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

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Abstract

This paper estimates a non-linear Interacted VAR model to assess whether the real effects of stimulative monetary policy shocks are milder during times of high 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 mitigation and uncertainty mean reversion. Generalized Impulse Response Functions à la Koop, Pesaran and Potter (1996) 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. Failing to account for endogenous uncertainty would bias responses and imply twice as powerful monetary policy during uncertain times as 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. The earliest empirical works with an uncertainty-dependent policy focus 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.[1]

[1] There is instead plenty of research investigating whether uncertainty shocks have a state-conditional impact, namely whether their real effects might depend on a particular phase experienced by the economy. 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, Mumtaz, Alessandri, and Mumtaz (2019) and Angelini, Bacchiocchi, Caggiano, and Fanelli (2019), who respectively investigate

This work sheds new light on the uncertainty-dependent effects of monetary policy shocks and shows that taking into account the endogenous move of uncertainty after the monetary stimuli is key in order not to disregard important transmission channels and hence to correctly estimate the effects of an unexpected monetary stimulus. We show that two unexplored channels of endogenous uncertainty can affect the monetary policy transmission mechanism.[2] On the one hand, uncertainty is mitigated by monetary policy easings (Bekaert, Hoerova, and Lo Duca (2013)). This uncertainty mitigation, according to Bernanke's quote above, may temporarily enhance policy effectiveness by reducing precautionary 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 and Preston (2005)), that uncertainty significantly affects firms' "wait and see" attitude in investment and hiring (Bernanke (1983), Bertola and Caballero (1994), Dixit and Pindyck (1994), Bloom, Bond, and Reenen (2007), Bloom (2009)), and that expected future uncertainty is important for decision making (Guiso and Parigi (1999) and Bloom, Davis, Foster, Lucking, Ohlmacher, and Saporta Eksten (2017)).[3] However, the literature is still silent on the importance of these two channels

whether financial or volatility 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).

[2]In our study – differently from Aastveit, Natvik, and Sola (2017) – 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: can move either because of the shock or irrespectively from it (depending on its value at the time of the shock).

[3]Following most of the empirical literature, we 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. Specifically, we use two baseline proxies for uncertainty, i) the Inter Quartile Range (IQR) of sales growth, a cross sectional firm-level uncertainty proxy computed by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), and ii) the VIX, a measure for the implied stock market volatility extensively used after Bloom's (2009) seminal paper. We also use the macro and firm-level uncertainty indices recently developed by Jurado, Ludvigson, and Ng (2015) to check the robustness of our main results.

for the monetary policy transmission mechanism.[4]

This paper's purpose is to quantify the uncertainty-dependent effects of monetary policy shocks in a general framework that can take account of endogenous uncertainty so that to also assess whether (and how) endogenous uncertainty matters for the monetary transmission. This purpose is tackled 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 uncertainty may endogenously move after the policy shock (both because monetary shocks themselves may affect uncertainty, on the one hand, and because uncertainty may irrespectively mean revert, on the other hand). The latter possibility creates, de facto, a feedback effect which makes the model Self-Exciting (or "fully" non-linear) in the iteration after a monetary policy shock.[5]

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

[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 presented in Terasvirta, Tjostheim, and Granger (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.

[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 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. The current paper scrutinizes for the first time the advantages and the implications of endogenizing conditioning variables within IVARs.

policy shocks – e.g., Aastveit, Natvik, and Sola (2017), Eickmeier, Metiu, and Prieto (2016) and Castelnuovo and 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 feedbacks on the dynamics of the system. In this way, we are able to capture both the effects of an endogenous move of 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 documenting 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, a finding which further supports the importance of treating uncertainty as an endogenous variable.

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. 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 show this difference is driven by the interaction of two endogenous uncertainty channels 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 channel, whose direction of effects depend from 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. 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, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)). While we find that, due to the two channels of endogenous uncertainty, monetary policy becomes less state dependent and hence 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 non-linear empirical models when it comes to 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 assessing alternative policies in environments characterized by uncertainty.[7]

Our study is also relevant for applied researchers because it shows the perils of not modelling endogenously the conditioning variable in a non-linear VAR. In the context of fiscal spending shocks Ramey and Zubairy (RZ, 2018) show that the difference of their findings on the US fiscal multipliers with respect to Auerbach and Gorodnichenko's (AG, 2012) ones are largely driven by the simplifying assumptions about the conditioning variable and the computation of impulse responses adopted in the latter study's non-

[7] 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 microfounded model is Mumtaz and Theodoridis (2019).

linear VAR.[8] 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 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 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 and analyzes the two channels that arise. Section 6 concludes. An online Appendix details the 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. Crucially, compared to their study, our work endogenizes uncertainty in a SEIVAR model and consistently computes fully non-linear 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 expansionary monetary policy shocks regardless of whether uncertainty is high or low. 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 significant. Third, we use our framework to perform a historical analysis of the effects of monetary policy shocks, something which

[8] AG use a Smooth-Transition VAR with conditioning variable given by (a moving average of) the growth rate of GDP and consider it as fixed (or exogenous) in the computation of responses. In Ramey and Zubairy's (2014, 2018) words: i) "the [AG] assumptions imply that a positive shock to government spending during a recession does not help the economy escape the recession" (RZ, 2014, p. 18) and ii) "their [AG] method assumes that the economy continues in recession indefinitely" ", but it is not a good approximation for recession states, which have a mean duration of only 3.3 quarters according to their moving average of growth rates definition" (RZ, 2018, p. 889-890). These two missed channels (i.e., not taking account of the direct shock effects on GDP growth and of the GDP growth's mean reversion consequences) are general and are the correspondent of the two channels of endogenous uncertainty that we study in this paper thanks to our framework. Our framework takes fully 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, Castelnuovo, Colombo, and Nodari (2015)).

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 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, 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 (2016), 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, 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.[9] 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.

On the theoretical side, two main explanations point to a lower effectiveness of

[9]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)).

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 stabilization policy.[10] 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.

Second, 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 (2019) find that nominal shocks have smaller effects on output

[10] As documented by a number of studies, it is well known that uncertainty shocks have an independent contractionary effect on the real economy too. A non-exhaustive list of such works includes Bloom (2009), Mumtaz and Theodoridis (2015), 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).

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.

Notice also that, 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 capture changes in precautionary motives after the monetary policy shock and their possible influence on the real effects of monetary policy shocks. In this way we can 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.

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 (2019) 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:

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

$$unc_t = e'_{unc} \mathbf{Y}_t \quad (2)$$

$$R_t = e'_R \mathbf{Y}_t \quad (3)$$

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

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.[11] We follow Ventzislav and Kilian (2005) and select the number of lags as suggested by the Hannan-Quinn criterion. As a result $L = 2$ (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 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.[12] Second, unlike abrupt change models featuring regime-specific coefficients like TVARs, the SEIVAR

[11] 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.

[12] 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

is estimated on the full sample (in other words, any regime is imposed prior to estimation).[13] 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 nonlinearity 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 nonlinear DSGE frameworks feature many interaction terms involving endogenous variables. However, a Montecarlo exercise recently proposed by Andreasen, Caggiano, Castelnuovo, and Pellegrino (2020) shows that our IVAR is able to recover the true impulse responses implied by a state-of-the-art nonlinear DSGE framework solved via a third-order approximation around its stochastic steady state, a feature of the solution which implies state-dependent dynamics. This evidence corroborates the use of parsimonious IVAR specifications for the investigation of nonlinear 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.[14] 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 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

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 IVAR could depend on the specific functional form employed. Section A4.2 of the Appendix further elaborates on the specific form on nonlinearity adopted and also shows that main results are robust to the use of a richer specification of the interaction between uncertainty and monetary policy (check *iv*).

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

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

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 of endogeneity of uncertainty is maximized, but in the robustness checks Section 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 and Karadi (2015).

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.

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 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 endogenous conditioning variable, we compute Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran, and Potter (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, 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, com-

puted 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, 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).[15] 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, Castelnuovo, Colombo, and Nodari (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 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. 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

[15] 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.

empirical responses for three reasons. First, Local Projections IRFs are not as informative as GIRFs because they provide just 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. Second, they produce responses that are often 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 commonly used Wu and Xia's (2016) "shadow rate" instead of the FFR and label shocks as "unconventional" monetary policy shocks. The 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.[16] 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.[17] Further details on the data sources are available in Section A6 of the Appendix.

[16] 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 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 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.

[17] 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).

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, 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 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 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.[18] More-

[18] 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.

over, 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 have 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 time-variation of GIRFs (whereas the full evidence is available in the form of a tridimensional graph in Figure A1 in the Appendix).[19] 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.

[19] 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.

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.[20] 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).[21] 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 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 and 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 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 binding ZLB period itself complicates the comparison between the effects of conventional and unconventional monetary policy shocks, as the mitigating power of

[20] 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).

[21] 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.

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.

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 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.[22] 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

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

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.[23] 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 in depth on 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.[24]

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 a result often found in the monetary VAR literature.[25] 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.[26] 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

[23] 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.

[24] 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.

[25] 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 and Karadi (2015).

[26] 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.

(2010) and Keating, Kelly, and Valcarcel (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 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, 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. 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 policy rate and uncertainty; iv) the case where 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; ix) the case the CPI is used instead than the GDP deflator price index; and x) the case monetary policy shocks are identified using high frequency surprises around policy announcements as external instruments as in Gertler and Karadi (2015).

Section A4.3 contains further material: 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 which is more directly related to the overall policy effectiveness; Figure A9 shows the decrease in uncertainty for the checks considered in Section A4.1.

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 treating uncertainty as exogenous).[27] 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 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).[28] Overall, we find that the difference between both peak and cumulative state-dependent responses of real variables gets halved

[27] 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.

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

when uncertainty is treated as endogenous versus when is not, implying that with endogenous uncertainty monetary policy effectiveness becomes half as state-dependent as with exogenous uncertainty.

To ensure that the counterfactual exercise above fully captures what happens when uncertainty is exogenously modelled in the non-linear VAR (as in, e.g., Aastveit, Natvik, and Sola (2017)), Figure A10 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.[29] As Figure A10 shows, virtually the same results as in Figure 7 are obtained.[30]

The finding that under exogenous uncertainty monetary policy is erroneously found twice as powerful during uncertain times as during tranquil times is mechanically explained by the neglect of the endogenous moves of uncertainty after the monetary policy shock hits. Specifically, the finding arises because conditionally-linear IRFs neglect 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

[29] 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.

[30] 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.

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.[31] Consistently with what expected, in the passage from these

[31] 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.

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 an 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 suggests two considerations. First, both channels can be quantitatively relevant. As Figure 9 documents, in 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.[32,33] Second, as Figure 8 documents, the mean reversion channel is the main responsible for halving the difference between state-dependent responses of real variables when uncertainty is treated as endogenous. Indeed, when the channel is the only channel shut down the difference is similar to the (fully) exogenous uncertainty case, whereas when it 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

[32] 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 8 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 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 an history $\boldsymbol{\omega}_{t-1}$ can be seen as:

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

, 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).

[33] 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 A11 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 one induced in the IQR of sales growth (as documented in Section 4.2).

makes responses less distant between the two states.

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 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 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, Bernanke's "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 uncertain times than tranquil times. Hence 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 while at the same time displaying empirically-grounded mean reversion.

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	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.

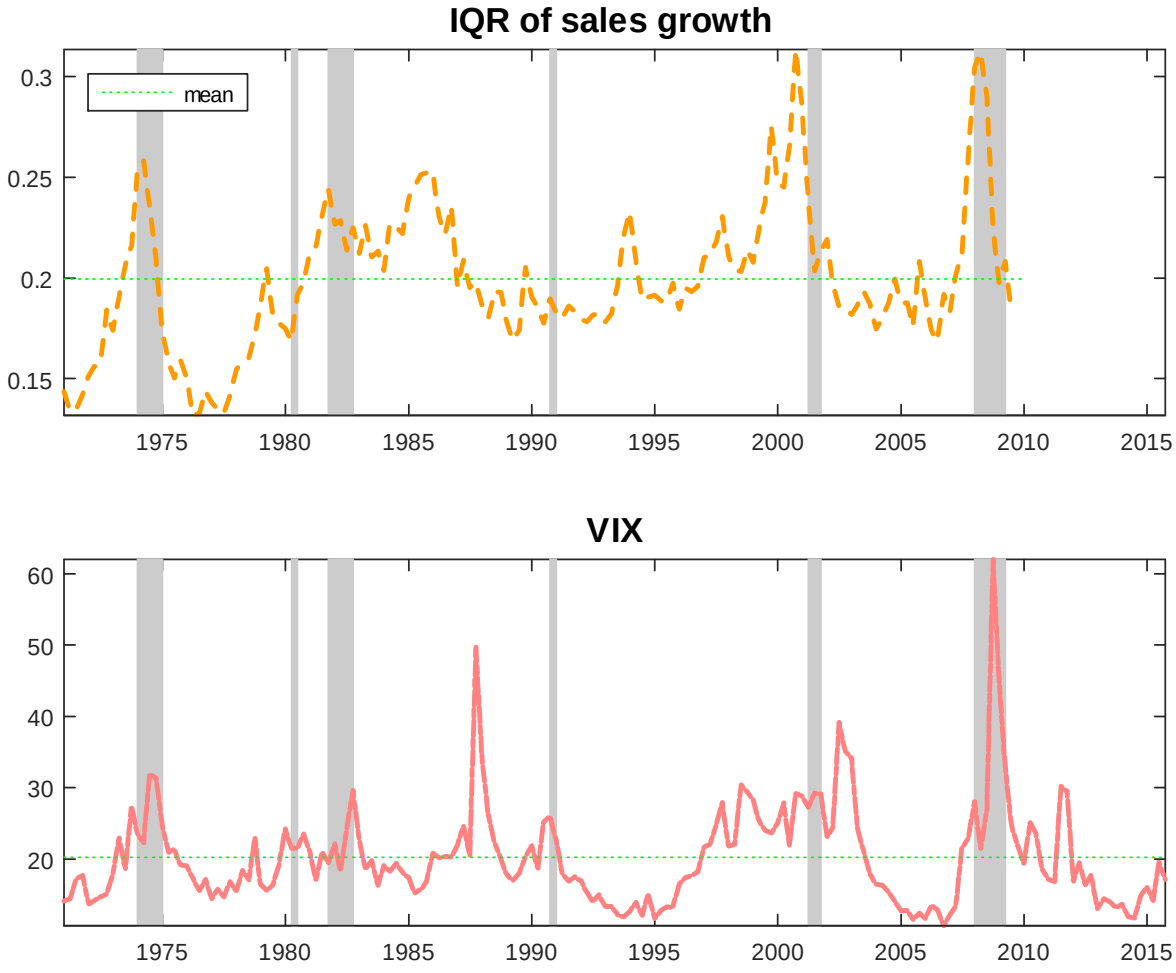

Figure 1: **Uncertainty indicators**. Orange dashed line: IQR of sales growth (sample: 1971Q1-2009Q3). Peach solid line: VIX (sample: 1971Q1-2015Q4). Grey areas: NBER recessionary quarters.

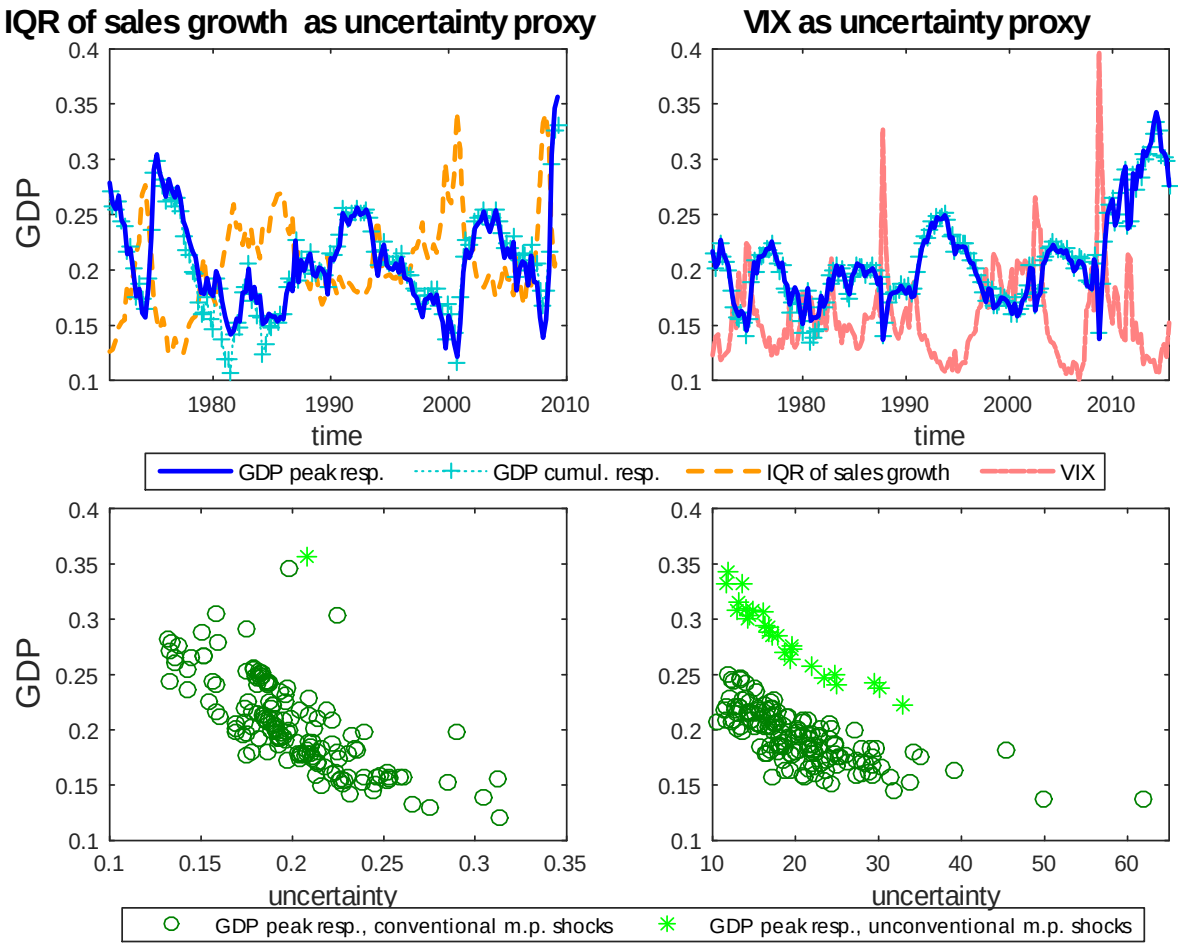

Figure 2: **Time-varying peak and cumulative response of GDP** (shock: 25 basis points unexpected decrease in the policy rate). Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Upper row: temporal evolution of the GIRFs peak and cumulative response (blue solid and cyan dotted lines respectively) along with the previous-quarter level of uncertainty. 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).

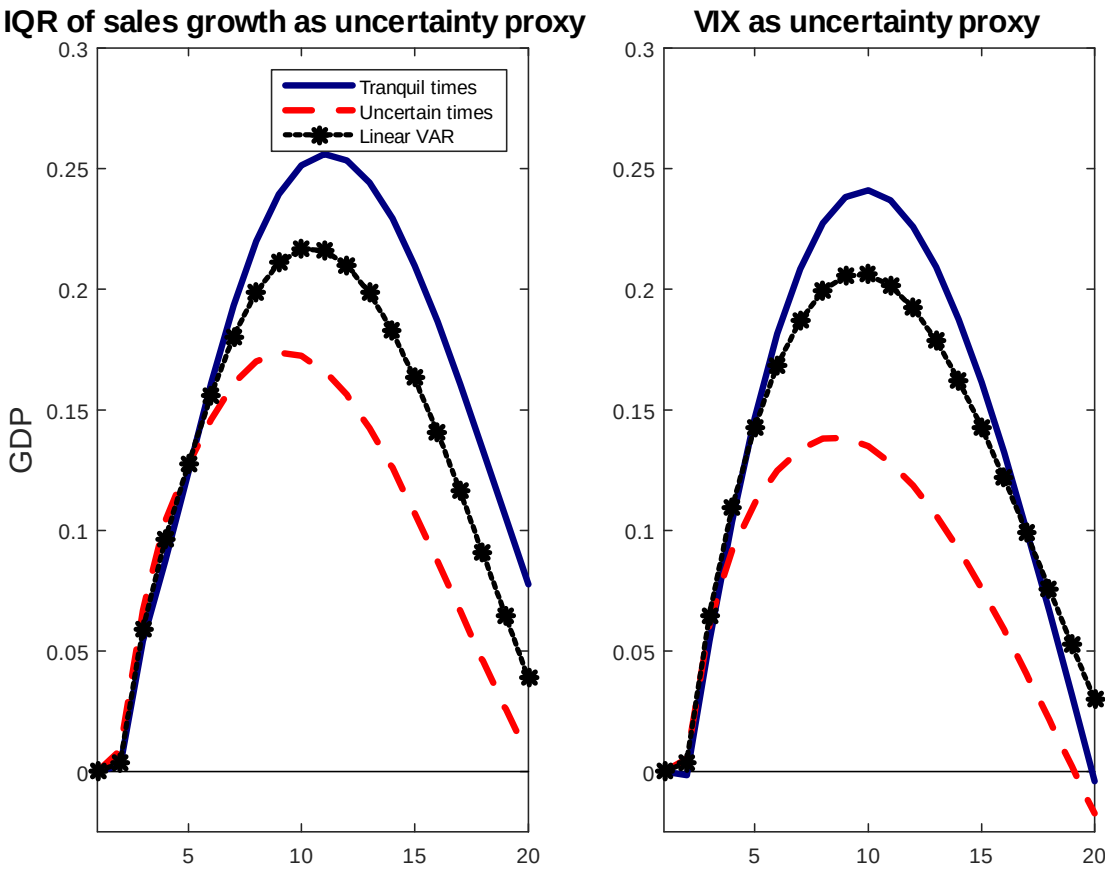

Figure 3: **Uncertain vs. tranquil times state-conditional responses for GDP in comparison to linear responses** (shock: 25 basis points unexpected decrease in the FFR). Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Solid blue (red dotted) line: state-conditional GIRF for the tranquil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

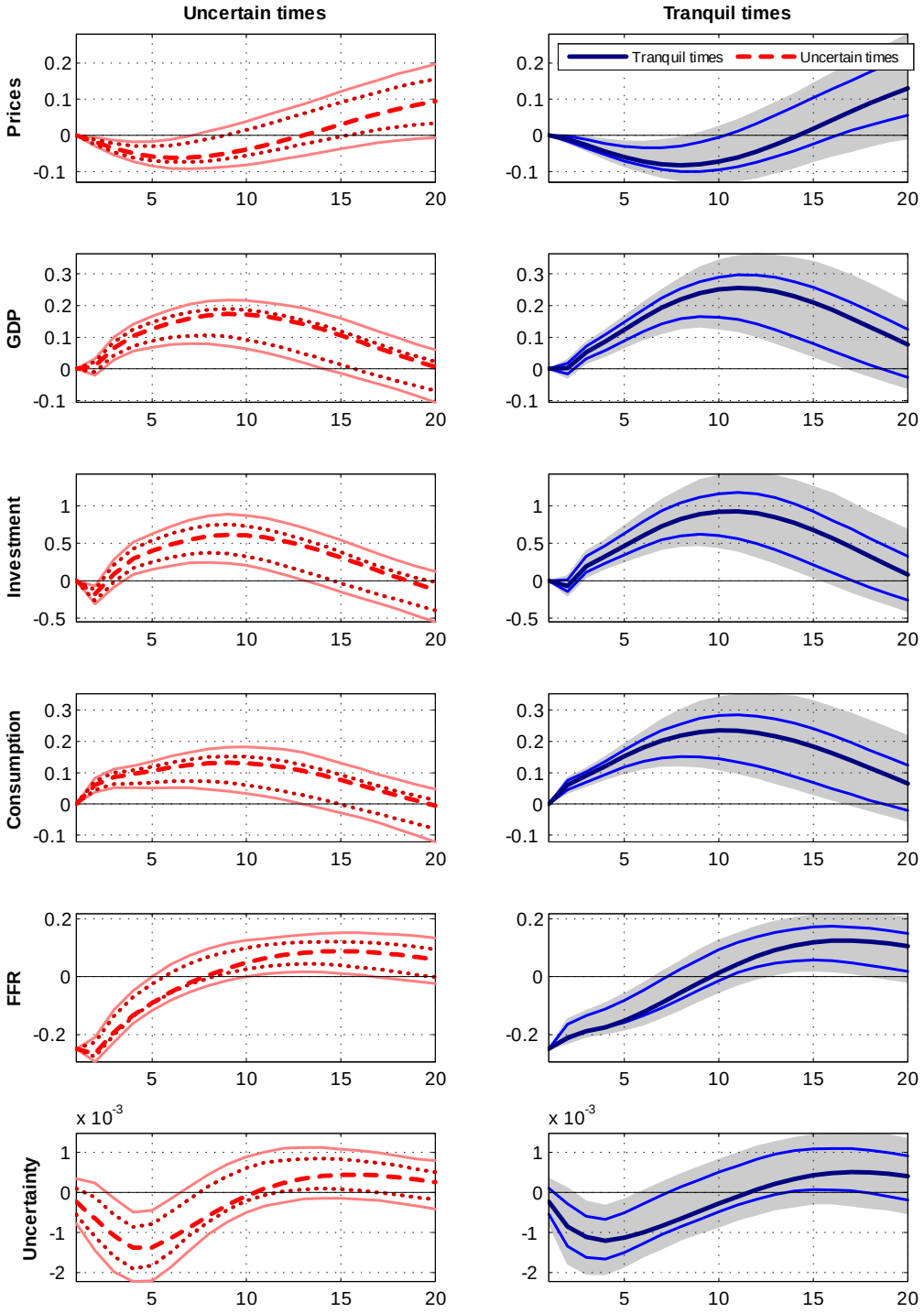

Figure 4: **Uncertain vs. tranquil times state-conditional GIRFs** (uncertainty proxy: IQR of sales growth). Blue solid lines, light blue bands and grey areas: point estimates, 68% and 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times state, respectively. Red dashed lines,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

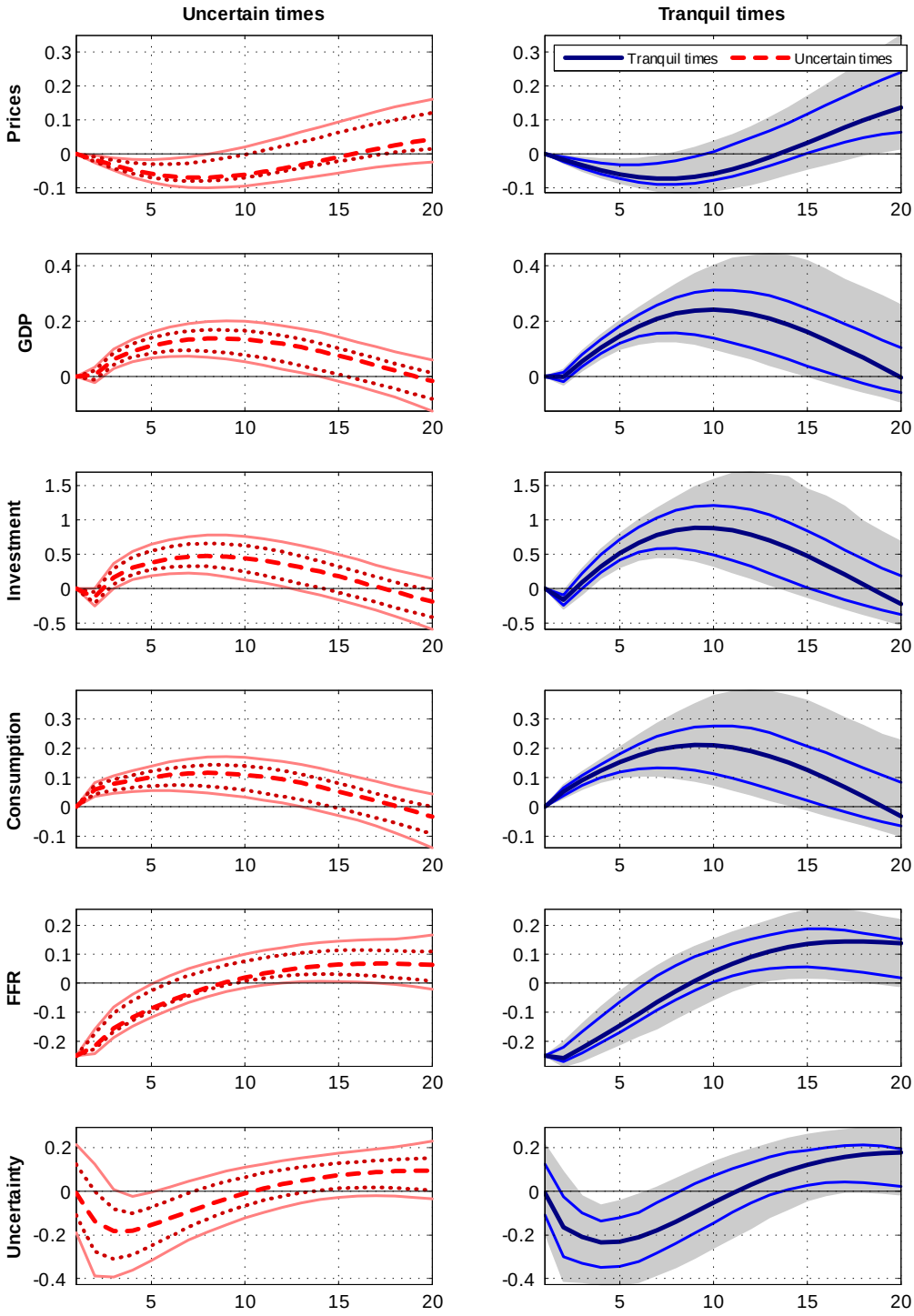

Figure 5: **Uncertain vs. tranquil times state-conditional GIRFs** (uncertainty proxy: VIX). Blue solid lines, light blue bands and grey areas: point estimates, 68% and 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times state, respectively. Red dashed lines, dark red dotted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

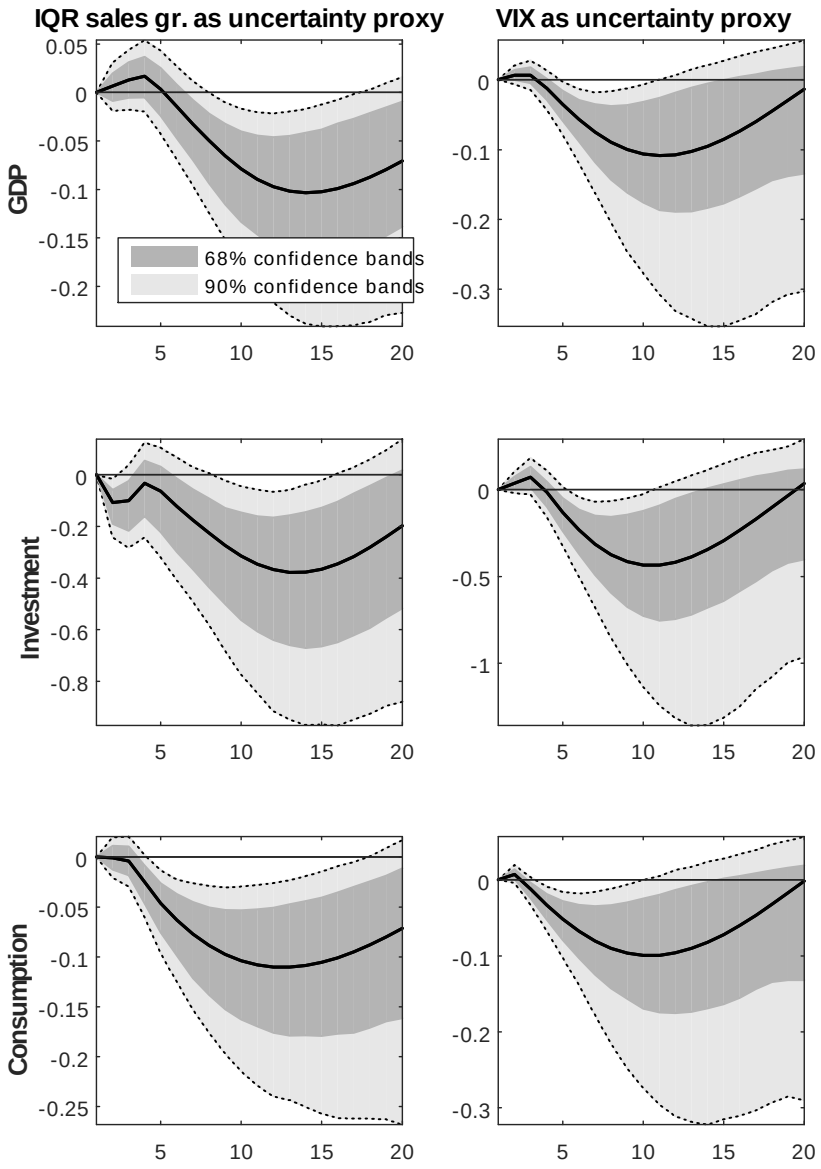

Figure 6: **Difference of state-conditional GIRFs between uncertain and tranquil times**. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Solid black lines: difference between point estimated state-conditional GIRFs (uncertain times conditional GIRF minus tranquil times conditional 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.

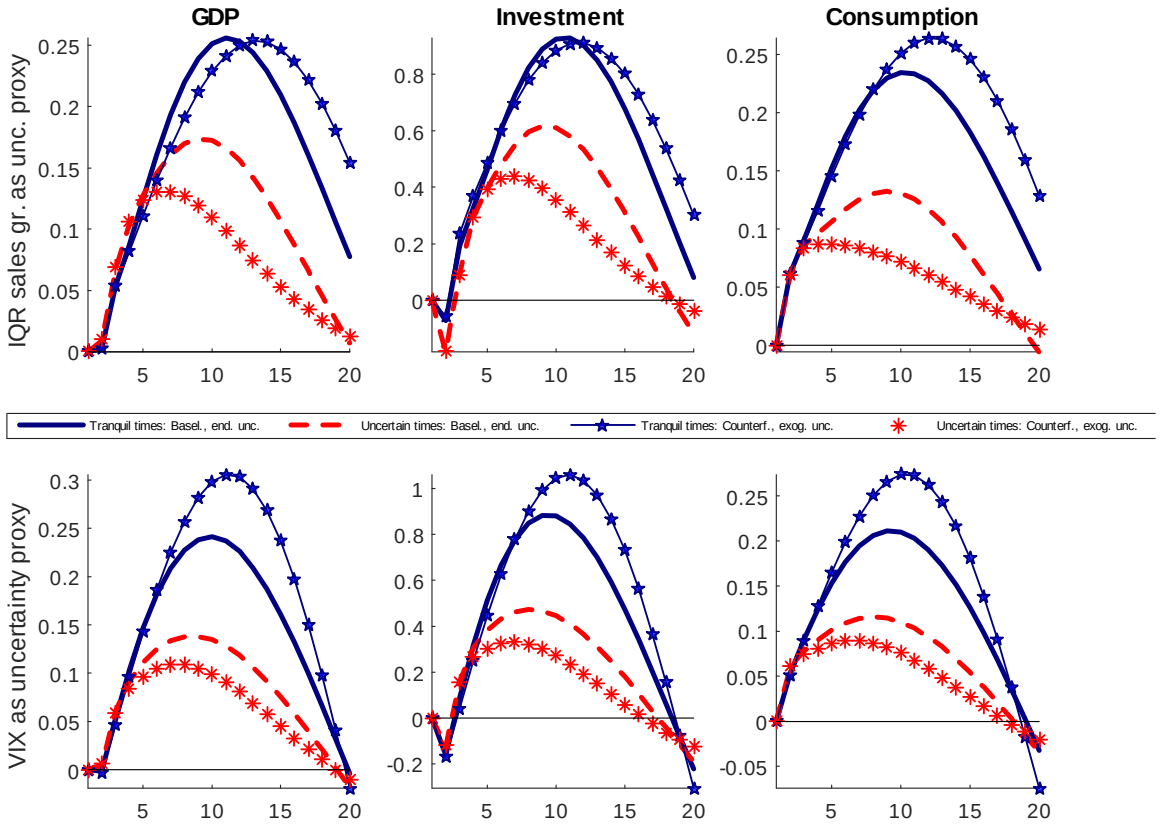

Figure 7: **Baseline GIRFs with endogenous uncertainty vs. counterfactual ones with exogenous uncertainty**. Upper (lower) row: IQR of sales growth (VIX) as uncertainty proxy. Blue solid and red dashed lines: baseline GIRFs conditional to a tranquil and uncertain times state, respectively. Starred blue 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.

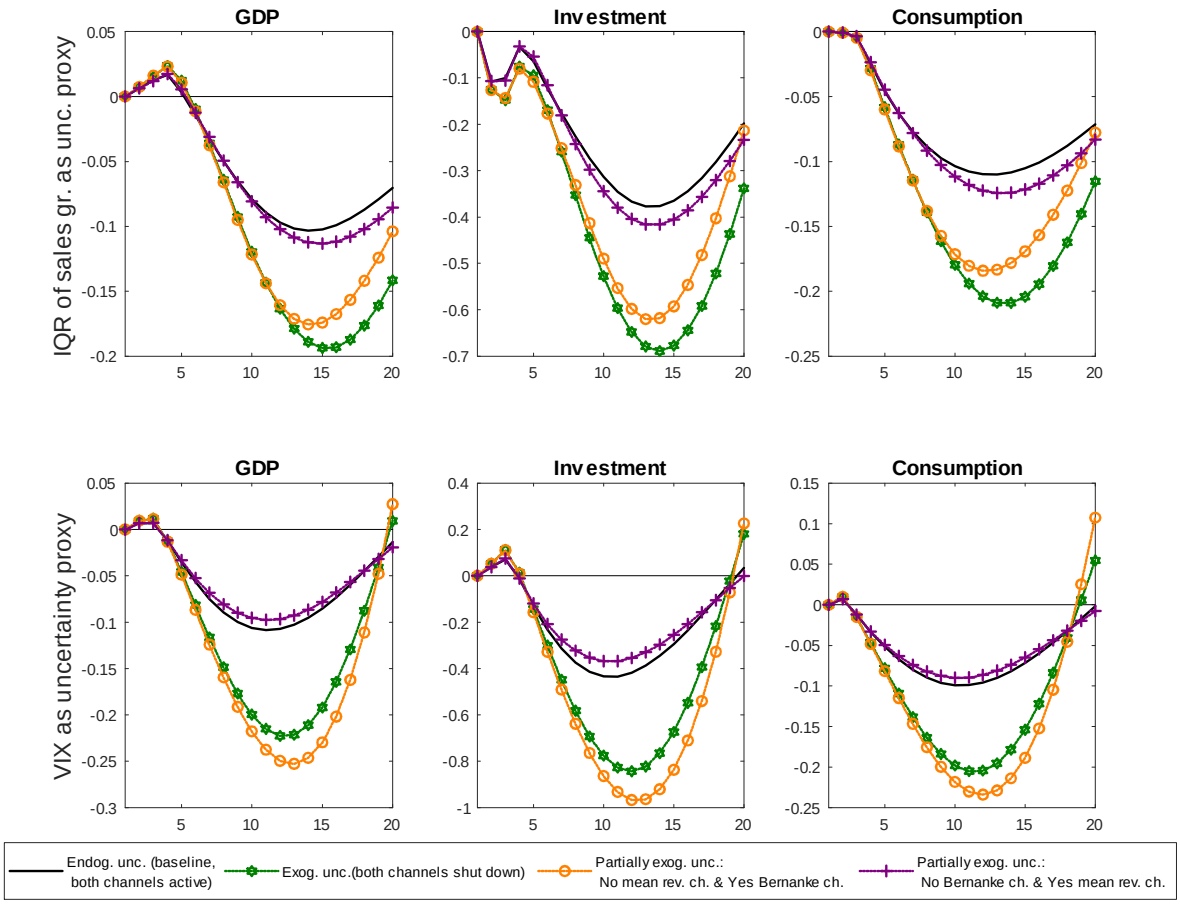

Figure 8: **Difference of the state-conditional real effects of monetary policy shocks between uncertain and tranquil times: endogenous uncertainty vs. alternative cases of fully (or partially) exogenous uncertainty.** Upper (lower) row: IQR of sales growth (VIX) as uncertainty proxy. Solid black lines: 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.

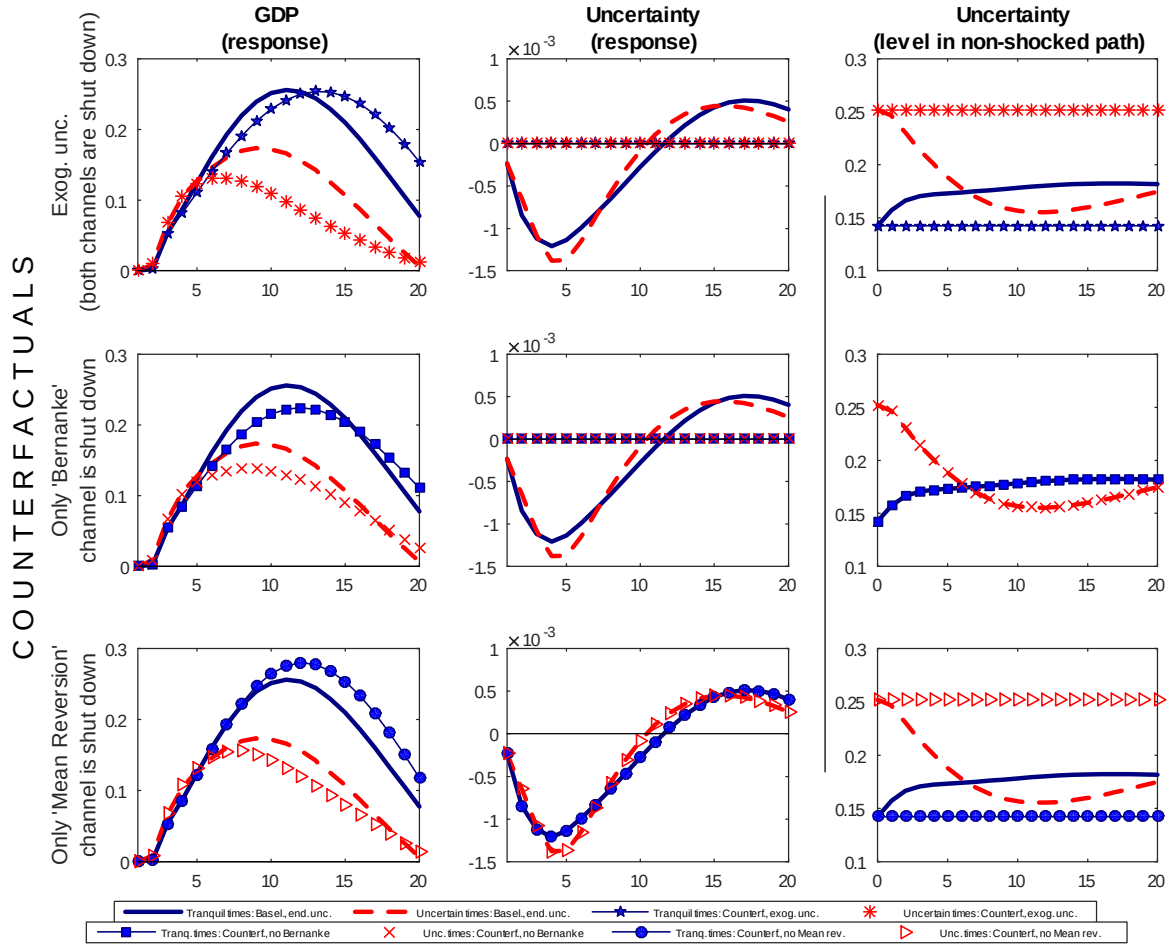

Figure 9: **Comparison among counterfactual exercises to study the role of "Bernanke"'s and "Mean reversion" channels** (uncertainty proxy: IQR of sales growth). Upper row: Baseline results vs. results obtained from the counterfactual in Figure 7. Middle row: Baseline results vs. results obtained from 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 and 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 27, 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 31. Note: x-axis in quarters.

Appendix
"Uncertainty and Monetary Policy in the US: A Journey into Non-Linear Territory" by Giovanni Pellegrino

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:

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

where $\mathbb{E}[\cdot]$ represents the expectation operator. The algorithm to estimate our history and 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 $\mathbf{u}_t^s$. In particular, we Cholesky-decompose $\widehat{\mathbf{\Omega}}= \mathbf{C}\mathbf{C}'$, 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. $\widehat{GIRF}_{Y,t}(\delta_t, \varpi_{t-1}) = \left\{\widehat{\mathbb{E}}\left[\mathbf{Y}_{t+h} \mid \delta_t, \varpi_{t-1}\right] - \widehat{\mathbb{E}}\left[\mathbf{Y}_{t+h} \mid \varpi_{t-1}\right]\right\}_{h=0}^{19}$. 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] ;

[A1] While we allow this to happen for bootstrapped simulated responses, we make sure that this does not happen for point-estimated responses (i.e. our responses estimated on actual data) so that to back up the stability of the estimated IVAR . The nonlinear DSGE literature has developed the pruning method in order to preserve stability (see Andreasen, Fernández-Villaverde, and Rubio-Ramírez (2017)) but this is not currently available for nonlinear VARs.

[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

8. history-dependent GIRFs obtained in step 7 are then averaged over the state they belong to to produce our estimate of the state-dependent GIRFs, i.e., our $\widehat{GIRF}_{Y,t}\left(\delta_t, \mathbf{\Omega}_{t-1}^{tranquil \quad times}\right)$ and $\widehat{GIRF}_{Y,t}\left(\delta_t, \mathbf{\Omega}_{t-1}^{uncertain\ times}\right)$;

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 though 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.

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.

[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.

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 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,

[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 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).

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 account 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. Klepacz (2017) studies whether individual prices in Producer Price Index micro data are more likely to move in the same direction when aggregate volatility is high, which would increase aggregate price flexibility and reduce the effectiveness of monetary policy. In line with my results, his findings suggest that increases in aggregate volatility do not substantially reduce the ability of monetary policy to stimulate output via the pricing channel.

A3 Supplementary results for Section 4.1

This Section presents extra results and material to the ones in Section 4.1 of 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

[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.

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).[A9A10] The findings suggests that, even though in each case the 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

[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 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.

support our conclusions in Section A2 we also present the response of prices.[A12] Figure A4 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 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. 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.[A13]

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

[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). Using the IQR of sales growth has also the advantage of dealing with an IVAR specification that remains more stable to perturbations.

[A13] 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.

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 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.[A14] 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.[A15] 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

[A14] 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.

[A15] 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.

policy shock.[A16] 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. 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.[A17]

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"

[A16] 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.

[A17] We note that having the Great Recession period in the sample sharpens the identification on 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 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.

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

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.[A20] Further, consistently with Hanson (2004) and Castelnuovo and Surico (2010), the price puzzle disappears when considering this starting date.[A21]

Turning to the "good luck" explanation, it seems appropriate to account for the 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)).[A22] This break, through the Cholesky decomposition, also allows for a different contemporaneous relationship between variables in the two sub-periods.[A23] As Figure A5 (second row) clarifies our

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

[A20] The FFR residuals implied by this IVAR are more volatile right at the beginning of the sample. This is due to the targeting of non borrowed reserves by Volcker in the '79-82 period. Starting the sample in 1983 avoids this problem and imply a bigger difference of the state-conditional effects of monetary policy shocks.

[A21] 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.

[A22] 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.

[A23] More precisely, we estimate the following reduced-form model: (1') $\mathbf{Y}_t = \boldsymbol{\alpha} + \boldsymbol{\gamma} \cdot \textit{linear trend} + \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \left[\sum_{j=1}^{L} \mathbf{c}_j unc_{t-j} \cdot R_{t-j}\right] + \mathbf{u}_t$, (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

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.[A24] 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 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.[A25] 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

decomposition of $\mathbf{\Omega}_1$ and $\mathbf{\Omega}_2$ 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.

[A24] 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.

[A25] Notice that, abstracting from the deterministic part, and assuming for simplificity $\mathbf{Y} =$

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.[A26] 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 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.

$[GDP, R, Unc]'$, we can rewrite the SEIVAR model in equations (1)-(3) in the following form:

$$\begin{pmatrix} GDP_t \\ R_t \\ Unc_t \end{pmatrix} = \sum_{j=1}^{L} \begin{pmatrix} a_{j,11} & a_{j,12} & a_{j,12} \\ a_{j,21} & a_{j,22} & a_{j,23} \\ a_{j,31} & a_{j,32} & a_{j,33} \end{pmatrix} \begin{pmatrix} GDP_{t-j} \\ R_{t-j} \\ Unc_{t-j} \end{pmatrix} + \left[\sum_{j=1}^{L} \begin{pmatrix} c_{j,1} \\ c_{j,2} \\ c_{j,2} \end{pmatrix} R_{t-j} \cdot unc_{t-j} \right] + \mathbf{u}_t$$

$$= \sum_{j=1}^{L} \begin{pmatrix} a_{j,11} & a_{j,12} + c_{j,1} \cdot unc_{t-j} & a_{j,12} \\ a_{j,21} & a_{j,22} + c_{j,2} \cdot unc_{t-j} & a_{j,23} \\ a_{j,31} & a_{j,32} + c_{j,3} \cdot unc_{t-j} & a_{j,33} \end{pmatrix} \begin{pmatrix} GDP_{t-j} \\ R_{t-j} \\ Unc_{t-j} \end{pmatrix} + \mathbf{u}_t.$$

Contrary to a standard linear VAR model, the coefficients attached to the policy rate in each equation are time-varying according to the level of uncertainty. Since the policy rate is the shocked variable considered, i.e., the variable which change ΔR we are interested in, this parsimonous SEIVAR allows us to obtain the real effects of a monetary policy shock depending on the historical level of uncertainty.

[A26] To be more precise, the model on which this check is based is the following: $\mathbf{Y}_t = \boldsymbol{\alpha} + \boldsymbol{\gamma} \cdot linear\ trend + \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \left[\sum_{j=1}^{L} (\mathbf{c}_j unc_{t-j} \cdot R_{t-j} + \mathbf{d}_j unc_{t-j}^2 \cdot R_{t-j} + \mathbf{e}_j unc_{t-j} \cdot R_{t-j}^2) \right] + \mathbf{u}_t$, $L = 2$.

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

viii) *Proxy SVAR.* In our baseline we identified monetary policy shocks by means of a recursive (Cholesky) strategy following Christiano, Eichenbaum, and Evans (1999) and Christiano, Eichenbaum, and Evans (2005). Recently the identification of monetary policy shocks by means of external instruments have gained popularity after the proposal of Proxy SVARs (Stock and Watson (2012), Mertens and Ravn (2013)). Gertler and Karadi (2015) show that monetary policy shocks identified using high frequency surprises around policy announcements as external instruments produce responses in output and inflation that are typical in monetary VAR analysis. We follow their approach and use as instrument the quarterly average of their three month ahead fed funds futures monthly surprises series (FF4) that spans the period 1991m1–2012m6.[A27] The last row of Figure A5 (second part) shows that our baseline results are robust also to this alternative identification scheme.

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

[A27] Taking quarter averages of the monthly FF4 instrument may cause important losses of information, e.g., since there are more FOMC meetings than quarters in a year. Based on this consideration, we preferred to adopt a Cholesky decomposition in our baseline analysis.

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 Supplementary results for Section 5

This Section presents extra results and material to the ones in Section 5 of the main paper. Figure A10 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 in the main paper are obtained. This ensures that the counterfactual exercise in the main paper fully captures what happens when uncertainty is exogenously modelled in the nonlinear VAR (as in, e.g., Aastveit, Natvik, and Sola (2017)). Figure A11 digs deeper into the drivers of the results in the second row of Figure 7, i.e., it is the equivalent of Figure 9 in the main paper when uncertainty is proxied by the VIX. In this case, the only channel that would induce a quantitatively relevant bias is the mean reversion channel. This is consistent with the fact that the decrease in the VIX induced by the monetary policy shock is of smaller relevance than the one induced in the IQR of sales growth (as documented in Section 4.2 of the main paper).

A6 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[A28]. 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[A29].[A30]

- **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.[A31] The uncertainty monthly series is obtained from Nick Bloom's website[A32] and is available up to the end of 2012. Quarterly data are obtained by quarterly averages.

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

[A28] https://sites.google.com/site/jingcynthiawu/home/wu-xia-shadow-rates

[A29] https://people.stanford.edu/nbloom/sites/default/files/census_data.zip (data_table1_sales.csv)

[A30] 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.

[A31] The VXO is an index of percentage implied volatility on a hypothetical at the money S&P100 option 30 days to expiration.

[A32] https://people.stanford.edu/nbloom/sites/default/files/r.zip

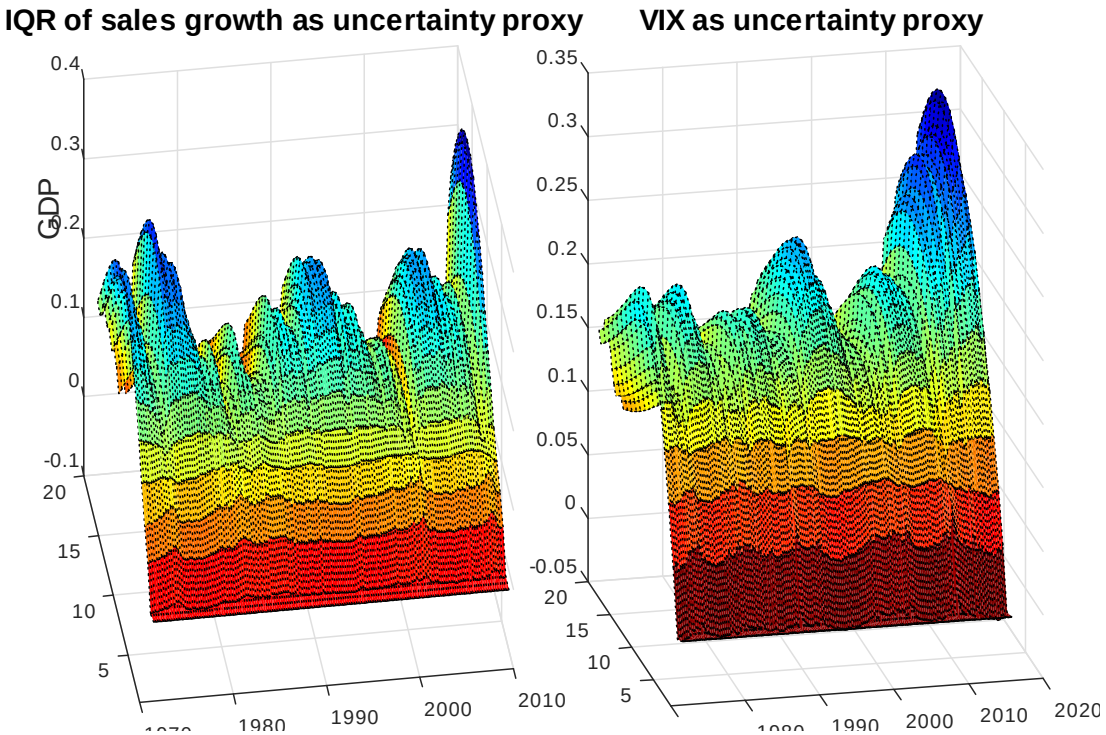

Figure A1: **Temporal evolution of point estimated GIRFs for GDP (shock: 25 basis points unexpected decrease in the policy rate)**. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Upper row: temporal evolution of the point estimated GIRFs. Colors ranging from blue (GIRFs peak values)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

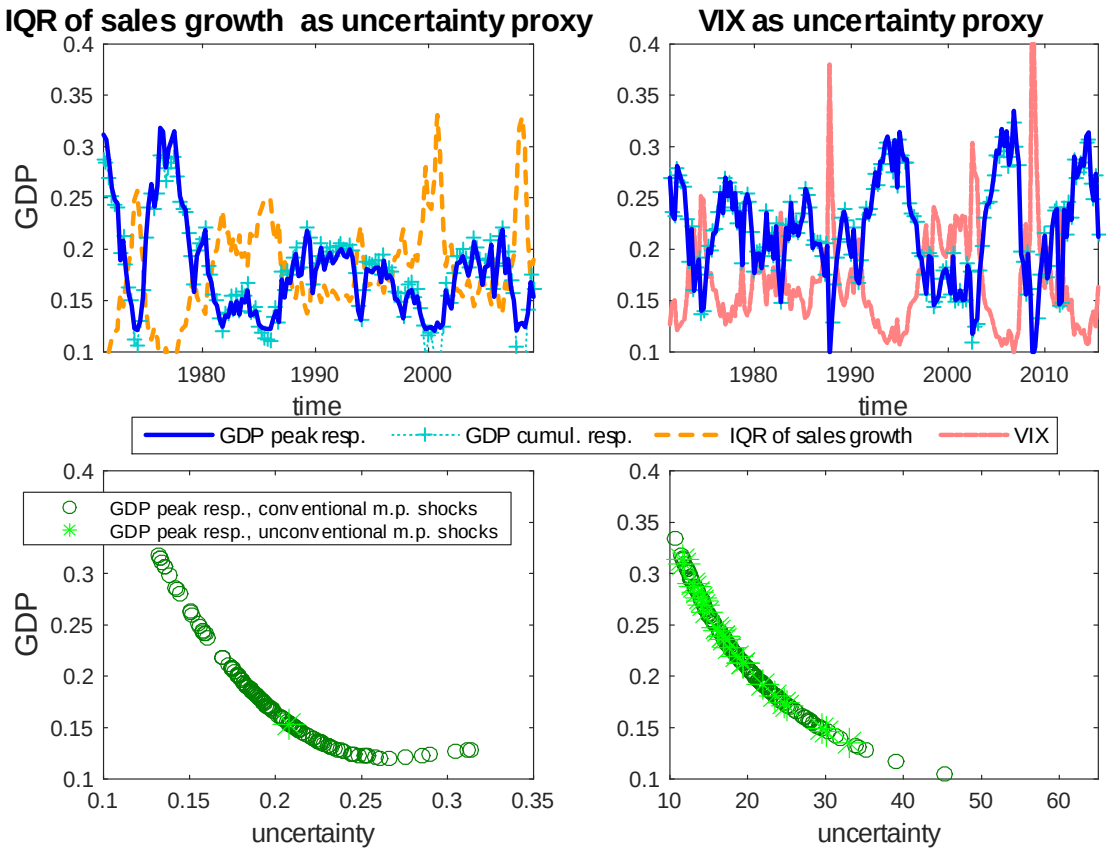

Figure A2: **Time-varying peak and cumulative response of GDP for a counterfactual that keeps the level of uncertainty at its pre-shock value. (shock: 25 basis points unexpected decrease in the policy rate)**. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Upper row: temporal evolution 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.

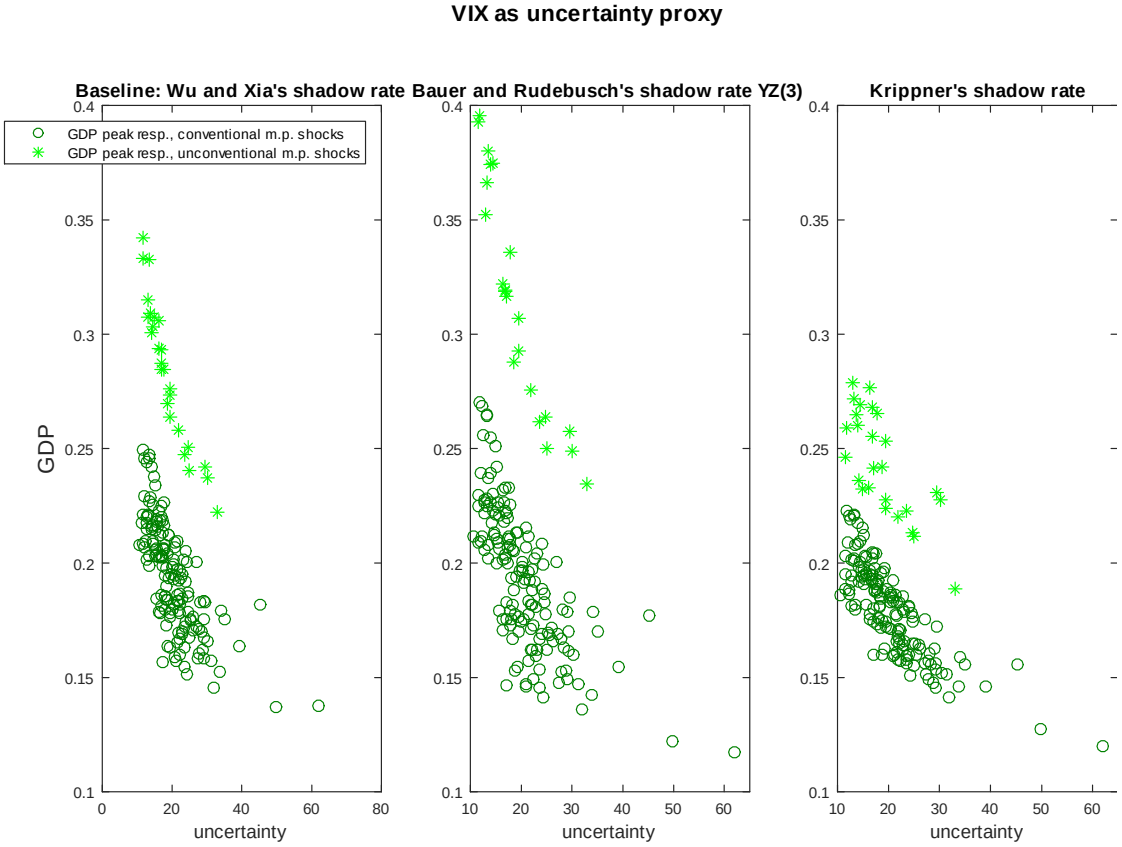

Figure A3: **Time-varying peak response of GDP for alternative shadow rates (shock: 25 basis points unexpected decrease in the policy rate; VIX as uncertainty proxy)**. GIRFs peak response in relation with the initial level of uncertainty (with a differentiation between conventional and unconventional 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.

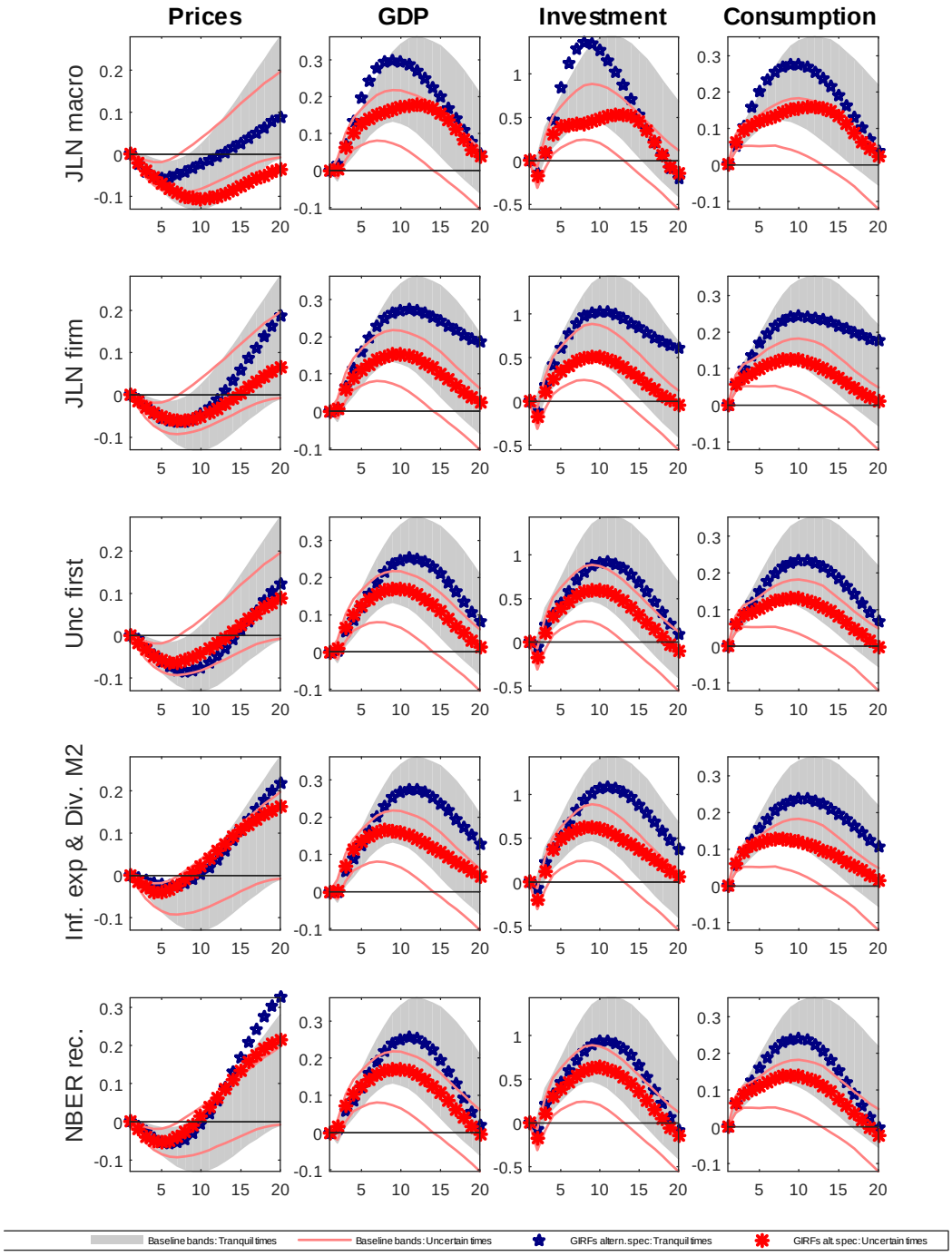

Figure A4: **Robustness checks for several perturbations of the baseline SEIVAR (shock: 25 basis points unexpected decrease in the FFR)**. Each row corresponds to a different SEIVAR specification. Grey areas (areas identified by red solid lines): 90% bootstrapped confidence bands for the GIRFs conditional 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: x-axis in quarters.

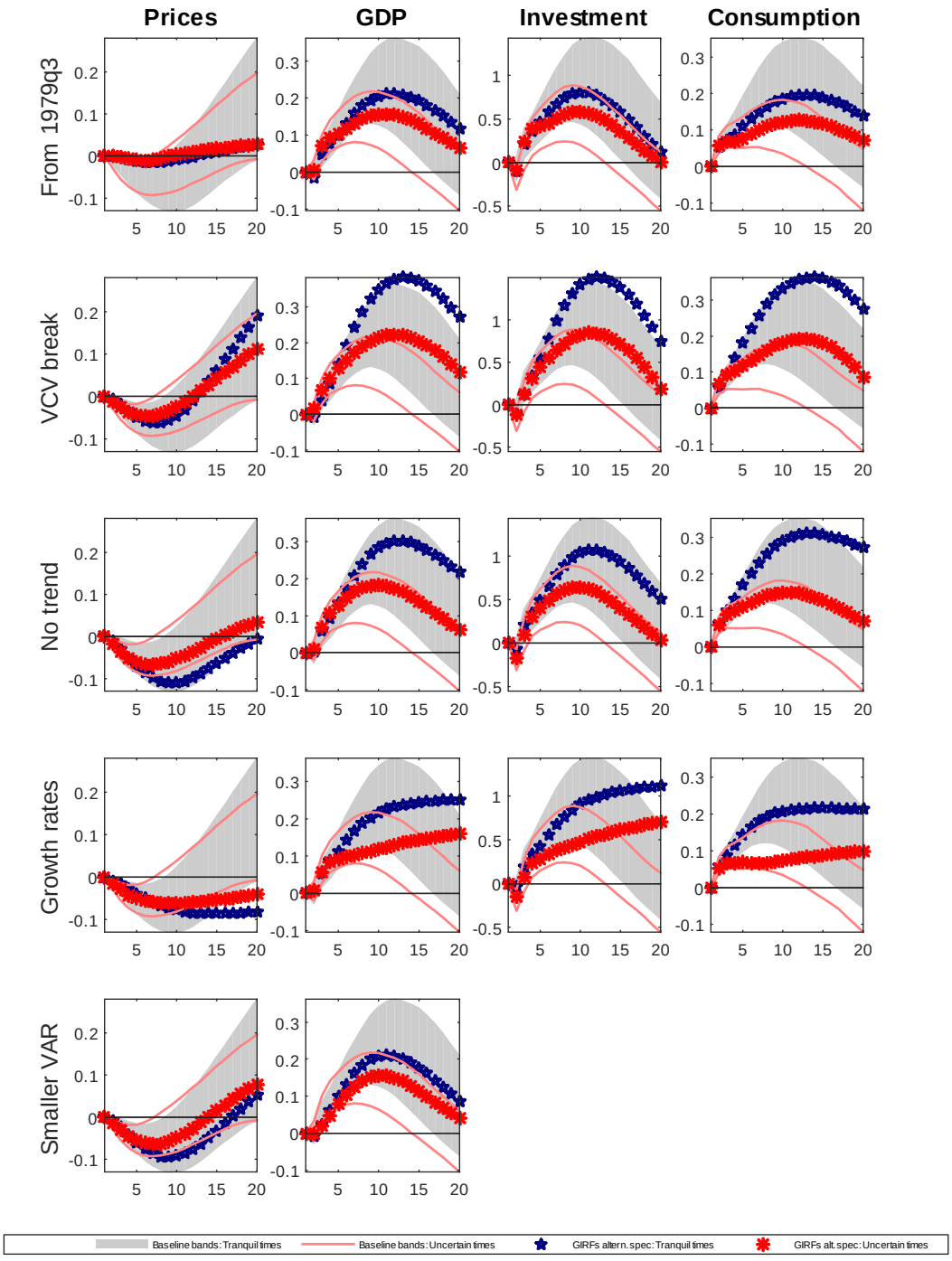

Figure A5: **Robustness checks for further perturbations of the baseline SEIVAR (shock: 25 basis points unexpected decrease in the FFR)**. Each row corresponds to a different SEIVAR specification. Grey areas (areas identified by red solid lines): 90% bootstrapped confidence bands for the GIRFs conditional 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. Note: x-axis in quarters.

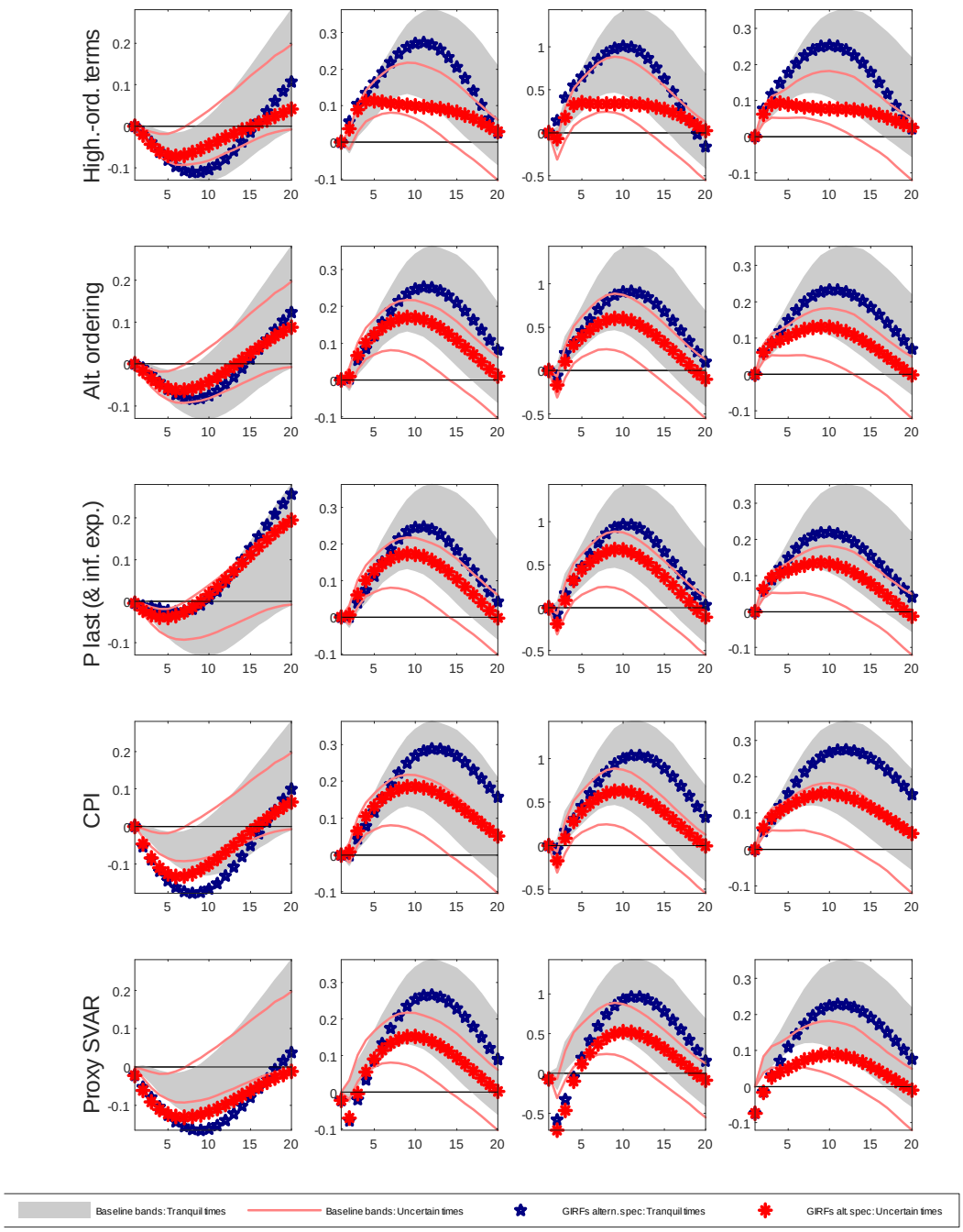

Figure A5: Continued.

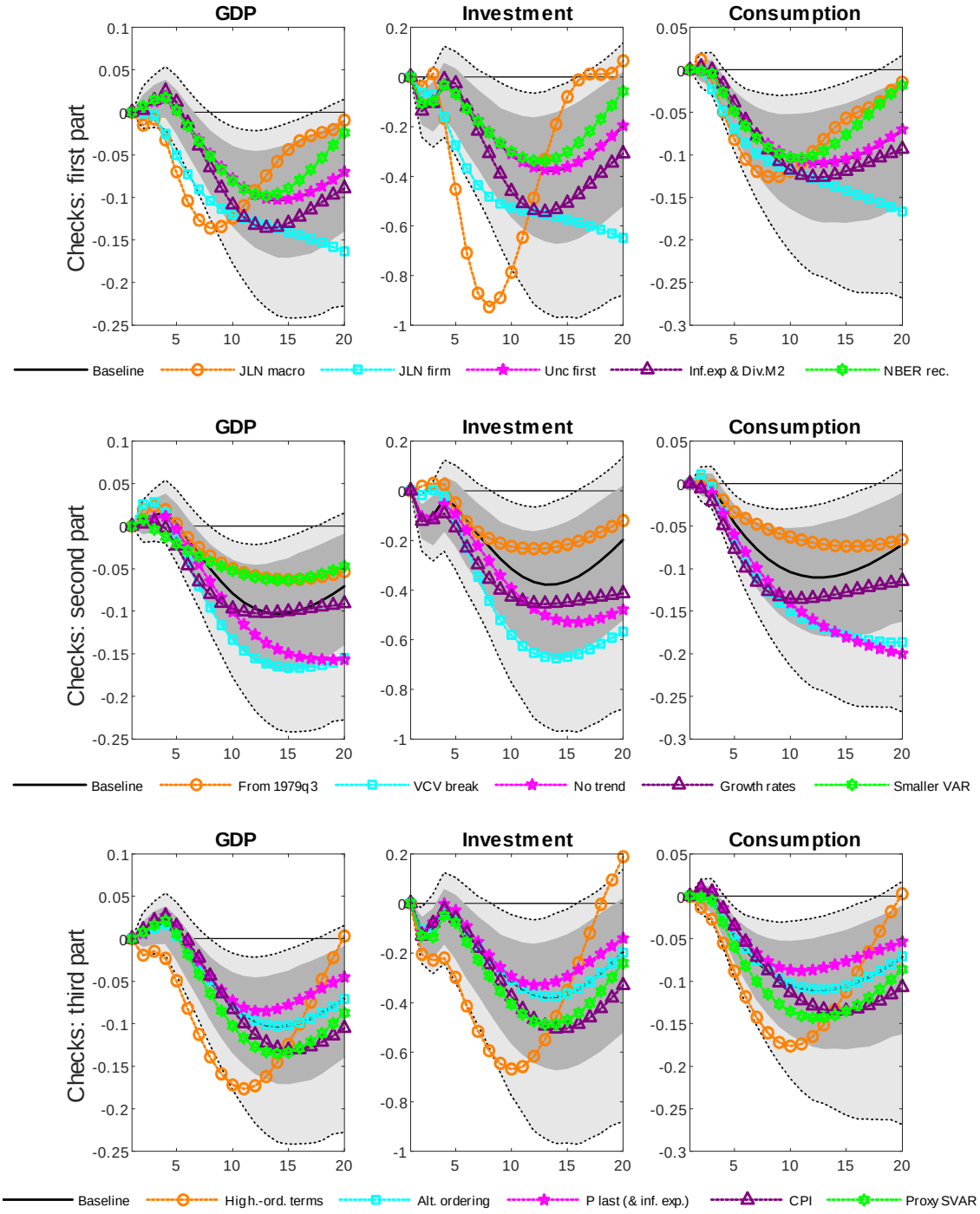

Figure A6: **Difference of state-conditional GIRFs between uncertain and tranquil times for further perturbations of the baseline SEIVAR**. IQR of sales growth as uncertainty proxy. Solid black lines: baseline difference between point estimated state-conditional GIRFs (uncertain times conditional GIRF 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. Note: x-axis in quarters.

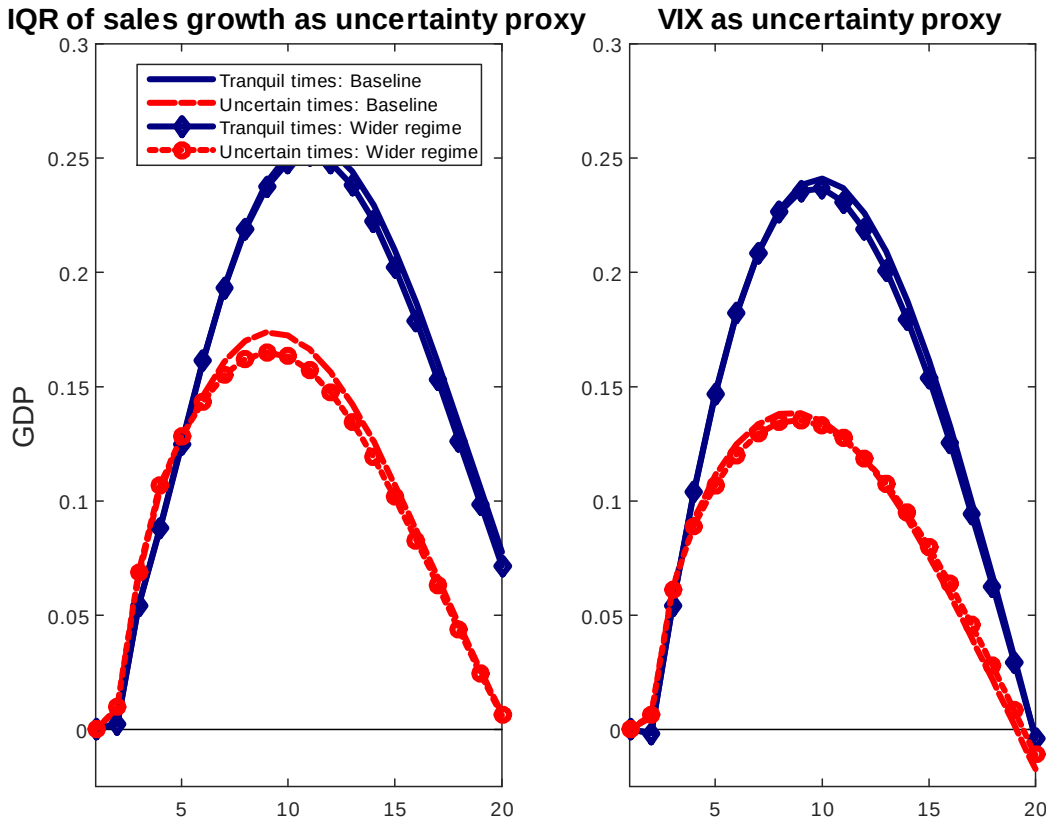

Figure A7: **Robustness to a wider definition of uncertain vs. tranquil times states (shock: 25 basis points unexpected decrease in the FFR)**. Left (right) column: IQR of sales growth (VIX) as uncertainty proxy. Solid blue (red dotted) line: baseline state-conditional GIRF for the tranquil times (uncertain 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. Note: x-axis in quarters.

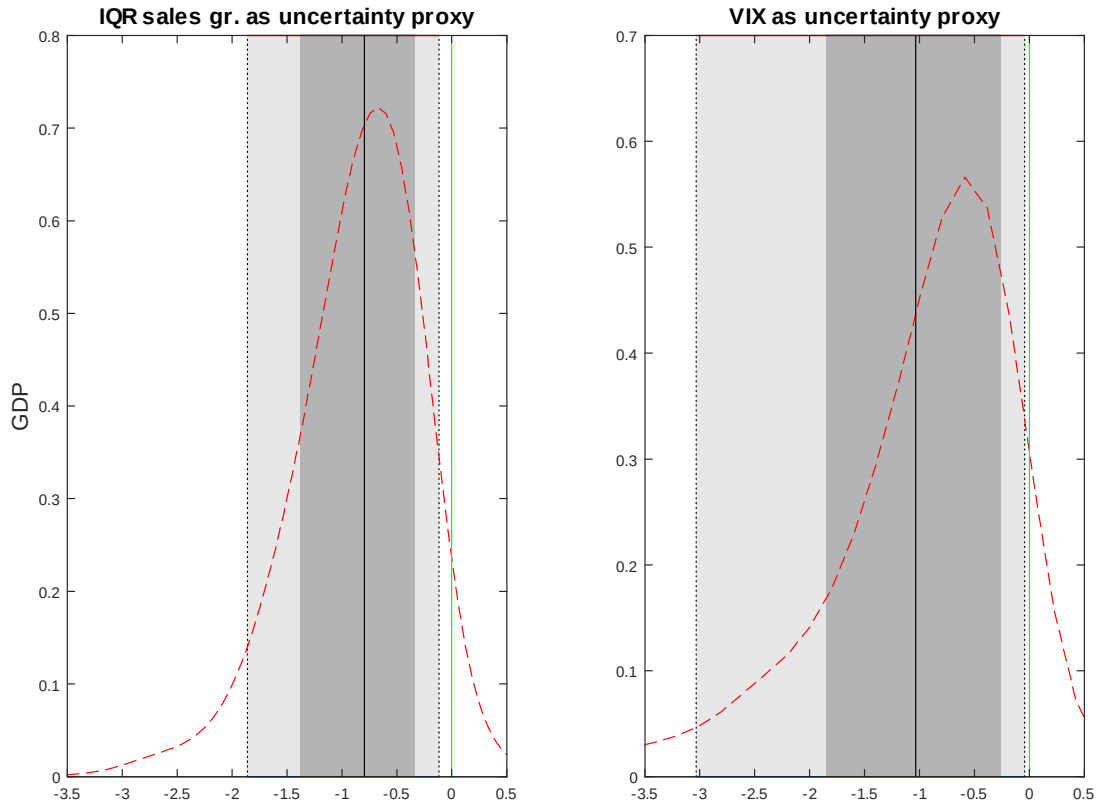

Figure A8: **Average difference between the cumulative effects of monetary policy shocks on GDP.** Red dashed line: Kernel density of the difference of the cumulative effects of the monetary policy shock between tranquil times and uncertain times (the density is based on the 2000 bootstrapped draws). 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.

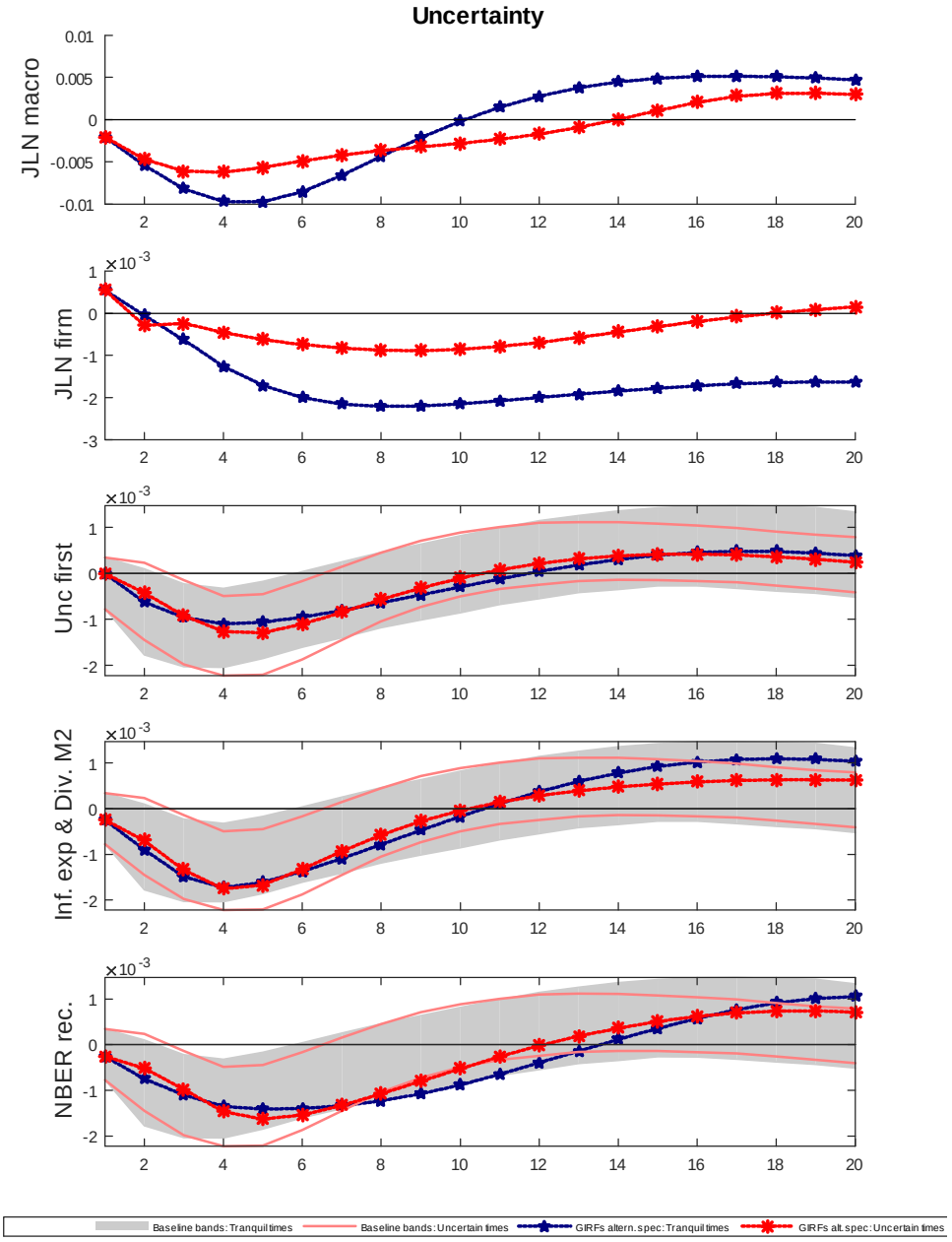

Figure A9: **Uncertainty response from robustness checks (shock: 25 basis points unexpected decrease in the FFR)**. Each row corresponds to a different SEIVAR specification. Grey areas (areas identified by red solid lines): 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times (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. Note: x-axis in quarters.

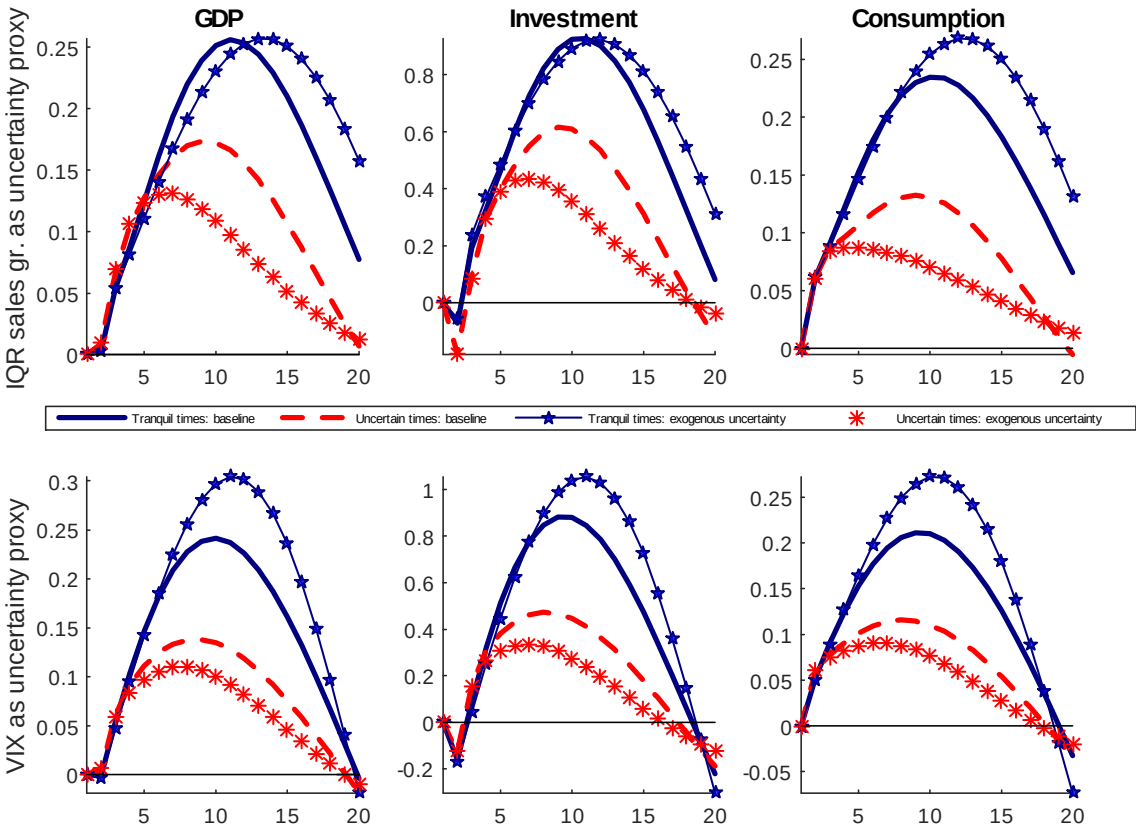

Figure A10: **Comparison among several state-conditional responses: Baseline GIRFs from SEIVAR with endogenous uncertainty vs. IRFs from IVAR with exogenous uncertainty**. Upper (lower) row: IQR of sales growth (VIX) as uncertainty proxy. Blue solid and red dashed lines: baseline GIRFs conditional to 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 IVAR. *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 IVAR model comparable to eqt. (1): $\tilde{\mathbf{Y}}_t = \boldsymbol{\alpha} + \boldsymbol{\gamma} \cdot linear\ trend + \sum_{j=1}^{L} \mathbf{A}_j \tilde{\mathbf{Y}}_{t-j} + \sum_{j=1}^{L} \mathbf{B}_j unc_{t-j} + \left[\sum_{j=1}^{L} \mathbf{c}_j R_{t-j} \times unc_{t-j}\right] + \mathbf{u}_t$, where this time $\tilde{\mathbf{Y}}$ 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, 2017)) 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 IVAR, the starting conditions do not matter. Note: x-axis in quarters.

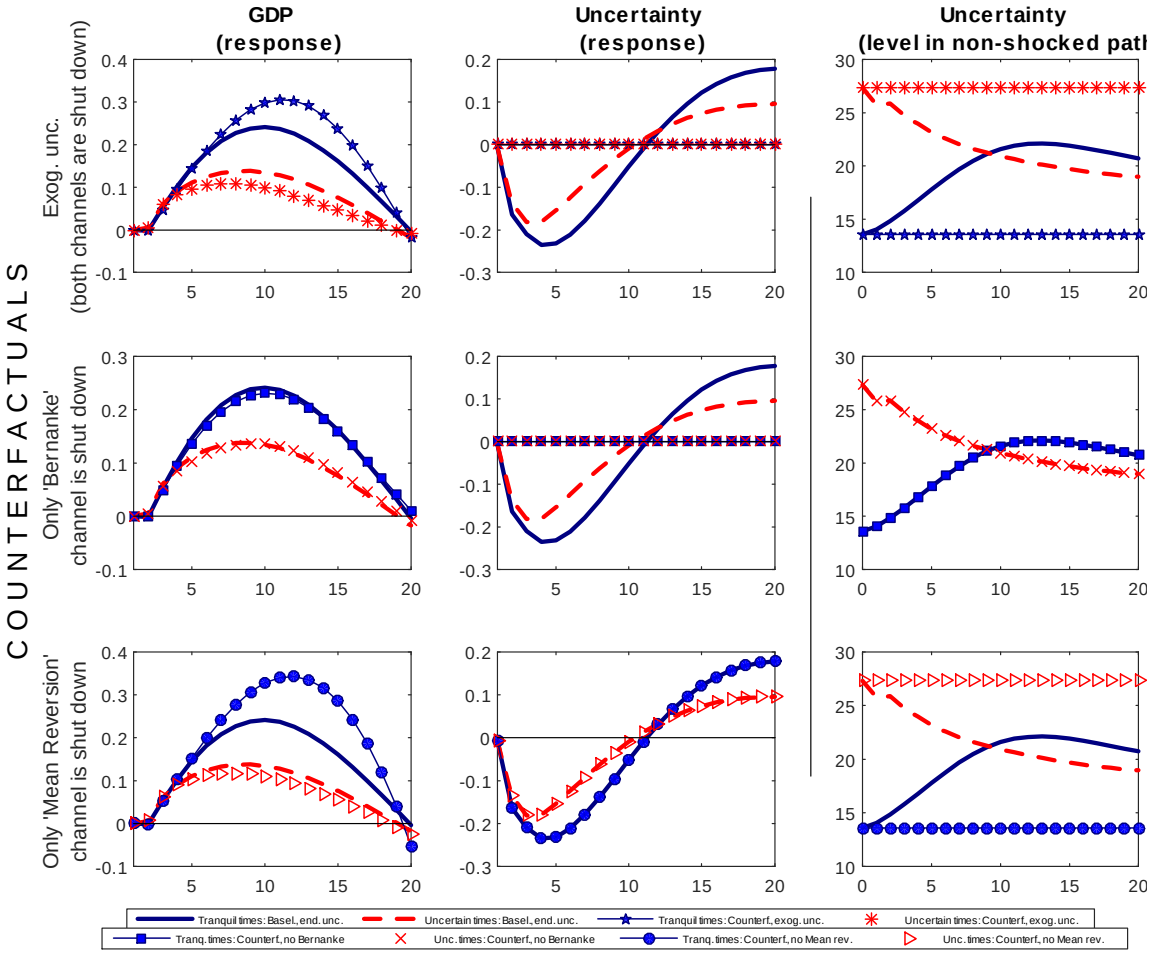

Figure A11: **Comparison among counterfactual exercises to study the role of the "Bernanke's" and "Mean reversion" channels** (uncertainty proxy: VIX). Upper row: Baseline results vs. results obtained from the counterfactual in Figure 7. Middle row: Baseline results vs. results obtained from a counterfactual 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 and 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 23 of the main paper, 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 25 of the main paper. Note: x-axis in quarters.

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