Uncertainty and Monetary Policy in the US: A Journey into Non-Linear Territory*

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Abstract

This paper estimates a non-linear VAR model to assess whether the real effects of monetary policy shocks depend on the level of uncertainty. Crucially, uncertainty is modeled endogenously in the VAR, thus allowing to take account of two unexplored channels of monetary policy transmission working through uncertainty direct reaction and uncertainty mean reversion. We find that monetary policy shocks are about 50-75% more powerful during tranquil times than during firm- and macro-level uncertain times. Failing to account for endogenous uncertainty would bias responses and imply twice more effective monetary policy during tranquil times, mainly because of the non-consideration of uncertainty mean reversion.

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

JEL codes: C32, E32, E52.

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"[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

"So when uncertainty is high, [firm] units optimally postpone hiring and investment decisions for a few months until business conditions become clearer. [...] [U]nits evaluate the uncertainty of their discounted value of marginal returns over the lifetime of an investment or hire, so high current uncertainty only matters to the extent that it drives up long-run uncertainty. ***When uncertainty is mean reverting, high current values have a lower impact on expected long-run values than if uncertainty were constant."***

Nicholas Bloom
The Impact of Uncertainty Shocks, Econometrica, 2009

1 Introduction

The COVID-19 shock has generated a level of uncertainty in the US economy similar to that realized during the Great Recession. Right after such a shock, the Federal Reserve has quickly intervened to inject liquidity in the system in an attempt of limiting the extent of the recession which will inevitably come. The contemporaneous occurrence of high uncertainty and policy interventions has naturally reignited the debate on the interferences of high levels of uncertainty on the transmission of monetary policy shocks to the business cycle. However, there is still limited empirical research on the role that uncertainty might play in influencing the effectiveness of unexpected policy stimuli.

This paper's purpose is to shed new light on the uncertainty-dependent effects of monetary policy shocks and, in particular, to show that taking into account the evolution of uncertainty after monetary stimuli is key in order not to disregard two unexplored channels of endogenous uncertainty that quantitatively affect the monetary policy transmission mechanism.[1] On the one hand, uncertainty is mitigated by monetary policy easings (Bekaert et al. (2013)). This uncertainty mitigation, according to Bernanke's quote above, may temporarily enhance policy effectiveness by reducing precautionary

[1] In our study – differently from close studies, i.e., Aastveit et al. (2017), Eickmeier et al. (2016), and Castelnuovo & Pellegrino (2018), to which we relate later in more detail – uncertainty is modeled among endogenous (or dependent) variables in the non-linear (Structural) VAR, thus allowing it to endogenously move after a monetary policy shock hits. In general, an endogenous variable in a non-linear VAR can move because of two reasons after a shock: either because of the shock or irrespectively from it (depending on its value at the time of the shock).

savings and by providing an extra kick to investment via a "more stable macroeconomic environment". On the other hand, uncertainty proxies also tend to mean revert in the short to medium run, a fact potentially playing a role in a state-dependent analysis (or in a "non-linear territory"). According to Bloom's quote above, in a context of mean reverting uncertainty, high current uncertainty will have a lower impact on expected future uncertainty than in a context of constant uncertainty, implying that consumers' and firms' expectations, and hence decisions, will be less extreme. In principle, the consequences of these two channels may be economically relevant provided that precautionary savings play a significant role in consumption fluctuations (Caballero (1990) and Parker & Preston (2005)), that uncertainty significantly affects firms' "wait and see" attitude in investment and hiring (Bernanke (1983), Bertola & Caballero (1994), Dixit & Pindyck (1994), Bloom et al. (2007), Bloom (2009)), and that expected future uncertainty is important for decision making (Guiso & Parigi (1999) and Bloom et al. (2017)). However, the literature is still silent on the importance of these two channels for the monetary policy transmission mechanism.[2]

The paper's purpose is tackled by proposing a Self-Exciting Interacted VAR (SEIVAR) model which we estimate with quarterly post-WWII US data. This non-linear 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 (we use the ninth and first deciles of the empirical distribution of the uncertainty proxy to define our two states). Crucially, we model both interaction variables endogenously and accordingly compute fully non-linear Generalized Impulse Response Functions (GIRFs) à la Koop et al. (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.[3] The current paper scrutinizes for the first

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

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

time the advantages and the implications of endogenizing conditioning variables within IVARs. Application-wise, it contrasts with the strategy employed by recent VAR analyses on the uncertainty-dependent effectiveness of monetary policy shocks – e.g., Aastveit et al. (2017), Eickmeier et al. (2016) and Castelnuovo & Pellegrino (2018) –, which work with non-linear 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 move of uncertainty (our conditioning indicator) after the policy shock and its feedback effects on the dynamics of the system.[4] In this way, we are able to capture both the effects of the endogenous move of uncertainty on precautionary savings and firms' willingness to invest and their state-dependent consequences.

Our baseline IVAR models a standard set of real aggregate variables – including GDP, investment and consumption–, the GDP price index, the policy rate, and an uncertainty proxy. Specifically, we use two baseline proxies for uncertainty: the Inter Quartile Range (IQR) of sales growth, a cross-sectional firm-level uncertainty proxy computed by Bloom et al. (2018), and the VIX, a measure for the implied stock market volatility extensively used after Bloom's (2009) seminal paper.[5]

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.[6]

Second, we find that there is 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 50%-75% stronger when the shock occurs in tranquil times than when it occurs in uncertain times, an economically important difference. We also find that uncertainty is mitigated by expansionary monetary policy shocks in both states, a finding which further supports the importance of treating uncertainty as an endogenous variable.

[4]These feedback effects make the model Self-Exciting, or "fully" non-linear, in the iteration after a monetary policy shock. The term "Self-Exciting" is borrowed from the time series literature (see, e.g., the SETAR model presented in Terasvirta et al. (2010)) 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.

[5]We also use Jurado, Ludvigson, and Ng's (2015) macro and firm-level uncertainty indices and Baker, Bloom, and Davis' (2016) Economic Policy Uncertainty (EPU) index to check the robustness of our main results.

[6]This result is a prerogative of our econometric strategy. Our SEIVAR model has the additional advantage – over previous related studies – of allowing historical initial conditions to play a meaningful role (Koop et al. (1996)), something which enables us to gain further insights on the effects of monetary policy shocks from a historical perspective.

Third, when analyzing the role of endogenous uncertainty through counterfactual exercises, we find that it has a non-negligible quantitative effect on the estimated state-conditional responses. Monetary policy effectiveness becomes around half as uncertainty-dependent when uncertainty is treated as an endogenous variable versus when it is not, e.g., in the case of exogenous uncertainty, we erroneously find monetary policy being approximately 100%-180% more effective on GDP during tranquil times than uncertain times. We show that this different result is driven by the interaction of two endogenous uncertainty channels which is captured by our baseline analysis but which cannot be captured by conditionally-linear responses (which are computed by assuming uncertainty to be exogenous, i.e., fixed and constant after the shock). On the one hand, there is the "uncertainty endogenous reaction" channel that Bernanke refers to in his statement, which operates through the reduction of uncertainty after a monetary policy easing. Such channel, *ceteris paribus*, works as an amplifier of the real effects of monetary policy shocks, irrespectively from the initial level of uncertainty. On the other hand, there is the "uncertainty mean reversion" channel that Bloom refers to in his passage, which operates through the mean reversion in uncertainty occurring after, but independently from, the monetary easing. Such a channel, whose direction of effects depends on the initial level of uncertainty, works in favor of making state-dependent responses of real variables less extreme. Our exercises, designed to disentangle the effects of each of these two channels, find that, although both channels are empirically relevant, the uncertainty mean reversion channel is the main responsible for making the real effectiveness of monetary policy shocks half as uncertainty-dependent when uncertainty is treated endogenously.[7] In other words, consistently with theory, we find that the first channel matters for the average effect of monetary policy shocks and the second one for the magnitude of state-dependence.

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 et al. (2018)). Even after endogenizing uncertainty, we still find that during uncertain times monetary policy is way less effective than during tranquil times, although to a lesser extent than what found in previous studies. With respect to previous studies, we find that allowing for mean reversion in uncertainty after monetary policy shocks increases the estimated effectiveness

[7] When we use the EPU index, the uncertainty mean reversion channel almost cancels out all the state-dependence in the real effects of monetary policy shocks that one would instead find in the exogenous uncertainty case. Hence, endogenous uncertainty can also imply qualitative differences with respect to the case of exogenous uncertainty. In particular, with our methodology, we are able to uncover that economic policy uncertainty is not an important determinant for the overall effectiveness of monetary policy shocks in the US.

of monetary policy shocks when it is most needed, i.e., during uncertain times. This suggests that policymakers should use fully non-linear empirical models when designing monetary policies to achieve a desired real effect. From a theoretical perspective, our analysis suggests that both modeling the endogenous reaction of uncertainty to policies (rather than considering it as an exogenous process) and modeling empirically-grounded mean-reverting uncertainty processes is crucial to correctly assess alternative policies in environments characterized by uncertainty.[8]

Our study is also relevant for applied researchers because it shows the perils of not modeling endogenously the conditioning variable in a non-linear VAR. In the context of fiscal spending shocks Ramey and Zubairy (2018) show that the difference of their findings on the US fiscal multipliers with respect to Auerbach and Gorodnichenko's (2012) ones are largely driven by the simplifying assumptions about the (exogenous) conditioning variable in the computation of (conditionally-linear) impulse responses adopted in the latter study's non-linear VAR.[9] Our work adds to this applied literature by proposing both a framework to study the relevance of endogenizing conditioning variables in non-linear VARs and a method to investigate the specific reason/channel why it is important. Understanding the latter is important to build theoretical models that account for the empirically relevant channels of propagation of a shock.

The present paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our empirical methodology. Section 4 presents the main results on the effectiveness of monetary policy shocks in tranquil vs. uncertain times. Section 5 focuses on the role of endogenous uncertainty and analyzes the two channels that arise. Section 6 concludes.

2 Related literature

The work closest to ours is Aastveit et al. (2017). With respect to them, we: adopt a more general econometric framework where at the same time uncertainty is modeled endogenously and initial conditions play a meaningful role thanks to the computation of non-linear GIRFs; show that taking into account endogenous uncertainty can have both quantitative implications (e.g., for our micro- and macro-level uncertainty proxies, where

[8]To the best of our knowledge, the only work that takes into account the endogenous uncertainty reaction to a monetary policy shock in the context of a micro-founded model is Mumtaz & Theodoridis (2019).

[9]Our framework takes full account of RZ's (2018, p. 888) point according to which "[c]onstructing impulse responses in nonlinear VAR models is far from straightforward since many complexities arise when one moves from linear to nonlinear systems" (see also Caggiano et al. (2015)).

monetary policy effectiveness becomes half uncertainty-dependent with respect to exogenous uncertainty) and qualitative implications (e.g., for the Baker, Bloom, and Davis' (2016) EPU index, where monetary policy almost loses all its uncertainty-dependence); explore the empirical relevance of two so far unexplored channels of endogenous uncertainty and explain their role in making monetary policy effectiveness less uncertainty-dependent.

Other related recent empirical works are Eickmeier et al. (2016), Castelnuovo & Pellegrino (2018) and Caggiano et al. (2020). 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 non-linear VAR models and interpret these facts via, respectively, a state-dependent calibration or estimation of a New-Keynesian Dynamic Stochastic General Equilibrium (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 et al. (2020) 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.[10]

On the theoretical side, several explanations point to a lower effectiveness of monetary policy shocks when uncertainty is high. First, in the presence of some form of fixed costs or partial irreversibilities in the investment or hiring processes heightened uncertainty can increase firms' option value of waiting to hire and invest, thus making the real economy less sensitive to any policy stimulus because of a "cautionary effect" (Bloom et al. (2007), Bloom (2009), Bloom et al. (2018)).[11] Bloom et al. (2018) simulate their general equilibrium model featuring time-varying volatility, non-convex adjustment costs in both capital

[10] Further connected empirical works are Weise (1999), Mumtaz & Surico (2015), Tenreyro & Thwaites (2016), and Alpanda et al. (2019), who investigate the transmission mechanism of monetary policy in good and bad business cycle 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, because by focusing on uncertainty we can 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, because 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. 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.

[11] 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.

and labor, and firm-level idiosyncratic shocks and find that heightened uncertainty makes firms less responsive to a policy stimulus. According to the authors, and in their words, their exercise implies that "uncertainty shocks not only impact the economy directly, but also indirectly change the response of the economy to any potential reactive stabilization policy." Our empirical results, obtained with a framework that allows us to take account of the indirect effects of endogenous uncertainty on monetary effectiveness, lend support to the theoretical results of these works.

Second, uncertainty can influence firms' price-setting behavior. 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 & Blanco (2019) 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 et al. (2013) use firm micro data and find that firms change prices more frequently when uncertainty is high, consistently with Vavra's model.

Lastly, in the presence of risk-averse agents, there will be higher precautionary savings during uncertain times (see Bloom's (2014) survey and references therein). The fact that uncertainty is endogenous in our framework enables us to account for the link between uncertainty, precautionary savings, and the effectiveness of monetary policy shocks that Bernanke refers to in his statement in the Introduction.

Turning to the other side of the interaction between uncertainty and monetary policy, i.e., how monetary policy influences uncertainty, Bekaert et al. (2013) find that uncertainty decreases in the medium run after an expansionary monetary policy shock identified with a linear VAR framework. Mumtaz & Theodoridis (2019) find the same result and explain it structurally 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 unconventional monetary policy shocks. Our framework allows us 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 variables.

The model is estimated by OLS.[12] We follow Ventzislav and Kilian's (2005) suggestions and select the number of lags as suggested by the Hannan-Quinn criterion. As a result, we use $L = 2$ (both for the non-linear and the nested linear model).

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

[12] 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.

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, based on the simple product between the policy rate and uncertainty lagged values, was chosen based on its parsimony and to avoid instability problems.[13] 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).[14] 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.

Our IVAR directly captures the non-linearity of one (or, potentially, more) monetary transmission channel(s) with respect to uncertainty via a parsimonious specification. Is this parsimony problematic? It is well known that the policy functions which represent the solution of non-linear DSGE frameworks feature many interaction terms involving endogenous variables. However, a Montecarlo exercise recently proposed by Andreasen et al. (2021) shows that our IVAR is able to recover the true non-linear impulse responses as implied by a state-of-the-art non-linear DSGE framework solved via a third-order approximation around its risky steady-state. This evidence corroborates the use of parsimonious IVAR specifications for the investigation of non-linear dynamic responses to identified macroeconomic shocks like the one conducted in this paper.

Notice that the SEIVAR model (1)-(4) is non-linear but symmetric and hence is not well suited to study the asymmetric effects of positive versus negative shocks.[15] Without loss of generality, we focus on expansionary monetary policy shocks.

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

[13] An IVAR 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 et al. (2017)) and it is difficult to impose conditions to ensure 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 IVAR could depend on the specific functional form employed. Section A4.2 of the Appendix further elaborates on the specific form of nonlinearity adopted and also shows that the main results are robust to the use of a richer specification of the interaction between uncertainty and monetary policy (check *iv*).

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

[15] See Barnichon & Matthes (2018) for a novel approach to directly investigate the role of the sign of shocks.

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 et al. (1999), Christiano et al. (2005) and Christiano et al. (2016)). Instead, uncertainty is allowed to react on-impact to policy rate moves. Here the degree of endogeneity of uncertainty is maximized, but later we do show, however, that our results are robust to modeling uncertainty as the first variable of the vector. Our results are robust also to the case monetary policy shocks are identified using fed funds futures surprises around policy announcements as external instruments in a Proxy SVAR as in Gertler & Karadi (2015) (Appendix A6 shows how to apply the external instrument identification to IVAR models).[16]

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 an associated p-value of 0.007. Similar evidence relates to the Jurado et al. (2015) uncertainty indicators that are used for robustness.

3.2 Generalized Impulse Response Functions

Unlike existing related studies, our conditioning variable, i.e., uncertainty, is also included in the vector of modeled endogenous variables. This is important to compute responses conditional on high/low uncertainty because, as shown later, uncertainty is found to endogenously move after a monetary policy shock, both because it directly reacts to the shock and because it mean reverts after the shock. Without accounting for this uncertainty endogenous movement, biased responses would arise as the feedbacks from such uncertainty movement 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

[16] Given our interest in a quarterly sample with key macroeconomic indicators, we preferred not to use the latter identification method as our baseline because taking quarterly averages of the Gertler and Karadi's fed funds futures *monthly* surprises series can cause important losses of information, e.g., since there are more FOMC meetings than quarters in a year. Consistently with this interpretation, our Appendix documents that the Proxy Interacted VAR with the quarterly instrument gives results overall in line with our baseline results for real variables, although, differently from what Gertler & Karadi (2015) find in their monthly linear VAR, it still implies some VAR "puzzles" such as the price puzzle and a negative short-run response of real activity. Based on this consideration, we preferred to adopt a Cholesky decomposition in our baseline analysis.

endogenous conditioning variable, we compute Generalized Impulse Response Functions (GIRFs) à la Koop et al. (1996) accounting for an orthogonal structural shock as in Kilian & Vigfusson (2011).[17] GIRFs take into account the fact that, in a fully non-linear model, the state of the system and therefore system's future evolution can vary endogenously after a shock. As a result, GIRFs return fully non-linear empirical responses that depend nontrivially on the initial conditions in place when the system is shocked (as well as on the sign and size of the shock). Theoretically, the GIRF at horizon h of the vector $\mathbf{Y}$ to a shock in date t, δ_t, 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 between the shocked and non-shocked paths of $\mathbf{Y}$:

$$GIRF_{Y,t}(h, \delta_t, \boldsymbol{\varpi}_{t-1}) = \mathbb{E}\left[\mathbf{Y}_{t+h} \mid \delta_t, \boldsymbol{\varpi}_{t-1}\right] - \mathbb{E}\left[\mathbf{Y}_{t+h} \mid \boldsymbol{\varpi}_{t-1}\right]. \tag{5}$$

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 averaged, per each horizon, over a particular subset of initial conditions 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 et al. (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).[18] Conditioning responses on extreme events, rather than on normal events, may be important in order not to confound similar states and hence miss empirical responses in favor of non-linearity (Caggiano et al. (2015)). Theoretically, our state-dependent GIRFs can be defined as:

$$GIRF_{Y,t}\left(h, \delta_t, \boldsymbol{\Omega}_{t-1}^{uncertain\ times}\right) = \mathbb{E}\left[GIRF_{Y,t}\left(h, \delta_t, \left\{\boldsymbol{\varpi}_{t-1} \in \boldsymbol{\Omega}_{t-1}^{uncertain\ times}\right\}\right)\right] \tag{6}$$

$$GIRF_{Y,t}\left(h, \delta_t, \boldsymbol{\Omega}_{t-1}^{tranquil\ times}\right) = \mathbb{E}\left[GIRF_{Y,t}\left(h, \delta_t, \left\{\boldsymbol{\varpi}_{t-1} \in \boldsymbol{\Omega}_{t-1}^{tranquil\ times}\right\}\right)\right] \tag{7}$$

where $\boldsymbol{\Omega}_{t-1}^{i}$ denotes the set of histories characterizing regime $i = \{uncertain\ times,\ \ tranquil\ times\}$. The algorithm at the basis of the simulation

[17]The reader is informed about two different definitions of GIRFs available in the literature that may create confusion: one, in Koop et al. (1996), which is about the simulation of *structural* impulse responses to shocks in a *non-linear* VAR and has nothing to do with identification (indeed in our case the Cholesky order continues to be valid); the other, in Pesaran & Shin (1998) and meant for linear VARs, which is about finding (non-structural) impulse responses that are invariant to the order of variables in the VAR (and that hence is incompatible with a Cholesky decomposition).

[18]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.

of our history-dependent and state-dependent 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. Owyang et al. (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 because they provide only the average reaction of the economy in a given state, whereas GIRFs allow us to obtain fully non-linear empirical responses for each given initial quarter in the sample, in line with our purposes. Second, provided that Local Projections implicitly catpure the evolution of uncertainty after the shock, they do not easily allow us to study the role of endogenous uncertainty. 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 commonly used Wu and Xia's (2016) "shadow rate" instead of the FFR and label shocks as "unconventional" monetary policy shocks. Wu and Xia's shadow rate turned negative since July 2009 (or quarterly, since 2009Q3) and consequently we take this as an indication that the ZLB constraint became actually binding for the FFR.[19] Both real

[19] The shadow rate is a model-implied interest rate that Wu & Xia (2016) estimate on the basis of a multifactorial shadow rate term structure model. It is allowed to turn negative over the ZLB period and they show that it can be used to proxy unconventional monetary policy at the ZLB. The quarterly

variables and prices are taken in logs and multiplied by 100. This implies that their VAR responses can be interpreted as percent deviations from the trend. The sample period starts in 1971Q1.[20] Further details on the data sources are available in Section A7 of 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 measure of uncertainty constructed by Bloom et al. (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 & Caballero (1994), Dixit & Pindyck (1994)) and price-setting behavior (see Vavra (2014) and references therein), and an important driver behind aggregate time-varying volatility (Carvalho & 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 et al. (2015) and the Baker, Bloom, and Davis' (2016) economic policy uncertainty (EPU) index to check the robustness of our main results. The Jurado et al. (2015) indices are based on the purely unforecastable components extracted from two large US datasets, whereas the EPU index aims to capture uncertainty over economic policy by selecting articles in major U.S. newspapers that discuss something about (i.e., contain terms about) the three topics of uncertainty, the economy, and policy.

Figure 1 plots the baseline uncertainty indicators against their mean (represented by dashed green lines) and NBER recessionary periods (represented by grey vertical bars). Two considerations follow. First, the uncertainty proxies tend to fluctuate around their mean. Typically, they remain very high/low only for a while before mean reverting. Our

Wu-Xia shadow rate was 75 and 22 basis points (bp) in 2009Q1 and 2009Q2, respectively, whereas the FFR value was 18 bp in both quarters.

[20] 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).

econometric strategy allows us to take this empirical feature into account in the computation of the uncertainty-dependent responses to monetary stimuli. Second, periods of high uncertainty and recessionary periods have not always coincided in the recent US history and hence in principle they are empirically distinguishable, a fact that allows us to have enough empirical identification to study the influence of "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.[21] Moreover, some recessions, e.g., the 1980 and 1990-91 ones, have not been characterized by particularly high levels of uncertainty.

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 has evolved through time according to the level of historical uncertainty. One characteristic of endogenously modeling uncertainty and computing fully non-linear 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 the time-variation of GIRFs (whereas the full evidence is available in the form of a tridimensional graph in Figure A1 in the Appendix).[22] 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 relationship 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

[21] 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 Monday 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.

[22] As Figure A1 documents, our estimated SEIVAR model is in-sample stable, meaning that we are able to obtain a non-diverging GIRF for each initial quarter in our sample.

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.[23] Thanks to our framework we are able to find 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 (a result suggesting that the effects of a cut in the FFR and an equally-sized cut in the shadow rate are not easily comparable).[24] Interestingly for us, even in the binding ZLB period we can observe a clear negative relationship 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 to study the average response of the economy to a monetary policy shock conditional on the state of uncertainty (high versus low), from now on we exclude from our estimation sample the period with unconventional monetary policy shocks (i.e., shocks to the Wu & Xia (2016) shadow rate for its implied period of binding ZLB 2009Q3-2015Q4) and focus on shocks to the FFR. 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, i.e., averaged over uncertainty levels, response of the effects of monetary policy shocks if we mix shocks to the FFR with shocks to the shadow rate. Second, Bauer & Rudebusch (2016) find that estimated shadow rates

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

[24]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 result is beyond the purposes of this paper and the investigations of the reasons behind it are left to future research.

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 binding ZLB period 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 et al. (2017), the effects of heightened uncertainty are particularly strong.

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 times" 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 (cumulative) reactions, real GDP reacts on average 47% (55%) and 74% (75%) 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 the average effects of a monetary policy shock, which, however, underestimate (overestimate) the impact of monetary policy shocks in tranquil (uncertain) times.[25]

We now consider the state-dependent evidence for all our six endogenous variables in our SEIVAR. Figure 4 (5) shows baseline results conditional to the use of the IQR of sales

[25] We note that having the Great Recession period in the estimation sample sharpens the identification of the effects of monetary policy shocks in presence of high uncertainty. This because the Great Recession was characterized both by a dramatic jump in uncertainty and by a spectacular drop in the FFR engineered by the Federal Reserve in the attempt of slowing down the fall of real GDP. Indeed, these are the facts that motivated this paper. Unsurprisingly, the exclusion of the Great Recession period would drastically reduce the precision of the estimated impulse responses and blur the difference between the cumulative effects of monetary policy shocks in the two states considered in this study.

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. 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 roughly between three-fifths and two-thirds of those 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 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.[26] 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). The next Section digs deeper into the role of endogenous uncertainty and shows its relevance for the estimated responses. There we will see that our estimated GIRFs for real variables take also implicitly into account the fact that uncertainty mean reverts after the monetary stimulus.[27]

Turning to the response of prices, Figures 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 a result often found in the monetary VAR literature.[28] 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

[26]The fact that the VIX is less endogenous to monetary policy shocks is consistent with the findings by Ludvigson et al. (2015) according to which financial uncertainty is more exogenous to the business cycle.

[27]This is not directly evident from the uncertainty responses in Figures 4 and 5 since the GIRF represents the deviation of uncertainty from its mean reversion path as caused by the monetary policy shock (see equation 5). Hence, for example, the negative response of uncertainty during tranquil times in the figures implies that, because of the monetary policy shock, uncertainty will mean revert more slowly to its higher unconditional level.

[28]The price puzzle is a common finding especially for sample periods that include Pre-Volcker observations (as ascertained in our checks below). As our robustness checks show, it occurs also in case we identify monetary policy shocks by means of an external instrument following Gertler & Karadi (2015).

one is to interpret it as a VAR-artefact due to omitted variables.[29] 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 & Surico (2010) and Keating et al. (2014)). The puzzling response of prices is significantly mitigated and the non-linear response of real activity to a monetary policy shock documented with our benchmark analysis turns out to be robust. A further consideration in relation to the reaction of prices is that notwithstanding the very different responses of real activity indicators, price responses hardly exhibit any different behavior between states.[30]

Finally, to examine whether the response of real variables is statistically different between states, a test 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 is based on the distribution of the difference between state-conditional responses stemming from the bootstrap procedure used.[31] 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 the first row of Figure A6). We employ alternative firm- and macro-level uncertainty measures (such as Jurado, Ludvigson, and Ng's (2015) macro- and firm-level uncertainty indexes), use the Baker, Bloom, and Davis' (2016) economic policy uncertainty (EPU) index, 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.

[29] As regards the "fact" interpretation, Christiano et al. (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 expansionary monetary policy shocks could hence be at the root of the price puzzle. As regards the "artifact" interpretation, Sims (1992) and Castelnuovo & 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.

[30] 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 for more research using microeconomic data (following, e.g., Bachmann et al. (2017)).

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

Section A4.2 motivates and presents the results from additional robustness checks we performed (summary in Figure A5 and the 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 policy rate and uncertainty; iv) the case where the linear trend is not included; v) the case trending variables are modeled 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 the last variable so that to allow for its on-impact response to the policy shock; ix) the case the CPI is used instead than the GDP deflator price index; x) the case monetary policy shocks are identified using high-frequency surprises around policy announcements as external instruments as in Gertler & Karadi (2015).[32]

Our main results are robust to all checks considered but to the use of the EPU index, for which the uncertainty-dependence of the effectiveness of monetary policy shocks almost vanishes. This implies that economic policy uncertainty does not seem important for the transmission of monetary policy shocks. The next section clarifies the role that endogenous uncertainty plays for this finding (given that, as shown in the Appendix, in case we did not model the EPU index endogenously in the VAR, we would erroneously find that it also implies state-dependent impulse responses of monetary policy shocks).

5 The role of endogenous uncertainty

This Section shows why modeling uncertainty as an endogenous variable in the non-linear VAR 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 considering uncertainty as exogenous).[33] As the Figure

[32] Section A4.3 of our Appendix contains further robustness material: Figure A7 shows the robustness of results to the use of 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 which is more directly related to the overall policy effectiveness.

[33] Following the same logic of the counterfactual exercises in Sims & Zha (2006), 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.

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 and Figure 8 complement the findings in Figure 7 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 (black solid and green starred lines in Figure 8, respectively).[34] Overall, we find that the difference between both peak and cumulative state-dependent responses of real variables gets halved when uncertainty is treated as endogenous versus when is not, implying that with endogenous uncertainty monetary policy effectiveness becomes around half as state-dependent as with exogenous uncertainty. For example, in passing from endogenous uncertainty to exogenous uncertainty, the GDP peak response turns from being 47% (74%) stronger during tranquil times for the IQR of sales growth (VIX) to being 94% (181%) so.

To ensure that the counterfactual exercise above fully captures what happens when uncertainty is exogenously modeled in the non-linear VAR (as in, e.g., Aastveit et al. (2017)), Figure A9 in the Appendix shows IRFs obtained from an alternative estimated IVAR comparable to equation (1) where uncertainty, which serves as our conditioning variable, is not modeled in the vector of endogenous variables, i.e.,:

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

where $\tilde{Y}$ does not include unc. In order to obtain the impulse responses, uncertainty is fixed either to its $9th$ decile value or to its $1st$ decile one – consistently with our baseline IVAR and similarly to Aastveit, Natvik, and Sola (2013, 2017) – and the conditionally-linear system is iterated onwards.[35] As Figure A9 shows, virtually the same results as in Figure 7 are obtained.[36]

The finding that under exogenous uncertainty monetary policy is erroneously found twice as powerful during tranquil times as during uncertain times is mechanically explained by the neglect of the endogenous moves of uncertainty after the monetary policy

[34] Figure 8 does not report the confidence bands for clarity reasons and because they are not helpful to assess statistical significance (provided results come from a counterfactual exercise). However, counterfactual responses are outside the 68% baseline confidence bands (results available upon request).

[35] A similar iterated procedure to get IRFs from a linear VAR is illustrated in Hamilton (1994, p. 319). Notice that this model is fully linear conditional on an uncertainty value and hence, unlike our baseline IVAR, the starting conditions do not matter.

[36] This reassures us against the relevance of the Lucas critique for the counterfactual exercise performed. We prefer to work with the counterfactual analysis in the main paper because allows us to distinguish between the two endogenous uncertainty channels, what we do next.

shock hits. Specifically, the finding arises because conditionally-linear IRFs fail to consider the two reasons why uncertainty can move after the monetary shock, or in other words because they neglect the interaction between two endogenous uncertainty channels. Figure 9 digs deeper into the drivers of the results in the first row of Figure 7 on the real effects of monetary stimuli (in particular, the first panel of Figure 9 coincides with the first panel of Figure 7). As the first row of Figure 9 documents, treating uncertainty as an exogenous variable – like in Figure 7 – both i) shuts down the (endogenous) reaction of uncertainty to the monetary policy shock and ii) prevents uncertainty to mean revert after the shock (second and third column, respectively). These are two different endogenous channels that can influence the GDP response to monetary policy shocks in different ways. In what follows we disentangle the effect of each of them. The aim is to decompose and rationalize the move from conditionally-linear IRFs – which do not take account of endogenous uncertainty – to our baseline GIRFs – which do take account of it.

On the one hand, the reduction in uncertainty induced by the expansionary monetary shock works in favor of enhancing, *ceteris paribus*, the response of real variables in each state with respect to a scenario with unreactive uncertainty. This is the "uncertainty endogenous reaction" channel that Bernanke refers to in his statement in the Introduction, according to which "the reduction in risk associated with an easing of monetary policy [...] may amplify the short run impact of policy". The decrease in uncertainty will increase monetary policy effectiveness via reduced precautionary savings and the shrinkage of firms' inaction regions. The second row of Figure 9 presents a counterfactual exercise that allows us to isolate the role played by this channel. Provided that this is the only channel shut down (i.e., uncertainty still mean reverts as in the baseline analysis), the passage from these counterfactual responses to baseline responses will only be explained by this channel. Consistently with Bernanke's predictions – and consistently with the short run baseline decrease in uncertainty after the monetary shock –, the real effectiveness of monetary policy shocks increases in the short run in the passage from counterfactual GDP responses to baseline ones, for both uncertain and tranquil times.

On the other hand, the mean reversion in uncertainty occurring after – but independently from – the monetary shock works in favor of making the state-dependent real responses less different between states with respect to a scenario of non mean reverting uncertainty. This is the mean reversion channel that Bloom refers to in his passage in the Introduction, according to which "when uncertainty is mean reverting, high current [uncertainty] values have a lower impact on expected long-run [uncertainty] values than if uncertainty were constant." Assuming non mean reverting uncertainty implies that uncertainty will be forever high or low. Since agents take decisions based on expected future uncertainty, then it is reasonable to expect that allowing uncertainty to mean revert will imply a less extreme agents' response in each state. The third row of Figure 9 confirms these intuitions with a counterfactual that isolates this "mean reversion" channel by shutting it down.[37] Consistently with what expected, in the passage from these counterfactual responses to baseline ones, the real effects of monetary policy shocks increase in uncertain times – provided that initially-high uncertainty mean reverts toward a lower value – and decrease in tranquil times – provided that initially-low uncertainty mean reverts toward a higher value.

Figure 8 also shows the difference in the state-conditional real effects of the monetary shock for the cases in which, with respect to the baseline case of endogenous uncertainty, either the Bernanke's or the mean reversion channels are shut down (purple crossed and orange circled lines, respectively).

Overall, this Section's findings suggest two considerations. First, both channels can be quantitatively relevant. As Figure 9 documents, in the case uncertainty is proxied by the IQR of sales growth, their neglect would induce quantitatively important biases in the estimated real responses to monetary policy shocks.[38,39] Second, as Figure 8 documents,

[37] In order to properly isolate this mean reversion channel, the right panels in Figure 8 plot the average *non-shocked* uncertainty path following the shock at time t, for each given state, i.e., $\mathbb{E}\left[unc_{t+h} \mid \{\boldsymbol{\varpi}_{t-1} \in \boldsymbol{\Omega}_{t-1}^{uncertain\ times}\}\right]$ and $\mathbb{E}\left[unc_{t+h} \mid \{\boldsymbol{\varpi}_{t-1} \in \boldsymbol{\Omega}_{t-1}^{tranquil\ times}\}\right]$ (see equation 5). In this way the mean reversion in uncertainty is independent from the uncertainty endogenous reaction to monetary policy shocks and only depends from the initial level of uncertainty.

[38] An attentive reader may wonder why both channels can be empirically relevant for GDP response even though the changes they induce in uncertainty are of very different magnitude (probably he/she would have compared Figure 9 second and third columns vertical axis scales). Remember, however, that the GDP response is given by its average shocked minus non-shocked path (see equation 5). As regards the Bernanke channel, the decrease in uncertainty induced by the shock will be directly translated into the responses (since uncertainty will decrease only in the shocked path). Instead, the mean reversion in uncertainty is something present in both uncertainty paths (shocked and non-shocked) and hence only a part of it would be indirectly transmitted into the response, via the non-linear interaction terms (think to the fact that only the interest rate would be different between paths – by definition of monetary policy shock – and that it would be multiplied with mean reverting uncertainty in the interaction term). Basically, in loose terms and over-simplifying on notation, the response of GDP for the endogenous uncertainty case at horizon h ahead for a time t shock to the policy rate R (δ_R shock at horizon $h = 0$) conditional on a history $\boldsymbol{\omega}_{t-1}$ can be seen as:

$$\left.\frac{\partial GDP(h)}{\partial R(0)}\right|_{\boldsymbol{\varpi}_{t-1}}^{end.\ unc.} = \left.\frac{\partial GDP(h)}{\partial R(0)}\right|^{ex.\ unc.} + \left.\frac{\partial GDP(h)}{\partial unc}\left(\frac{\partial unc}{\partial R(0)} + \frac{\partial unc}{\partial time}\cdot\left[\frac{\partial\left(R\cdot unc\right)}{\partial\left(R(0)\ \&\ time\right)} - \frac{\partial\left(R\cdot unc\right)}{\partial\left(time\right)}\right]\right)\right|_{\boldsymbol{\varpi}_{t-1}}$$

, for $h = 0, 1, ..., H$. It is easy to see that when uncertainty is exogenously modeled and fixed to a constant to recover state-dependent responses, then both endogenous uncertainty channels are shut down, i.e., $\frac{\partial unc}{\partial R(0)} = 0$ (Bernanke's channel turned off) and $\frac{\partial unc}{\partial time} = 0$ (mean reversion turned off). Notice that in a non-linear model the two channels may also interact (think to a negligible extra term in the parenthesis which our baseline GIRFs can also capture).

[39] In case uncertainty is instead proxied by the VIX, the only channel that would induce a quantitatively relevant bias is the mean reversion channel (see Figure A10 in the Appendix). This is consistent with the fact that the decrease in the VIX induced by the monetary policy shock is of smaller relevance than

the mean reversion channel is the main responsible for reducing (in this case halving) the difference between state-dependent responses of real variables when uncertainty is treated as endogenous. Indeed, when the mean reversion channel is the only channel shut down the difference is similar to the (fully) exogenous uncertainty case, whereas when it is the only channel active the difference is similar to the baseline case of endogenous uncertainty. This is consistent with the fact that the mean reversion channel, as seen above, is the only channel that makes impulse responses less distant between the two states.[40]

6 Conclusion

We propose a non-linear VAR framework in order to study the macroeconomic effects of monetary policy shocks during tranquil versus uncertain times while taking into account that uncertainty may endogenously move after monetary stimuli. We show that modeling uncertainty as 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 50%-75% stronger during tranquil times than during uncertain times. While being an important difference, we show that it is considerably smaller – for our baseline analysis around a half – than what one would get by disregarding the endogenous move of uncertainty after the stimulus. 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 two novel endogenous uncertainty channels, the "uncertainty endogenous reaction" and "uncertainty mean reversion" channels, which we find empirically relevant for the propagation of monetary policy shocks. The uncertainty mean reversion channel is the one connected to monetary policy effectiveness becoming half as state-dependent with endogenous uncertainty as with exogenous uncertainty.

Our findings have implications for policy because they suggest that, even when considering the "endogenous uncertainty" channels, monetary policy remains significantly less effective during (firm- and macro-level) uncertain times than tranquil times. Hence our evidence lends empirical support to the call for more aggressive policies in uncertain times (Bloom (2009), Bloom et al. (2018)). Our findings also offer some suggestions

the one induced in the IQR of sales growth (as documented in Section 4.2).

[40] If strong enough, the mean reversion channel can also cancel out – while moving from exogenous uncertainty to endogenous uncertainty – any uncertainty-dependence in the effects of monetary policy shocks. This is the case of the EPU index, as shown in Figure A11 of the Appendix.

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 while at the same time displaying empirically-grounded mean reversion.

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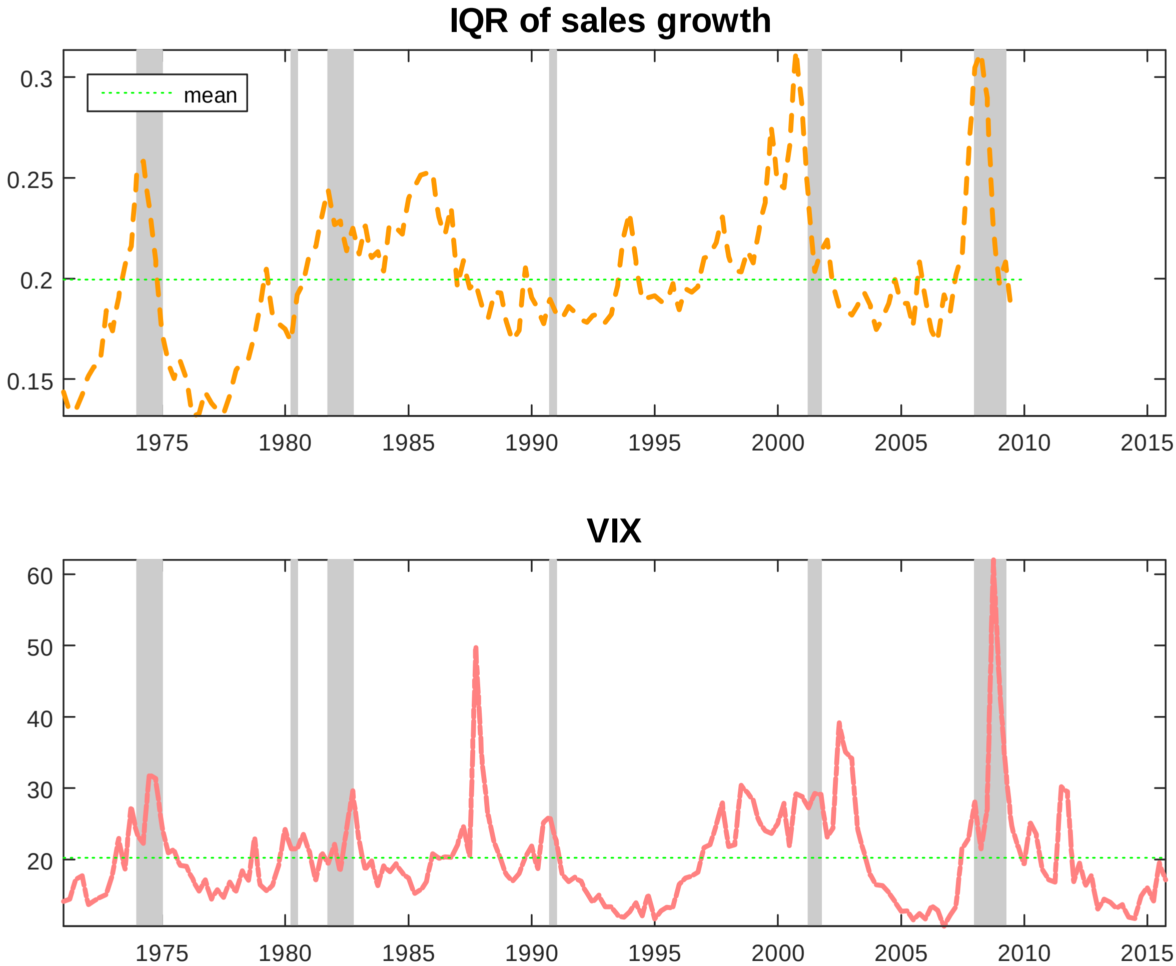
TABLE 1

	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**

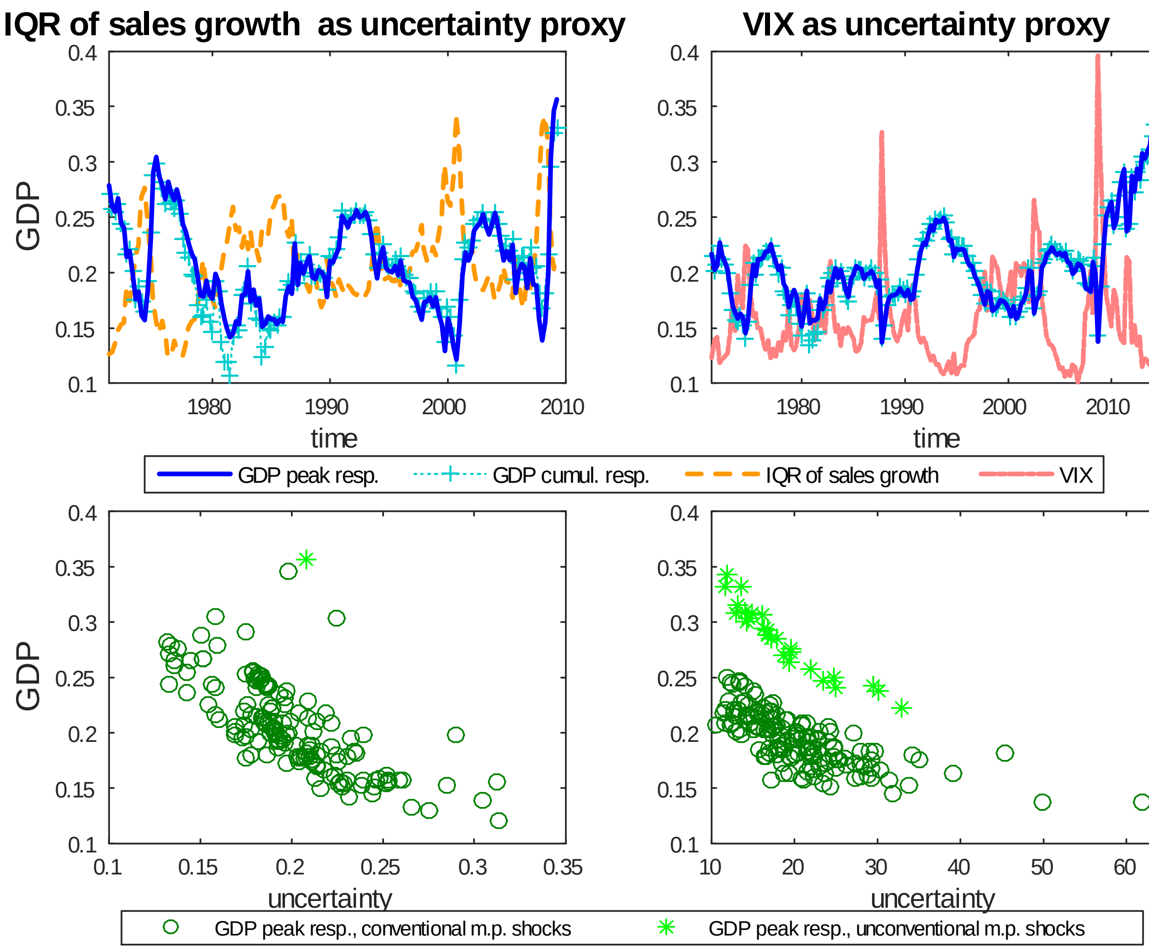
Difference of the state-conditional peak and cumulative real effects of monetary policy shocks between uncertain and tranquil times: endogenous vs. exogenous uncertainty. The difference is computed as the effects in uncertain times minus the effects in tranquil times.

FIGURE 1



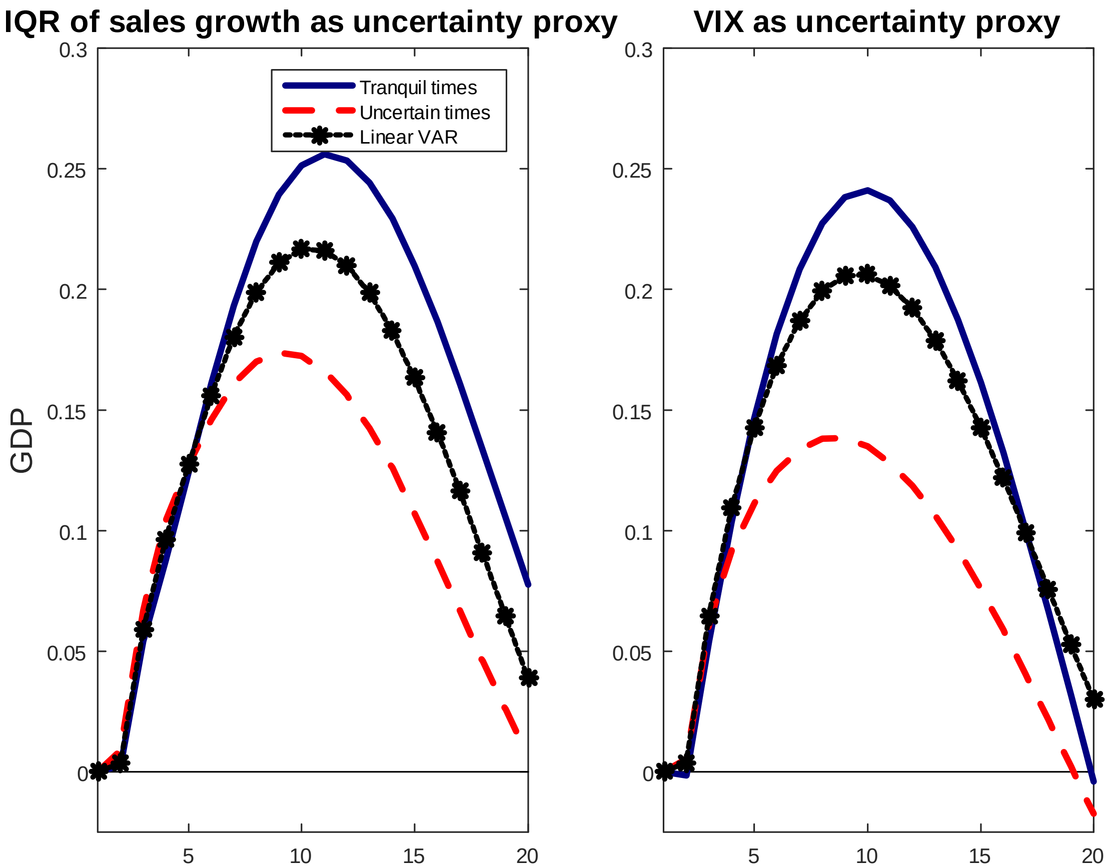
Uncertainty indicators. Orange dashed line: IQR of sales growth (sample: 1971Q1-2009Q3). Peach solid line: VIX (sample: 1971Q1-2015Q4). Grey areas: NBER recessionary quarters.

FIGURE 2



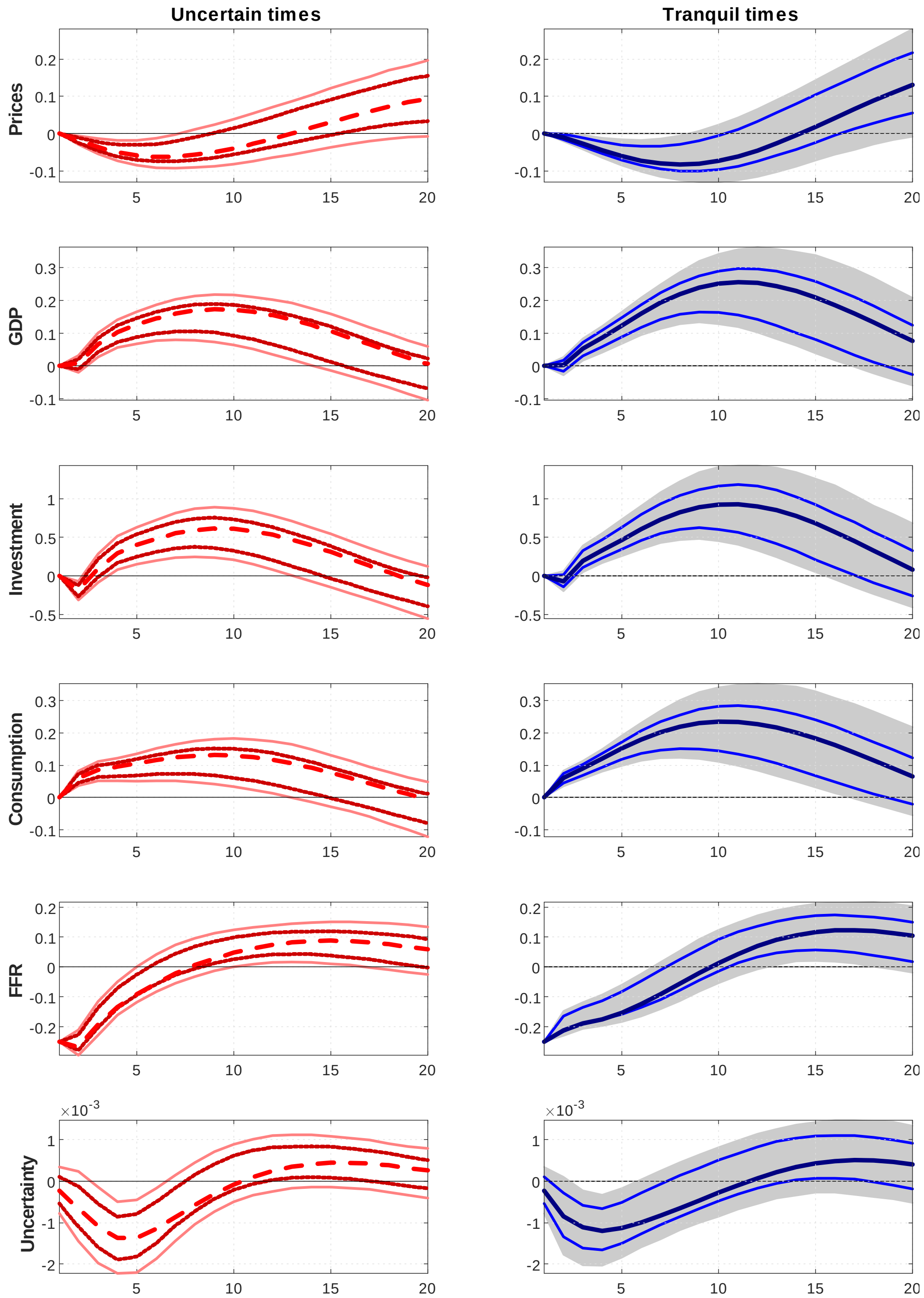
Time-varying peak and cumulative response of GDP (shock: 25 basis points unexpected decrease in the policy rate). Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Upper row: temporal evolution of the GIRFs peak and cumulative response (blue solid and cyan dotted lines respectively) along with the previous-quarter level of uncertainty. 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



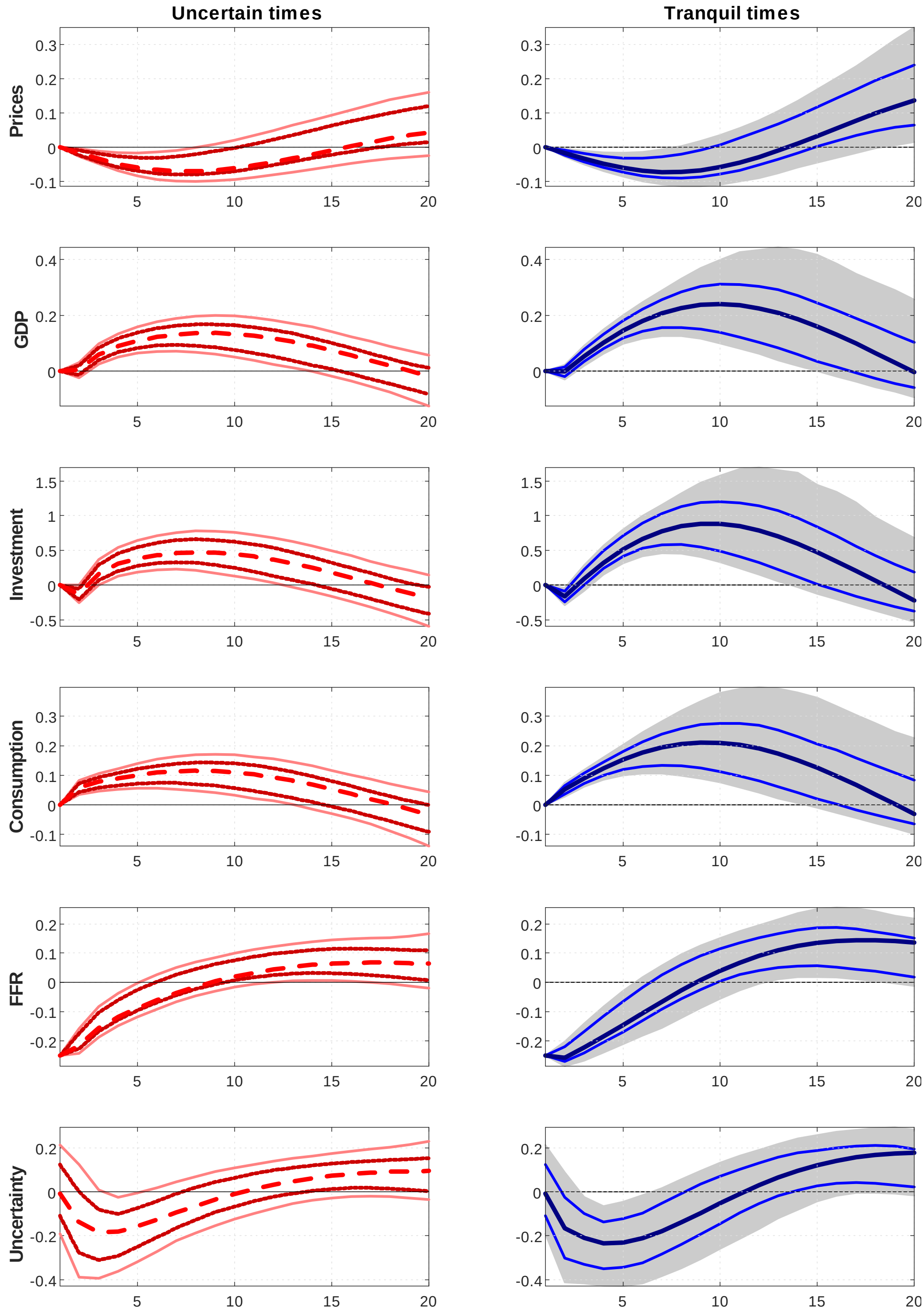
Uncertain vs. tranquil times state-conditional responses for GDP in comparison to linear responses (shock: 25 basis points unexpected decrease in the FFR). Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Solid blue (red dotted) line: state-conditional GIRF for the tranquil times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

FIGURE 4



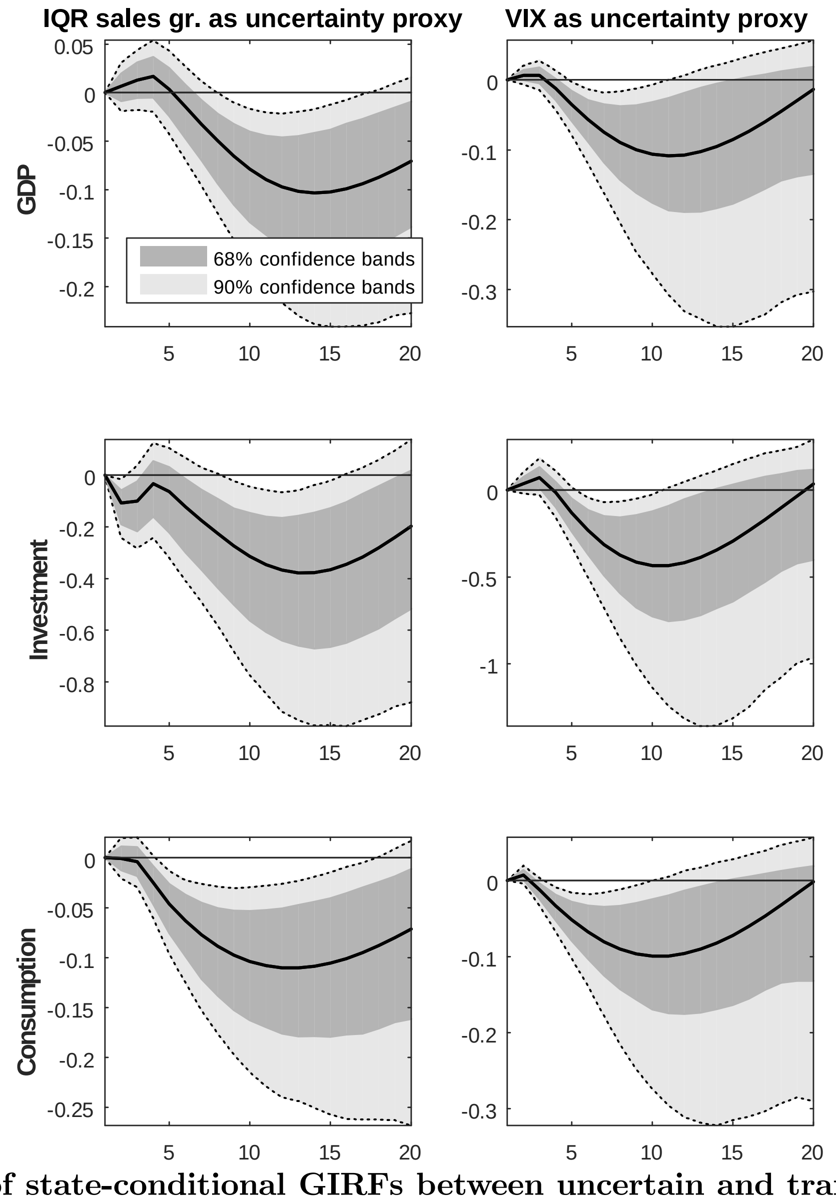
Uncertain vs. tranquil times state-conditional GIRFs (*uncertainty proxy: IQR of sales growth*). Blue solid lines, light blue bands and grey areas: point estimates, 68% and 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times state, respectively. Red dashed lines, dark red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

FIGURE 5



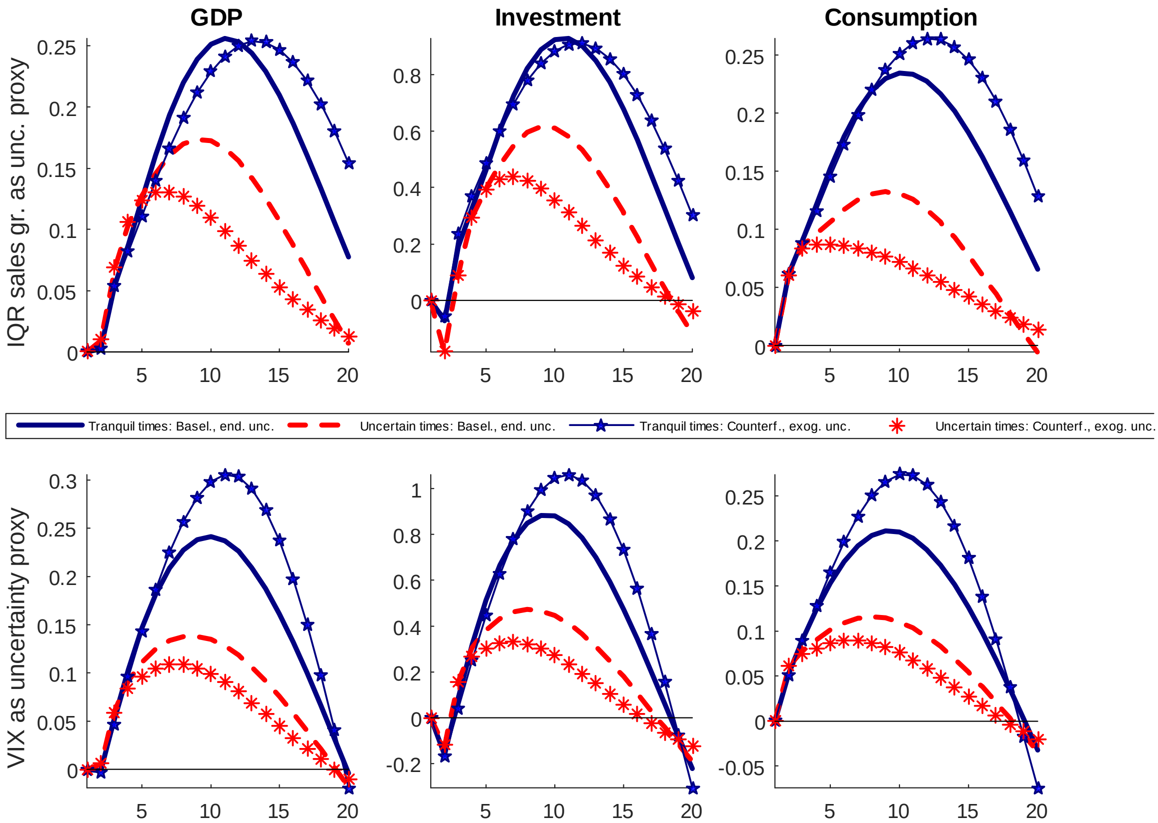
Uncertain vs. tranquil times state-conditional GIRFs (*uncertainty proxy: VIX*). Blue solid lines, light blue bands and grey areas: point estimates, 68% and 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times state, respectively. Red dashed lines, dark red dotted and light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

FIGURE 6



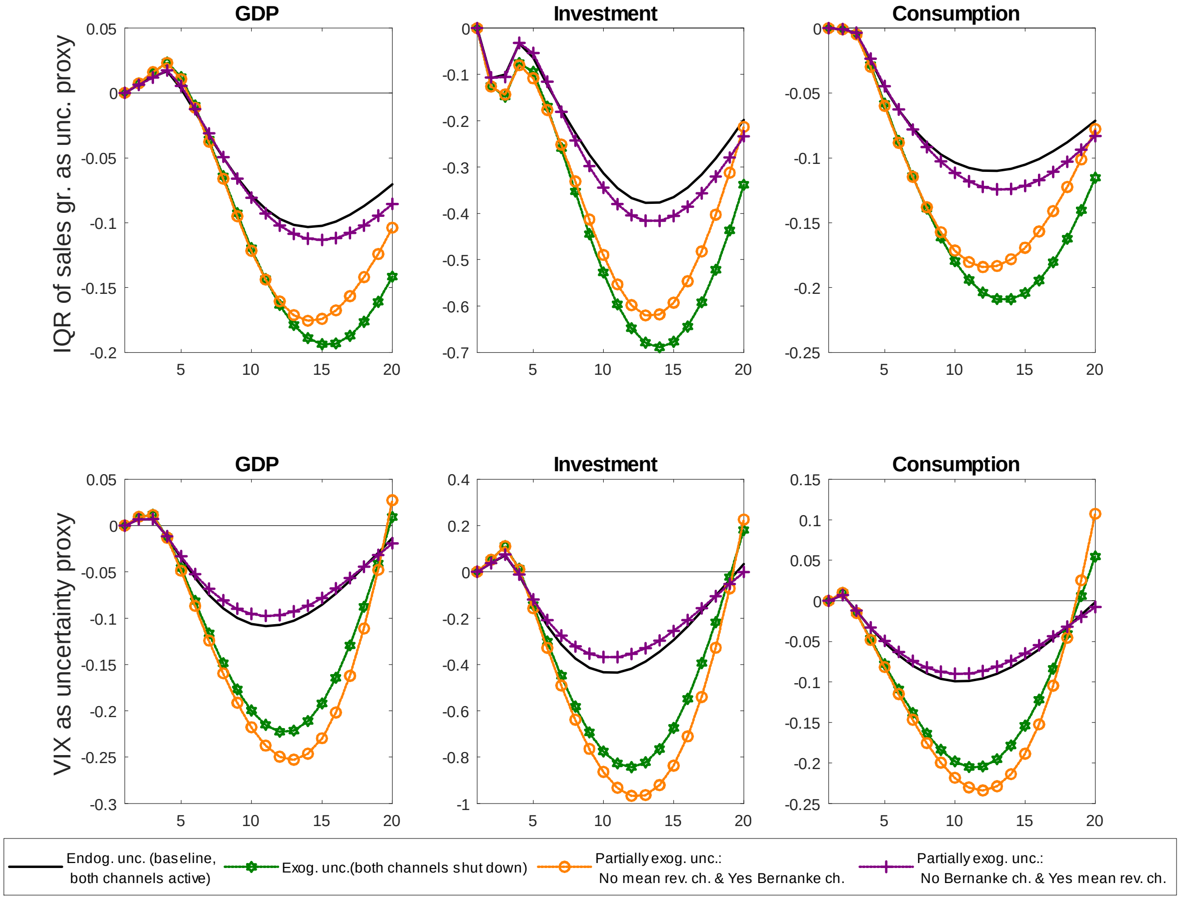
Difference of state-conditional GIRFs between uncertain and tranquil times. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Solid black lines: difference between point estimated state-conditional GIRFs (uncertain times conditional GIRF minus tranquil times conditional GIRF). Interior 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. Note: x-axis in quarters.

FIGURE 7



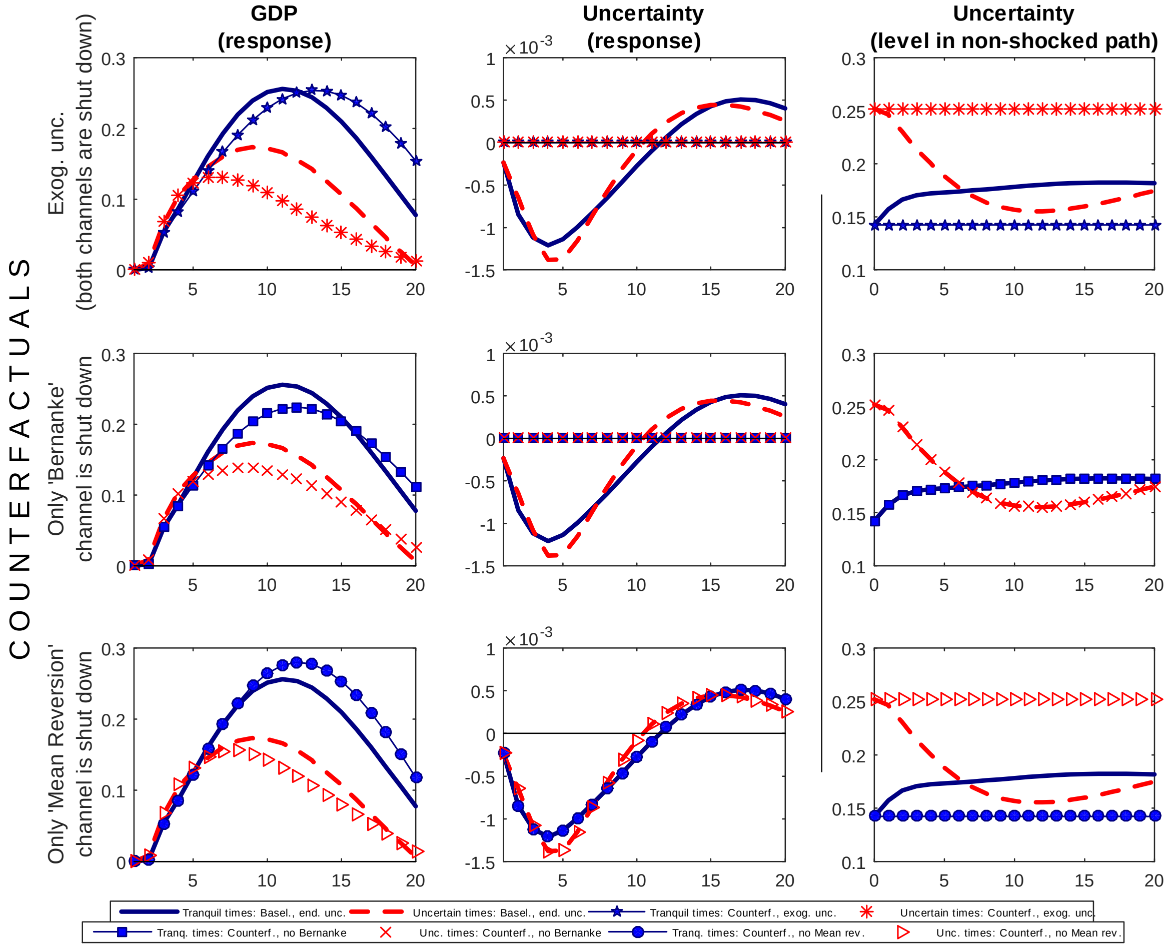
Baseline GIRFs with endogenous uncertainty vs. counterfactual ones with exogenous uncertainty. Upper (lower) row: IQR of sales growth (VIX) as uncertainty proxy. Blue solid and red dashed lines: baseline GIRFs conditional to a tranquil and uncertain times state, respectively. Starred blue lines and starred 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. Note: x-axis in quarters.

FIGURE 8



Difference of the state-conditional real effects of monetary policy shocks between uncertain and tranquil times: endogenous uncertainty vs. alternative cases of fully (or partially) exogenous uncertainty. Upper (lower) row: 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) for the baseline case of endogenous uncertainty. Green starred lines: previous difference for the case of fully exogenous uncertainty. Orange circled lines: difference for the counterfactual case with just the mean reversion channel shut down with respect to the baseline case. Purple crossed lines: difference for the counterfactual case with just the Bernanke's channel shut down with respect to the baseline case. Note: x-axis in quarters.

FIGURE 9



Comparison among counterfactual exercises to study the role of "Bernanke"'s and "Mean reversion" channels (*uncertainty proxy: IQR of sales growth*). Upper row: Baseline results vs. results obtained from the counterfactual in Figure 7. Middle row: Baseline results vs. results obtained from a counterfactual that leaves inactive only "Bernanke's" channel (i.e., starting from baseline GIRFs computation, fictitious shocks to uncertainty are used to zeroing the uncertainty response, similarly to Kilian & Lewis (2011)). Lower row: Baseline results vs. results obtained from a counterfactual that leaves inactive only the "Mean reversion" channel (i.e., starting from the counterfactual explained in footnote 33, fictitious shocks to uncertainty are used to replicate the baseline uncertainty response). The legend explains the different lines. Lines in the first two columns refer to responses while lines in the last column refer to the non-shocked uncertainty average (level) paths as explained in footnote 37. Note: x-axis in quarters.