idiosyncratic shocks with the aim of identifying the effect of uncertainty on the effectiveness of a policy stimulus (which in their Real Business Cycle model they take to be a wage bill subsidy). What they find is that heightened uncertainty makes firms less responsive to the policy stimulus, implying that time-variation in uncertainty leads to time-variation in policy effectiveness. According to the authors, an implication of their exercise is that uncertainty not only impacts the economy directly, but also indirectly changes the response of the economy to any potential reactive stabi-

[8] In the words of Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), "[...] recessions are periods of both first- and second-moment shocks". Two further comments are worth making. First, uncertainty and financial shocks can be difficult to discriminate (see, among others, Stock and Watson (2012)). Second, the causal role between uncertainty and recessions has not yet been established in the literature although it is widely recognized that unexpected increases in uncertainty have contractionary effects on the real economy. As explored by some studies, uncertainty might also be a consequence of recessions (see, e.g., Bachmann and Moscarini (2012)).

[9] However, the reader has to bear in mind the fact that in general it is very difficult to disentangle empirically among these two explanations

lization policy. Our results, obtained with a framework which allows for the estimation of the real effects of monetary policy shocks in phases of high or low uncertainty, lends support to the claims of these works, even in a world with endogenous uncertainty.

Another possible explanation is that uncertainty can influence firms' price setting behavior. Several authors have developed structural calibrated models to assess whether an uncertainty motive can be at the root of the empirical fact that both the frequency and dispersion of price changes are higher during recessions. Vavra's (2014) general equilibrium price setting menu cost model suggests that a greater price flexibility induced by firm-level uncertainty can have monetary policy shocks lose up to 50% of their effectiveness relative to tranquil times. Baley and Blanco (2018) find that nominal shocks have smaller effects on output during firm-specific uncertain times also in the context of a price setting model that includes information frictions in addition to menu costs. Bachmann, Born, Elstner, and Grimme (2013) use firm micro data and find that firms change prices more frequently when uncertainty is high, consistently with Vavra's model.

A final explanation for a lower reactiveness of real activity to monetary policy shocks could be represented, in the presence of risk averse agents, by higher precautionary savings during uncertain times (see Bloom's (2014) survey and references therein). In our framework, the fact that uncertainty is endogenous enables to capture changes in precautionary motives after the monetary policy shock.

Lastly, turning to the other side of the interaction between uncertainty and monetary policy, i.e., how monetary policy influences uncertainty, Bekaert, Hoerova, and Lo Duca (2013) decompose the VIX in two components, a proxy for risk aversion and one for a pure uncertainty component, and find that both uncertainty and risk aversion decrease in the medium run after an expansionary monetary policy shock identified with a linear VAR framework. Mumtaz and Theodoridis (2015a) provide further empirical evidence on the uncertainty consequences of monetary policy shocks and study them in the context of a New-Keynesian model. Lutz (2014) works with a Factor-Augmented linear VAR model and finds that uncertainty decreases also after an unconventional monetary policy shock. Our framework allows to take account of both the endogenous reaction of uncertainty and the influence it has on the effectiveness of monetary policy.

3 The empirical methodology

3.1 The Self-Exciting Interacted-VAR

Specification. We employ a fully non-linear, or Self-Exciting, Interacted VAR model to empirically study whether the real effects of monetary policy shocks are different across tranquil and uncertain times. This model augments an otherwise standard linear VAR with an interaction term, which in this work involves two endogenously modeled variables: the variable via which we identify exogenous monetary policy changes, i.e. the policy rate, and the variable whose influence on the effects of monetary shocks is under assessment, i.e. uncertainty. This latter variable will serve as a conditioning variable allowing us to obtain the impact of monetary policy shocks in tranquil versus uncertain times. In addition to the policy rate and an uncertainty indicator, the vector of endogenous variables also includes measures of real activity and prices.

The estimated SEIVAR model is the following:

$$\mathbf{Y}_t = \boldsymbol{\alpha} + \boldsymbol{\gamma} \cdot \; linear\ trend + \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \left[\sum_{j=1}^{L} \mathbf{c}_j R_{t-j} \cdot unc_{t-j} \right] + \mathbf{u}_t \tag{1}$$

$$unc_t = e_{unc}^{'} \mathbf{Y}_t \tag{2}$$

$$R_t = e_R^{'} \mathbf{Y}_t \tag{3}$$

$$E(\mathbf{u}_t \mathbf{u}_t') = \boldsymbol{\Omega} \tag{4}$$

where $\mathbf{Y}_t$ is the $(n \times 1)$ vector of the endogenous variables, $\boldsymbol{\alpha}$ is the $(n \times 1)$ vector of constant terms, $\boldsymbol{\gamma}$ is the $(n \times 1)$ vector of slope coefficients for the time trend included, $\mathbf{A}_j$ are $(n \times n)$ matrices of coefficients, and $\mathbf{u}_t$ is the $(n \times 1)$ vector of error terms, whose variance-covariance (VCV) matrix is $\boldsymbol{\Omega}$. The interaction term in brackets makes an otherwise standard VAR a SEIVAR model. It includes a $(n \times 1)$ vector of coefficients, $\mathbf{c}_j$, a measure of uncertainty, unc_t, and the policy rate, R_t. e_y is a selection vector for the endogenous variable y in $\mathbf{Y}$. In other words, uncertainty and the policy rate are both treated as endogenous.

The model is estimated by OLS.[10] We follow Ventzislav and Kilian (2005) and select a number of lags $L = 2$ as suggested by the Hannan-Quinn criterion (both for the non-linear and the nested linear model).

[10] This is possible since, although non-linear in variables, the model is linear in parameters and does not depend on unobservable variables or nuisance parameters. Conversely from some of the most commonly used non-linear state-dependent models that reach non-linearity by combining two or more regime-specific linear VARs (e.g., Threshold VARs and Smooth Transition VARs), the Interacted-VAR model is non-linear because of its interaction terms.

The SEIVAR model presents several advantages for our purposes over alternative non-linear specifications that also feature an observed conditioning variable like Smooth-Transition (ST-)VARs and Threshold (T-)VARs. First, our SEIVAR directly captures the non-linearity in which we are interested (which has to do with the interaction between the monetary policy instrument and uncertainty) without appealing to the estimation of more parameterized and computationally intensive models. In this regard, it does not require us to identify thresholds, as in TVARs, or to estimate/calibrate transition functions, as in STVARs. The specific functional form (1)-(4) employed was chosen based on its parsimony and to avoid instability problems.[11] Second, unlike abrupt change models featuring regime-specific coefficients like TVARs, the SEIVAR is estimated on the full sample (in other words, any regime is imposed prior to estimation).[12] This allows us to avoid the issue of not having enough degrees of freedom to precisely estimate empirical responses in different states of the world referring to the extreme events of the uncertainty distribution. This is particularly relevant for the research question at hand.

Identification and statistical motivation. To identify the monetary policy shocks from the vector of reduced form residuals, we adopt the conventional short-run restrictions implied by the Cholesky decomposition. The vector of endogenous variables is ordered in the following way: $\mathbf{Y} = [P, GDP, Inv, Cons, R, Unc]'$, where, in order, we have a price index, the GDP, investment, consumption, the policy rate, and an uncertainty proxy (data are described in Section 3.3). Notice that, while the policy rate is allowed to react instantaneously to the price index and the real variables, these variables are not allowed to react on-impact to policy rate changes (like in Christiano, Eichenbaum, and Evans (1999) and Christiano, Eichenbaum, and Evans (2005)). Instead, uncertainty is allowed to react on-impact to policy rate moves. Here the degree

[11] An I-VAR might be seen as a special case of a Generalized Vector Autoregressive (GAR) model (Mittnik (1990)), i.e., a polynomial system involving monomials of increasing order of products of the vector of endogenous variables, and hence might share its possible problems. In particular GAR models might feature instability when the squares or other higher moments of the endogenous variables are included as covariates (Granger (1998) and Aruoba, Bocola, and Schorfheide (2017)) and it is difficult to impose conditions to insure their stability in general (Ruge-Murcia (2015)). Our model appears not to suffer from these problems because of its parsimonious specification that features the simple products of the lags of the policy rate and those of the uncertainty indicator. Still the dynamics captured by our I-VAR could depend on the specific functional form employed. A check in Section A4 of the Appendix shows that very similar dynamics are obtained once we allow for a richer specification of the interaction between uncertainty and monetary policy.

[12] This can let the dynamics captured by the IVAR model be less dependent on the presence of outliers in a particular regime.

of endogeneity of uncertainty is maximized, but in the robustness checks sections we do show, however, that our results are robust to modeling uncertainty as the first variable of the vector.

Importantly, a likelihood-ratio test for the overall exclusion of the interaction terms from model (1)-(4) allows us to reject the null hypothesis of linearity at any conventional level in favor of the alternative of our SEIVAR model. In particular, when uncertainty is proxied by the IQR of sales growth, the LR test suggests a value for the test statistic $\chi_{12} = 29.26$, with an associated p-value of 0.005, whereas in the VIX uncertainty case we have a value $\chi_{12} = 27.53$, with associated p-value of 0.007. Similar evidence relates to the Jurado, Ludvigson, and Ng (2015) uncertainty indicators that are used for robustness.

As regards the econometric motivation for modeling uncertainty in $\mathbf{Y}$, from the last equation of our VAR, we find that the policy rate Granger-causes our uncertainty measures ($F_2^{robust} = 3.34$ – with p-value=0.04 – for the IQR of sales growth case and $F_2^{robust} = 2.55$ – with p-value=0.08 – for the VIX case). This is an indication that the policy rate is useful to predict uncertainty. Later, structural generalized impulse responses will clarify that uncertainty significantly reacts to monetary policy shocks. According to simple linear VAR evidence (from the linear VAR nested in specification (1)-(4)), conventional monetary policy shocks explain on average around 10% (6%) of the 2-years-ahead forecast error variance of uncertainty in case it is proxied by the IQR of sales growth (VIX).[13]

3.2 Generalized Impulse Response Functions

Unlike existing studies employing an IVAR model, our conditioning variable, i.e. uncertainty, is also included in the vector of modeled endogenous variables. This is important because, as shown later, uncertainty is found to decrease after an expansionary monetary policy shock. Without accounting for this endogenous reaction, biased IRFs would arise as the feedbacks from such uncertainty reaction on the dynamics of the economy would be disregarded. In order to correctly estimate empirical responses from a non-linear model in the presence of an endogenous conditioning variable, we compute Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran, and Potter

[13] The fact that the VIX is less endogenous to monetary policy shocks is consistent with the findings by Ludvigson, Ma, and Ng (2015) according to which financial uncertainty is more exogenous to the business cycle. As we will show in Section 5, however, taking account of the endogenous response of the VIX is also equally important to precisely estimate responses.

(1996) accounting for an orthogonal structural shock as in Kilian and Vigfusson (2011). GIRFs take into account the fact that in a fully non-linear model a shock can influence the state of the system and therefore its following evolution. As a result, GIRFs return fully non-linear empirical responses that depend nontrivially on the initial conditions in place when the system is shocked. Theoretically, the GIRF at horizon h of the vector $\mathbf{Y}_t$ to a shock of size δ computed conditional on an initial history (or initial conditions), $\boldsymbol{\varpi}_{t-1} = \{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-L}\}$, is given by the following difference of conditional expectations:

$$GIRF_{Y,t}(h, \delta_t, \varpi_{t-1}) = E\left[\mathbf{Y}_{t+h} \mid \delta, \boldsymbol{\varpi}_{t-1}\right] - E\left[\mathbf{Y}_{t+h} \mid \boldsymbol{\varpi}_{t-1}\right].$$

In principle, we have as many history-dependent GIRFs referring to a generic initial quarter $t-1$ as there are quarters in our estimation sample. Once these GIRFs are horizon-wised averaged over a particular subset of initial quarters of interest we can obtain our state-dependent GIRFs, which reflect the average response of the economy to a shock in a given state. Consistently with Vavra (2014) and Bloom, Bond, and Reenen (2007), we assume the "tranquil times" state to be characterized by initial quarters with uncertainty around the first decile of its empirical distribution, and the "uncertain times" state by initial quarters around its ninth decile (a five-percentiles tolerance band around the top and bottom deciles is used).[14] Conditioning responses on extreme events, rather than on normal events, may be important in order not to confound similar states and hence missing empirical responses in favor of non-linearity (Caggiano, Castelnuovo, Colombo, and Nodari (2015)). The algorithm at the basis of the simulation of our GIRFs is provided in Section A1 of the Appendix.

An alternative methodology to GIRFs to compute non-linear empirical responses would be to use Local Projections à la Jordà (2005). Similarly to GIRFs, this methodology allows estimated responses to implicitly incorporate the average evolution of the economy between the time the shock hits and the time the shock effects are evaluated. In a recent work, Owyang, Ramey, and Zubairy (2013) use Local Projections to extract empirical responses to an exogenously identified shock from a univariate Threshold Autoregressive model. This strategy is not, however, used here as the tool to estimate empirical responses for three reasons. First, Local Projections IRFs are not as informative as GIRFs since they provide just the average reaction of the economy in a given

[14] This definition allows both each given state to feature a number of GIRFs large enough to obtain representative state-conditional responses and to have results that do not depend on particularly extreme observations.

state, whereas GIRFs allow us to obtain fully non-linear empirical responses for each given initial quarter in the sample. Second, they produce responses that are generally erratic and that display oscillations at long horizons (as documented and explained in Ramey (2012)). Third, in our application they would suffer significantly from the issue of insufficient degrees of freedom to estimate precisely the empirical responses referring to extreme events.

3.3 Data

Our VAR jointly models an indicator of uncertainty, measures of US real activity, the GDP deflator and the monetary policy instrument. Real activity is captured by real GDP, real gross private domestic investment and real personal consumption expenditures. Investment and consumption are considered in addition to GDP since they allow us to investigate the different transmission mechanism of monetary policy shocks between uncertain and tranquil times. In theoretical models uncertainty influences investment through real-option effects and consumption through precautionary savings. The federal funds rate (FFR) is meant to be the instrument of monetary policy as commonly assumed in the empirical literature studying the impact of monetary shocks. For the part of our sample that overlaps with the binding zero lower bound period in the U.S. we use the common used Wu and Xia's (2016) "shadow rate" instead of the FFR and label shocks in it as "unconventional" monetary policy shocks.[15] The Wu and Xia's shadow rate turned negative since July 2009 (or quarterly, since 2009Q3) and consistently we take this as an indication that the ZLB constraint became actually binding. Both real variables and prices are taken in logs and multiplied by 100. This implies that their VAR responses can be interpreted as percent deviations from trend. The sample period starts in 1971Q1.[16] Further details on the data sources are available in the Appendix.

Uncertainty is measured by a number of different indicators proposed in the literature. As baseline indicators we use alternatively a micro-level and a macro-level uncertainty measure. Regarding the first indicator, we use a cross sectional firm-level

[15] The shadow rate is a model-implied interest rate that Wu and Xia (2016) estimate on the basis of a multifactorial shadow rate term structure model. It is similar to the FFR for the period before the zero lower bound (ZLB) period, but it is allowed to turn negative over the ZLB period. They show that the shadow rate can be used to proxy unconventional monetary policy at the ZLB.

[16] The starting date is dictated by the availability of the uncertainty measures (i.e., to have a common initial date across all the four uncertainty indicators employed). It also proves useful, given our employment of the series for inflation expectations that we use in our robustness check (available since 1970Q2).

measure of uncertainty constructed by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), i.e. the interquartile range (IQR) of sales growth for a sample of Compustat firms, which is available up to 2009Q3. Unlike aggregate volatility indicators, this disaggregate indicator is also likely to capture idiosyncratic (i.e., firm-specific) shocks. These firm-level factors, it is suggested by several studies, constitute one of the most important factors in explaining both firms' investment behavior (see, among others, Bernanke (1983), Bertola and Caballero (1994), Dixit and Pindyck (1994)) and price setting behavior (see Vavra (2014) and references therein), and an important driver behind aggregate time-varying volatility (Carvalho and Grassi (2015)).

Our second indicator of uncertainty is the stock market Volatility IndeX (VIX) used by Bloom (2009). We update the Bloom's series up to 2015Q4. The VIX index has been widely used in the empirical literature on the impact of uncertainty shocks and represents the degree of real-time implied volatility as quantified by financial markets. Along with these baseline uncertainty indicators, for which detailed results are presented, we also use the macro and firm-level uncertainty indices developed by Jurado, Ludvigson, and Ng (2015) to check the robustness of our main results. These indices are based on the purely unforecastable components extracted from two large US datasets.

Figure 1 plots the baseline uncertainty indicators against NBER recessionary periods (represented by grey vertical bars). Notice that periods of high uncertainty and recessionary periods have not always coincided in the recent US history and in principle they are empirically distinguishable, something that allows us to talk about "uncertainty" as opposed to "recessions". In fact, although the global maximum of both uncertainty indicators occurred during the recent Great Recession, and, more generally, uncertainty is on average higher in recessions, many spikes occurred during expansions.[17] Moreover, some recessions, e.g., the 1980 and 1990-91 ones, have not been characterized by particularly high levels of uncertainty.

[17] Referring to the VIX case (for which we can use the major volatility episodes identified by Bloom (2009, Table A.1)), see, among others, the spikes associated with the Black Market crash at the end of 1987, the Asian crisis in 1997, the Worldcom and Enron financial scandals in 2002 and the Gulf War in 2003.

4 The uncertainty-dependent effects of monetary policy shocks

4.1 Historical evidence for the full sample

We start our empirical analysis by examining whether the effectiveness of monetary policy shocks have evolved through time according to the level of historical uncertainty. One characteristic of endogenously modeling uncertainty and computing fully nonlinear responses is indeed the possibility to recover an empirical response for each given quarter in the sample. Consider a fixed-size monetary shock equal to a 25 basis points unexpected decrease in the policy rate hitting each quarter. Figure 2 presents summary evidence of time-variation of GIRFs (whereas the full evidence is available in the form of a tridimensional graph in Figure A1 in the Appendix). The upper panels of Figure 2 present the temporal evolution of the peak (i.e. maximum) and cumulative percent response of real GDP for the expansionary monetary shock happening in quarter t and put this response in comparison with the initial level of uncertainty in the previous quarter. The lower panels use a scatter plot to further analyze the relation between the initial level of uncertainty at time $t-1$ and the GDP peak response for a shock happening in t. Left (right) panels refer to the case the IQR of sales growth (VIX) is used as the uncertainty proxy.

Two considerations are in order. First, the real effects of monetary policy shocks depend on the initial level of uncertainty. The shape of time variation of the GDP peak and 5-year cumulative effects in the upper panels of Figure 2 tracks closely the historical behavior (with the reversed sign) of uncertainty. This evidence suggests that the effects of policy shocks are less powerful, and hence monetary policy is less effective, if the shock hits the economy in an uncertain phase relative to a tranquil one.

Second, as lower panels of Figure 2 show, the relationship between initial uncertainty and the effectiveness of monetary policy shocks is not perfect – although clearly negative on average–, in the sense that once a given initial level of uncertainty is selected, we can observe different quantitative responses to an equally sized monetary policy shock. The linear correlation coefficient between the peak effect of monetary policy shocks and the initial level of uncertainty is -0.70 (-0.52) for the IQR of sales growth (VIX). This is a clear indication that historical initial conditions (besides just uncertainty) play a meaningful role in our responses.[18] Thanks to our framework we are able to find

[18] Notice that, if instead uncertainty was exogenously modeled, and therefore conditionally-linear IRFs were computed, we would observe a perfect relationship between initial uncertainty and the

that, among other historical conditions, the period of binding ZLB and unconventional monetary policy shocks clearly introduced an important instability in the effects of monetary policy shocks (something supposedly implying that the effects of a cut in the FFR and an equally-sized cut in the shadow rate are not easily comparable).[19] Interestingly for us, even in the binding ZLB period we can observe a clear negative relation between uncertainty and the power of (unconventional) monetary policy shocks (refer at the VIX case for which we have a longer sample).

Since the purpose of the next part of our analysis is that of studying the state-conditional, averaged response of the economy to a monetary policy shock, from now on we exclude from our estimation sample the period with unconventional monetary policy shocks (i.e. shocks to the Wu and Xia (2016) shadow rate for the implied period of binding ZLB) and focus on conventional monetary policy (for the sample period 1971Q1-2009Q2). We do this for three reasons. First, given the clear instability documented in Figure 2, it would be difficult to obtain a representative state-conditional, averaged response of the effects of monetary policy shocks if we included the ZLB sample. Second, Bauer and Rudebusch (2016) find that estimated shadow rates are quite sensitive to several modeling assumptions and hence argue that the use of shadow rates as indicators of monetary policy at the ZLB may be problematic. Some exercises conducted in the Appendix (Figure A3) document that the power of unconventional monetary policy shocks depends on the specific shadow rate used, something that affects also the power of conventional monetary policy shocks and that hence would be reflected with a bias in the averaged response. Third, the presence of the ZLB itself complicates the comparison between the effects of conventional and unconventional monetary policy shocks, as the mitigating power of expansionary monetary policy shocks on uncertainty (that we will show in the next Section) may be more beneficial for the economy in ZLB, when, as documented by Caggiano, Castelnuovo, and Pellegrino (2017), the effects of heightened uncertainty are particularly strong.

effectiveness of monetary policy shocks (given that no temporal dimension could be associated with responses, as shown in Figure A2 of the Appendix).

[19] The findings suggest that unconventional monetary policy has been apparently more effective on average than conventional monetary policy shocks. This is consistent with Wu and Xia (2016, Fig. 9, p. 271) that find a cut in their shadow rate to be more effective in affecting unemployment than an equally-sized cut in the FFR. However, this results is beyond the purposes of this paper and the investigations of the reasons behind it are left to future research.

4.2 Average evidence for conventional monetary policy shocks

Baseline results. This Section analyzes the state-dependent effects of monetary policy shocks. We start with the empirical quantification of the averaged effects in our "uncertain time" and "tranquil times" states (which refer to the extreme deciles of uncertainty as defined in Section 3.2) and then turn to test their statistical difference.

Figure 3 presents the point estimates for the state-conditional GIRFs of real GDP together with the corresponding IRFs coming from the linear VAR nested in our SEIVAR model (throughout the analysis we consider the same 25 basis points expansionary shock in the FFR). Two results can be drawn from the figure. First, the GIRFs suggest that monetary policy shocks are on average less effective during uncertain times. Specifically, focusing on peak reactions, real GDP reacts on average 47% and 74% more during tranquil times for the IQR of sales growth case and the VIX case, respectively. Second, linear responses are within our state-conditional responses. Hence, standard linear VARs are likely to capture average effects of a monetary policy shock, which, however, underestimate (overestimate) the impact of monetary policy shocks in tranquil (uncertain) times.

We now consider the state-dependent evidence for all our six endogenous variables in our SEIVAR. Figure 4 (5) show baseline results conditional to the use of the IQR of sales growth (VIX) as the uncertainty indicator. These figures present the GIRFs conditional on the uncertain times (left panels) and tranquil times states (right panels) along with their 68 and 90% bootstrapped confidence bands.[20] Looking first at real variables, GDP, investment and consumption all increase in both states after the expansionary shock. However, both the magnitude and the persistence of this increase depend on the state of the economy. During tranquil times investment increases by a maximum of around 1% and consumption and GDP by around 0.25% . During uncertain times, instead, their maximum reactions are around two-thirds weaker than during tranquil times. This suggests not only that monetary policy shocks are less effective when they occur during economic phases characterized by high uncertainty, but also that they are so in an economically important manner.

Figures 4 and 5 also document a significant decrease in uncertainty in response to the considered expansionary monetary policy shock. To appreciate the size of the decrease in uncertainty, notice that a one standard deviation monetary policy shock would cause a maximum decrease in uncertainty of around 1/3 of the standard deviation

[20] The bootstrapped confidence bands take full account of sampling variability, i.e., of parameters uncertainty.

of uncertainty shocks when uncertainty is proxied by the IQR of sales growth and of around 1/6 when uncertainty is proxied by the VIX. This significant and sizable decrease in uncertainty confirms the necessity of modeling uncertainty as an endogenous variable and, accordingly, that of computing GIRFs à la Koop et al. (1996). If uncertainty were exogenously modeled, and conditionally-linear state-dependent IRFs were computed, these linear impulse responses would fail to account for the mitigating effects of an expansionary monetary policy shock on uncertainty and the feedback that this decrease in uncertainty has on the economy. The next Section digs deeper on the role of the endogenous decrease in uncertainty to show its relevance for estimated responses.

Turning to the response of prices, Figure 4 and 5 document the appearance of a "price puzzle". The price response predicts, contrary to conventional wisdom, a significant short-run decrease in prices following a monetary policy expansion, with prices starting to increase with respect to trend only later. This is something very frequent in the monetary VAR literature. The literature has proposed two main ways to interpret this apparent puzzle. One way is to interpret the reaction of prices as a VAR-fact while the other one is to interpret it as a VAR-artefact due to omitted variables.[21] In Section A4 of the Appendix we perform a check considering inflation expectations and Divisia money as further variables in our VAR (following, respectively, Castelnuovo and Surico (2010) and Keating, Kelly, and Valcarcel (2014)). The puzzling response of prices is significantly mitigated and the nonlinear response of real activity to a monetary policy shock documented with our benchmark analysis turns out to be robust. A further consideration on the reaction of prices is that notwithstanding the very different responses of real activity indicators, price responses hardly exhibit any different behavior between states. This is, at a first glance, evidence against the empirical relevance of Vavra's (2014) mechanism centered on price setting as the main driver behind our results. In Section A2 of our online Appendix we clarify some reasons why it is important to be cautious in this respect when interpreting our results – e.g., our VAR setting and our use of aggregate data –, and conclude on the need of more research using microeconomic data (following, e.g., Bachmann, Born, Elstner, and Grimme (2017)).

Finally, in order to examine whether the response of real variables is statistically

[21] As regards the "fact" interpretation, Christiano, Eichenbaum, and Evans (2005) rationalize the price puzzle via a working capital channel which justifies the presence of a short-term interest rate in firms' marginal costs due to the fact that firms must borrow money to finance their wage bill before the goods market opens. The reduction in marginal costs after an expansionary monetary policy shocks could hence be at the root of the price puzzle. As regards the "artefact" interpretation, Sims (1992) and Castelnuovo and Surico (2010) attribute the price puzzle evidence to variables that are omitted in the VAR but that are instead considered by the monetary authority in taking their policy decisions.

different between states, a test statistic is proposed in Figure 6, both for the IQR of sales growth (left panels) and the VIX case (right panels). The computation of this test statistic is based on the distribution of the difference between state-conditional responses stemming from the bootstrap procedure used. This allows us to take into account the correlation between the estimated impulse responses. We report the percentiles referring to the 68 and 90 percent confidence levels. The confidence bands point to a statistically different response of real activity between uncertain and tranquil times in the medium run, i.e. in the period in which monetary policy exerts the maximum of its power before becoming neutral in the long run.

Robustness checks. The robustness of our baseline results is assessed along several dimensions in Section A4.1 of our online Appendix (summary in Figure A4 and first row of Figure A6). We employ alternative uncertainty measures (such as Jurado, Ludvigson and Ng's (2015) macro- and firm-level uncertainty indexes), sharpen the identification of the monetary policy shocks (by considering either inflation expectations or a different Cholesky ordering with uncertainty first) and consider a NBER dummy as a potentially relevant omitted variable.

Section A4.2 motivates and presents the results from additional robustness checks we performed (summary in Figure A5 and last two rows of Figure A6). It is shown that baseline results are robust to: i) the estimation over the post-Volcker sample; ii) the case of a break in the variance-covariance matrix that accounts for lower volatility during the Great Moderation period; iii) the employment of a richer specification of our SEIVAR model that allows for higher order interaction terms between the FFR and uncertainty; iv) the case the linear trend is not included; v) the case trending variables are modelled in growth rates; vi) the estimation of a smaller-scale SEIVAR; vii) the employment of an alternative Cholesky ordering in which uncertainty is allowed to contemporaneously react to real activity but not to monetary policy; viii) the ordering of prices as last variable so that to allow for its on-impact response to the policy shock and ix) the case the CPI and PPI are used instead than the GDP deflator price index.

Section A4.3 contains further information: Figure A7 uses a wider tolerance band in defining the two states; Figure A8 proposes a statistical test for the difference of the cumulative effect of monetary policy shocks; Figure A9 shows the decrease in uncertainty for the checks considered in Section A4.1.

5 The role of endogenous uncertainty

This Section shows that modeling the endogenous response of uncertainty to monetary shocks is crucial to properly estimate the real effects of monetary policy shocks.

Figure 7 makes a comparison between our baseline state-conditional GIRFs and the IRFs obtained from a counterfactual exercise based on the same estimated baseline SEIVAR model but where responses are computed by keeping the level of uncertainty at its pre-shock value, i.e., by shutting down the (endogenous) reaction of uncertainty to a monetary policy shock.[22] As the figure documents, state-conditional responses of real variables get more distant between states when uncertainty is kept fixed in the computation of (conditionally-linear) counterfactual responses than when its endogenous reaction is considered in computing (fully non-linear) responses. Table 1 complements the figure by making a comparison between the difference in the state-conditional real effects of the monetary shock for the cases of endogenous and exogenous uncertainty. Overall, we have that the difference between both peak and cumulative state-dependent responses of real variables gets halved when uncertainty is treated as endogenous.

The result above is due to the interaction between two endogenous uncertainty channels at work which cannot be captured by conditionally-linear IRFs, and whose neglection leads to inflating the differences between tranquil times and uncertain times.

On the one hand, the reduction in uncertainty after an expansionary monetary shock will, *ceteris paribus*, amplify the response of real variables in each state. This is the "indirect uncertainty channel" that Bernanke refers to in his statement in the Introduction, which works via reduced precautionary savings and a shrinkage of firms' inaction regions. This channel is at work in both states – uncertain and tranquil times – but is expected to be larger when uncertainty is high (see Jones and Enders (2013)).[23] Hence, the difference of the response of real variables between uncertain and tranquil times will be smaller with uncertainty modeled as endogenous with respect to the case in which the response of uncertainty is not taken into account.

On the other hand, due to the reduction in uncertainty after an expansionary monetary policy shock, the persistence of the central bank intervention will in general be

[22] Following the same logic of the counterfactual exercises in Sims and Zha (2006b), we perform this exercise by making uncertainty completely unresponsive to other variables in the system (i.e., uncertainty remains fixed to its pre-shock value during all the iterations needed to compute the GIRFs). The response we get is technically a conditionally-linear response for which starting conditions do not play any role.

[23] Jones and Enders (2013) find that an unexpected change in uncertainty is more relevant in a state of high initial uncertainty.

lower with respect to the case of exogenous uncertainty. Given the better economic stance due to the decrease in uncertainty, the central bank will act less expansively than in the case of exogenous uncertainty.[24] This effect, which compensates the previous amplification effect, is expected to be stronger when uncertainty is low because of higher inflationary pressures related to the stronger expansionary effect of monetary policy shocks. Therefore, compared to the case of exogenous uncertainty, the real effects of the initial monetary policy shock will be lower in tranquil times, relative to uncertain times. Again, GIRFs – which take account of endogenous uncertainty – will provide a smaller difference in the response of real activity with respect to IRFs computed disregarding the response of uncertainty to the monetary policy shock.

The two proposed channels are meant to rationalize the move from conditionally-linear IRFs to GIRFs. This is exactly what Figure 7 documents. First, looking just at uncertain times responses, the reaction of real variables to the shock is overall bigger when uncertainty is endogenously modeled than when it is exogenously modelled, consistently with the fact that the interest rate response does not particularly differ across the two different modeling cases. Second, looking just at tranquil times responses, the reaction of real variables is instead more moderate when uncertainty is endogenously modeled than when it is not, consistently with the less persistent drop of the FFR we observe in the medium run in this modeling case.

To ensure that the counterfactual exercise above fully captures what happens when uncertainty is exogenous modelled (as in, e.g., Aastveit, Natvik, and Sola (2017)), Figure A10 in the Appendix shows IRFs obtained from an alternative IVAR where uncertainty, which serves as our conditioning variable, is not modeled in the vector of endogenous variables and hence where conditionally-linear IRFs are computed (as done so far in the literature). As Figure A10 shows, the same results as in Figure 7 are obtained.

6 Conclusion

We propose a non-linear framework designed to study the macroeconomic effects of monetary policy shocks during tranquil versus uncertain times taking into account that uncertainty may react to monetary stimuli. We show that modeling uncertainty as

[24] This can be explained with a Taylor-type rule of systematic conduct of monetary policy once considered the indirect positive consequences of the decrease in uncertainty on real GDP and inflation. Further, there may also be a direct systematic response of monetary policy to uncertainty, as recently argued by Evans, Fisher, Gourio, and Krane (2015) and Caggiano, Castelnuovo, and Nodari (2017), something which would strengthen our point.

endogenous is key, both economically and econometrically, in order not to disregard important transmission channels and hence to correctly estimate the effects of unexpected monetary stimuli. We find that, on average, an unexpected monetary policy shock has real effects around two-thirds smaller during uncertain times than during tranquil times. While being an important difference, we show that it is considerably smaller than what one would get by disregarding the reaction of uncertainty. Our results lend support to real option effects in investment and durable goods as a potential theoretical explanation behind the reduced effectiveness of monetary policy shocks. Further, our results point to the existence of a novel indirect uncertainty transmission mechanism for the propagation of monetary policy shocks.

Our findings have implications for policy because they suggest that, even when considering the "endogenous uncertainty" mechanism, monetary policy remains less effective during uncertain times than tranquil times. Our evidence lends empirical support to the call for more aggressive policies in uncertain times (Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)). Our findings also offer some suggestions for theoretical modeling, in particular pointing to the relevance of developing non-linear micro-founded models where uncertainty can play a state-conditional role and possibly where, instead of being a completely exogenous process, it can react to policy stimuli.

References

Aastveit, K. A., G. J. Natvik, and S. Sola (2013): "Macroeconomic Uncertainty and the Effectiveness of Monetary Policy," Norges Bank Working Paper No. 2013/17.

——— (2017): "Economic Uncertainty and the Influence of Monetary Policy," *Journal of International Money and Finance*, 76, 50–67.

Alessandri, P., and H. Mumtaz (2018): "Financial Regimes and Uncertainty Shocks," *Journal of Monetary Economics*, Forthcoming.

Aruoba, S. B., L. Bocola, and F. Schorfheide (2017): "Assessing DSGE model nonlinearities," *Journal of Economic Dynamics and Control*, 83, 34–54.

Bachmann, R., B. Born, S. Elstner, and C. Grimme (2013): "Time-Varying Business Volatility, Price Setting, and the Real Effects of Monetary Policy," NBER Working Paper No. 19180.

——— (2017): "Time-Varying Business Volatility and the Price Setting of Firms," University of Notre Dame, University of Bonn, RWI Essen and ifo Institute, mimeo.

Bachmann, R., S. Elstner, and E. Sims (2013): "Uncertainty and Economic Activity: Evidence from Business Survey Data," *American Economic Journal: Macroeconomics*, 5(2), 217–249.

Bachmann, R., and G. Moscarini (2012): "Business Cycles and Endogenous Uncertainty," RWTH Aachen University and Yale University, mimeo.

Baker, S., N. Bloom, and S. J. Davis (2016): "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, 131(4), 1539–1636.

Baley, I., and J. A. Blanco (2018): "Firm Uncertainty Cycles and the Propagation of Nominal Shocks," *American Economic Journal: Macroeconomics*, Forthcoming.

Barnett, W. A. (1980): "Economic Monetary Aggregate: An Application of Index Number and Aggregation Theory," *Journal of Econometrics*, 14, 11–48.

Bauer, M. D., and G. D. Rudebusch (2016): "Monetary policy expectations at the zero lower bound," *Journal of Money, Credit and Banking*, 48(7), 1439–1465.

Bekaert, G., M. Hoerova, and M. Lo Duca (2013): "Risk, Uncertainty and Monetary Policy," *Journal of Monetary Economics*, 60, 771–788.

Bernanke, B. S. (1983): "Irreversibility, Uncertainty, and Cyclical Investment," *Quarterly Journal of Economics*, 98(1), 85–106.

Bertola, G., and R. J. Caballero (1994): "Irreversibility and Aggregate Investment," *Review of Economic Studies*, 61, 223–246.

Bloom, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77(3), 623–685.

Bloom, N., S. Bond, and J. V. Reenen (2007): "Uncertainty and Investment Dynamics," *Review of Economic Studies*, 74, 391–415.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018): "Really Uncertain Business Cycles," *Econometrica*, Forthcoming.

Boivin, J., and M. Giannoni (2006): "Has Monetary Policy Become More Effective?," *Review of Economics and Statistics*, 88(3), 445–462.

Boivin, J., M. Giannoni, and I. Mihov (2009): "Sticky Prices and Monetary Policy: Evidence from Disaggregated U.S. Data," *The American Economic Review*, 99(1), 350–384.

Caballero, R. (1990): "Consumption Puzzles and Precautionary Savings," *Journal of Monetary Economics*, 25, 113–136.

Caggiano, G., E. Castelnuovo, V. Colombo, and G. Nodari (2015): "Estimating Fiscal Multipliers: News From a Nonlinear World," *Economic Journal*, 125(584), 746–776.

Caggiano, G., E. Castelnuovo, and J. M. Figueres (2017): "Economic Policy Uncertainty and Unemployment in the United States: A Nonlinear Approach," *Economics Letters*, 151, 31–34.

Caggiano, G., E. Castelnuovo, and N. Groshenny (2014): "Uncertainty Shocks and Unemployment Dynamics: An Analysis of Post-WWII U.S. Recessions," *Journal of Monetary Economics*, 67, 78–92.

Caggiano, G., E. Castelnuovo, and G. Nodari (2017): "Uncertainty and Monetary Policy in Good and Bad Times," Melbourne Institute Working Paper(No. 9/17).

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.

Carriero, A., H. Mumtaz, K. Theodoridis, and A. Theophilopoulou (2015): "The Impact of Uncertainty Shocks under Measurement Error: A Proxy SVAR Approach," *Journal of Money, Credit and Banking*, 47(6), 1223–1238.

Carvalho, V. M., and B. Grassi (2015): "Large Firm Dynamics and the Business Cycle," Barcelona GSE Working Paper(No. 824).

Castelnuovo, E., and G. Pellegrino (2018): "Uncertainty-dependent Effects of Monetary Policy Shocks: A New-Keynesian Interpretation," *Journal of Economic Dynamics and Control*, forthcoming.

Castelnuovo, E., and P. Surico (2010): "Monetary Policy Shifts, Inflation Expectations and the Price Puzzle," *Economic Journal*, 120(549), 1262–1283.

Christiano, L. J., M. Eichenbaum, and C. Evans (1999): "Monetary Policy Shocks: What Have We Learned and to What End?," In: J.B. Taylor and M. Woodford (eds.): Handbook of Macroeconomics, Elsevier Science, 65–148.

——— (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113(1), 1–45.

Clarida, R., J. Galí, and M. Gertler (2000): "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 115, 147–180.

Colombo, V. (2013): "Economic policy uncertainty in the US: Does it matter for the Euro Area?," *Economics Letters*, 121(1), 39–42.

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

Eickmeier, S., N. Metiu, and E. Prieto (2016): "Time-Varying Volatility, Financial Intermediation and Monetary Policy," CAMA Working Paper No. 32/2016.

Evans, C., J. D. M. Fisher, F. Gourio, and S. Krane (2015): "Risk Management for Monetary Policy Near the Zero Lower Bound," *Brookings Papers on Economic Activity*, pp. 141–219.

Gertler, M., and P. Karadi (2015): "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 7(1), 44–76.

Gilchrist, S., J. W. Sim, and E. Zakrajšek (2014): "Uncertainty, Financial Frictions, and Investment Dynamics," Boston University and Federal Reserve Board of Governors, mimeo.

Granger, C. W. (1998): "Overview of Nonlinear Time Series Specification in Economics," University of California, San Diego.

Hamilton, J. D. (1994): Time Series Analysis, Princeton University Press, Princeton, New Jersey.

Hanson, M. (2004): “The "Price Puzzle" Reconsidered,” *Journal of Monetary Economics*, 51, 1385–1413.

Jones, P. M., and W. Enders (2013): “The Asymmetric Effects of Uncertainty on Macroeconomic Activity,” University of Alabama, mimeo.

Jordà, O. (2005): “Estimation and Inference of Impulse Responses by Local Projections,” *American Economic Review*, 95(1), 161–182.

Jurado, K., S. C. Ludvigson, and S. Ng (2015): “Measuring Uncertainty,” *American Economic Review*, 105(3), 1177–1216.

Keating, J. W., L. J. Kelly, and V. J. Valcarcel (2014): “Solving the price puzzle with an alternative indicator of monetary policy,” *Economics Letters*, 124(2), 188–194.

Kilian, L., and R. Vigfusson (2011): “Are the Responses of the U.S. Economy Asymmetric in Energy Price Increases and Decreases?,” *Quantitative Economics*, 2, 419–453.

Kim, C., and C. Nelson (1999): “Has the U.S. Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle,” *The Review of Economics and Statistics*, 81, 608–616.

Koop, G., M. Pesaran, and S. Potter (1996): “Impulse response analysis in nonlinear multivariate models,” *Journal of Econometrics*, 74(1), 119–147.

Krippner, L. (2015): Term Structure Modeling at the Zero Lower Bound: A Practitioner’s Guide, Palgrave-Macmillan.

Lanau, S., and T. Wieladek (2012): “Financial Regulation and the Current Account,” International Monetary Fund Working Paper(No. 98).

Leduc, S., and Z. Liu (2016): “Uncertainty Shocks are Aggregate Demand Shocks,” *Journal of Monetary Economics*, 82, 20–35.

Lubik, T., and F. Schorfheide (2004): “Testing for Indeterminacy: An Application to U.S. Monetary Policy,” *American Economic Review*, 94(1), 190–217.

Ludvigson, S. C., S. Ma, and S. Ng (2015): “Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?,” Working Paper 21803, National Bureau of Economic Research.

Lutz, C. (2014): “Unconventional Monetary Policy and Uncertainty,” Copenhagen Business School, mimeo.

Lütkepohl, H. (2013): “Identifying Structural Vector Autoregressions via Changes in Volatility,” *Advances in Econometrics*, 32, 169–203.

McConnell, M., and G. Perez-Quiros (2000): “Output Fluctuations in the United States: What Has Changed Since the Early 1980s?,” *American Economic Review*, 90, 1464–1476.

Mittnik, S. (1990): "Modeling Nonlinear Processes With Generalized Autoregressions," *Applied Mathematics Letters*, 3(4), 71–74.

Mumtaz, H., and P. Surico (2015): "The Transmission Mechanism in Good and Bad Times," *International Economic Review*, 56, 1237–1260.

Mumtaz, H., and K. Theodoridis (2015a): "Dynamic effects of monetary policy shocks on macroeconomic volatility," Working Paper 760, School of Economics and Finance, Queen Mary University of London.

Mumtaz, H., and K. Theodoridis (2015b): "The International Transmission of Volatility Shocks: An Empirical Analysis," *Journal of the European Economic Association*, 13(3), 512–533.

Mumtaz, H., and F. Zanetti (2013): "The Impact of the Volatility of Monetary Policy Shocks," *Journal of Money, Credit and Banking*, 45(4), 535–558.

Nodari, G. (2014): "Financial Regulation Policy Uncertainty and Credit Spreads in the U.S.," *Journal of Macroeconomics*, 41, 122–132.

Owyang, M., V. A. Ramey, and S. Zubairy (2013): "Are Government Spending Multipliers Greater During Periods of Slack? Evidence from 20th Century Historical Data," *American Economic Review Papers and Proceedings*, 103(3), 129–134.

Parker, J. A., and B. Preston (2005): "Precautionary saving and consumption fluctuations," *The American Economic Review*, 95(4), 1119–1143.

Pellegrino, G. (2017): "Uncertainty and the Real Effects of Monetary Policy Shocks in the Euro Area," *Economics Letters*, forthcoming.

Ramey, V. A. (2012): "Comment on Roads to Prosperity or Bridges to Nowhere? Theory and Evidence on the Impact of Public Infrastructure Investment," *NBER Macroeconomics Annual*, 27, 147–153, National Bureau of Economic Research.

Ricco, G., G. Callegari, and J. Cimadomo (2016): "Signals from the Government: Policy Disagreement and the Transmission of Fiscal Shocks," *Journal of Monetary Economics*, 82, 107–118.

Romer, C., and D. Romer (2004): "A New Measure of Monetary Policy Shocks: Derivation and Implications," *American Economic Review*, 94(4), 1055–1084.

Ruge-Murcia, F. (2015): "Indirect Inference Estimation of Nonlinear Dynamic General Equilibrium Models: With an Application to Asset Pricing under Skewness Risk," McGill University, mimeo.

Sims, C. (1992): "Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy," *European Economic Review*, 36(5), 975–1000.

Sims, C., and T. Zha (2006a): "Were There Regime Switches in U.S. Monetary Policy?," *American Economic Review*, 96(1), 54–81.

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

SIMS, C. A., AND T. ZHA (2006b): "Does Monetary Policy Generate Recessions?," *Macroeconomic Dynamics*, 10, 231–272.

STOCK, J. H., AND M. W. WATSON (2002): "Has the Business Cycle Changed and Why?," in M Gertler and K. Rogoff (eds.): NBER Macroeconomic Annual, MIT Press, Cambridge, MA.

STOCK, J. H., AND M. W. WATSON (2012): "Disentangling the Channels of the 2007-2009 Recession," *Brookings Papers on Economic Activity*, Spring, 81–135.

SÁ, F., P. TOWBIN, AND T. WIELADEK (2014): "Capital Inflows, Financial Structure and Housing Booms," *Journal of the European Economic Association*, 12(2), 522–546.

TENREYRO, S., AND G. THWAITES (2015): "Pushing on a String: US Monetary Policy is Less Powerful in Recessions," *American Economic Journal: Macroeconomics*, forthcoming.

——— (2016): "Pushing on a string: US monetary policy is less powerful in recessions," *American Economic Journal: Macroeconomics*, forthcoming.

TOWBIN, P., AND S. WEBER (2013): "Limits of floating exchange rates: The role of foreign currency debt and import structure," *Journal of Development Economics*, 101(1), 179–101.

VAVRA, J. (2014): "Inflation Dynamics and Time-Varying Volatility: New Evidence and an Ss Interpretation," *Quarterly Journal of Economics*, 129(1), 215–258.

VENTZISLAV, I., AND L. KILIAN (2005): "A Practitioner's Guide to Lag Order Selection For VAR Impulse Response Analysis," *Studies in Nonlinear Dynamics & Econometrics*, 9(1), 1–36.

WEISE, C. L. (1999): "The Asymmetric Effects of Monetary Policy: A Nonlinear Vector Autoregression Approach," *Journal of Money, Credit and Banking*, 31(1), 85–108.

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(2-3), 253–291.

	Difference between state-conditional:					
	peak effects			cumulative effects		
	GDP	Inv.	Cons.	GDP	Inv.	Cons.
IQR of sales growth						
endogenous uncertainty	-0.10	-0.38	-0.11	-1.13	-4.63	-1.48
exogenous uncertainty	-0.19	-0.69	-0.21	-1.99	-8.02	-2.59
endog. unc./exog. unc.	**0.53**	**0.55**	**0.53**	**0.57**	**0.58**	**0.57**
VIX						
endogenous uncertainty	-0.11	-0.43	-0.10	-1.18	-4.19	-1.12
exogenous uncertainty	-0.22	-0.84	-0.21	-2.23	-7.70	-2.05
endog. unc./exog. unc.	**0.49**	**0.52**	**0.48**	**0.53**	**0.55**	**0.55**

Table 1: **Difference of the state-conditional peak and cumulative real effects of monetary policy shocks between uncertain and tranquil times: endogenous vs. exogenous uncertainty.** The difference is computed as the effects in uncertain times minus the effects in tranquil times.

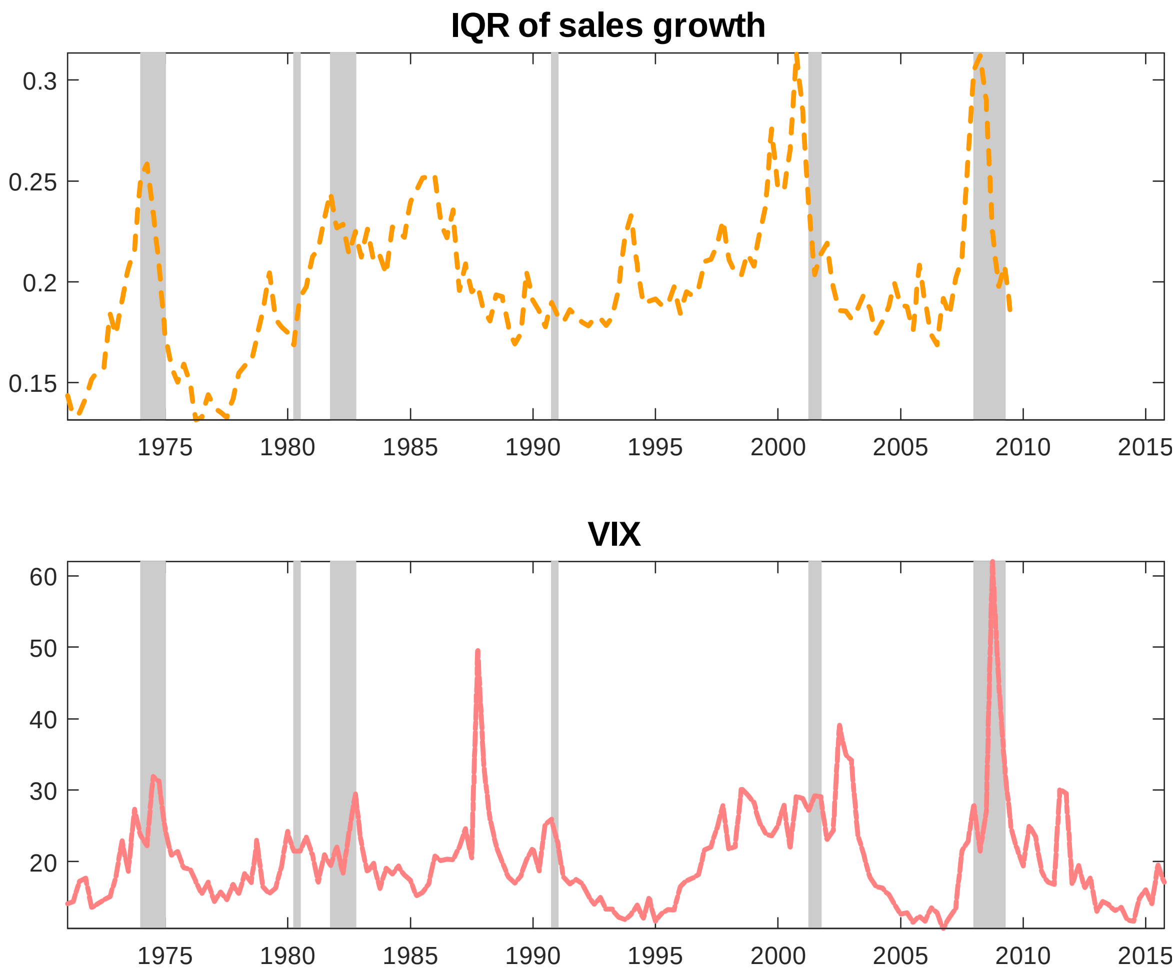

Figure 1: **Uncertainty indicators**. Orange dashed line: IQR of sales growth (sample: 1971Q1-2009Q3). Peach solid line: VIX (sample: 1971Q1-2015Q4). Grey areas: NBER recessionary quarters.

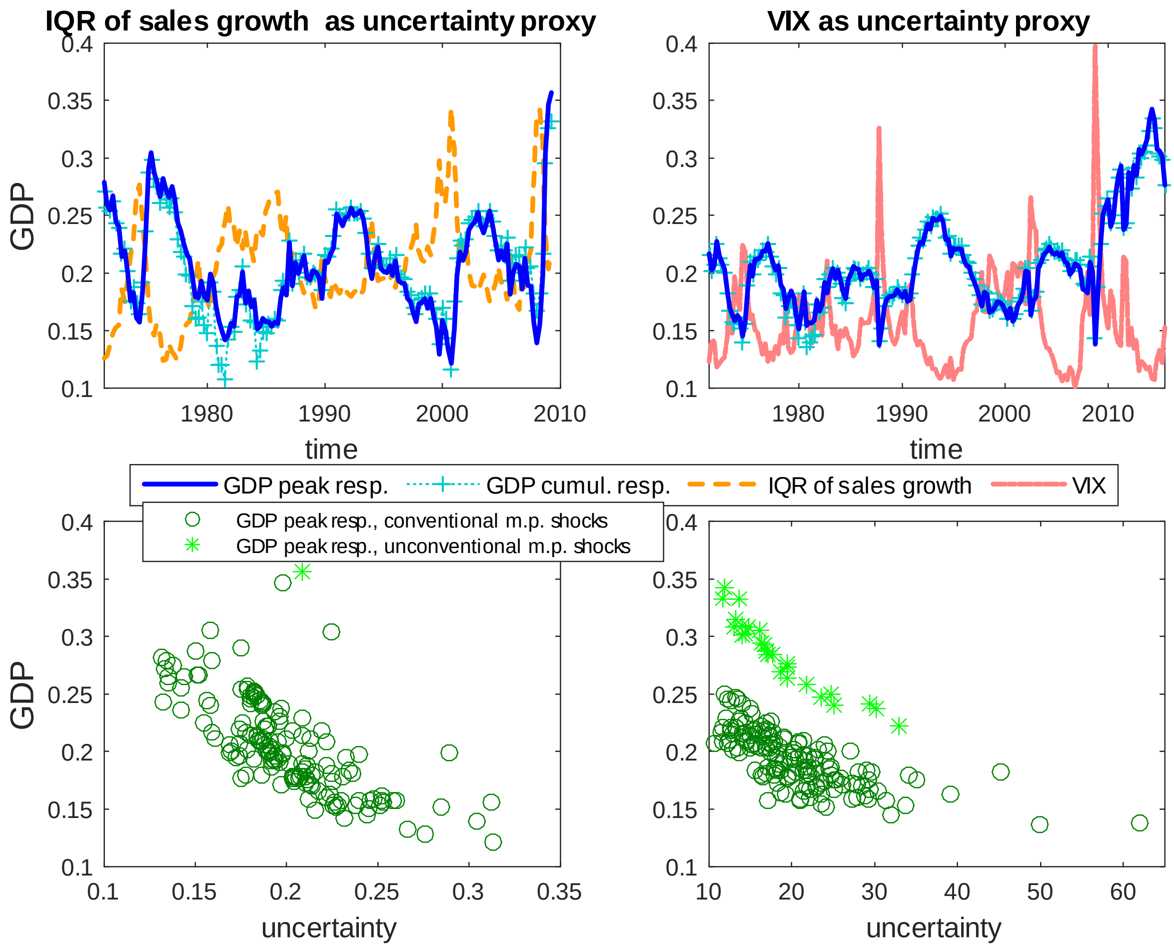

Figure 2: **Time-varying peak and cumulative response of GDP (shock: 25 basis points unexpected decrease in the policy rate)**. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Upper row: temporal evolution of the GIRFs peak and cumulative response (blue solid and cyan dotted lines respectively) along with the previous-quarter level of uncertainty and NBER recessions (shaded areas). The cumulative effects and uncertainty measures are standardized to the mean and standard deviation of the peak effects. Lower row: GIRFs peak response in relation with the initial level of uncertainty (with a differentiation between conventional and unconventional monetary policy shocks). Unconventional monetary policy shocks are shocks to the Wu and Xia's (2016) shadow rate in the period of binding ZLB (i.e., of negative shadow rate).

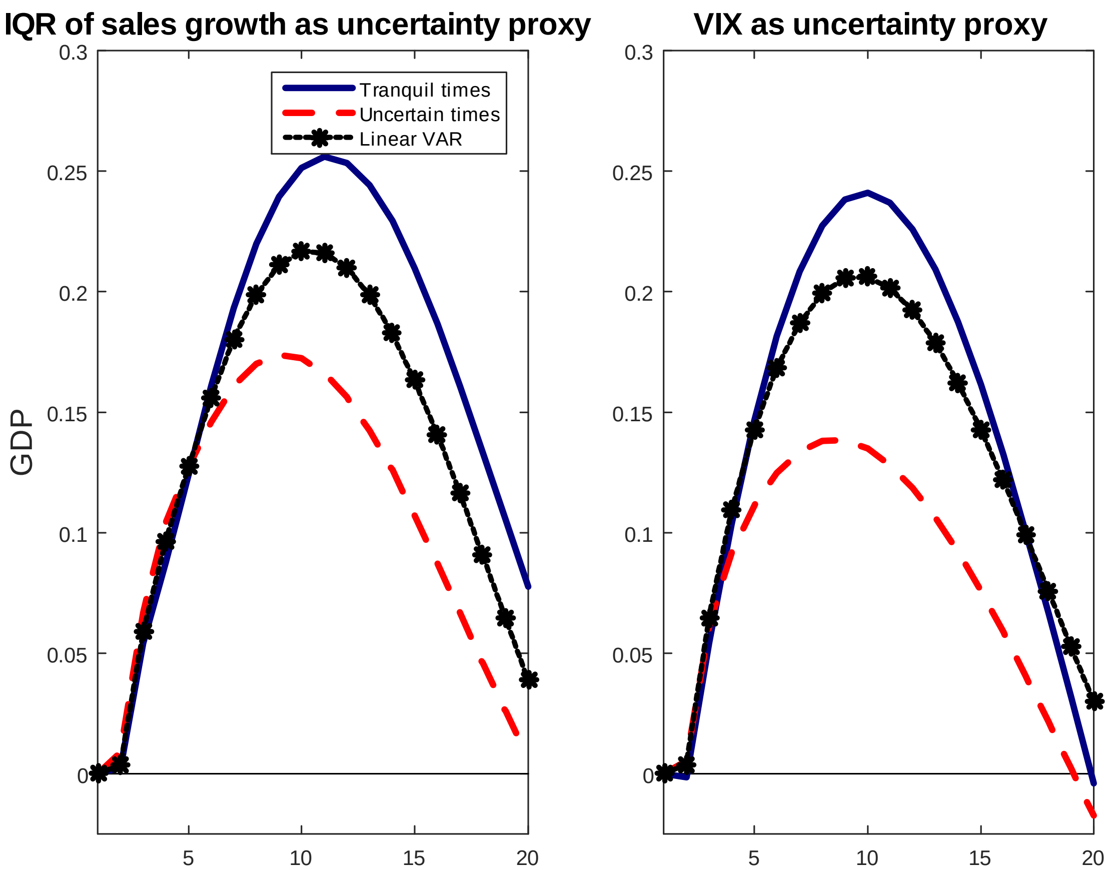

Figure 3: **Uncertain vs. tranquil times state-conditional responses for GDP in comparison to linear responses (shock: 25 basis points unexpected decrease in the FFR)**. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Solid blue (red dotted) line: state-conditional GIRF for the tranquil times (uncertain times) state. Purple starred line: IRF from the nested linear VAR.

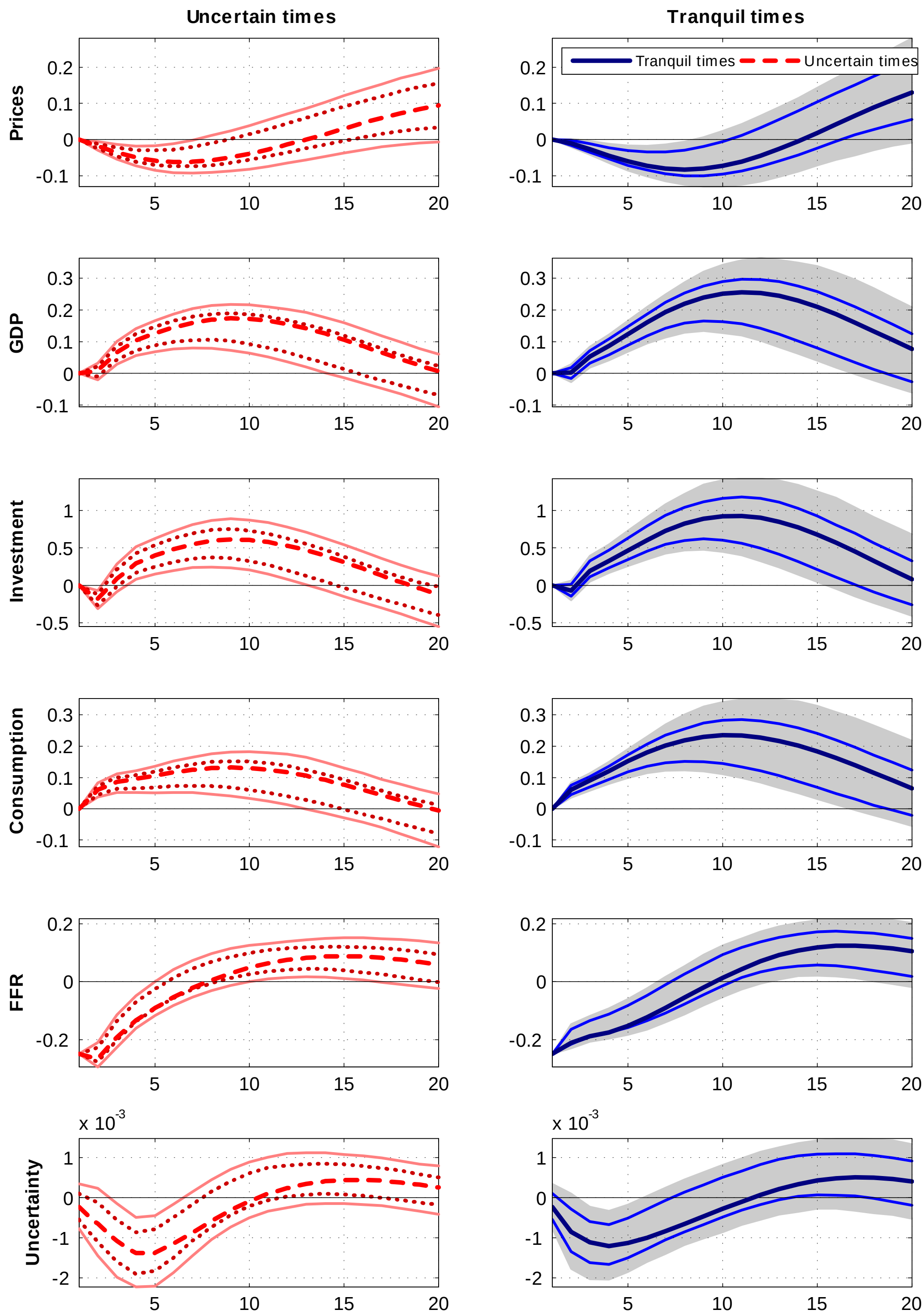

Figure 4: **Uncertain vs. tranquil times state-conditional GIRFs (uncertainty proxy: IQR of sales growth)**. Blue solid lines, light blue bands and grey areas: point estimates, 68% and 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times state, respectively. Red dashed lines, dark red dotted and light red solid bands: point estimates, 68% and 90% bootstrapped confidence bands for the GIRFs conditional to a uncertain times state, respectively.

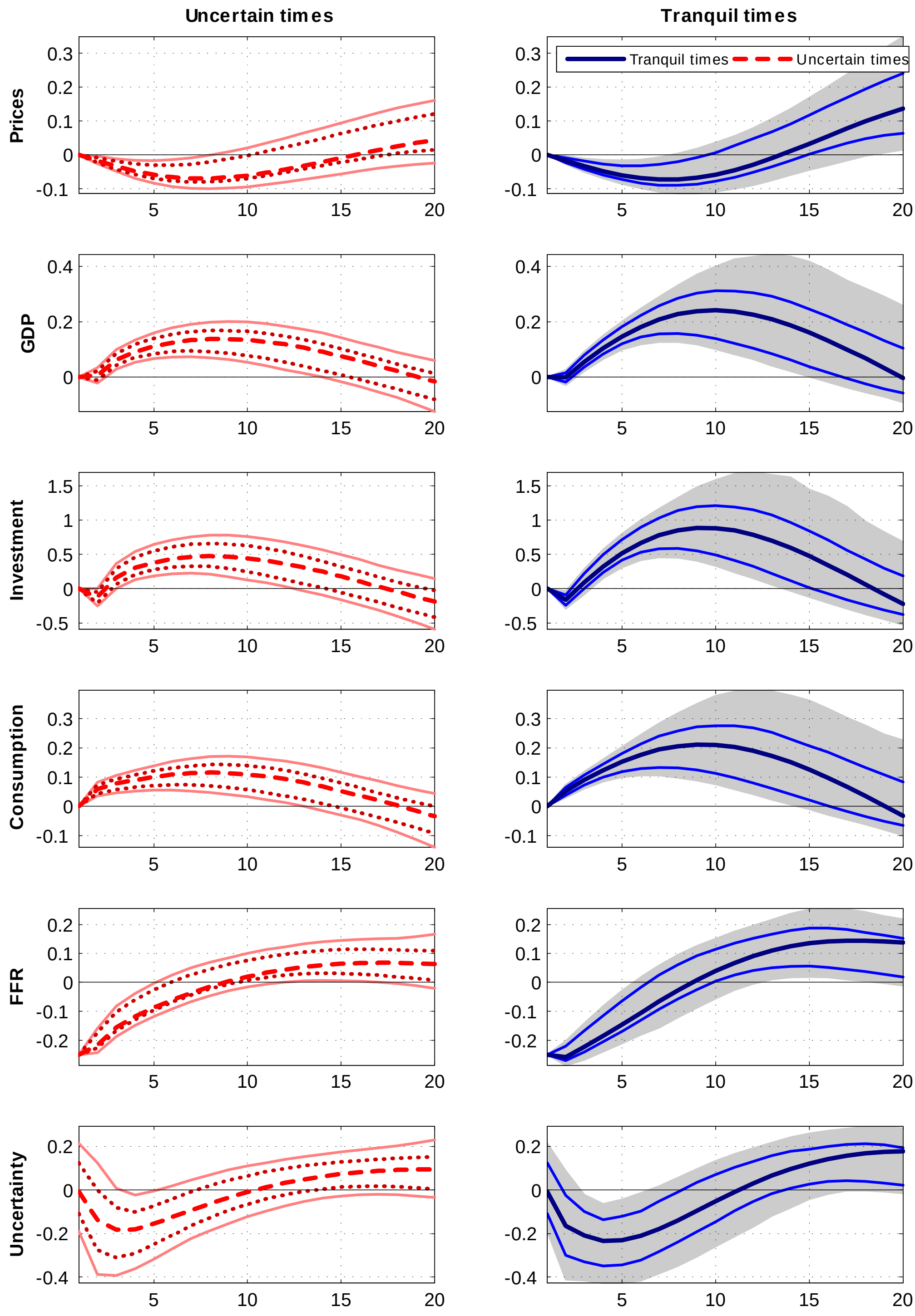

Figure 5: **Uncertain vs. tranquil times state-conditional GIRFs (uncertainty proxy: VIX)**. Blue solid lines, light blue bands and grey areas: point estimates, 68% and 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times state, respectively. Red dashed lines, dark red dotted and light red solid bands: point estimates, 68% and 90% bootstrapped confidence bands for the GIRFs conditional to a uncertain times state, respectively.

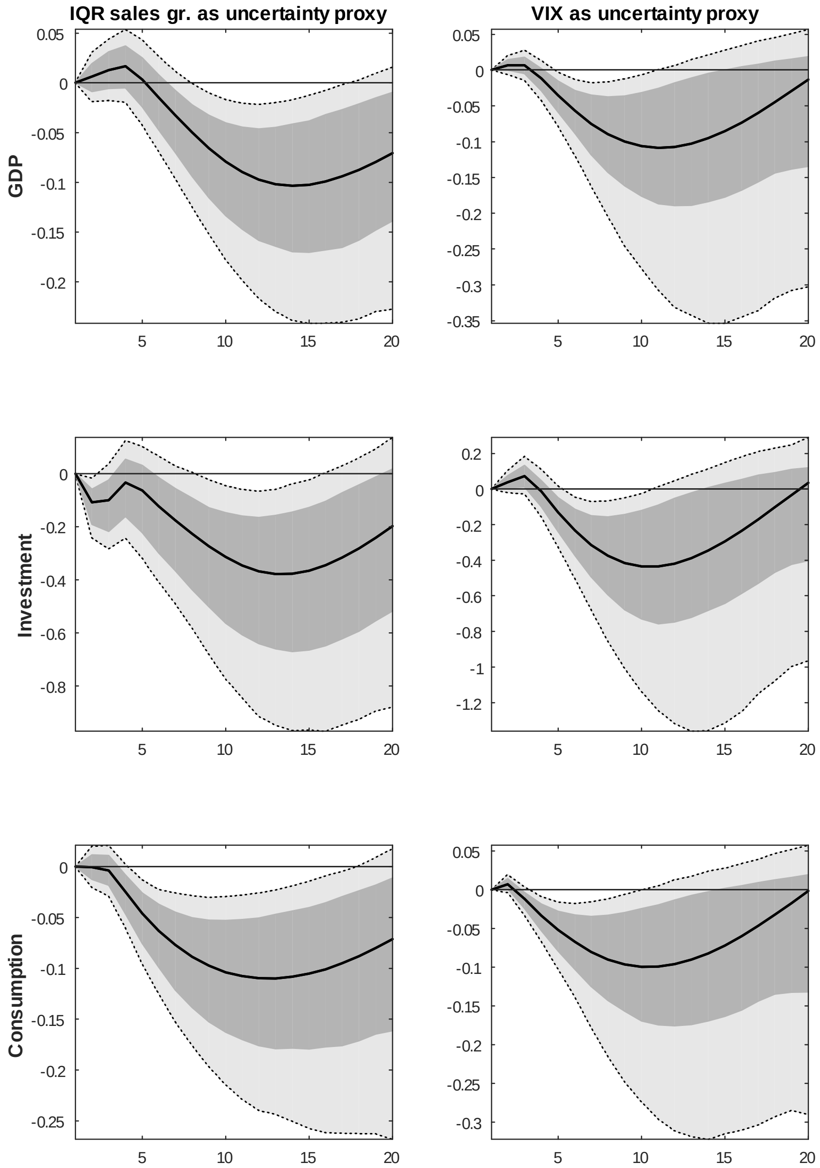

Figure 6: **Difference of state-conditional GIRFs between uncertain and tranquil times**. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Solid black lines: difference between point estimated state-conditional GIRFs (uncertain times conditional GIRF minus tranquil times conditional GIRF). Interior dark grey areas: 68 percent confidence bands for the difference (from the distribution of the difference stemming from the 2000 bootstrap draws). Exterior light grey areas: 90 percent confidence bands.

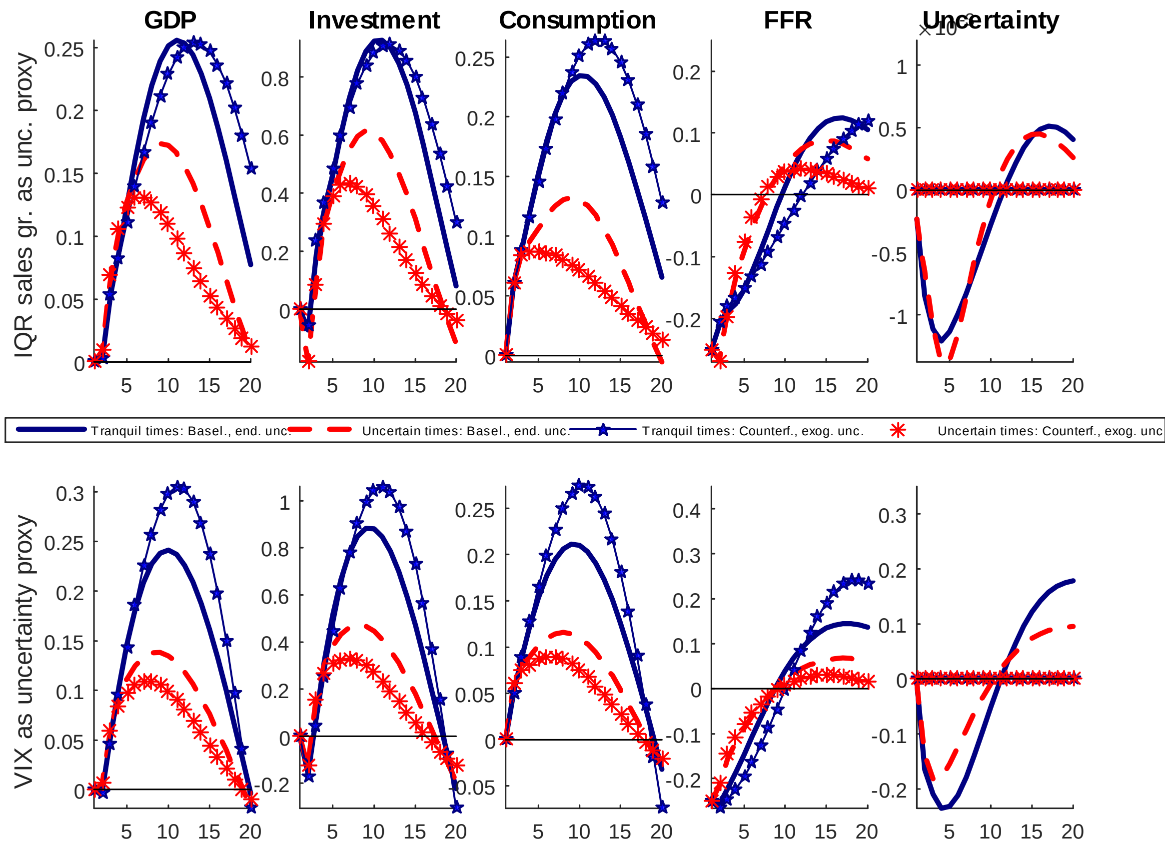

Figure 7: **Comparison among several state-conditional responses: Baseline GIRFs with endogenous uncertainty vs. counterfactual ones with exogenous uncertainty**. Upper (lower) row: IQR of sales growth (VIX) as uncertainty proxy. Blue solid and red dashed lines: baseline GIRFs conditional to a tranquil and uncertain times state, respectively. Starred blue lines and starred red points: point estimated GIRFs conditional respectively to a tranquil and uncertain times state for the counterfactual exercise in which the value of uncertainty is kept at its pre-shock value.

Appendix

A1 Computation of the Generalized Impulse Response Functions

This Section documents the algorithm employed to compute the GIRFs and their confidence intervals. The algorithm follows Koop, Pesaran, and Potter (1996), with the modification of considering an orthogonal structural shock, as in Kilian and Vigfusson (2011).

The theoretical GIRF of the vector of endogenous variables $\mathbf{Y}$, h periods ahead, for a starting condition $\varpi_{t-1} = \{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-L}\}$, and a structural shock in date t, δ_t, can be expressed – following Koop, Pesaran, and Potter (1996) – as:

$$GIRF_{Y,t}(h, \delta_t, \varpi_{t-1}) = E\left[\mathbf{Y}_{t+h} \mid \delta_t, \varpi_{t-1}\right] - E\left[\mathbf{Y}_{t+h} \mid \varpi_{t-1}\right], \quad h = 0, 1, \ldots, H$$

where $E[\cdot]$ represents the expectation operator. The algorithm to estimate our state-conditional GIRF reads as follows:

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

2. draw randomly (with repetition) a sequence of (n-dimensional) residuals $\{\mathbf{u}_{t+h}\}^s$, $h = 0, 1, ..H = 19$, from the empirical distribution $d(\mathbf{0}, \widehat{\mathbf{\Omega}})$, where $\widehat{\mathbf{\Omega}}$ is the estimated VCV matrix. In order to preserve the 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 on the estimated model (1)-(4), use the sequence of residuals $\{\mathbf{u}_{t+h}\}^s$ to simulate the evolution of the vector of endogenous variables over the following H periods to obtain the path $\mathbf{Y}^s_{t+h}$ 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 on the estimated model (1)-(4), use the sequence of residuals $\{\mathbf{u}_{t+h}\}^s$ to simulate the evolution of the vector of endogenous variables over the following H periods when a structural shock δ_t is imposed to $\mathbf{u}^s_t$. In particular, we Cholesky-decompose $\widehat{\mathbf{\Omega}} = \mathbf{CC}'$, where $\mathbf{C}$ is a lower-triangular matrix. Then,

we recover the structural innovation associated to $\mathbf{u}_t^s$ by $\boldsymbol{\varepsilon}_t^s = \mathbf{C}^{-1}\mathbf{u}_t^s$ and add a quantity $\delta < 0$ to the scalar element of $\boldsymbol{\varepsilon}_t^s$ that refers to the FFR, i.e. $\varepsilon_{t,ffr}^s$. We then move again to the residual associated with the structural shock $\mathbf{u}_t^{s,\delta} = \mathbf{C}\boldsymbol{\varepsilon}_t^{s,\delta}$ to proceed with simulations as in point 3. Call the resulting path $\mathbf{Y}_{t+h}^{s,\delta}$;

5. compute the difference between the previous two paths for each horizon and for each variable, i.e. $\mathbf{Y}_{t+h}^{s,\delta} - \mathbf{Y}_{t+h}^{s}$ 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 , i.e. $\widehat{GIRF}_{Y,t}(\delta_t, \varpi_{t-1}) = \left\{\widehat{E}\left[\mathbf{Y}_{t+h} \mid \delta_t, \varpi_{t-1}\right] - \widehat{E}\left[\mathbf{Y}_{t+h} \mid \varpi_{t-1}\right]\right\}_{h=0}^{19}$. 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 $\{\mathbf{u}_{t+h}\}^s$, in the sense that the response of the variable shocked diverges instead than reverting to zero), it is discarded and not considered for the computation of state-conditional responses at the next step[A1];

7. repeat steps 2-6 to obtain an 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 $\varpi_{t-1} = \{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-L}\}$ is classified to belong to the "uncertain times" state if unc_{t-1} is within a 5-percentiles tolerance band from the top decile of the uncertainty empirical distribution (i.e. within its 85th and 95th percentiles) and to the "tranquil times" state if unc_{t-1} is within the same band around the bottom decile of the uncertainty distribution[A2] ;

8. history-dependent GIRFs obtained in step 7 are then averaged over the state they belong to to produce our state-dependent GIRFs, i.e., our $\widehat{GIRF}_{Y,t}(\delta_t, tranquil\ times)$

[A1] This happens from never (for point estimated responses, i.e. our responses estimated on actual data) to quite rarely (for bootstrapped simulated responses).

[A2] This choice is motivated on the basis of two arguments. First, in this way we are consistent with other works in the literature that estimate the response of the economy referring to the extreme deciles of the uncertainty distribution (see, e.g., Vavra (2014) and Bloom, Bond, and Reenen (2007)). Conditioning responses on extreme events might be important in finding empirical responses in favor of nonlinearities, which might be missed when conditioning on normal events (see Caggiano, Castelnuovo, Colombo, and Nodari (2015) and Pellegrino (2017)). Second, this choice allows each given regime both to feature a number of GIRFs large enough to obtain representative state-conditional responses and to have results that do not depend on particularly extreme observations. Figure A7 presents a robustness check for a wider definition of the two regimes.

and $\widehat{GIRF}_{Y,t}(\delta_t, uncertain\ times)$;

9. confidence bands around the point estimates obtained in point 8 are computed through bootstrap[A3]. In particular, we simulate $R = 2000$ datasets statistically equivalent to the actual sample and for each of them interaction terms are constructed coherently with the simulated series. Then, for each dataset, (i) we estimate our Interacted-VAR model and (ii) 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_{t-1}^r and $\widehat{\mathbf{\Omega}}^r$. Of the resulting distribution of state-conditional GIRFs, we take the 5th and 95th (16th and 84th) percentiles to construct the 90% (68%) confidence bands.

A2 The response of prices and the price channel explanation

Analyzing the price response in Figures 4 and 5 in the paper can in principle help us to empirically assess Vavra's proposed mechanism centered on firms price-setting behavior. More reactive prices during firm-level uncertain times would directly translate into smaller real effects of monetary shocks. Is the reduced monetary policy effectiveness we find during uncertain times due to more flexible prices? If this was the case, we would expect to see a different response of prices in the two regimes, together with an higher price level during uncertain times. However, looking at Figures 4 and 5, this is not what we observe from our responses. Even tough we find very different responses of real activity indicators, price responses hardly exhibit any different behavior between states. This is, at a first glance, evidence against Vavra's (2014) mechanism. However, before drawing a conclusion here, it is important to be cautious about three things when interpreting our results.

First, as already documented in the paper, our IVARs display a "price puzzle", something very frequent in the monetary VAR literature.[A4] In principle, the price

[A3]The Matlab code for generating bootstrap artificial draws for the endogenous variables is built on that provided in the VAR Toolbox by Ambrogio Cesa-Bianchi https://sites.google.com/site/ambropo/MatlabCodes. The bootstrap used is similar to the one used by Christiano, Eichenbaum and Evans (1999, footnote 23). Our code repeats the explosive artificial draws to be sure that exactly 2000 draws are used. In our simulations, this happens only a negligible fraction of times.

[A4]The persistence of the price puzzle we find is consistent with the literature too. For example, Hanson (2004) finds that after two years from a contractionary monetary shock prices are still above trend (see his Figure 1, last row). He also shows that the persistence of the price puzzle is a function response makes the results difficult to be interpreted in light of the theoretical model proposed by Vavra (2014). However, as shown in some of the checks in the Section A4 of this Appendix, even when the puzzling response of prices is significantly mitigated and results are shown to be robust (e.g., by controlling for inflation expectations and Divisia money as further variables in our VAR), there is still no detectable difference in the response of prices between regimes.

Second, our recursive identification precludes a contemporaneous reaction of prices to monetary policy shocks, which is instead what Vavra's (2014) predictions mostly pertain to.[A5] However, two comments are worth making. First, even when using alternative identification assumptions it is hard to find that prices react in the same quarter to monetary policy shocks. Rather, they display an inertial behavior (see, e.g., Romer and Romer (2004) and Gertler and Karadi (2015)).[A6] The same is confirmed in a check in the next Section of this Appendix once we order prices after the FFR in a VAR that considers also inflation expectations as the first ordered variable. Second, Vavra's model is a stylized model with little internal propagation which, more than fitting the macro data response to a monetary shocks well, aims at proposing a transmission channel based on some micro-data related evidence he finds on firms' price setting behavior during uncertain times.

Third, studying the aggregate response of prices to a monetary policy shock may not carry enough information to unveil the importance of an uncertainty-dependent firms' price-setting behavior, both because monetary shocks account little for the observed aggregate fluctuations of prices and because firms react sluggishly to them. Boivin, Giannoni, and Mihov (2009) find that disaggregated prices appear sticky in response to macroeconomic and monetary disturbances, but flexible in response to sector-specific shocks, implying that the flexibility of disaggregated prices is perfectly compatible with stickiness of aggregate price indices. Further, they find that sector-specific shocks ac-

of the sample period considered. Consistent with his findings, a robustness check in the Section A4 of this Appendix that considers only the post-Volcker sample period delivers no evident price puzzle. This is also consistent with Castelnuovo and Surico (2010).

[A5]In the most realistic, calibrated version of Vavra's (2014) model, he finds that the price level reacts as much as 36% more on-impact during firm-level uncertain times than tranquil times.

[A6]Romer and Romer (2004) construct a monthly series of narratively identified monetary policy shocks by the changes in the FFR around FOMC meetings that are orthogonal to the real time Fed's information set, consisting in several variables. When evaluating the effects of these shocks on the price level (fig. 4) they find that prices hardly move in the short-run. Gertler and Karadi (2015) identify monetary policy shocks using high frequency surprises around policy announcements as external instruments and show that this methodology produces responses in output and inflation that are typical in monetary VAR analysis. Interestingly for us, they find that the price level does not move statistically in the same quarter of monetary policy shocks (fig. 1).

count on average for 85 percent of the monthly fluctuations of disaggregated prices. Thus, even though firms may change prices more frequently in presence of high firm-level uncertainty (as Bachmann, Born, Elstner, and Grimme (2013) find), this fact can be mostly driven by firms' response to micro-level shocks, rather than to macro-level ones like monetary policy shocks.

To wrap up, our findings suggest that Vavra's price-setting mechanism does not seem a main driver at the macro level to explain the very different reactions of real aggregate variables to a monetary policy shock between uncertain and tranquil times. However, this does not imply that the mechanism is not at play during uncertain times.[A7] Further research focusing on microeconomic data is needed in this dimension.

A3 Supplementary results and material

This Section persents extra results and material to the ones in the main paper. Figure A1 presents the full evidence of time-variation of the GDP GIRF summarized in Figure 2 in the paper. Figure A2 shows how Figure 2 would look like in case uncertainty was kept fixed to its pre-shock level in the computation of responses (on the basis of the same counterfactual in Section 5). In this case, the relation between the power of monetary policy shocks and the initial level of uncertainty becomes perfect given that in a conditionally-linear model only the initial level of uncertainty matters (historical initial conditions of other variables do not play any role).[A8] Figure A3 shows how the lower panels of Figure 2 would have appeared in case we had used two alternative shadow rates available in the literature (in particular the Krippner's (2015) one made available on the website of the Reserve Bank of New Zealand and Bauer and Rudebush's (2016) $YZ(3, r^{\min} = 0)$ one).[A9][A10] The findings suggests that, even though in each case the

[A7]We admit that alternative specifications of our SEIVAR can provide different answers as regards the price-channel explanation (for example, in some of the checks we perform in Section A4 – like, e.g., the JLN macro uncertainty case – the response of prices appears more state-dependent than our baseline responses). For the purposes of our work we only make sure that our baseline results regarding the uncertainty-dependent effects of monetary policy shocks are robust across modelling scenarios. A deeper study of the price-channel explanation for the lower real effects of monetary policy shocks is left to future research.

[A8]Pellegrino (2017) shows that, in a context in which initial conditions matters, it is possible to construct a counterfactual historical decomposition for monetary policy shocks in order to investigate the empirical relevance of the influence of uncertainty for the effectiveness of monetary stimuli.

[A9]Bauer and Rudebusch (2016) find that estimated shadow rates are quite sensitive to both the specific short-term yields included in the model used and the assumption about the numerical lower bound for interest rates.

[A10]Krippner's shadow rate was downloaded from the Reserve Bank of New Zealand website (https://www.rbnz.govt.nz/-/media/ReserveBank/Files/Publications/Research/Additional%20research/Leo%20Kripp period of binding ZLB introduces an important instability in the effects of monetary policy shocks, the magnitude of this instability – as well as the real effect of both conventional and unconventional monetary policy shocks – is sensitive to the shadow rate used. Figure A4 contrasts our baseline GIRFs with the IRFs obtained from an alternative IVAR where uncertainty, which serves as our conditioning variable, is not modeled in the vector of endogenous variables and hence where conditionally-linear IRFs are computed (as so far done in the literature, e.g., in Aastveit, Natvik, and Sola (2017)).[A11] The same results of the counterfactual in Figure 7 are obtained.

A4 Robustness checks

A4.1 First round of robustness checks

In this Section we consider perturbations of the baseline specification of our SEIVAR model to check the robustness of our baseline results for real activity, along several dimensions. We employ alternative uncertainty indicators, sharpen the identification of the monetary policy shocks and consider potentially relevant omitted variables. To support our conclusions in Section A2 we also present the response of prices.[A12] Figure A5 shows the results for the robustness checks we consider. Each row reports the GIRFs from each of the alternative specifications considered and the confidence bands for baseline responses. We comment on these checks below.

JLN uncertainty indexes. In the baseline analysis we have used the IQR of sales growth and the VIX as uncertainty indicators. Even though for our purposes we are not interested in identifying exogenous movements (shocks) in uncertainty, which is rather the territory of empirical studies on the real impact of unexpected heightened uncertainty, we do need an uncertainty measure which is relevant for economic decision making. In this regard, what really matters for economic decision making, according

monthly-update-April-2016-reference-only.xlsm?la=en). The Bauer and Rudebusch's shadow rate was downloaded for the website of the Federal Reserve Bank of San Francisco (http://www.frbsf.org/economic-research/economists/shadow_rates.csv). Quarterly averages have been taken.

[A11] For more details on the alternative model and how IRFs are computed please refer to the Figure notes. Notice that, in the working paper version of Aastveit, Natvik, and Sola (2017), e.g., Aastveit, Natvik, and Sola (2013), where the authors perform the analysis also for Canada, UK and Norway, they adopt an IVAR specification more dissimilar from ours and find more different responses between states with respect to their published version.

[A12] A part from the checks that consider alternative uncertainty indicators, robustness checks are based on the IQR of sales growth as uncertainty proxy. Given its firm level nature it will be helpful to evaluate the response of prices (as explained in Section 3.3).

to Jurado, Ludvigson, and Ng (2015) (JLN henceforth), is whether the economy has become more or less predictable, rather than whether particular economic indicators have become more or less variable or disperse per se. Hence, in this case, if the volatility captured by our baseline uncertainty proxies were in large part forecastable, our results could be spurious.[A13] To control for this eventuality we employ the macro and firm-level uncertainty indicators constructed by Jurado, Ludvigson, and Ng (2015), which are computed as the common factor of the time-varying volatility of the estimated h-steps-ahead forecast errors of a large number of economic time series. Their macro dataset embeds the information of 132 macroeconomic and financial indicators, while their firm-level dataset consists of 155 firm-level observations on profit growth normalized by sales.[A14]

Figure A4 (first two rows) documents that baseline results are confirmed for JLN alternative uncertainty indicators. For the JLN macro uncertainty indicator, the peak response of investment becomes even more distant between the two states.

Uncertainty ordered first. In our baseline analysis we have ordered uncertainty last in order to maximize its degree of endogeneity in the VAR. Uncertainty was allowed to react contemporaneously to monetary moves while the policy rate could not react contemporaneously to uncertainty moves. However, in case the monetary policy systematic conduct responded also to uncertainty (as recently argued by Evans, Fisher, Gourio, and Krane (2015) and Caggiano, Castelnuovo, and Nodari (2017)), its missed consideration may potentially affect our results. Here, we perform a robustness check where uncertainty is ordered first in the VAR so that to identify monetary policy shocks which are safely purged from moves in all variables, included the uncertainty measure. As the third row of Figure A4 clarifies, our baseline results continue to hold.

Inflation expectations and Divisia money. Our baseline analysis displays a puzzling response of prices. As explained in Section 4.2, several explanations have been suggested in the literature for this quite common empirical fact, but one which surely deserves further investigation here is the omitted variables explanation. As argued

[A13] This could be the case for the VIX index which Jurado, Ludvigson, and Ng (2015) find to be partially predictable.

[A14] Both uncertainty indicators were downloaded from the data section in Sydney Ludvigson's webpage (i.e. http://www.econ.nyu.edu/user/ludvigsons/). Both indicators used refer to a forecasting horizon equal to 1 quarter. We take quarterly averages to pass to quarterly frequencies. In order to use the firm-level indicator as conditioning variable we HP-filter it (lambda=1600) to avoid instability problems due to the non-stationary features of the series. The use of the macro index forces us to use a longer sample (up to the end of 2010) with respect to our baseline sample (up to mid 2009) in order to avoid maxima at the end of the sample and hence in-sample instability of some quarter-specific GIRFs.

by Sims (1992), the monetary authority when setting its policy rate could have more information about future inflation than that which is embedded in a simple VAR. Hence, to the extent that the Fed in anticipation of future inflation systematically reacts by raising the interest rate, something which for the VAR-econometrician would constitute a policy shock, we would observe that prices increase after a contractionary policy shock, i.e., the emergence of the price puzzle. To tackle these issues and possibly mitigate the price puzzle, we follow Castelnuovo and Surico (2010) and add a measure of inflation expectations to our VAR as first-ordered variable.[A15] Furthermore, we also add Divisia M2 in the vector of endogenous variables and order it after the policy rate to allow for a on-impact liquidity effect.[A16] According to Keating, Kelly, and Valcarcel (2014) Divisia money helps to solve the price puzzle. Figure A4 (forth row) shows that while this alternative IVAR specification does not alter our baseline results, it prevents the appearance of a significant and persistent price puzzle. There is only an insignificant evidence of a short-run price decrease, while it is now evident that prices increase above their trend faster, i.e., starting from two years from the expansionary monetary policy shock.[A17] Also in this case there is, however, no detectable difference in the response of prices between uncertain and tranquil times. This result confirms that an uncertainty-dependent price-setting channel does not seem a key driver of the weaker effects of monetary policy shocks in presence of high uncertainty.

NBER recession dummy indicator. As discussed in the paper, several studies (e.g., Weise (1999), Tenreyro and Thwaites (2016) and Mumtaz and Surico (2015)) find that monetary policy shocks are less effective during bad times, defined in terms of economic downturns. One could then argue that economic recessions is an omitted variable from our IVAR model and that this omission is partially driving our results.

[A15] In particular we use expectations for one-year-ahead annual average inflation, measured by the GDP price index, available in the Survey of Professional Forecaster (SPF) by the Federal Reserve Bank of Philadelphia (http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/historical-data/inflation.xls). The series used is INFPGDP1YR and is available since 1970Q2.

[A16] Divisia M2 has been proposed by Barnett (1980) to account for the fact that the official measure M2 employed by the Federal Reserve is constructed by considering the simple sum of monetary aggregates. Divisia money instead accounts for the imperfect degree of substitution characterizing different assets featuring different returns with the intent of tracking variations in the flow of monetary services in a more accurate manner. Data were downloaded from http://www.centerforfinancialstability.org/amfm/Divisia_Narrow.xls . Quarterly averages of monthly levels are taken.

[A17] Hanson (2004) shows that even when considering most potentially relevant omitted variables it is not possible to solve the price puzzle for a sample that includes the pre-Volcker period. Consistently with Hanson (2004) and Castelnuovo and Surico (2010), in a check below we find that by considering only the post-Volcker sample the price-puzzle disappears.

If this were the case we would expect that its addition to the model would make the coefficients referring to uncertainty, particularly those inside the interaction terms, less relevant. Therefore, our uncertainty-conditional responses would get closer between the uncertain and tranquil times states. To check for this eventuality we add the NBER recession dummy indicator as an exogenous variable to our VAR. Figure A4 (last row) delivers results similar to baseline ones also along this dimension.

A4.2 Additional checks[A18]

Here we motivate and discuss additional robustness checks for baseline results. The results obtained are summarized in Figure A5.

i) *Post-Volcker sample / Break in the VCV matrix.* Our sample spans both pre- and post-Great Moderation periods. This notwithstanding, our baseline IVAR has not accounted for possible structural breaks in economic relationships that may have occurred over time. We propose two checks that consider some adjustments in the conditional mean and variance of our IVAR model to account for the two main explanations that have been proposed in the literature for the Great Moderation period, i.e., "good policy" vs. "good luck". Regarding the first, and somewhat related to our research question, Boivin and Giannoni (2006) investigate the effects of monetary policy shocks in and before the Great Moderation period and find that monetary shocks are less effective in the Great Moderation period because monetary policy has stabilized the economy more effectively in the post-1980 period by responding more strongly to inflation expectations.[A19] To control for the possibility that our results spuriously depend on that, we estimate an IVAR model on a sample starting from 1979:q3 (i.e., from the break date considered in Boivin and Giannoni (2006) as well as in Lubik and Schorfheide (2004)). Figure A5 (first row) shows that even though the GIRFs documenting the reaction of real variables get closer between states (consistently with Boivin and Giannoni (2006)), results are still consistent with baseline ones. Further, consistently with Hanson (2004) and Castelnuovo and Surico (2010), the price puzzle disappears when considering this starting date.[A20]

Turning to the "good luck" explanation, it seems appropriate to account for the

[A18] We thank both referees and the editor for their questions and suggestions which led us to conduct several new checks documented here.

[A19] This is consistent with the findings in Clarida, Galí, and Gertler (2000).

[A20] These last two studies consider when Paul Volcker was appointed as Chairman of the Federal Reserve Board and split the sample accordingly. This means we should consider 1979:q4 as starting quarter, but a check (not shown) confirms that virtually the same results would be obtained.

fact that the volatility of shocks may have changed in the sample, in particular having been lower with the starting of the Great Moderation period. According to Stock and Watson (2002) and Sims and Zha (2006a), among others, the Great Moderation consisted mostly in a change in the volatility of aggregate variables rather than in their conditional mean behavior. To account for this possibility, we estimate an IVAR model with a break in the VCV matrix in 1984:1 (the temporal break estimated by Kim and Nelson (1999) and McConnell and Perez-Quiros (2000)).[A21] This break, through the Cholesky decomposition, also allows for a different contemporaneous relationship between variables in the two sub-periods.[A22] As Figure A5 (second row) clarifies our results turn robust also to this check.

ii) *No time trend / Trending variables in first difference.* Our baseline VAR models a time trend and trending variables in (log-)levels. The specification of the VAR in levels allows for implicit cointegrating relationships in the data (Sims, Stock, and Watson (1990)). Figure A5 (third and forth rows) shows results in case the time trend is excluded and in case trending variables (i.e., P, GDP, Inv and $Cons$) are modelled in growth rates and then cumulated responses are obtained.[A23] Since first differencing variables is equivalent to the imposition of a unit root in the level of the series, cumulated responses now are more persistent than our baseline ones. Notwithstanding the possibility of a misspecified VAR, monetary policy shocks are still found to be less effective during uncertain times.

iii) *Smaller-scale VAR.* Figure A5 (fifth row) displays a check assessing the robustness of our results when a smaller-scale VAR is estimated. A common choice in the literature is to employ a VAR with a measure of prices, GDP and the policy rate. Our check considers just uncertainty on top of these variables since its endogenous role has

[A21] For the sake of simplicity we are considering the period after the Great Recession as inside the Great Moderation period. However, a look at the quarterly growth rate of real GDP reassures us that the volatility in the series is still overall consistent with the Great Moderation period, and anyway much lower than the volatility in the pre-Great Moderation period.

[A22] More precisely, we estimate the following reduced-form model: (1') $\mathbf{Y}_t = \boldsymbol{\alpha} + \boldsymbol{\gamma} \cdot$ *linear trend*$+ \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \left[\sum_{j=1}^{L} \mathbf{c}_j unc_{t-j} \cdot R_{t-j}\right] + \mathbf{u}_t$, (2') $E(\mathbf{u}_t \mathbf{u}_t') = \boldsymbol{\Omega}_r$ with $r = 1$ if $t < 1984:1$ and $r = 2$ if $t \geq 1984:1$. The estimation of (1') is performed by feasible GLS after the estimation of $\boldsymbol{\Omega}_r$, $r = 1, 2$, from the residuals referring to the relevant sub-sample periods obtained from equationwise OLS estimation of (1') (see Lütkepohl (2013, equation 9 and previous one)). The Cholesky decomposition of $\boldsymbol{\Omega}_1$ and $\boldsymbol{\Omega}_2$ allows to recover the effects of the structural monetary shock depending on the time t of the shock. In computing GIRFs the series of future shocks with which the non-linear system is hit (point 2. of the algorithm in section A1) also considers the initial time t of the shock and residuals are extracted from the ones belonging to the subsample in which t belongs.

[A23] The VAR with growth rates misses one observation. It does not include a time trend. Growth rates are computed as the difference between logarithmic values.

been shown to be crucial for our results.

iv) *Higher-order interaction terms.* The SEIVAR model that we adopt in this study assumes a specific functional form of nonlinearity. With respect to an otherwise standard linear VAR model, we considered to add, in each equation of the VAR, the simple products of the lags of the policy rate and those of the uncertainty indicator. We must admit though that if the aim is to reach nonlinearity by adding polynomial terms to an otherwise standard linear VAR, several options are available. This makes the choice of the non-linear specification a non trivial choice. However, two main reasons, both related to the concept of parsimony, brought us to rely on our baseline model (1)-(4). First, the interaction term between uncertainty and the policy rate is strictly related to our research question. The focus on this interaction term indeed allows us to directly ask whether the dynamic responses to a monetary policy shock depend on the level of uncertainty in the economic system. Second, the adoption of simple products rather than squares or higher order polynomial terms allows on the one hand to maximize the degrees of freedom in the estimation and on the other hand to minimize the possibility of instability problems (as already notices in the second footnote of section 3.1). To the extent that there is evidence in the data that the effects of monetary policy shocks are less effective under high uncertainty, we think that our SEIVAR model can capture it, even though admittedly perhaps not in the richest manner. In order to be sure that our model is not missing important dynamics in the uncertainty-conditional response to a monetary policy shock we conducted a check with a richer specification of the interaction between monetary policy and uncertainty that considers also higher-order terms related to the monetary policy stance and uncertainty.[A24] As it can be seen from Figure A5 (second part, first row), findings are similar to baseline ones, if not stronger.

v) *Alternative ordering.* Our baseline ordering and the check with uncertainty ordered first have not considered the case in which uncertainty contemporaneously reacts to real activity but not to monetary policy. To this end we conducted a check in which uncertainty and the policy rate are the last two variables, so that monetary policy may contemporaneously react to uncertainty. Results are displayed in Figure A5 (second part, second row).

vi) *P last (and inflation expectations).* Our baseline recursive ordering does not allow the price level to react contemporaneously to monetary policy shocks. We perform a check where we order prices as the last variable in our VAR to allow their on-impact

[A24] To be more precise, the model on which this check is based is the following: $\mathbf{Y}_t = \boldsymbol{\alpha} + \boldsymbol{\gamma} \cdot$ *linear trend*$+ \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \left[\sum_{j=1}^{L} (\mathbf{c}_j unc_{t-j} \cdot R_{t-j} + \mathbf{d}_j unc^2_{t-j} \cdot R_{t-j} + \mathbf{e}_j unc_{t-j} \cdot R^2_{t-j}) \right] + \mathbf{u}_t$, $L = 2$.

response to the shock. To be sure that monetary shocks are anyway correctly identified we consider also (the previous indicator of) inflation expectations and order it as first ordered variable to allow the policy rate to contemporaneously react to it (consistently with a Taylor-type conduct of monetary policy). Results, displayed in Figure A5 (second part, third row), are similar to baseline ones. Consistently with what explained in Section A2, we do not find any evidence that prices react on impact.

vii) *CPI and PPI.* In our baseline we have use the GDP price index as a measure of prices. In the last two rows of Figure A5 (second part) we check the robustness of our results to the case either the CPI or the PPI are used. It turns out that our results for real variables are still robust, even tough the price puzzle is now bigger.

Figure A6 puts in comparison the differences of the responses of real variables for each of the checks performed in this section with the baseline confidence bands for the same differences. In all the cases the differences are within baseline bands. The only exception is the difference of investment for the JLN macro index, where an even stronger difference is found.

A4.3 Further checks and material

Figure A7 is the alternative of Figure 3 in case a wider tolerance band is used to define the two states, i.e. a ten-percentiles tolerance band. It shows that ours results do not depend on the use of our baseline five-percentiles tolerance band. Figure A8 proposes a further statistical test for the difference of the effects of monetary policy shocks. It asks whether the *cumulative* effect of monetary policy shocks is statistically different between uncertain and tranquil times in the period in which the real effects of monetary policy shocks are statistically relevant (which Figures 4 and 5 suggest not being longer than 4 years). As the figure shows, we can statistically reject the fact that the GDP cumulative effect of monetary policy shocks is the same between states. Finally, Figure A9 shows the decrease in uncertainty for the checks considered in Section A4.1. It makes clear that our results on the decrease of uncertainty after an expansionary monetary policy shock is very robust, also when considering alternative uncertainty measures like the Jurado, Ludvingson and Ng's (2015) indicators.

A5 Data sources

This section complements Section 3.3 of the main paper with more details on the data used for the baseline analysis, in particular as regards sources and series construction.

- **US real variables, price index and FFR.** The data source is the Federal Reserve Bank of St. Louis' database (FRED2 database). The precise names of the series we use are the following: Real Gross Domestic Product, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate; Real Gross Private Domestic Investment, 3 decimal, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate; Real Personal Consumption Expenditures, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate; Effective Federal Funds Rate, Percent, Quarterly, Not Seasonally Adjusted; Gross Domestic Product: Implicit Price Deflator.

- **Shadow rate.** For the part of our sample that overlaps with the binding zero lower bound period in the U.S. we use the Wu and Xia's (2016) "shadow rate" instead of the FFR and label shocks in it as "unconventional" monetary policy shocks. Data source: Cynthia Wu's website[A25]. We take quarterly averages of the series.

- **Interquartile range (IQR) of sales growth.** This is a cross sectional firm-level measure of uncertainty constructed by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) and represents the interquartile range (IQR) of sales growth for a sample of Compustat firms, which is available up to 2009Q3. The IQR of sales growth is constructed on 2,465 publicly quoted firms spanning all sectors of the economy. It is available on-line at Nick Bloom's website[A26].[A27]

- **Stock Market Volatility Index.** We update the Bloom's Stock Market Volatility Index series up to 2015Q4 by using the VXO series available at the Federal Reserve Bank of St. Louis database (FRED2 database, mnemonic VXOCLS). The volatility index is constructed by Bloom (2009) by splicing the Chicago Board Options Exchange VXO index for the period after 1986 with the quarterly standard deviation of the daily S&P500 for the period before that.[A28] The uncertainty monthly series is obtained from Nick Bloom's website[A29] and is available up to the end of 2012. Quarterly data are obtained by quarterly averages.

[A25] https://sites.google.com/site/jingcynthiawu/home/wu-xia-shadow-rates

[A26] https://people.stanford.edu/nbloom/sites/default/files/census_data.zip (data_table1_sales.csv)

[A27] The IQR of sales growth is the only non-financial high-frequency uncertainty indicator referring to disaggregated firm-level data used by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) for their results in Table 1.

[A28] The VXO is an index of percentage implied volatility on a hypothetical at the money S&P100 option 30 days to expiration.

[A29] https://people.stanford.edu/nbloom/sites/default/files/r.zip

As regards the data used in robustness checks, all the details are given in the robustness checks section.

References

Aastveit, K. A., G. J. Natvik, and S. Sola (2013): "Macroeconomic Uncertainty and the Effectiveness of Monetary Policy," Norges Bank Working Paper No. 2013/17.

——— (2017): "Economic Uncertainty and the Influence of Monetary Policy," *Journal of International Money and Finance*, 76, 50–67.

Alessandri, P., and H. Mumtaz (2018): "Financial Regimes and Uncertainty Shocks," *Journal of Monetary Economics*, Forthcoming.

Aruoba, S. B., L. Bocola, and F. Schorfheide (2017): "Assessing DSGE model nonlinearities," *Journal of Economic Dynamics and Control*, 83, 34–54.

Bachmann, R., B. Born, S. Elstner, and C. Grimme (2013): "Time-Varying Business Volatility, Price Setting, and the Real Effects of Monetary Policy," NBER Working Paper No. 19180.

——— (2017): "Time-Varying Business Volatility and the Price Setting of Firms," University of Notre Dame, University of Bonn, RWI Essen and ifo Institute, mimeo.

Bachmann, R., S. Elstner, and E. Sims (2013): "Uncertainty and Economic Activity: Evidence from Business Survey Data," *American Economic Journal: Macroeconomics*, 5(2), 217–249.

Bachmann, R., and G. Moscarini (2012): "Business Cycles and Endogenous Uncertainty," RWTH Aachen University and Yale University, mimeo.

Baker, S., N. Bloom, and S. J. Davis (2016): "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, 131(4), 1539–1636.

Baley, I., and J. A. Blanco (2018): "Firm Uncertainty Cycles and the Propagation of Nominal Shocks," *American Economic Journal: Macroeconomics*, Forthcoming.

Barnett, W. A. (1980): "Economic Monetary Aggregate: An Application of Index Number and Aggregation Theory," *Journal of Econometrics*, 14, 11–48.

Bauer, M. D., and G. D. Rudebusch (2016): "Monetary policy expectations at the zero lower bound," *Journal of Money, Credit and Banking*, 48(7), 1439–1465.

Bekaert, G., M. Hoerova, and M. Lo Duca (2013): "Risk, Uncertainty and Monetary Policy," *Journal of Monetary Economics*, 60, 771–788.

Bernanke, B. S. (1983): "Irreversibility, Uncertainty, and Cyclical Investment," *Quarterly Journal of Economics*, 98(1), 85–106.

Bertola, G., and R. J. Caballero (1994): "Irreversibility and Aggregate Investment," *Review of Economic Studies*, 61, 223–246.

Bloom, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77(3), 623–685.

Bloom, N., S. Bond, and J. V. Reenen (2007): "Uncertainty and Investment Dynamics," *Review of Economic Studies*, 74, 391–415.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018): "Really Uncertain Business Cycles," *Econometrica*, Forthcoming.

Boivin, J., and M. Giannoni (2006): "Has Monetary Policy Become More Effective?," *Review of Economics and Statistics*, 88(3), 445–462.

Boivin, J., M. Giannoni, and I. Mihov (2009): "Sticky Prices and Monetary Policy: Evidence from Disaggregated U.S. Data," *The American Economic Review*, 99(1), 350–384.

Caballero, R. (1990): "Consumption Puzzles and Precautionary Savings," *Journal of Monetary Economics*, 25, 113–136.

Caggiano, G., E. Castelnuovo, V. Colombo, and G. Nodari (2015): "Estimating Fiscal Multipliers: News From a Nonlinear World," *Economic Journal*, 125(584), 746–776.

Caggiano, G., E. Castelnuovo, and J. M. Figueres (2017): "Economic Policy Uncertainty and Unemployment in the United States: A Nonlinear Approach," *Economics Letters*, 151, 31–34.

Caggiano, G., E. Castelnuovo, and N. Groshenny (2014): "Uncertainty Shocks and Unemployment Dynamics: An Analysis of Post-WWII U.S. Recessions," *Journal of Monetary Economics*, 67, 78–92.

Caggiano, G., E. Castelnuovo, and G. Nodari (2017): "Uncertainty and Monetary Policy in Good and Bad Times," Melbourne Institute Working Paper(No. 9/17).

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.

Carriero, A., H. Mumtaz, K. Theodoridis, and A. Theophilopoulou (2015): "The Impact of Uncertainty Shocks under Measurement Error: A Proxy SVAR Approach," *Journal of Money, Credit and Banking*, 47(6), 1223–1238.

Carvalho, V. M., and B. Grassi (2015): "Large Firm Dynamics and the Business Cycle," Barcelona GSE Working Paper(No. 824).

Castelnuovo, E., and G. Pellegrino (2018): "Uncertainty-dependent Effects of Monetary Policy Shocks: A New-Keynesian Interpretation," *Journal of Economic Dynamics and Control*, forthcoming.

Castelnuovo, E., and P. Surico (2010): "Monetary Policy Shifts, Inflation Expectations and the Price Puzzle," *Economic Journal*, 120(549), 1262–1283.

Christiano, L. J., M. Eichenbaum, and C. Evans (1999): "Monetary Policy Shocks: What Have We Learned and to What End?," In: J.B. Taylor and M. Woodford (eds.): Handbook of Macroeconomics, Elsevier Science, 65–148.

——— (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113(1), 1–45.

Clarida, R., J. Galí, and M. Gertler (2000): "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 115, 147–180.

Colombo, V. (2013): "Economic policy uncertainty in the US: Does it matter for the Euro Area?," *Economics Letters*, 121(1), 39–42.

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

Eickmeier, S., N. Metiu, and E. Prieto (2016): "Time-Varying Volatility, Financial Intermediation and Monetary Policy," CAMA Working Paper No. 32/2016.

Evans, C., J. D. M. Fisher, F. Gourio, and S. Krane (2015): "Risk Management for Monetary Policy Near the Zero Lower Bound," *Brookings Papers on Economic Activity*, pp. 141–219.

Gertler, M., and P. Karadi (2015): "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 7(1), 44–76.

Gilchrist, S., J. W. Sim, and E. Zakrajšek (2014): "Uncertainty, Financial Frictions, and Investment Dynamics," Boston University and Federal Reserve Board of Governors, mimeo.

Granger, C. W. (1998): "Overview of Nonlinear Time Series Specification in Economics," University of California, San Diego.

Hamilton, J. D. (1994): Time Series Analysis, Princeton University Press, Princeton, New Jersey.

Hanson, M. (2004): "The "Price Puzzle" Reconsidered," *Journal of Monetary Economics*, 51, 1385–1413.

Jones, P. M., and W. Enders (2013): "The Asymmetric Effects of Uncertainty on Macroeconomic Activity," University of Alabama, mimeo.

Jordà, O. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95(1), 161–182.

Jurado, K., S. C. Ludvigson, and S. Ng (2015): "Measuring Uncertainty," *American Economic Review*, 105(3), 1177–1216.

Keating, J. W., L. J. Kelly, and V. J. Valcarcel (2014): "Solving the price puzzle with an alternative indicator of monetary policy," *Economics Letters*, 124(2), 188–194.

Kilian, L., and R. Vigfusson (2011): "Are the Responses of the U.S. Economy Asymmetric in Energy Price Increases and Decreases?," *Quantitative Economics*, 2, 419–453.

Kim, C., and C. Nelson (1999): "Has the U.S. Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle," *The Review of Economics and Statistics*, 81, 608–616.

Koop, G., M. Pesaran, and S. Potter (1996): "Impulse response analysis in nonlinear multivariate models," *Journal of Econometrics*, 74(1), 119–147.

Krippner, L. (2015): Term Structure Modeling at the Zero Lower Bound: A Practitioner's Guide, Palgrave-Macmillan.

Lanau, S., and T. Wieladek (2012): "Financial Regulation and the Current Account," International Monetary Fund Working Paper(No. 98).

Leduc, S., and Z. Liu (2016): "Uncertainty Shocks are Aggregate Demand Shocks," *Journal of Monetary Economics*, 82, 20–35.

Lubik, T., and F. Schorfheide (2004): "Testing for Indeterminacy: An Application to U.S. Monetary Policy," *American Economic Review*, 94(1), 190–217.

Ludvigson, S. C., S. Ma, and S. Ng (2015): "Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?," Working Paper 21803, National Bureau of Economic Research.

Lutz, C. (2014): "Unconventional Monetary Policy and Uncertainty," Copenhagen Business School, mimeo.

Lütkepohl, H. (2013): "Identifying Structural Vector Autoregressions via Changes in Volatility," *Advances in Econometrics*, 32, 169–203.

McConnell, M., and G. Perez-Quiros (2000): "Output Fluctuations in the United States: What Has Changed Since the Early 1980s?," *American Economic Review*, 90, 1464–1476.

Mittnik, S. (1990): "Modeling Nonlinear Processes With Generalized Autoregressions," *Applied Mathematics Letters*, 3(4), 71–74.

Mumtaz, H., and P. Surico (2015): "The Transmission Mechanism in Good and Bad Times," *International Economic Review*, 56, 1237–1260.

Mumtaz, H., and K. Theodoridis (2015a): "Dynamic effects of monetary policy shocks on macroeconomic volatility," Working Paper 760, School of Economics and Finance, Queen Mary University of London.

Mumtaz, H., and K. Theodoridis (2015b): "The International Transmission of Volatility Shocks: An Empirical Analysis," *Journal of the European Economic Association*, 13(3), 512–533.

Mumtaz, H., and F. Zanetti (2013): "The Impact of the Volatility of Monetary Policy Shocks," *Journal of Money, Credit and Banking*, 45(4), 535–558.

Nodari, G. (2014): "Financial Regulation Policy Uncertainty and Credit Spreads in the U.S.," *Journal of Macroeconomics*, 41, 122–132.

Owyang, M., V. A. Ramey, and S. Zubairy (2013): "Are Government Spending Multipliers Greater During Periods of Slack? Evidence from 20th Century Historical Data," *American Economic Review Papers and Proceedings*, 103(3), 129–134.

Parker, J. A., and B. Preston (2005): "Precautionary saving and consumption fluctuations," *The American Economic Review*, 95(4), 1119–1143.

Pellegrino, G. (2017): "Uncertainty and the Real Effects of Monetary Policy Shocks in the Euro Area," *Economics Letters*, forthcoming.

Ramey, V. A. (2012): "Comment on Roads to Prosperity or Bridges to Nowhere? Theory and Evidence on the Impact of Public Infrastructure Investment," *NBER Macroeconomics Annual*, 27, 147–153, National Bureau of Economic Research.

Ricco, G., G. Callegari, and J. Cimadomo (2016): "Signals from the Government: Policy Disagreement and the Transmission of Fiscal Shocks," *Journal of Monetary Economics*, 82, 107–118.

Romer, C., and D. Romer (2004): "A New Measure of Monetary Policy Shocks: Derivation and Implications," *American Economic Review*, 94(4), 1055–1084.

Ruge-Murcia, F. (2015): "Indirect Inference Estimation of Nonlinear Dynamic General Equilibrium Models: With an Application to Asset Pricing under Skewness Risk," McGill University, mimeo.

Sims, C. (1992): "Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy," *European Economic Review*, 36(5), 975–1000.

Sims, C., and T. Zha (2006a): "Were There Regime Switches in U.S. Monetary Policy?," *American Economic Review*, 96(1), 54–81.

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

Sims, C. A., and T. Zha (2006b): "Does Monetary Policy Generate Recessions?," *Macroeconomic Dynamics*, 10, 231–272.

Stock, J. H., and M. W. Watson (2002): "Has the Business Cycle Changed and Why?," in M Gertler and K. Rogoff (eds.): NBER Macroeconomic Annual, MIT Press, Cambridge, MA.

Stock, J. H., and M. W. Watson (2012): "Disentangling the Channels of the 2007-2009 Recession," *Brookings Papers on Economic Activity*, Spring, 81–135.

Sá, F., P. Towbin, and T. Wieladek (2014): "Capital Inflows, Financial Structure and Housing Booms," *Journal of the European Economic Association*, 12(2), 522–546.

Tenreyro, S., and G. Thwaites (2015): "Pushing on a String: US Monetary Policy is Less Powerful in Recessions," *American Economic Journal: Macroeconomics*, forthcoming.

——— (2016): "Pushing on a string: US monetary policy is less powerful in recessions," *American Economic Journal: Macroeconomics*, forthcoming.

Towbin, P., and S. Weber (2013): "Limits of floating exchange rates: The role of foreign currency debt and import structure," *Journal of Development Economics*, 101(1), 179–101.

Vavra, J. (2014): "Inflation Dynamics and Time-Varying Volatility: New Evidence and an Ss Interpretation," *Quarterly Journal of Economics*, 129(1), 215–258.

Ventzislav, I., and L. Kilian (2005): "A Practitioner's Guide to Lag Order Selection For VAR Impulse Response Analysis," *Studies in Nonlinear Dynamics & Econometrics*, 9(1), 1–36.

Weise, C. L. (1999): "The Asymmetric Effects of Monetary Policy: A Nonlinear Vector Autoregression Approach," *Journal of Money, Credit and Banking*, 31(1), 85–108.

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(2-3), 253–291.

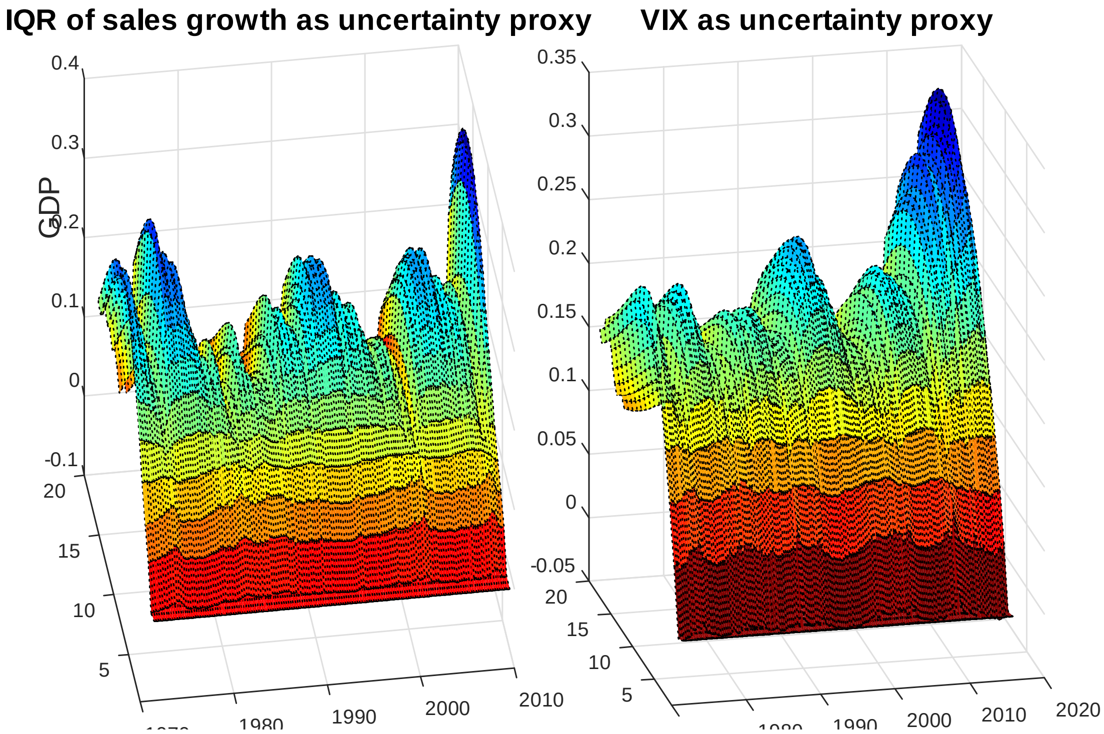

Figure A1: **Temporal evolution of point estimated GIRFs for GDP (shock: 25 basis points unexpected decrease in the policy rate)**. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Upper row: temporal evolution of the point estimated GIRFs. Colors ranging from blue (GIRFs peak values) to red (GIRFs trough values). The figure is best seen in color.

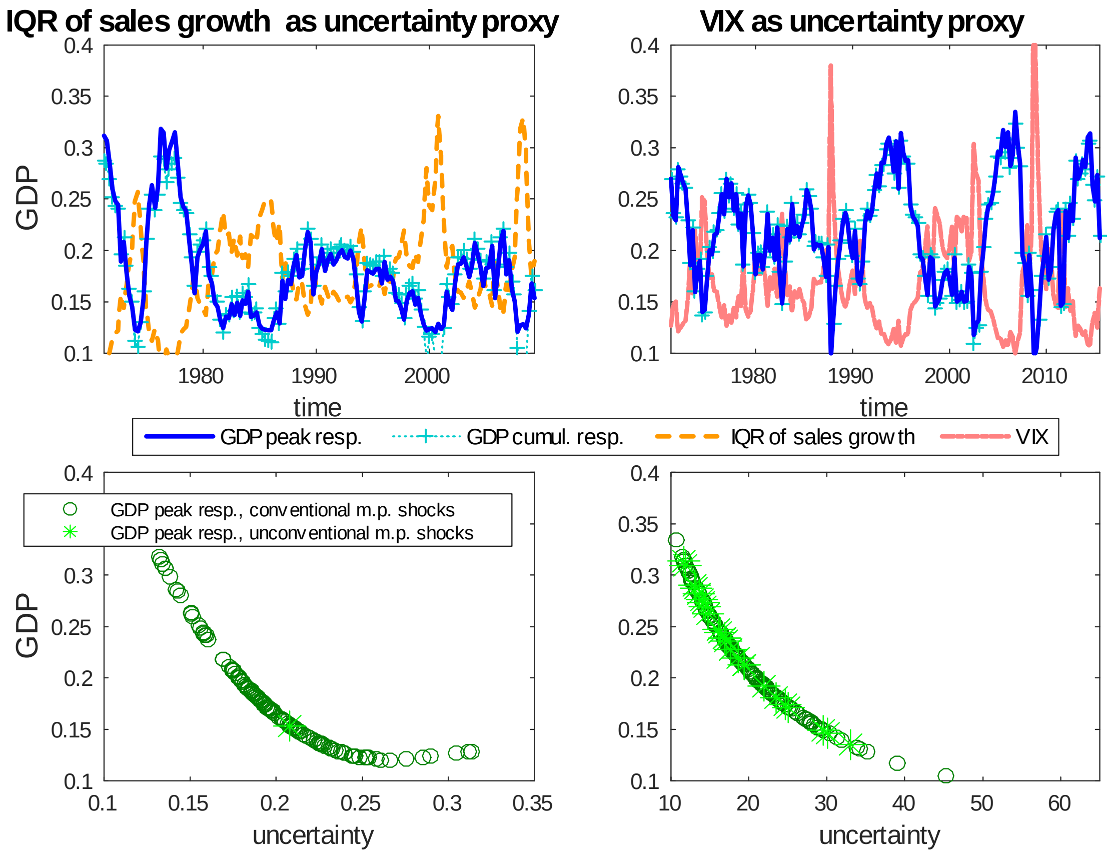

Figure A2: **Time-varying peak and cumulative response of GDP for a counterfactual that keeps the level of uncertainty at its pre-shock value**. **(shock: 25 basis points unexpected decrease in the policy rate)**. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Upper row: temporal evolution of the GIRFs peak and cumulative response (blue solid and cyan dotted lines respectively) along with the previous-quarter level of uncertainty and NBER recessions (shaded areas). The cumulative effects and uncertainty measures are standardized to the mean and standard deviation of the peak effects. Lower row: GIRFs peak response in relation with the initial level of uncertainty (with a differentiation between conventional and unconventional monetary policy shocks). Unconventional monetary policy shocks are shocks to the Wu and Xia's (2016) shadow rate in the period of binding ZLB. *Note*: see Section 5 for more details on the counterfactual exercise. Practically the same results are obtained in case uncertainty is exogenously modeled.

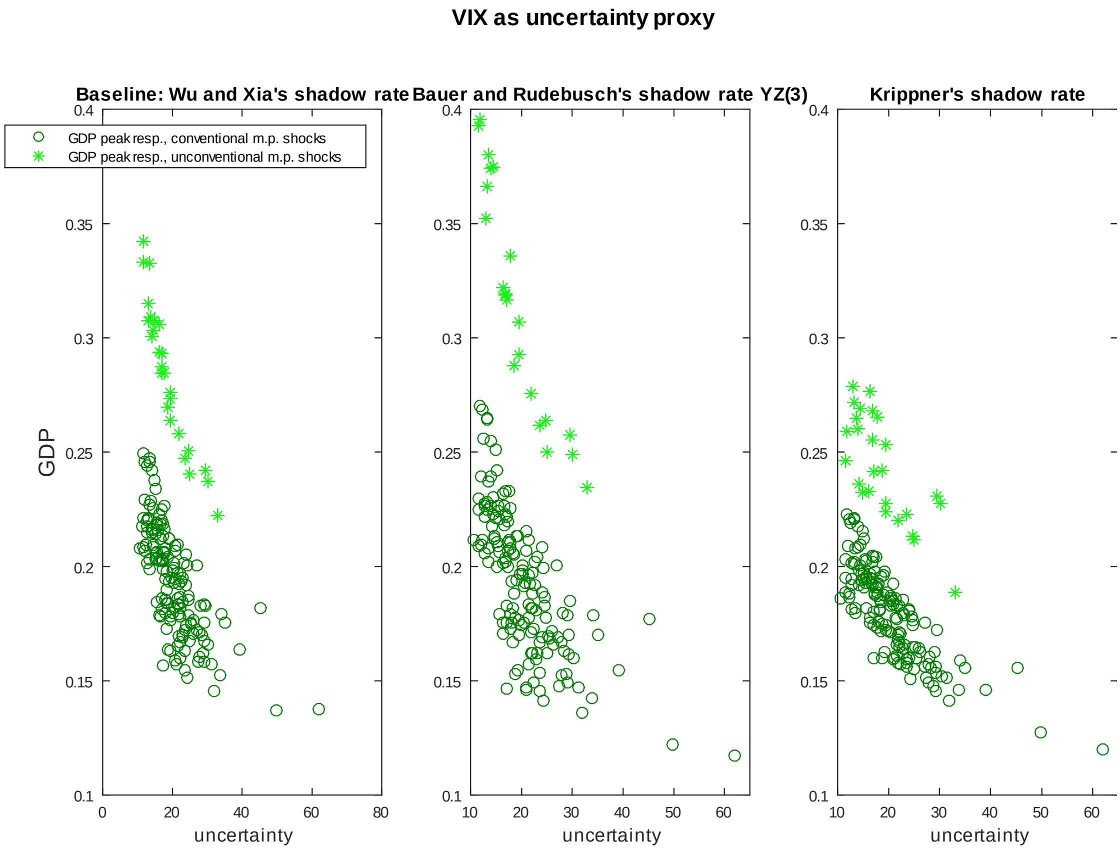

Figure A3: **Time-varying peak response of GDP for alternative shadow rates (shock: 25 basis points unexpected decrease in the policy rate; VIX as uncertainty proxy)**. GIRFs peak response in relation with the initial level of uncertainty (with a differentiation between conventional and unconventional monetary policy shocks). Unconventional monetary policy shocks are shocks to the shadow rate in the period of binding ZLB. *Note*: To ease comparison between panels the period of binding ZLB is the same and has been identified with the Wu and Xia's (2016) shadow rate (i.e., starting from 2009q3). The shadow rate by Bauer and Rudebush (2016) is available up to 2014q4.

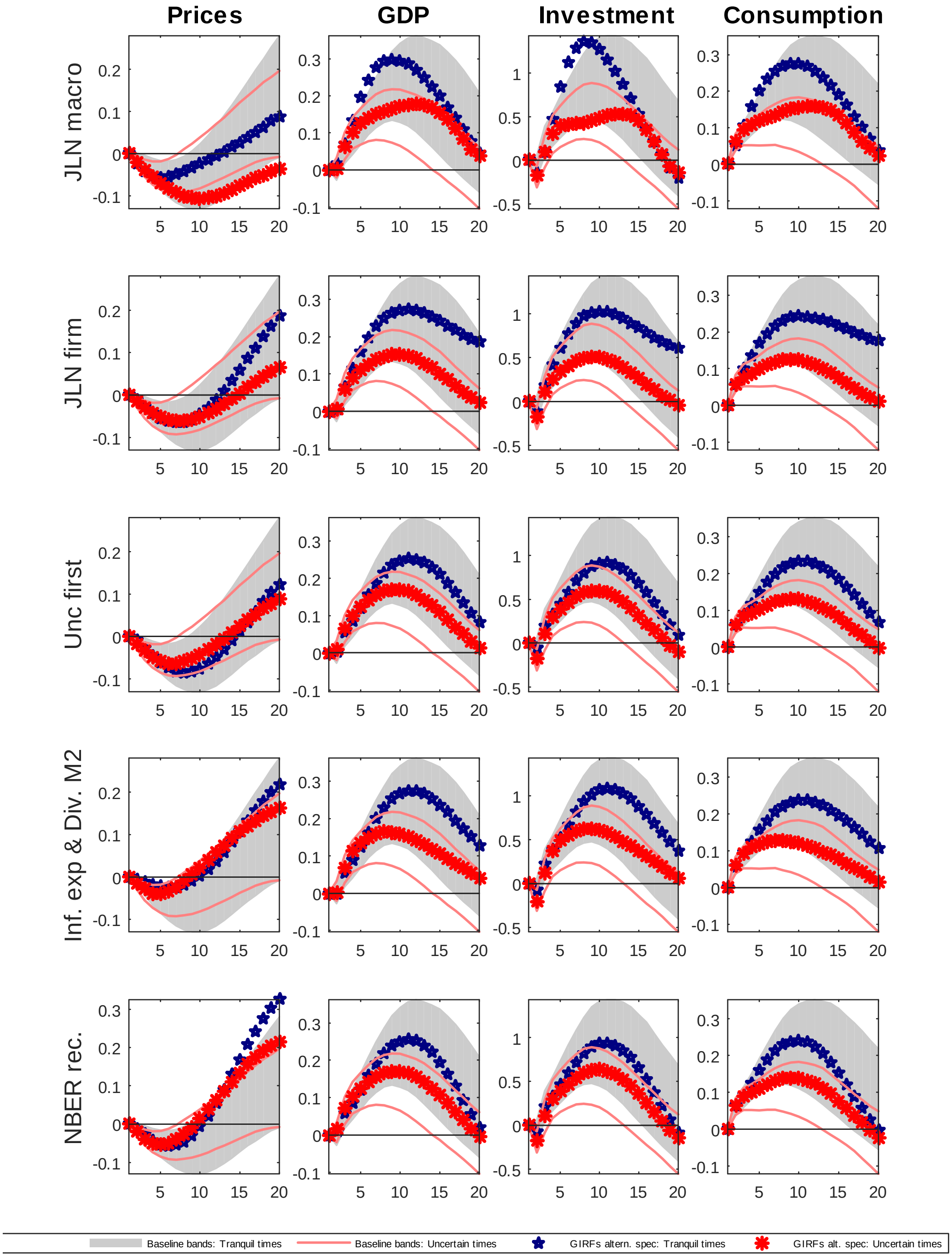

Figure A4: **Robustness checks for several perturbations of the baseline SEIVAR (shock: 25 basis points unexpected decrease in the FFR)**. Each row corresponds to a different I-VAR specification. Grey areas (areas identified by red solid lines): 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times (uncertain times) state of the baseline SEIVAR with the IQR of sales growth as the uncertainty proxy. Blue (red) stars: tranquil times (uncertain times) state-conditional GIRF for the alternative SEIVAR specification considered.

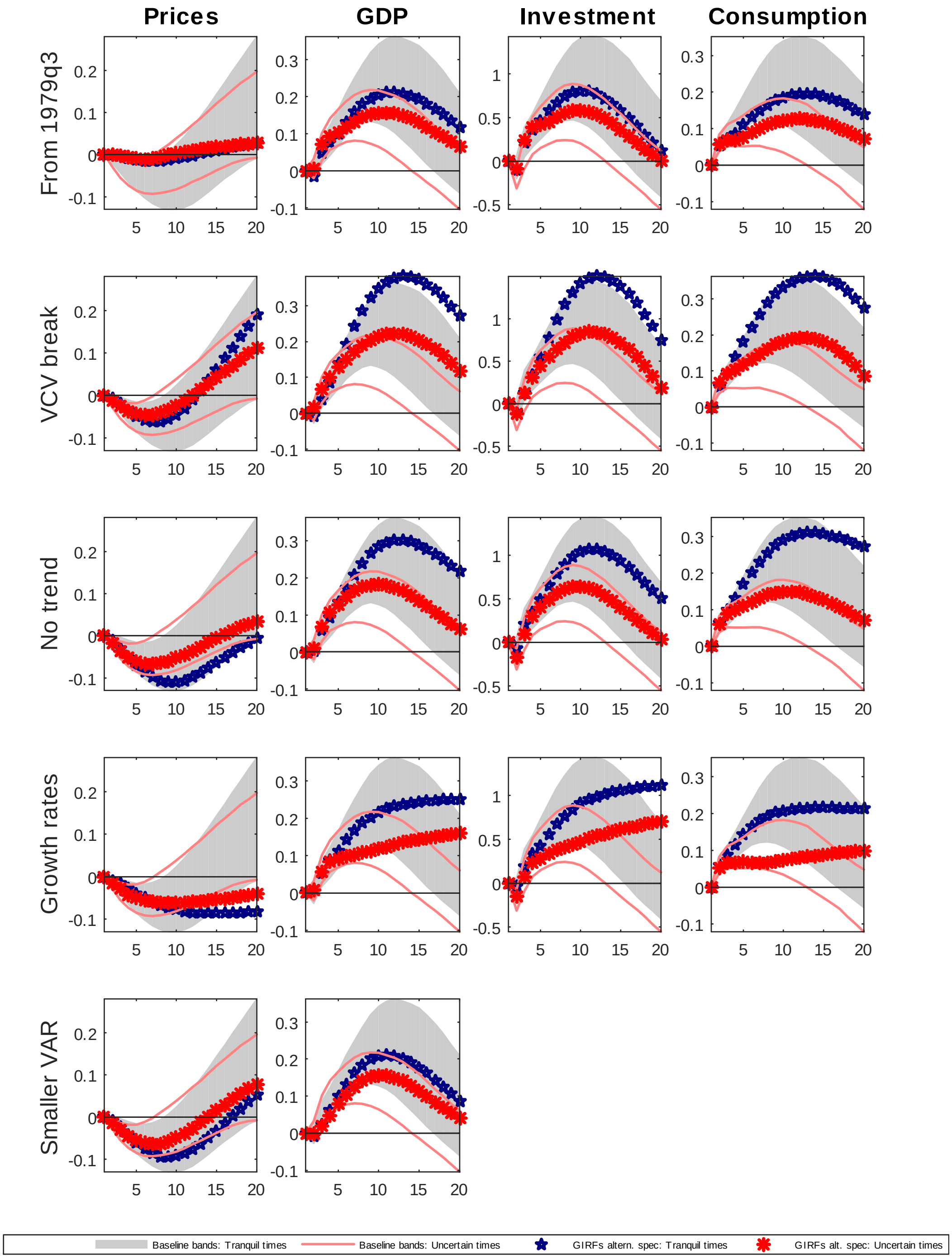

Figure A5: **Robustness checks for further perturbations of the baseline SEIVAR (shock: 25 basis points unexpected decrease in the FFR)**. Each row corresponds to a different SEIVAR specification. Grey areas (areas identified by red solid lines): 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times (uncertain times) state of the baseline SEIVAR with the IQR of sales growth as the uncertainty proxy. Blue (red) stars: tranquil times (uncertain times) state-conditional GIRF for the alternative SEIVAR specification considered.

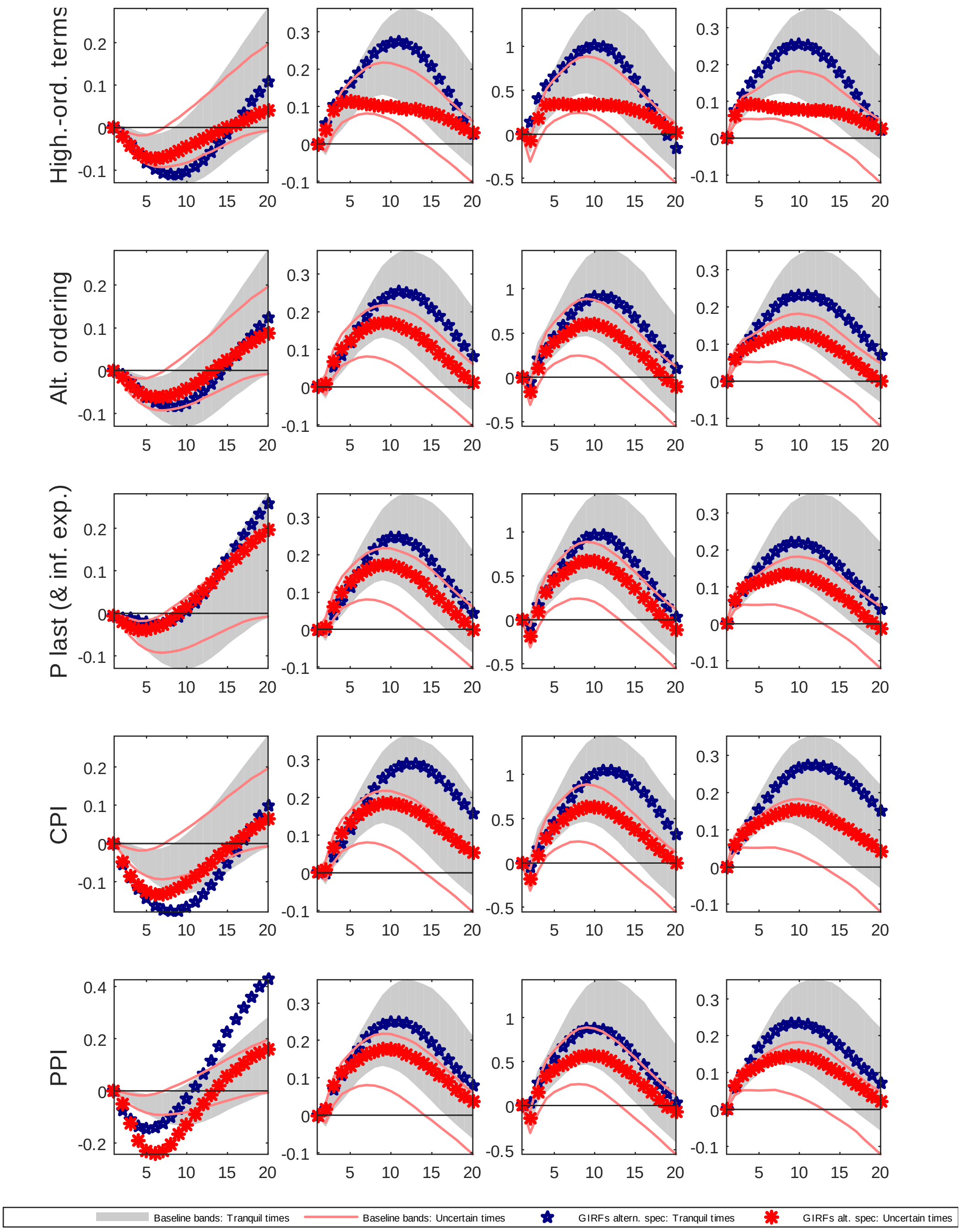

Figure A5: Continued.

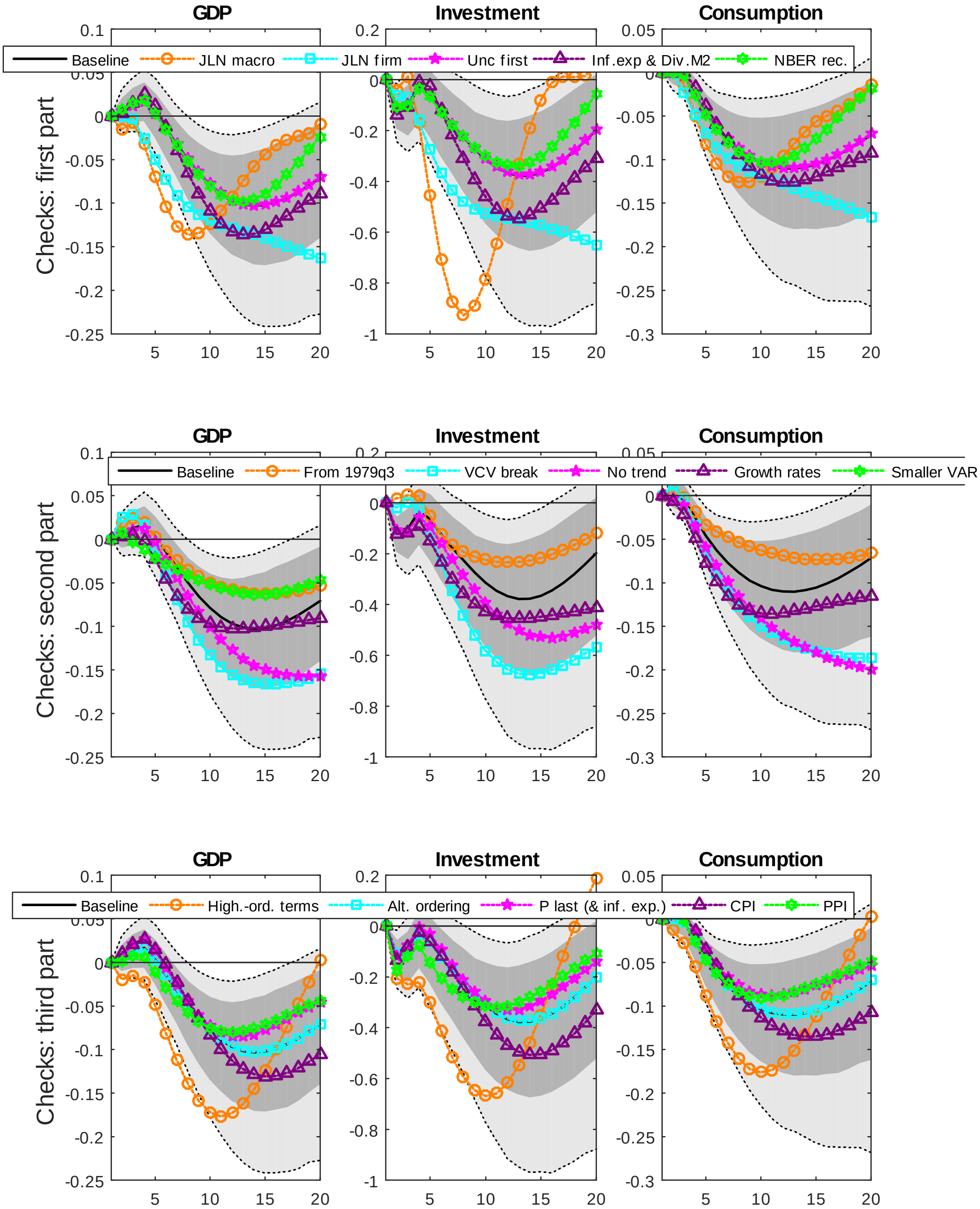

Figure A6: **Difference of state-conditional GIRFs between uncertain and tranquil times for further perturbations of the baseline SEIVAR**. IQR of sales growth as uncertainty proxy. Solid black lines: baseline difference between point estimated state-conditional GIRFs (uncertain times conditional GIRF minus tranquil times conditional GIRF). Interior dark grey areas: 68 percent confidence bands for the baseline difference (from the distribution of the difference stemming from the 2000 bootstrap draws). Exterior light grey areas: 90 percent confidence bands for the baseline difference. The other lines with different colors and markers refer to the difference for further perturbations of the baseline IVAR model (see the legend). Each row corresponds to a different set of five checks.

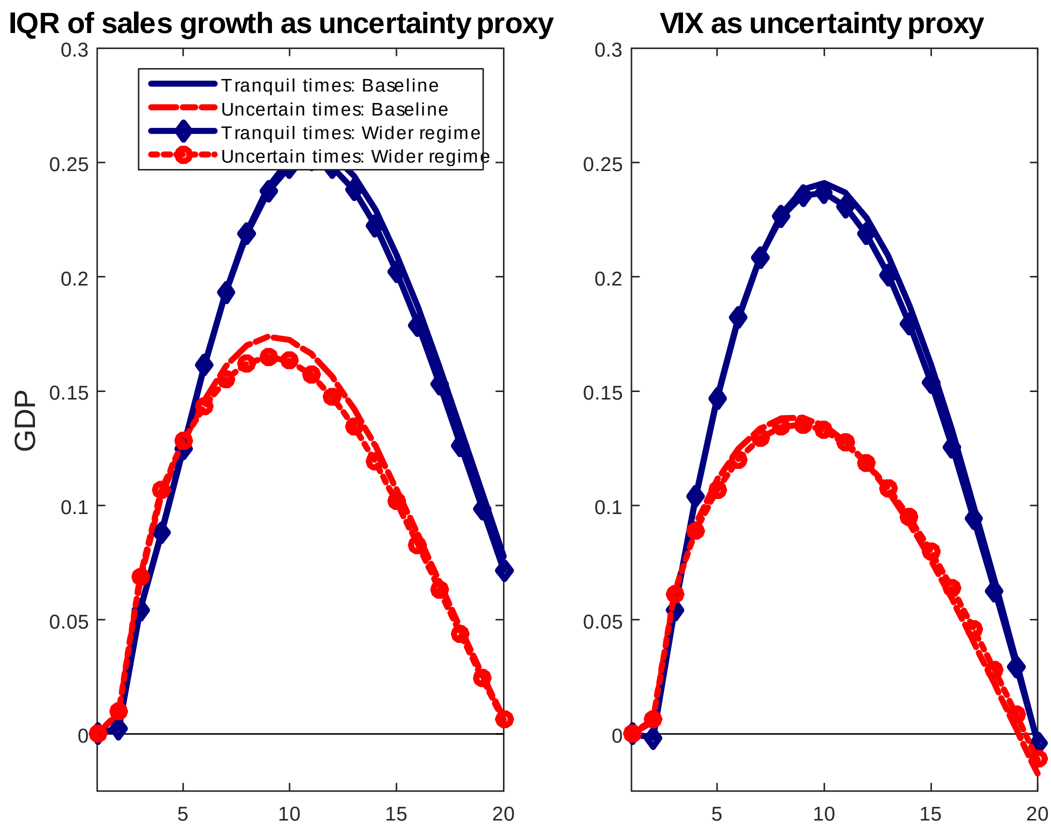

Figure A7: **Robustness to a wider definition of uncertain vs. tranquil times states (shock: 25 basis points unexpected decrease in the FFR)**. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Solid blue (red dotted) line: baseline state-conditional GIRF for the tranquil times (uncertain times) state. Blue diamonds (red circles) line: state-conditional GIRF for the tranquil times (uncertain times) state when states are defined by a ten-percentiles tolerance band around the first and ninth deciles of the distribution of uncertainty.

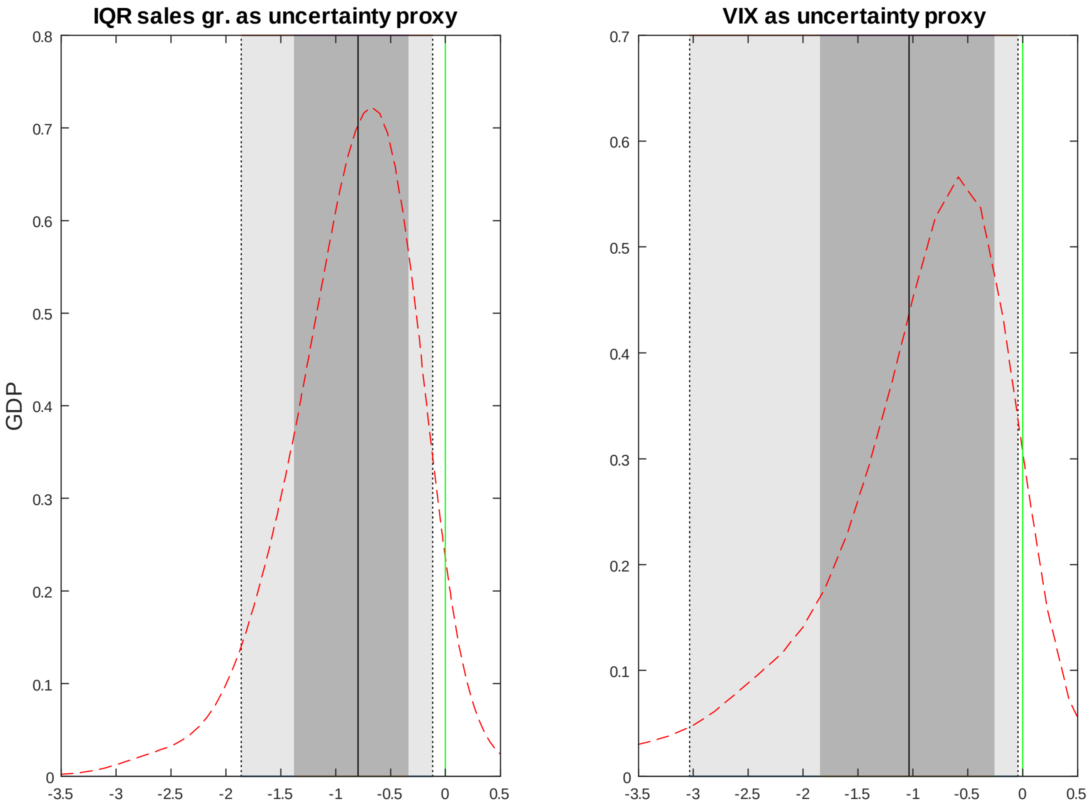

Figure A8: **Average difference between the cumulative effects of monetary policy shocks on GDP.** Red dashed line: Kernel density of the difference of the cumulative effects of the monetary policy shock between tranquil times and uncertain times (the density is based on the 2000 bootstrapped draws). Interior dark (exterior light) grey shaded area: 68% (90%) confidence interval for the difference. Black solid line: mean of the difference distribution. Green solid line: zero-vertical line identifying the "no difference" value. *Note*: the test is computed for the 4-year cumulative effect of monetary policy shocks.

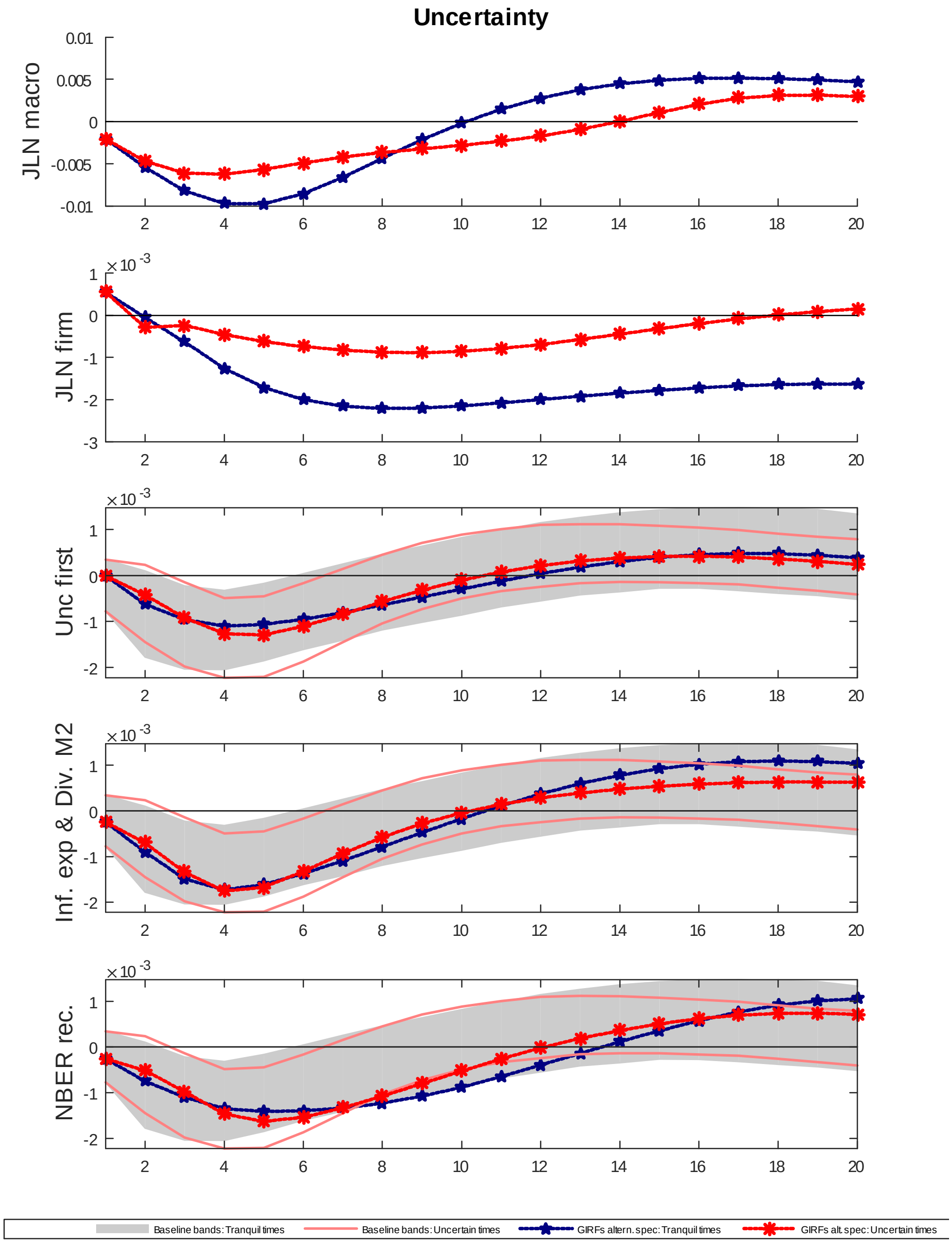

Figure A9: **Uncertainty response from robustness checks (shock: 25 basis points unexpected decrease in the FFR)**. Each row corresponds to a different SEIVAR specification. Grey areas (areas identified by red solid lines): 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times (uncertain times) state of the baseline SEIVAR with the IQR of sales growth as the uncertainty proxy. Blue (red) stars: tranquil times (uncertain times) state-conditional GIRF for the alternative SEIVAR specification considered. *Note*: for comparability reasons baseline confidence bands are shown just for specifications that do not consider alternative uncertainty indicators.

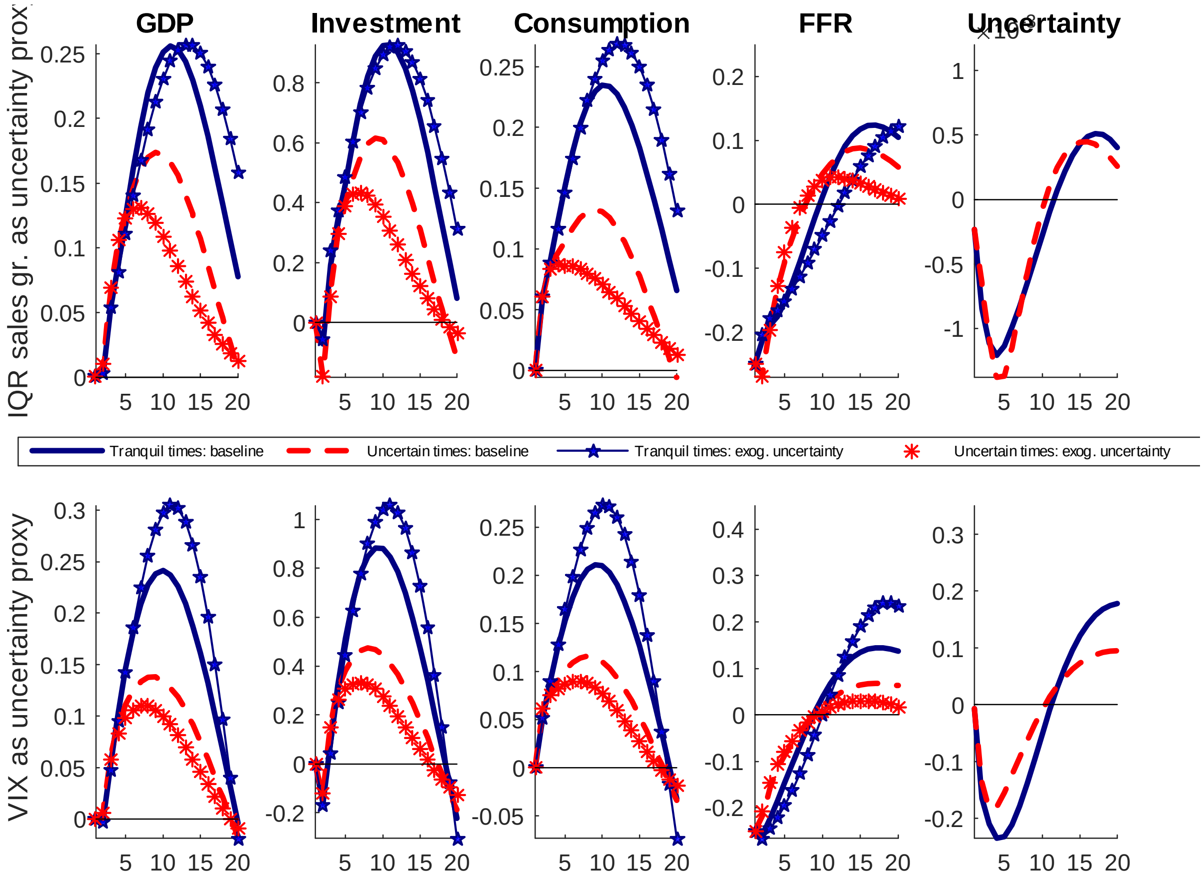

Figure A10: **Comparison among several state-conditional responses: Baseline GIRFs from SEIVAR with endogenous uncertainty vs. IRFs from IVAR with exogenous uncertainty**. Upper (lower) row: IQR of sales growth (VIX) as uncertainty proxy. Blue solid and red dashed lines: baseline GIRFs conditional to a tranquil and uncertain times state, respectively. Starred blue lines and starred red points: point estimated GIRFs conditional respectively to a tranquil and uncertain times state for the case uncertainty is not endogenously modeled in the I-VAR. *Notes***.** All the VARs for which responses are reported are estimated on a similar number of lags and sample period (equal to our baseline ones) for comparison purposes. Price responses are not reported. In order to obtain the (conditionally-linear) responses when uncertainty is not modeled endogenously, we estimate the following I-VAR model comparable to eqt. (1): $\mathbf{Y}_t = \boldsymbol{\alpha} + \boldsymbol{\gamma} \cdot linear\ trend + \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \sum_{j=1}^{L} \mathbf{B}_j unc_{t-j} + \left[\sum_{j=1}^{L} \mathbf{c}_j R_{t-j} \times unc_{t-j}\right] + \mathbf{u}_t$, where this time $\mathbf{Y}$ does not include unc. Then, in order to obtain responses, uncertainty is fixed either to its 9th decile value or to its 1st decile one (a choice similar to Aastveit, Natvik and Sola (2013)) and the conditionally-linear system is iterated on (a similar iterated procedure to get IRFs from a linear VAR is illustrated in Hamilton (1994, p. 319 and around)) . Notice that this model is fully linear conditional on an uncertainty value and hence, unlike our baseline I-VAR, the starting conditions do not matter.