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UNCERTAINTY AND MONETARY POLICY IN THE US: A JOURNEY INTO NON-LINEAR TERRITORY

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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 in order to assess whether the real effects of monetary policy shocks are lower during times of high uncertainty. In a novel way with respect to the literature, uncertainty, which serves as the conditioning indicator discriminating "high" from "low" uncertainty states, is modeled endogenously in the VAR and is found to reduce after the shocks. Generalized Impulse Response Functions à la Koop, Pesaran and Potter (1996) suggest that monetary policy shocks are significantly less effective during uncertain times, with the peak reactions of a battery of real variables being about two-thirds milder than those during tranquil times. We also show that, consistently with Vavra's (2014) predictions, the reaction of prices appears greater during firm-level uncertain times.

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

JEL codes: C32, E32, E52.

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1 Introduction

Uncertainty is widely recognized as playing an important role in influencing economic activity. As documented by a number of recent studies, when an unexpected unconditional increase in uncertainty hits the economy, a contractionary effect on real aggregate variables generally follows[1]. More recently, the empirical literature has also started to enquire whether uncertainty shocks might have a state-conditional impact, namely whether their effects on the economy depend on the particular phase the economy is experiencing[2]. However, there has still been little empirical research on the possible role that uncertainty might play in influencing the effects of other structural shocks in the economic system.

This paper is concerned with the effects of monetary policy shocks conditional on different levels of uncertainty. Theoretically, several explanations may be behind the lower effectiveness of monetary policy shocks when uncertainty is high. The first of these is that uncertainty can influence firms' price setting behavior. Vavra (2014a) and Bachmann, Born, Elstner and Grimme (2013) develop structural calibrated models to assess whether a deep uncertainty motive can be at the root of some new empirical facts on the frequency and dispersion of price changes, suggesting that both are higher during recessions. Vavra's (2014a) general equilibrium price setting menu cost model suggests that a greater price flexibility induced by high firm-level uncertainty can let monetary policy shocks lose up to 50% of their effectiveness relative to tranquil times. Quite differently, Bachmann et al's (2013) Calvo-style New Keynesian business cycle model suggests that, if uncertainty plays any role in the transmission mechanism of monetary policy shocks, this role is likely to be minor[3]. On the other hand, consistently with Vavra's (2014a) predictions, Baley and Blanco (2015) find that nominal shocks

[1] A nonexclusive list of such works includes Bloom (2009), Mumtaz and Theodoridis (2012), Baker, Bloom, and Davis (2013), Gilchrist, Sim and Zakrajsek (2013), Bachmann, Elstner and Sims (2013), Leduc and Liu (2013), Colombo (2013), Mumtaz and Zanetti (2013), Nodari (2014), Jurado, Ludvingson and Ng (2014) and Carriero, Mumtaz, Theodoridis, and Theophilopoulou (2015), who employ structural VAR models to study the impact of uncertainty shocks on the economy.

[2] See, among others, Nodari (2014), Caggiano, Castelnuovo and Groshenny (2014), and Caggiano, Castelnuovo and Nodari (2014), who enquire whether recessionary vs. non-recessionary phases are important in determining the impact of uncertainty shocks, Alessandri and Mumtaz (2014), who enquire whether good vs. bad financial regimes are important, and Caggiano, Castelnuovo and Pellegrino (2015), who enquire whether the Zero Lower Bound (ZLB) also matters.

[3] A general concern of Calvo-type DGSEs, however, is that firms' decisions on changing price are not modelled endogenously, but exogenously given (see, e.g., Fernández-Villaverde (2010, section 6.1)). This contrasts with Vavra's finding that the 80% of the reduced effectiveness of monetary policy during uncertain times comes through the extensive margin, that is through a change in the mix of who decides to change prices.

also have smaller effects on output during firm-specific uncertain times in the context of a price setting model, including information frictions in addition to menu costs.

The second explanation concerns the fact that the presence of some form of fixed costs or partial irreversibilities in the investment or hiring processes could also 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) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014)). Stimulus policies may therefore need to be more aggressive in uncertain times, when agents' inaction regions are wider and policy effectiveness lower (Bloom (2014)). Finally, in the presence of risk averse agents, higher precautionary savings during uncertain times could represent another possible driver of the lower reactiveness of real activity to monetary policy shocks (see Bloom's (2014) survey and references therein).

The main goal of this paper is to empirically assess the real impact of monetary policy shocks in the presence of high vs. low uncertainty times by estimating a non-linear VAR model with quarterly US post-WWII data. To this aim we employ a non-linear Interacted VAR (I-VAR) model, which presents two main advantages for our purposes. First, it parsimoniously captures the non-linearity we are interested in (which relates to the interaction between the monetary policy stance and uncertainty) without appealing to the estimation of more parameterized models (like Smooth-Transition VARs and Regime-Switching VARs). Second, it uses all available observations for estimation, which, unlike abrupt change models featuring a regime-specific estimation approach like Threshold VARs, preserves enough degrees of freedom to estimate empirical responses referring at the extreme events of the uncertainty distribution. In this way we can be consistent with Vavra's theoretical work (2014a) and focus on the extreme deciles of uncertainty to define our high vs. low uncertainty states.

Our I-VAR model augments an otherwise standard VAR with an interaction term including two variables, i.e., the variable used to identify the monetary policy shock (the federal funds rate) and the conditioning variable that identifies the "uncertain times" and "tranquil times" states (uncertainty). Importantly, and similarly to the I-VAR in Caggiano, Castelnuovo and Pellegrino (2015), we model both interaction variables endogenously, which implies the computation of fully non-linear Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran and Potter (1996). This novel modelling strategy contrasts with that employed by previous contributions dealing with I-VARs, in that they typically work with an exogenous conditioning variable and therefore compute conditionally-linear IRFs. Our strategy enables us to consider both the possible endogenous reaction of uncertainty to the policy shock and its feedbacks on the dynamics of the system. One of the results of this paper is exactly that of showing the far-from-negligible quantitative differences one obtains when modeling the conditioning variable (uncertainty, in our case) as exogenous vs. endogenous.

Our VAR models a standard set of real aggregate variables, including GDP, investment and consumption, the GDP price index and an uncertainty proxy. This latter will in the baseline analysis be either the VIX (a measure for the implied stock market volatility extensively used as uncertainty proxy after Bloom's (2009) seminal paper) or the Inter Quartile Range (IQR) of sales growth (a cross sectional firm-level uncertainty proxy computed by Bloom et al. (2014)), which, given its more disaggregated nature, can be important in that to capture firms' price setting behavior (see, among others, Golosov and Lucas (2007), Klenow and Kryvtsov (2008), Vavra (2014a)). The importance of considering firm-level measures of uncertainty is stressed also by Vavra's (2014b) results. He estimates a regime-dependent forward looking New-Keynesian Phillips Curve and finds that its slope increases with microeconomic volatility but not with the business cycle or aggregate volatility. His results therefore suggest a worsening of the inflation-output trade-off in firm-level uncertain times.

In connection with this latter point, another aim of the paper is to test empirically Vavra's (2014a) theoretical predictions regarding price reactions to monetary shocks in different firm-level uncertainty times. The results here derive primarily from Local Projections (proposed by Jordà (2005)). This method allows us to recover a state-conditional on-impact reaction of prices, which is important for Vavra's (2014a) predictions but which cannot be captured by our baseline recursively identified VAR. Importantly, this exercise will also serve as a further robustness check for baseline results. Specifically, following Owyang, Ramey and Zubairy (2013), we use Local Projections to extract empirical responses to an exogenously identified shock from a Threshold Autoregressive model. In our case this shock will consist either in the monetary policy shocks identified in our baseline analysis or in Romer and Romer's (2004) narratively identified monetary policy shocks as extended by Coibion, Gorodnichenko, Kueng and Silvia (2012) up to the end of 2008.

Our main results can be summarized as follows. First, an unexpected decrease in the federal funds rate has expansionary effects on the real economy irrespective of the times in which it occurs. Second, and more interestingly, there is clear and robust evidence of weaker real effects of monetary policy shocks during uncertain times, something which lends support to the theoretical predictions of Bloom (2009), Vavra (2014a) and Baley and Blanco (2014). 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. Third, in line with Bekaert, Hoerova and Lo Duca (2013), uncertainty decreases after an expansionary monetary policy shock and it turns out that the endogenous modelling of uncertainty has a non-negligible effect on the estimated state-conditional responses. Fourth, consistently with Vavra (2014a), we find that during firm-level uncertain times prices increase more in the immediate aftermath of a monetary policy shock than during times of greater firm-level certainty.

Our findings are relevant both from a policy and modelling standpoint. From a policy perspective, our results corroborate several findings in the literature, which can be linked together as follows. First, they empirically validate the results of more structural studies claiming that uncertainty reduces the real activity sensitivity to nominal stimulus policies. This, in turn, might suggest that a more aggressive intervention by policy makers is to be recommended in uncertain times (as suggested by Bloom (2014)). However, a call for more policy aggressiveness might meet the difficulty of a worsened output-inflation trade-off (consistently with Vavra's (2014a,b) findings), for which at least in the short run a higher price level should be tolerated[4]. From a modelling perspective, this study makes two contributions. First it adds to the rising, empirically related, call for the development and employment of non-linear micro-founded models that can assess the state-conditional relevance of uncertainty more structurally, as argued by recent empirical studies (see, among others, Caggiano, Castelnuovo and Nodari (2014)). Second, our results also suggest that modelling the endogenous reaction of uncertainty to policies, rather than considering it as an exogenous process, might be an important and fruitful path for future theoretical modelling to follow[5].

To our knowledge, few empirical works shed light on similar issues. Specifically we know of no studies that empirically assess the reaction of prices to monetary policy

[4]In addition, other difficulties might undermine the argument for an aggressive monetary policy in uncertain times, although these are not explicitly addressed in this paper. For example, it is difficult to implement a more aggressive stimulus near the ZLB, at least with conventional policy moves; a fact which feeds the debate on the pros and cons of raising the inflation target (see, among others, Blanchard, Dell'Ariccia and Mauro (2010)). Moreover, to avoid further increases in uncertainty, aggressive policies should be clearly communicated and explained to the public (see Baker, Bloom and Davis (2015).

[5]To the best of our knowledge, we are not aware of any model allowing for this. Just as an example, Bloom et al. (2012, p. 22) notice, in assessing the effectiveness of stimulus policies in the presence of heightened uncertainty, that they ignore the direct impact of policies on uncertainty since that would be too difficult to include in their model. For a discussion of the possible effects of policies on uncertainty see Baker, Bloom and Davis (2013) and references therein.

shocks in different uncertainty times. The work closest to ours is Aastveit et al. (2013) who estimate a Bayesian I-VAR model. Notwithstanding a comparable I-VAR environment, they find that monetary policy is from two to five times more effective under low uncertainty. Our Appendix reports a comparison between the results documented in the main text of this paper and those one would obtain if uncertainty were modeled as exogenous. This comparison shows that modeling uncertainty as exogenous leads to an overestimation of the difference between the real effects of monetary policy shocks in tranquil and uncertain times. This result reconciles our empirical findings and those proposed by Aastveit et al. (2013). Another related work is Caggiano, Castelnuovo and Nodari (2014), who estimate a Smooth-Transition VAR model to investigate the stabilizing effectiveness of *systematic* monetary policy in presence of heightened uncertainty. Our work is complementary to theirs, in that it focuses on the effects of monetary policy *shocks* conditional on different levels of uncertainty.

Other relevant recent works are Tenreyro and Thwaites (2013) and Mumtaz and Surico (2014), who investigate the transmission mechanism of monetary policy in good and bad circumstances[6]. Their results suggest that monetary policy shocks are less effective during bad times. Unlike these studies, ours explicitly focuses on the relevance of uncertainty in the transmission of monetary policy shocks. This is important for two reasons. First, to test empirically the predictions of the aforementioned theoretical papers which suggest uncertainty-related explanations for a state-conditional impact of monetary policy shocks. Second, conditioning to recessions could bring spurious results since recessions can have a range of causes among which heightened uncertainty is one, but also, financial distress, oil shocks, policy switches and so on[7]. In order to pursue our aim, several checks are proposed to ensure that our methodology can capture deeper factors connected specifically with uncertainty.

The present paper is organized as follows. Section 2 describes our empirical methodology and the data employed. In section 3, our main results on the effectiveness of monetary policy shocks in tranquil vs. uncertain times and a number of robustness

[6] These two works can be seen as part of the literature in a more established research area, studying the effects of monetary policy shocks in different phases of the business cycle (one of the most cited papers in this literature is Weise (1999)).

[7] In the words of Bloom et al. (2012, p. 21), "recessions are periods of both first- and second-moment shocks". Two further comments are worth noting. First, uncertainty causes can be difficult to disentangle from financial causes (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)).

checks for these are presented. In section 4, the results pertaining to the employment of Local Projections are shown. Section 5 concludes.

2 The empirical methodology

2.1 The Interacted-VAR

In order to study empirically whether the real effects of monetary policy shocks are different across tranquil and uncertain times, we employ an I-VAR model[8]. This model augments an otherwise standard linear VAR with an interactions term, which in this work involves two endogenously modeled variables: the variable that will help us to identify exogenous monetary policy changes, i.e. the federal funds rate (FFR), 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 across tranquil versus uncertain times. In addition to the FFR and an uncertainty indicator, the vector of endogenous variables also includes measures of real activity and prices.

The estimated I-VAR model is the following:

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

$$\varepsilon_t \sim N(0, \mathbf{\Omega}) \tag{2}$$

where $\mathbf{Y}_t$ is the $(n \times 1)$ vector of the endogenous variables, α is the $(n \times 1)$ vector of constant terms, γ is the $(n \times 1)$ vector of slope coefficients for the time trend included, $\mathbf{A}_j$ are $(n \times n)$ matrices of coefficients, ε_t is the $(n \times 1)$ vector of error terms, whose variance-covariance (VCV) matrix is $\mathbf{\Omega}$. The interaction term in brackets makes an otherwise standard VAR a non-linear I-VAR model. It includes a $(n \times 1)$ vector of coefficients, $\mathbf{c}_j$, a measure of uncertainty, unc_t, and the FFR, ffr_t [9].

[8]Several contributions that have recently employed I-VARs are Towbin and Weber (2013), Sà, Towbin and Wieladek (2014), Lanau and Wieladek (2012) and Aastveit, Natvik and Sola (2014). Unlike the present study, they use a fixed conditioning variable in computing empirical responses.

[9]Notice that an I-VAR might be seen as a special case of a Generalized Vector Autoregressive (GAR) model (Mittnik (1990)), and hence might share its possible problems. In particular GAR models might feature instability when the squares or other higher moments of the endogenous variables are included as covariates (Granger (1998) and Aruoba, Bocola and Schorfheide (2012)). However, our model appears not to suffer from these problems, both because of its parsimonious nature (that it avoids

The I-VAR model presents several advantages in our context over the alternative non-linear specifications like Smooth-Transition (ST-) VARs and Threshold (T-)VARs. First, it parsimoniously 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 notice that it does not require us to identify thresholds, as in T-VARs, or to estimate/calibrate transition functions, as in ST-VARs. Second, unlike abrupt change models featuring regime-specific coefficients like T-VARs, the I-VAR is estimated on the full sample. This characteristic allows us avoid the issue of not having enough degrees of freedom to precisely estimate empirical responses conditional on the extreme events of the uncertainty distribution. In this way we can be consistent with Vavra's theoretical work (2014a) which focuses on the extreme deciles of uncertainty[10].

2.2 Generalized Impulse Response Functions

Unlike existing studies employing an I-VAR model, our conditioning variable, i.e. uncertainty, is also included in the vector of modeled endogenous variables. This is important because, as shown later, uncertainty is found to decrease after an expansionary monetary policy shock. In the absence of consideration of this endogenous reaction, biased IRFs are likely to arise as no feedback going from the monetary policy shock to uncertainty is explicitly modelled[11].

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) (a detailed algorithm is presented in the Appendix). In this way, again, we are able to take into account the fact that a shock can influence the state of the system and therefore its following evolution. As a result, GIRFs return fully non-linear empirical responses that depend nontrivially on the initial conditions when the system is shocked[12]. Therefore, in principle we have

squares of endogenous variables) and because the use of GIRFs might help to mitigate this problem (Koop et al (1996, section 3.3)).

[10] As shown by Caggiano, Castelnuovo, Colombo and Nodari (2015) as regards countercyclical fiscal multipliers, 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.

[11] Ramey and Zubairy (2014) raise similar concerns about the conditionally-linear responses recovered by Auerbach and Gorodnichenko (2012) from their Smooth-Transition VAR investigating the economy's reaction to an expansionary fiscal spending shock during expansionary or recessionary times. In Ramey and Zubairy's words: "the assumption implies that a positive shock to government spending during a recession does not help the economy escape the recession".

[12] By initial conditions we mean the set of historical values for the right-hand-side variables of our

as many history-dependent GIRFs referring to a generic initial quarter $t-1$ as there are quarters in our sample[13]. Once these GIRFs are averaged over a particular subset of initial quarters of interest we can obtain our state-dependent GIRFs. Consistently with Vavra (2014a), we assume the "tranquil times" state to be characterized by initial quarters with uncertainty around its 10th percentile and the "uncertain times" state by initial quarters around its 90th percentile[14].

An alternative methodology to GIRFs to compute non-linear empirical responses would be to use Local Projections (proposed by Jordà (2005)). Consistently with 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. Moreover, it is less sensitive to mis-specification vis-à-vis the dynamics of VAR models (see Jordà (2005)) and, when an exogenous narratively identified shock series is used, it permits us to circumvent Structural VAR restrictions such as the short run restrictions typical of recursively identified VARs like ours. Therefore, in section 4, in order both to provide a robustness check for baseline results and to enquire the on-impact reaction of prices, we will apply Local Projections to a Threshold autoregression, as in Owyang, Ramey and Zubairy (2013). Local Projections are not, however, used as the main tool to estimate empirical responses for three reasons. First, they are not as informative as GIRFs since they provide just the average reaction of the economy whereas GIRFs allow us to obtain fully non-linear empirical responses for each given initial quarter in the sample. Second, they produce responses that are generally erratic at long horizons. Third, in our application it turns out that they suffer significantly from the issue of not enough degrees of freedom in the uncertain regime.

2.3 Data and some empirical facts

Our VAR jointly models an indicator of uncertainty, measures of U.S. real activity, the GDP deflator and the FFR. Real activity is captured by real GDP, real gross private domestic investment and real personal consumption expenditures. The FFR rate is meant to be the instrument of monetary policy as commonly assumed in the empirical

I-VARs in (1), $\varpi_{t-1} = \{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-L}\}$. Notice indeed that for a non-linear model responses can depend on the particular history taken as initial condition, on the shock sign and size (and on the particular sequences of future shocks hitting the system) (Koop et al. (1996)).

[13] In reality we should subtract the number of lags to the number of quarters.

[14] To be precise, five-percentiles bands around the top and bottom deciles are used. This 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.

literature studying the impact of monetary shocks. Both real variables and prices are taken in logs and multiplied by 100. The data source is the Federal Reserve Bank of St. Louis' database (FRED2 database). The sample period starts at 1971Q1[15].

Uncertainty is measured by a number of different indicators proposed in the literature. As baseline indicators we use both 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 (2014), i.e. the inter-quartile range (IQR) of sales growth for a sample of Compustat firms, which is available up to 2009Q3[16]. Unlike aggregate volatility indicators, this disaggregate indicator is also likely to capture idiosyncratic (i.e., firm-specific) shocks. These, it is suggested by several studies, constitute either one of the most important factors in explaining price setting behavior (see, among others, Golosov and Lucas (2007), Klenow and Kryvtsov (2008), Vavra (2014a,b)) or 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) and available up to the end of 2012 on Bloom's website[17]. It has been widely used in the empirical literature on the impact of uncertainty shocks and represents the degree of volatility implied 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, Ludvingson, and Ng (2015) to check the solidity of our main results. As detailed later, these indices are based on the purely unforecastable components extracted from two large US datasets.

Figure 1 plots the baseline uncertainty indicators against NBER recessionary periods (represented by grey vertical bars) and our uncertain and tranquil times states (given by the initial quarters respectively within horizontal dashed red and dotted blue bands). Two considerations are worth noticing. First, although the global maximum of both

[15] The starting date is dictated by the availability of the uncertainty measures (i.e., to have a common initial date across the samples employed). It also proves useful, given our employment of the Romer and Romer's (2004) monetary policy shocks (available since 1969) and of the series for inflation expectations that we use in section 3.3 (available since 1970Q2).

[16] In particular it is constructed on 2,465 publicly quoted firms spanning all the sectors of the economy. It is available on-line at http://www.stanford.edu/~nbloom/RUBC.zip . The IQR of sales growth is the unique non-financial high-frequency dispersion indicator referring to disaggregated firm-level data used by Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2014) for their results in table 1.

[17] The VIX is constructed from the Chicago Board Options Exchange VXO index for the period after 1986 and from the quarterly standard deviation of the daily S&P500 for the period before that. The VXO is an index of percentage implied volatility on a hypothetical at the money S&P100 option 30 days to expiration. VIX monthly series is obtained from http://www.stanford.edu/~nbloom/R.zip. Quarterly data are obtained by quarterly averages.

uncertainty indicators occurred during a recession, i.e. the recent Great Recession, many spikes occurred during expansions[18]. As a result, our uncertain times state comprises many initial quarters in expansionary periods. Second, some recessions, e.g. the 1980 and 1990-91 ones, have not been characterized, overall, by particularly high levels of uncertainty and as a result they do not enter our uncertain times state. These facts will be seen as important when we distinguish between the roles of uncertainty and recessions in driving our results. A more in-depth empirical investigation is the object of section 3.1 .

2.4 Specification, identification and I-VAR statistical motivation

Model (1)-(2) is estimated by OLS. The lag order used is $L = 2$ as suggested by the Hannan-Quinn criterion (both for the non-linear and the nested linear model)[19]. 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: $Y = [Unc, P, GDP, Inv, Cons, ffr]'$, where abbreviations have been used for variables names. Notice that, while the FFR is allowed to react instantaneously to uncertainty, the price index and the real variables, these other variables are not allowed to react on-impact to FFR changes. In the robustness checks sections we do, however, consider also the case in which uncertainty is allowed to react on-impact to FFR moves.

Finally, when a likelihood-ratio test for the overall exclusion of the interaction terms from model (1)-(2) is performed, the null hypothesis of linearity is rejected at any significance level in favor of the alternative of our I-VAR model. In particular, when uncertainty is proxied by the IQR of sales growth, the LR test suggests a value for the test statistic $\chi_{12} = 28.516$, with an associated p-value of 0.005, whereas in the VIX uncertainty case we have a value $\chi_{12} = 27.97$, with associated p-value of 0.006. Similar conclusions can be drawn for the other uncertainty indicators used.

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

[19] We follow Kilian and Ivanov (2005) who, for quarterly data and sample size like ours, suggest the use of the Hannan-Quinn criterion when the primary objective is to recover the structural impulse responses. The same lag order is suggested also when the Jurado, Ludvingson and Ng's (2015) uncertainty indicators are used. The results are in any case robust when higher lags, e.g., 3 or 4, are used (results available on request).

3 The uncertainty-dependent effects of monetary policy shocks

3.1 Historical evidence

We start our empirical analysis by examining whether the real effects of monetary policy shocks might have evolved through time according to the degree of historical uncertainty. The upper panels in figure 2 present the history-dependent GIRFs of real GDP to a 1% unexpected increase in the FFR[20]. In addition to the usual quantities shown for the IRFs of a standard VAR (i.e., the percentage reaction of GDP and the forecast horizon ahead considered), the horizontal axes also shows the quarter when the system is shocked.

On the basis of these upper panels, three considerations suggest themselves (further clarified then by lower panels). First, apart from small differences, the two surfaces (left and right) share a very similar shape and seem overall to suggest that the effects of policy shocks are less persistent, and hence monetary policy is less effective, if the shock hits the economy in a high uncertainty phase. Second, the effectiveness of monetary policy shocks appears substantially lower during recessions only if these are characterized by high uncertainty levels. The '74-75, '81-82 and 2001 recessions and the recent Great Recession are examples of recessions characterized by high uncertainty, while the ‘80 and ‘90-91 recessions are examples of recessions characterized by low uncertainty[21]. Third, several episodes of reduced policy effectiveness are also observed during expansionary phases. For two striking episodes referring to the VIX case see the less persistent GDP reaction in the quarters around the Black Monday in 1987 or in the quarters between the end of 2002 and the beginning of 2003, corresponding respectively to the WorldCom and Enron financial scandals and the Gulf War II. Alternatively, for the IQR of sales growth case see, for example, the period '84-86.

The lower panels in figure 2 provide further support for the latter two claims above. The attempt is to discern between the role of uncertainty and the role of recessions in driving the effectiveness of policy shocks. In particular, six history-dependent responses

[20] Here we use a contractionary shock because the resulting figure is easier to interpret. Below, given our purposes, we will turn to an expansionary shock. For the purposes of our paper, we report responses up to 2009Q3 in the figure (i.e., the GIRFs with starting quarter up to the end of the Great Recession according to the NBER), which coincides with the end of the IQR of sales growth sample. The figure is best seen in color.

[21] Interestingly, during the '80 recession the real effects of monetary policy shocks reach a local maximum (in terms of persistence of the shock effects), which seems to be because, during this recession, both uncertainty indicators reached a local minimum (see figure 1).

are selected, for both indicators, according to the levels of uncertainty: two with starting quarters referring to the most uncertain recessions according to both our uncertainty proxies, i.e. the Great Recession and the '74-75 recession, two to the most tranquil recessions, i.e. '90-91 and '80 recessions, and two to the most uncertain episodes during expansions[22]. Two points stand out. First, the real effects of monetary policy shocks appear lower during uncertain times, irrespective of whether or not they occur during a recession. Second, among the responses considered, policy effectiveness reaches its maximum during tranquil recessions. Hence, from these pictures, high uncertainty periods, not recessionary ones, seem to have the biggest negative effect on the effectiveness of monetary shocks. In section 3.3 we will present another check for this finding.

Preparing the ground for the state-conditional analysis in the next subsection, we now select from the responses in the upper panels in figure 2 those that are relevant for our uncertain and tranquil times states. The selected GDP responses, distinguished according to the state they belong to, are displayed in figure 3 (from now on an expansionary policy shock equal to a 1% decrease in the FFR is considered). Notice that most of the responses selected for the uncertain times state refer to an expansionary starting quarter, i.e. 10 out of 15 for the IQR of sales growth case and 10 out of 17 for the VIX case. Hence, our uncertain times state seems well tailored to capture uncertain times rather than recessionary times. Bold lines represent our point estimates for the state-conditional GIRFs, i.e. the horizon-wise average across the selected history-specific GIRFs. From the figure it is clear that, although there are differences between responses depending on the initial quarter considered, responses under a particular uncertainty state behave similarly. Overall, these responses suggest that monetary policy shocks are on average less effective during uncertain times. The next section elaborates on this point.

3.2 Average evidence

We can now consider the state-dependent evidence for all our six endogenous variables. First, take the IQR of sales growth as the uncertainty indicator. Figure 4 presents the GIRFs conditional on the uncertain and tranquil times states along with their 90% bootstrapped confidence intervals. Looking first at real variables, notice that they

[22] To be more precise we select as starting quarters for our responses those corresponding to the maxima of both uncertainty indicators for the uncertain (recessionary and expansionary) episodes and to the minima for the tranquil (recessionary) episodes. The initial quarters selected for the uncertain expansionary episodes are 1999Q4 and 2000Q4 for the IQR of sales growth and 1987Q4 and 2002Q3 for the VIX.

increase in both states after the expansionary shock. However, both the magnitude and the persistence of this increase depend on the uncertainty times in which the economy stands. Focusing on the magnitude of the increase, during tranquil times investment increases by a maximum of around 3.5% and consumption and GDP by around 1%. During uncertain times, however, real variables react less: their maximum reactions in this state are around two-thirds weaker than during tranquil times. Specifically, focusing on GDP peak reactions, it reacts 54% more during tranquil times. This is consistent with the findings of Vavra (2014a) and suggests that monetary policy shocks are less effective when they occur during economic phases characterized by high uncertainty[23].

As discussed in the Introduction, several theoretical explanations could in principle explain why the economy is less reactive to monetary stimuli during uncertain times. One can think either of the presence of real option effects in a world with fixed costs and partial irreversibilities in the investment and hiring process, or of the presence of precautionary savings in a world with risk averse agents. Moreover, as theorized by Vavra (2014a) and Baley and Blanco (2015), firms price setting behavior could also play a role. If prices were more reactive to expansionary nominal stimulus during firm-level uncertain times, this reduced price stickiness would directly translate into an *higher price level* and a smaller real effect of monetary shocks in our uncertain times state. Although this study wishes also to test Vavra's (2014a) predictions on price changes empirically, the recursively identified I-VAR of this section is not suitable for this purpose for two reasons. First, even though in figure 4 there might be some evidence of a higher price in the uncertain times state, the presence of a price puzzle[24] in the early part of the empirical response of P makes it difficult to interpret this result. Second, common recursively identified monetary VAR models, which assume that prices react with a lag to monetary policy shocks, cannot be used to test properly Vavra's (2014a) predictions, which mostly pertain to the on-impact reaction of prices. For these reasons, we postpone a more careful investigation of the possible state-conditional behavior of prices to section 4, where an alternative methodology capable of dealing with these two

[23]In the most realistic, calibrated version of his model, Vavra finds that the cumulative output reaction to monetary policy shocks is 45% larger at the 10th percentile of volatility than at the 90th percentile of volatility. To make a direct comparison with his results consider that GDP in our case reacts 59% cumulatively more during tranquil times, hence quite similarly to what Vavra (2014a) found (and to what is suggested by our peak reactions).

[24]Indeed, price response predicts, contrary to the conventional wisdom, a significant decrease in prices following a monetary policy expansion. This fact is generally attributed to different sources: to an omitted variables problem (see Sims (1992), Castelnuovo and Surico (2010)), to the sample period considered (see Castelnuovo and Surico (2010)), and to the short-run restrictions imposed by the Cholesky decomposition (see Uhlig (2005)).

issues will be employed.

Figure 5 shows state-conditional responses where the VIX is the uncertainty indicator used. Here too real variables exhibit a reaction at their peaks that is approximately two-thirds milder during uncertain times. GDP peak reaction is 46 percent greater during tranquil times.

In order to conclude whether real variables state-conditional responses differ statistically between uncertainty states, a test statistic is shown in figure 6, for both the IQR of sales growth (upper panels) and the VIX case (lower panels)[25]. It provides statistical evidence which lends support to the predictions from theoretical studies like Vavra (2014a) and Baley and Blanco (2015), i.e., that the real economy reacts less to monetary policy shocks during uncertain times. The responses differ in a statistically significant way across the two states. This holds true mostly in the medium run when response distance is maximized. In addition, the statistical difference is higher for the case of IQR of sales growth.

Finally, notice that figures 4 and 5 also document a significant decrease in uncertainty in response to an expansionary monetary policy shock. As anticipated in the Introduction, this result is in line with the results by Bekaert, Hoerova and Lo Duca (2013)[26]. They decompose the VIX in two components, a proxy for risk aversion and one for a pure uncertainty component, and find from a standard VAR analysis that both the uncertainty component and the risk aversion one decrease (the latter more so) in the medium run after an expansionary monetary policy shock[27].

This significant decrease justifies our endogenous modelling of uncertainty and, accordingly, the computations of GIRFs à la Koop et al. (1996). Indeed, if uncertainty were exogenously modeled, and conditionally-linear state-dependent IRFs were computed, this would not allow the conditioning variable (uncertainty) to change over the

[25] It is based on the distribution of the difference between state-conditional responses stemming from the 2000 draws-bootstrap procedure used. In more detail, for each of the 2000 bootstrapped simulated samples we subtract horizon-wise the corresponding simulated state-conditional GIRFs for the tranquil times state from the GIRFs for the uncertain times state. Then the percentiles corresponding to a particular confidence level (e.g. 90 or 68 percent) are reported. Notice that the construction of the test statistic takes into account the correlation between the estimated impulse responses. A similar test is used, among others, by Aastveit, Natvik and Sola (2013) and Caggiano, Castelnuovo and Nodari (2014).

[26] The decrease in uncertainty after the monetary policy shock we find is a very robust result, and one which holds true for any of the robustness checks presented below, including the use of JLN macro and firm-level uncertainty indicators (results available on request).

[27] Intriguingly, Lutz (2014) works with a Factor-Augmented VAR model and finds that uncertainty also decreases after an unconventional monetary policy shock (which, however, is not treated in this paper).

horizon of interest after a monetary policy shock. We would therefore miss the effects that a reduction of uncertainty has on the economy, such as a shrinking of agents' inaction regions and its state-conditional consequences. The importance of endogenizing uncertainty to study the uncertainty-conditional effectiveness of monetary policy shocks is documented and discussed in more depth in our Appendix. There it is shown that uncertainty endogenous modelling has a non-negligible effect on the estimated state-conditional responses once these are compared to the ones obtained when uncertainty is modelled exogenously.

To sum up, our methodology allows for a careful estimation of the empirical responses needed in order to answer to our research question. Our results suggest that monetary policy shocks are less effective during uncertain times, though the quantitative effect is smaller than has been found in previous contributions, such as Aastveit et al. (2013). As detailed in the Introduction, a careful assessment of the real effects of monetary policy shocks is necessary so that the monetary authority could accurately predict the impact of nominal stimulus policies and hence tailor them appropriately.

3.3 Robustness checks

In this section we perturb the baseline specification of our I-VAR model, in several ways, in order to check the robustness of our results in several dimensions: relative to the uncertainty indicators used, the identification of the monetary policy shocks and potential neglected omitted variables.

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, Ludvingson 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[28]. To control for this eventuality we employ the macro and firm-level

[28] This could be the case for the VIX index which Jurado, Ludvingson and Ng (2015) find to be partially predictable. For the exogeneity of VIX to first moment shocks see Bloom (2009) and Caggiano, Castelnuovo and Nodari (2014) .

uncertainty indicators constructed by Jurado, Ludvingson 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, at the root of the macro uncertainty index, uses 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[29].

Uncertainty ordered last. In our baseline analysis we have ordered uncertainty first. This is a common choice in the literature studying the impact of uncertainty shocks, since it allows real variables to react on-impact to uncertainty moves. In our case, it also allows us to identify a monetary policy shock purged by the contemporaneous reaction of the FFR to uncertainty movements. However, when uncertainty is ordered first, our identification through the standard Cholesky decomposition of the variance-covariance matrix implies that uncertainty movements within a quarter are fully explained by uncertainty shocks. This could therefore limit the degree of endogeneity of our uncertainty measure, first and foremost not allowing its contemporaneous reaction to FFR movements. To check whether this eventuality is quantitatively important for our results we order uncertainty last, soon after the FFR.

Inflation expectations. Our baseline analysis has displayed a price puzzle in the response of prices. As detailed in footnote 24 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. This possibility indeed would particularly mine our results to the extent that the same monetary policy shock could be not properly identified. As argued by Sims (1992), the monetary authority when setting its policy rate could have more information about future inflation than what 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, we follow Castelnuovo and Surico (2010) and sharpen the identification of our monetary policy shocks by adding to our VAR, as first-ordered

[29] Both uncertainty indicators were downloaded from the data section in Sydney Ludvigson's webpage (i.e. http://www.econ.nyu.edu/user/ludvigsons/). The macro indicator is currently available up to 2013M6 (we take quarterly averages to pass to quarter frequencies), while the firm-level one is available up to 2011Q2. Both indicators used refer to a forecasting horizon equal to 1 quarter. In order to use the firm-level indicator as conditioning variable we HP-filter it (lambda=1600) to avoid instability problems due to the highly non-stationary features of the series.

variable, a measure of inflation expectations[30].

NBER recession dummy indicator. As seen in the Introduction, several studies (e.g., Weise (1999), Tenreyro and Twaites (2013) and Mumtaz and Surico (2014)) have found that monetary policy shocks are less effective during bad times, defined in terms of economic downturns. In section 3.1 we have shown that our methodology makes it unlikely that our results speak about recessions rather than uncertainty as a deep reason for the effectiveness of policy stimulus. However, one could still argue that economic recessions is an omitted variable from our I-VAR model and that it is partially driving the results obtained. 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 unavoidably 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 (in its lags) to our VAR.

Figure 7 shows the results of all robustness checks. Only GDP, investment and consumption responses are reported[31]. The upper panels display the responses for the tranquil times state while the lower panels those for the uncertain times state. The baseline results turn out to be very robust to all perturbations considered. First, results are confirmed when JLN indicators are used as uncertainty proxies. For the JLN macro uncertainty indicator, intriguingly, investment peak reactions becomes even more distant between the two states. Second, responses remain practically the same for the other sensitivity checks, i.e., when we order uncertainty last, when we add inflation expectations and when we add the NBER recession dummy indicator. Overall, the main results obtained with the baseline specification continue to hold.

4 An alternative methodology: Local Projections and Threshold Autoregressions

We now move to an alternative methodology. We employ a threshold autoregression model from which we extract impulse responses by using Local Projections (see Jordà

[30] 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.

[31] The baseline case is taken to be the IQR of sales growth case. The entire set of results regarding the robustness checks is available upon request.

(2005), Owyang, Ramey and Zubairy (2013))[32]. We do so for two reasons. First, to provide an alternative check on baseline results by using an alternative methodology and, second, to enquire into the possible state-conditional behavior of prices in response to monetary policy shocks. As mentioned in the Introduction, Vavra's (2014a) theoretical predictions point to a bigger reaction (mostly on-impact) of prices during firm-level uncertain times[33]. Coherently, this methodology allows modeled variables to display a (possibly state-dependent) on-impact reaction to monetary policy shocks.

Borrowing from Owyang, Ramey and Zubairy (2013), the model we set up is the following:

$$\begin{aligned} z_{t+h} = I_{t-1} \cdot [\alpha_h^U + \beta_h^U(L)\mathbf{Y}_{t-1} + \pi_h^U \cdot shock_t] \\ + (1 - I_{t-1}) \cdot [\alpha_h^T + \beta_h^T(L)\mathbf{Y}_{t-1} + \pi_h^T \cdot shock_t] \\ + \gamma \cdot linear\ trend + \varepsilon_t \qquad , \ h = 0, 1, \ldots, H \end{aligned} \tag{3}$$

where z_t is either equal to P_t or GDP_t, $\mathbf{Y}_t = [Unc_t, P_t, GDP_t, ffr_t]'$ [34], $shock_t$ is either i) the monetary policy shocks series identified from the baseline I-VAR model or ii) the Romer and Romer's (2004) narratively identified monetary policy shocks series extended up to the end of 2008 by Coibion et al. (2012)[35], L is the number of lags of the polynomials in the lag operator and is set as in the baseline analysis, I_t is a dummy variable taking the value of one when our firm-level uncertainty proxy is above a threshold and hence allowing us to discriminate between a firm-level uncertain times state and a tranquil times one. The threshold is set to the 66th percentile of uncertainty,

[32] The pros and cons of this alternative methodology for our purposes are analyzed in section 2.1 and 2.2.

[33] In the most realistic, calibrated version of his model, he finds the price level reacts as much as 36% more on-impact during firm-level uncertain times than tranquil times.

[34] We here focus on a subset of our variables in order to permit a more precise estimation of the empirical responses given the two-regime estimation approach used in this section. Notice that when using Local Projections the variables in $\mathbf{Y}$ serve merely as controls and not to compute the dynamics or to identify orthogonal shocks (see Auerbach and Gorodnichenko (2013)).

[35] i) The first shocks series is the one obtained when uncertainty is proxied by the IQR of sales growth in our baseline I-VAR model (results are anyway robust to the use of the shocks series obtained when uncertainty is proxied by the VIX). ii) The second shocks series is constructed by Romer and Romer (2004) by the changes in the FFR around FOMC meetings that are orthogonal to the real time Fed's information set, which includes the current FFR level as well as previous quarter, contemporaneous and two quarters ahead Greenbook forecasts about the level and changes for inflation, real output growth and unemployment. Then, on the basis of these residuals, a monthly series for the shocks is obtained (for more details refer to Romer and Romer (2004)). We obtain a quarterly measure of the shock by taking quarterly sums of Coibion et al. (2012) updated shocks series (hence obtaining a series similar to the one in figure 1.a in Romer and Romer (2004)). The resulting series is used starting from 1971Q3 (to be consistent with the starting date of our baseline monetary policy shocks series).

so as to have one-third of the observations in the top state (as in Owyang, Ramey and Zubairy (2013))[36]. Finally π_h^U and π_h^T are our coefficients of interest: they define the impulse response of GDP and P to the monetary policy shock in the uncertain and tranquil times states respectively, i.e., they directly provide the average response of the economy according to the uncertainty state in which the shock initially hit and the quarters h passed.

Figure 8 shows the results in the case of a one percent expansionary monetary policy shock as identified by our baseline I-VAR. Linear responses, state-conditional responses and a robust t-statistic of the null hypothesis that $\pi_h^U - \pi_h^T = 0$ are reported[37]. Starting from linear responses, notice that the GDP response is hump-shaped and consistent with our baseline results, and, further, that the price level starts to rise about 2 years after the shock. Unfortunately, state-conditional responses are less precisely estimated and feature a more erratic behavior. This is likely due to the loss of degrees of freedom for the two-regimes estimation approach used, of which the uncertain time state suffers most because of having the fewer observations. This provides empirical support for the superiority of our baseline empirical methodology, i.e., the GIRFs – Interacted VARs combination, in answering our primary research question. This issue notwithstanding, results prove to be useful in any case for the two aims of this section. First, the GDP t-stat suggests that, for forecast horizons very similar to the ones found in the baseline analysis, GDP reacts significantly less to monetary shocks during uncertain times. Second, the prices t-stat provides some statistical evidence (at the 68% confidence level) that, consistently with Vavra's (2014a) predictions, prices might increase more on-impact (i.e., in the same quarter as the shock) during uncertain times.

Figure 9 considers the case of a one percent monetary shock as identified by Romer and Romer (2004). State-conditional responses are even less precisely estimated than before. As before, this is more severe for the uncertain times state where GDP barely move significantly. Interestingly though, the t-statistic allows us to conclude again that GDP reacts less during uncertain times, again for forecast horizons consistent with those found in the baseline analysis (there are around two years of statistical difference when the 68 percent confidence band is used). Prices are found to increase more on-impact

[36] For the IQR of sales growth this threshold value allows the monetary policy shocks outliers, mostly concentrated during the mid-70s' and the early 80s', to be distributed fairly well across the two uncertainty states, which is necessary in order to get reliable estimates for the IRFs. A figure showing this is available on request. Results are robust to reasonable changes in the threshold.

[37] It tests whether empirical responses differ across states. A similar t-stat test is used by Tenreyro and Thwaites (2013).

during uncertain times and to remain statistically higher than during tranquil times for two-to-three quarters. There is also some statistical evidence of higher prices between two and three years after the shock, but this seems too tiny and isolated to conclude that prices remains higher in the medium run[38]. Further research is needed along this line.

In summary, consistently with Vavra's (2014a) and Baley and Blanco's (2015) theoretical predictions and Vavra's (2014b) empirical evidence, prices appear to react more to nominal stimulus during firm-level uncertain times. Therefore, as suggested by Vavra's micro-founded studies, this could be a channel which (along with others such as real option effects and precautionary savings) is likely to play a non-negligible role in the transmission mechanism of monetary policy shocks in high uncertainty times.

5 Conclusion

While the relevance of uncertainty shocks as a factor influencing economic activity has been studied by a number of recent pieces of empirical research, how important it is as a factor conditionally influencing the effectiveness of monetary policy shocks has still received a limited empirical ascertainment. This paper asks this question by using a non-linear model which allows us to study the interaction between uncertainty and the monetary policy stance and in particular all the feedback one variable has on the other. We find that monetary policy unexpected stimuli have real effects around two-thirds smaller during uncertain times than during tranquil times and have mitigating power on uncertainty. The results also support the fact that (at least part of) the reduced effectiveness under high uncertainty can be due to more reactive prices, as theorized by Vavra (2014a).

Our findings have implications for policy, mainly by offering support for more aggressive policies during uncertain times. They also support some suggestions for theoretical modelling, in particular the development of non-linear micro-founded models where uncertainty can play a state-conditional role and possibly where, instead of being a completely exogenous process, it could react to monetary policy stimuli. The structural

[38] The same conclusions can be drawn when we employ the PPI for finished goods, i.e. the baseline price indicator used by Romer and Romer (2004) in their analysis. If, however, we use the CPI for all urban consumers, we have less statistical evidence of a larger on-impact reaction of prices, but larger evidence (at the 90% confidence level) of a higher price level in the medium run (figure available on request).

assessment of this claim and the identification of the possible channels through which it can happen is left to future research.

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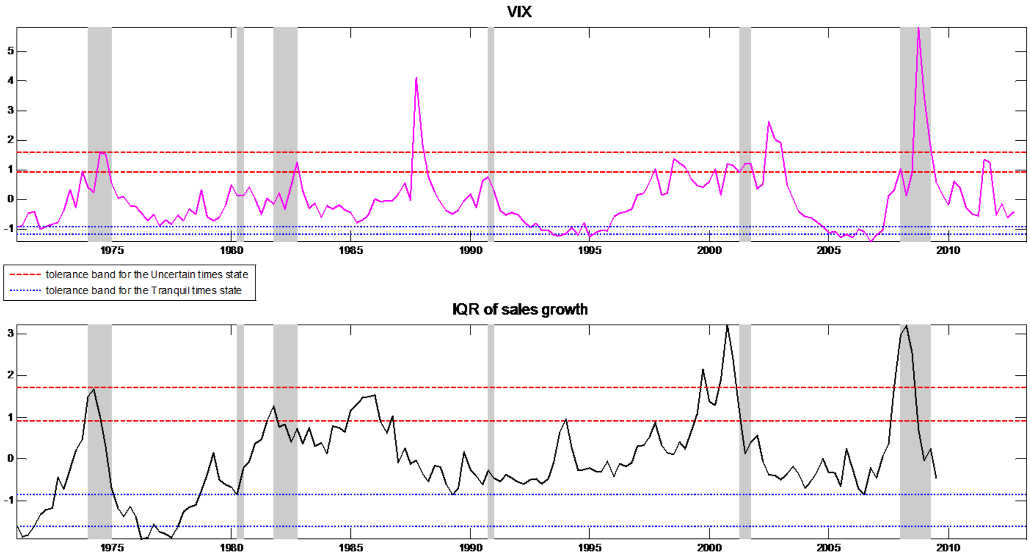

Figure 1: **Uncertainty indicators: uncertain vs. tranquil times**. Magenta solid line: VIX (normalized, sample: 1971Q1-2012Q4). Black solid line: IQR of sales growth (normalized, sample: 1971Q1-2009Q3). Grey areas: NBER recessionary quarters. The red dotted band identifies the quarters relevant for the definition of the uncertain times state. The blue dotted band identifies the quarters relevant for the definition of the tranquil times state.

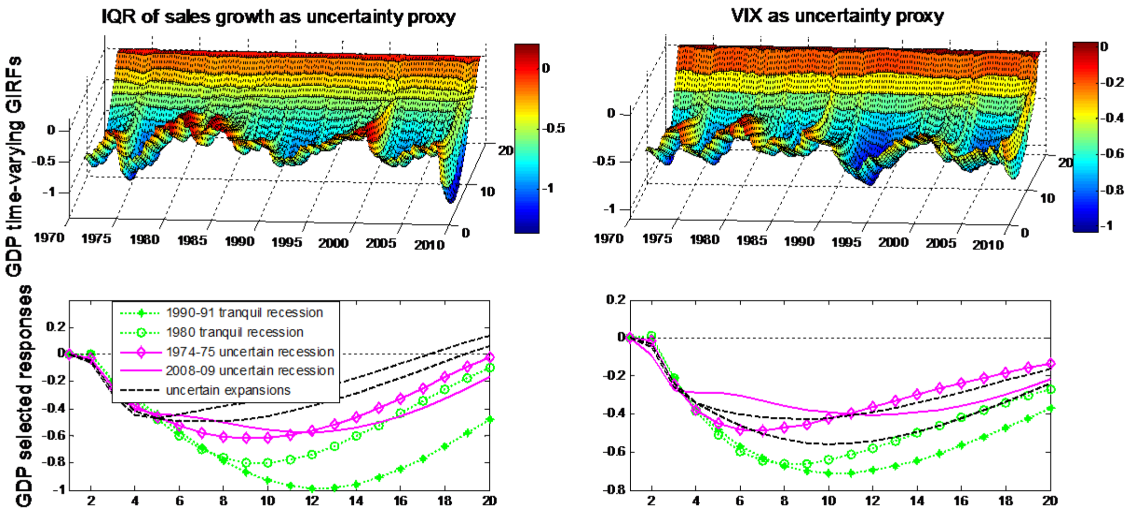

Figure 2: **Time-varying and selected GIRFs for GDP(shock: one percent unexpected increase in the FFR)** . Reported GIRFs: 1971Q3-2009Q3. Left column: IQR of sales growth as uncertainty proxy. Right column: VIX as uncertainty proxy. Upper row: temporal evolution of the point estimated GIRFs. Colors ranging from red (GIRFs peak values) to blue (GIRFs trough values). Lower row: selected quarter-specific GIRFs. Green dotted GIRFs refer to recessions characterized by low levels of uncertainty (1980 and 1990-91 recessions). Magenta solid GIRFs refer to recessions characterized by high levels of uncertainty (1974-75 and 2008-2009 recessions). Black dashed GIRFs refer to expansions characterized by high levels of uncertainty.

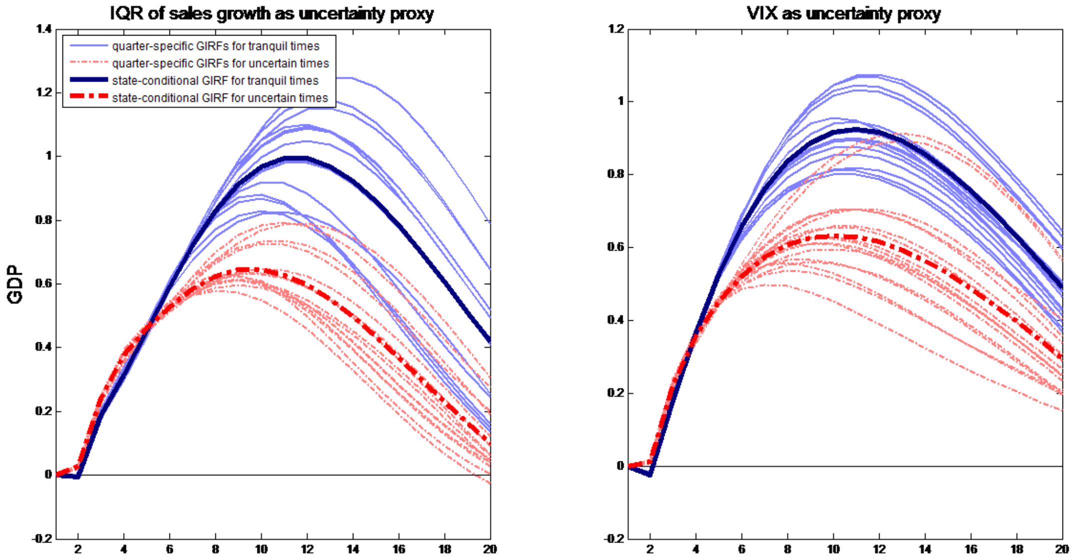

Figure 3: **GDP responses defining the uncertain and tranquil times states (shock: one percent unexpected decrease in the FFR)**. Left column: IQR of sales growth as uncertainty proxy. Right column: VIX as uncertainty proxy. Tiny blue solid lines: quarter-specific GIRFs defining the tranquil times state. Bold solid blue line: state-conditional GIRF for the tranquil times state. Tiny red dotted lines: quarter-specific GIRFs defining the uncertain times state. Bold red dotted line: state-conditional GIRF for the uncertain times state.

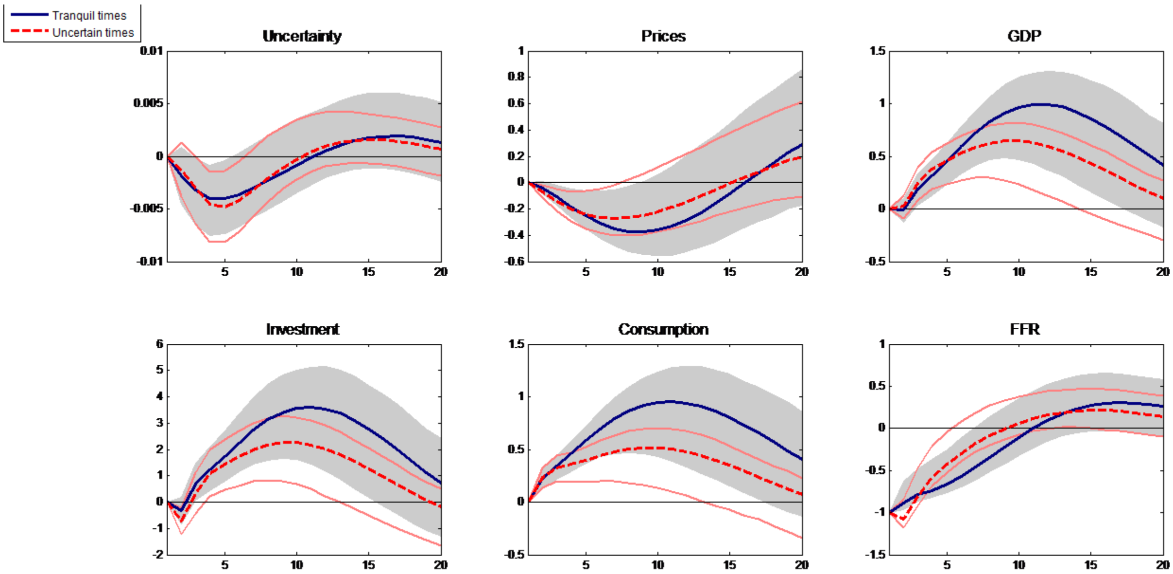

Figure 4: **Uncertain vs. tranquil times state-conditional GIRFs (uncertainty proxy: IQR of sales growth; shock: one percent unexpected decrease in the FFR)**. Blue solid lines and grey areas: point estimates and 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times state. Red solid and dotted lines: point estimates and 90% bootstrapped confidence bands for the GIRFs conditional to a uncertain times state.

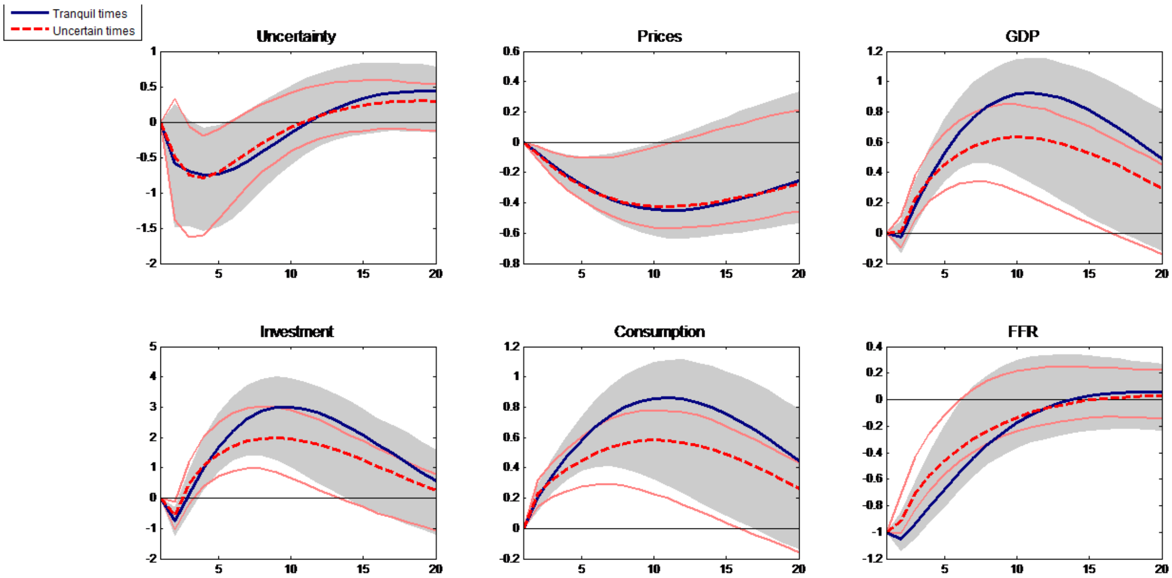

Figure 5: **Uncertain vs. tranquil times state-conditional GIRFs (uncertainty proxy: VIX; shock: one percent unexpected decrease in the FFR)**. Blue solid lines and grey areas: point estimates and 90% bootstrapped confidence bands for the GIRFs conditional to a tranquil times state. Red solid and dotted lines: point estimates and 90% bootstrapped confidence bands for the GIRFs conditional to a uncertain times state.

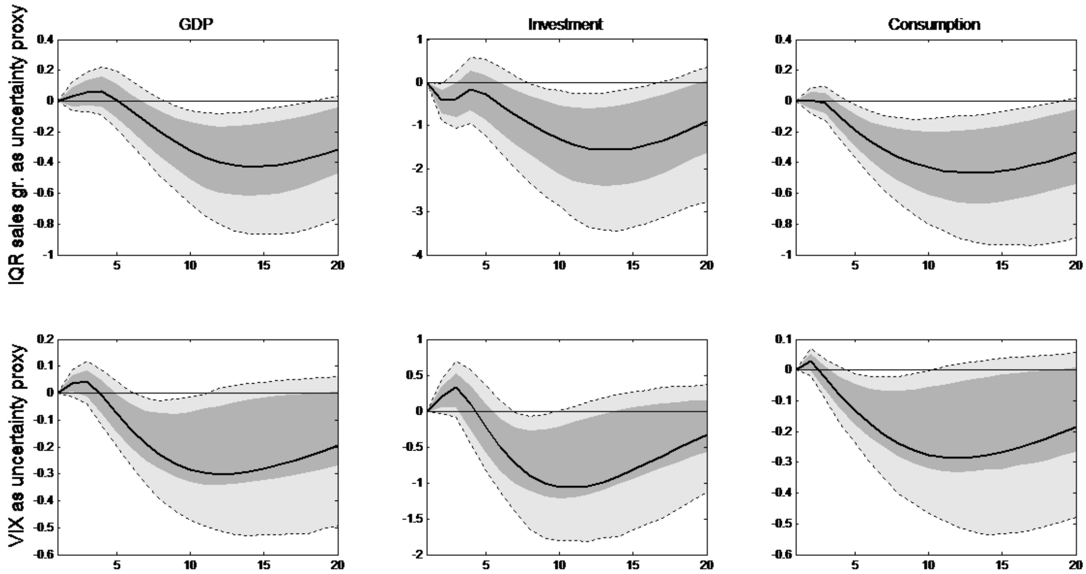

Figure 6: **Difference of state-conditional GIRFs across uncertainty times**. Upper row: IQR of sales growth as uncertainty proxy. Lower row: VIX as uncertainty proxy. Solid black lines: difference between point estimated state-conditional GIRFs (uncertain times conditional GIRF minus tranquil times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

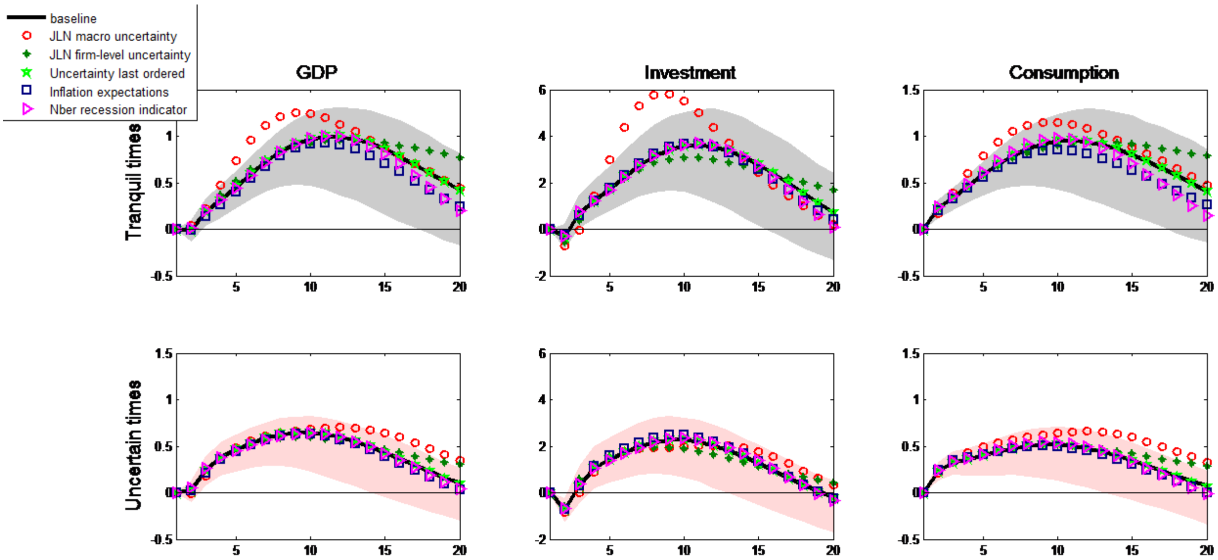

Figure 7: **Robustness check: uncertain vs. tranquil times state-conditional GIRFs (shock: one percent unexpected decrease in the FFR)**. Upper row: GIRFs for the tranquil times state for several perturbations of the baseline I-VAR. Lower row: GIRFs for the uncertain times state for several perturbations of the baseline I-VAR. Baseline GIRFs: IQR of sales growth as uncertainty proxy.

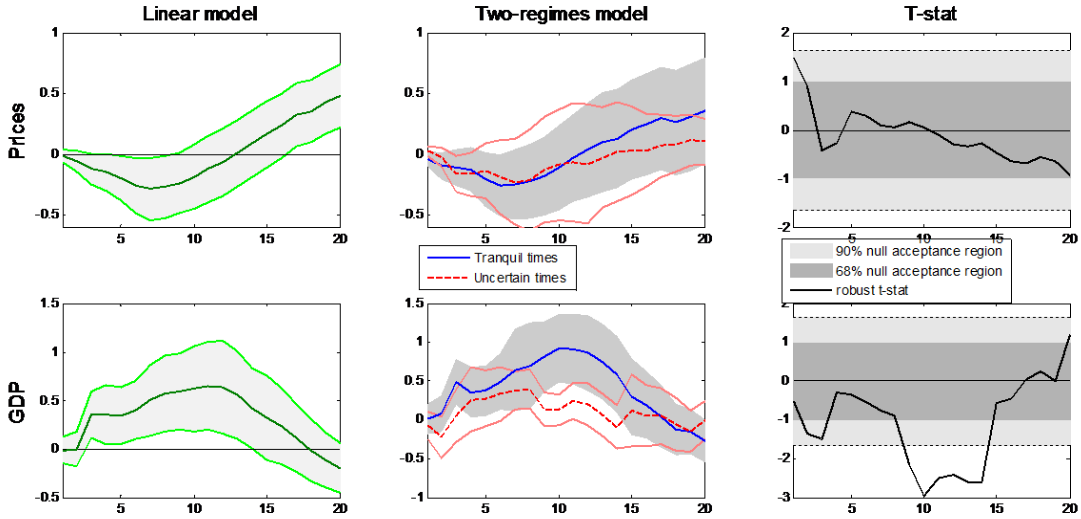

Figure 8: **IRFs by Local Projections and t-stat for the difference across uncertain vs. tranquil times (shock: one percent decrease in the monetary policy shock identified from the baseline I-VAR model with the IQR of sales growth)**. Left column: IRFs (dark green lines) and asymptotic confidence bands (green lines) for the linear model (sample: 1971Q3-2009Q3). Central column: IRFs and asymptotic confidence bands for the tranquil and uncertain times states (respectively given by the blue solid lines and grey areas and by red dashed and solid lines). 90% asymptotic confidence bands are computed by employing Newey-West standard errors with lag correction selected to increase with the horizon hof the IRFs being considered (as in Jordà (2005) and Owyang, Ramey and Zubairy (2013)). Right column: robust (Newey-West corrected) t-stat for the difference of the IRFs across uncertain and tranquil times (solid black line) along with 68% and 90% two-sided acceptance regions for the null hypothesis of no difference (respectively given by the interior dark grey and exterior light grey areas).

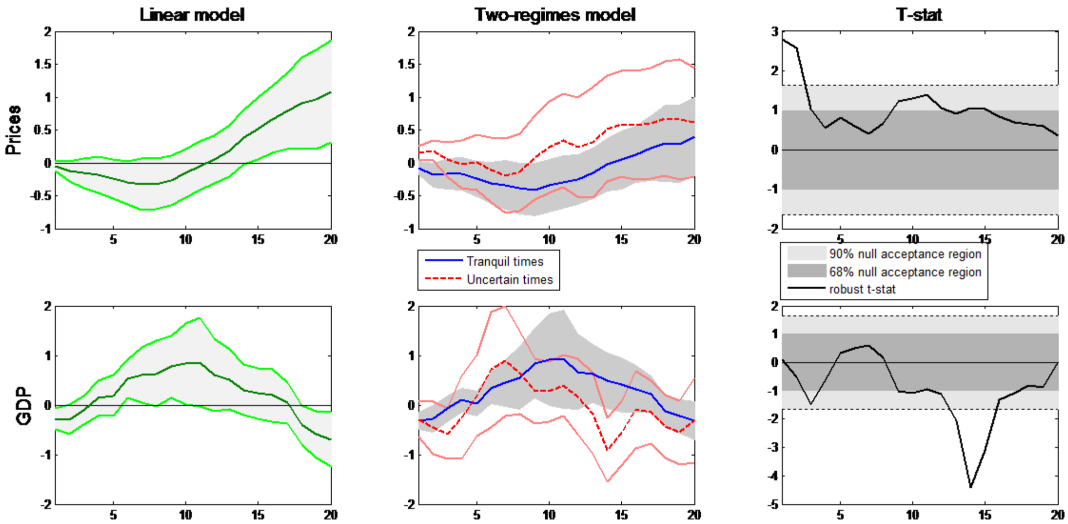

Figure 9: **IRFs by Local Projections and t-stat for the difference across uncertain vs. tranquil times (shock: one percent decrease in the Romer and Romer's (2004) narratively identified monetary policy shock extended by Coibion et al. (2012))**. Left column: IRFs (dark green lines) and asymptotic confidence bands (green lines) for the linear model (sample: 1971Q3-2008Q4). Central column: IRFs and asymptotic confidence bands for the tranquil and uncertain times states (respectively given by the blue solid lines and grey areas and by red dashed and solid lines). 90% asymptotic confidence bands are computed by employing Newey-West standard errors with lag correction selected to increase with the horizon h of the IRFs being considered (as in Jordà (2005) and Owyang, Ramey and Zubairy (2013)). Right column: robust (Newey-West corrected) t-stat for the difference of the IRFs across uncertain and tranquil times (black solid line) along with 68% and 90% two-sided acceptance regions for the null hypothesis of no difference (respectively given by the interior dark grey and exterior light grey areas).

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

Modelling the endogenous reaction of uncertainty matters

In this section, on the basis of the significant decrease in uncertainty in response to a monetary policy shock found in the main analysis, we explore the reasons why modelling the endogenous response of uncertainty to monetary shocks is important in order to properly address our research question.

Figure A1 makes a direct comparison between the point estimates of several kinds of responses that can be obtained for our modeled variables: our baseline state-conditional GIRFs, the IRFs stemming from the nested linear model and the IRFs obtained when uncertainty, which serves as our conditioning variable, is not modeled endogenously (as in Aastveit, Natvik and Sola (2013))[39]. Two comments are in order. First, linear responses are within our state-conditional responses. Hence standard VARs are likely to capture the total sample averaged effects of a monetary policy shock, which, however, might underestimate the impact of monetary policy shocks in tranquil times and, vice versa, overestimate it in uncertain times. Second, state-conditional empirical responses get more distant across uncertainty states when uncertainty is kept fixed in the computation of empirical (conditionally-linear) responses rather than when its endogenous reaction is considered in computing (fully non-linear) responses. Interestingly, in the former case, our results collapse to those of Aastveit, Natvik and Sola's (2013), which find that real variables react from two to five times more during tranquil times than during uncertain times. For example, referring to the VIX case (for comparison purposes with Aastveit, Natvik and Sola (2013), who also use it), if we look, for example,

[39] All the VARs for which responses are reported are estimated on a similar number of lags and sample period (equal to our baseline ones) for comparison purposes. Price responses are not reported. In order to obtain the (conditionally-linear) responses when uncertainty is not modeled endogenously, we estimate the following I-VAR model comparable to (1): $\mathbf{Y}_t = \alpha + \gamma \cdot linear\ trend + \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \sum_{j=1}^{L} \mathbf{B}_j unc_{t-j} + \left[\sum_{j=1}^{L} \mathbf{c}_j unc_{t-j} \times ffr_{t-j} \right] + \varepsilon_t$, where this time $\mathbf{Y}$ does not include unc. Then, in order to obtain responses, uncertainty is fixed either to its 9th decile value or to its 1st decile one (a choice similar to Aastveit, Natvik and Sola (2013)) and the conditionally-linear system is iterated on (a similar iterated procedure to get IRFs from a linear VAR is illustrated in Hamilton (1994, p. 319 and around). Notice that this model is fully linear conditional to an uncertainty value and hence, unlike with our baseline I-VAR, the starting conditions do not matter.

at consumption, for which it is particularly evident, we find, similarly to them, that it reacts around three times more during tranquil times. This is very different from the around 50% suggested by our baseline results.

The results above could be interpreted as the interaction between two mechanisms at work which cannot be captured by conditionally-linear IRFs. On the one hand, a given uncertainty reduction after the shock could trigger ceteris paribus a bigger reaction of real variables in each state, therefore causing an unenvisaged (for a conditional linear model) amplification of the real effects of the shock. On the other hand, though, the interest rate could display a state-dependent reaction to the uncertainty move which also needs to be taken into account. In principle, we may expect, firstly, the amplification effect to be bigger during uncertain times since agents inaction regions are wider[40], and secondly that its potential in driving higher future inflation may raise more concerns in the monetary authority during tranquil times (mostly associated with good times). Importantly, our GIRFs allow us to capture a similar type of state-dependent feedback effect across uncertainty and the interest rate. Figure A1 confirms intuitions mentioned previously. First, the reaction of real variables to the shock is overall greater during uncertain times when uncertainty is endogenously modeled, consistently with the fact that the interest rate response does not differ particularly across the two different modelling cases. Second, for most real variables their reaction is instead less during tranquil times when uncertainty is endogenously modeled, consistently with the somewhat less persistent response of the FFR in this modelling case.

Computation of the Generalized Impulse Response Functions

Here it is presented the algorithm employed to compute the GIRFs and their confidence intervals. It follows Koop, Pesaran and Potter (1996), with the modification of considering an orthogonal structural shock, as in Kilian and Vigfusson (2011)[41]. Before

[40] Think of a model in the spirit of Bloom (2009) with both irreversibilities in hiring and investment decisions and positive productivity growth and labor attrition. In this case, in an initial situation of heightened uncertainty (and hence wide inaction regions), a monetary policy shock that reduced uncertainty would let firms hire and invest at a faster rate in the aftermath of the policy shock than would be the case if the same reduction in uncertainty occurred in the presence of an initial lower level of uncertainty.

[41] A similar algorithm is used by Caggiano, Castelnuovo and Pellegrino (2015) to compute GIRFs for their I-VAR model. Also Fazzari et al. (2015) use a similar approach to obtain GIRFs for a Threshold VAR model, although they do not use our bootstrap procedure as they use Bayesian techniques to

of that, notice that 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 et al. (1996) – as:

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

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

1. We 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 $\{\varepsilon_{t+h}\}^s$, $h = 0, 1, ..H = 19$, 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} , on the estimated model (1)-(2) and using $\{\varepsilon_{t+h}\}^s$ 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}, on the estimated model (1)-(2) and using $\{\varepsilon_{t+h}\}^s$ simulate the evolution of the vector of endogenous variables over the following H periods when a structural shock δ_t is imposed to ε^s_t. In particular, we Cholesky-decompose $\widehat{\mathbf{\Omega}} = \mathbf{CC}\prime$, where $\mathbf{C}$ is a lower-triangular matrix. Then, we recover the structural innovation associated to ε^s_t by $\mathbf{u}^s_t = \mathbf{C}^{-1}\varepsilon^s_t$ and add a quantity $\delta < 0$ to the scalar element of $\mathbf{u}^s_t$ that refers to the FFR, i.e. $u^s_{t,ffr}$. We then move again to the residual associated with the structural shock $\varepsilon^{s,\delta}_t = \mathbf{C}\mathbf{u}^{s,\delta}_t$ to proceed with simulations as in point 3. Call the resulting path $\mathbf{Y}^{s,\delta}_{t+h}$;

5. compute the difference between the previous two paths for each horizon and for each variable, i.e. $\mathbf{Y}^{s,\delta}_{t+h} - \mathbf{Y}^s_{t+h}$ for $h = 0, 1 \ldots, H$;

obtain confidence bands.

6. repeat steps 2-5 for a number of $S = 500$ different extractions for the residuals and then take the average across s. Notice that in this computation the starting quarter $t-1$ does not change. In this way we obtain a consistent point estimate of the GIRF for each given starting quarter in our sample , i.e. $\widehat{GIRF}_{Y,t}(\delta_t, \varpi_{t-1}) = \left\{\widehat{E}\left[\mathbf{Y}_{t+h} \mid \delta_t, \varpi_{t-1}\right] - \widehat{E}\left[\mathbf{Y}_{t+h} \mid \varpi_{t-1}\right]\right\}_{h=0}^{19}$. If a given initial condition ϖ_{t-1} brings an explosive response (namely if this is explosive for most of the sequences of residuals drawn $\{\varepsilon_{t+h}\}^s$, in the sense that the response of the variable shocked diverges instead than reverting to zero) is discarded and not considered for state-conditional responses at the next step[42];

7. these history-dependent GIRFs are then averaged over a particular subset of initial conditions of interest to produce our state-dependent GIRFs. To do so, 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. In this way we obtain our $\widehat{GIRF}_{Y,t}(\delta_t, tranquil\ times)$ and $\widehat{GIRF}_{Y,t}(\delta_t, uncertain\ times)$;

8. confidence bands around the point estimates obtained in point 7 are computed through bootstrap[43]. 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 1-7 . In implementing this procedure this time we have that starting conditions and VCV matrix in the computation depend on the particular dataset r used, i.e. ϖ^r_{t-1} and $\widehat{\mathbf{\Omega}}^r$. Of the resulting distribution of state-conditional GIRFs the 5th and 95th percentiles are taken to construct the confidence bands.

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

[43] 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) (see their note 23). Our code repeats the explosive artificial draws to be sure that exactly 2000 draws are used. In our simulations, this happens a negligible fraction of times.

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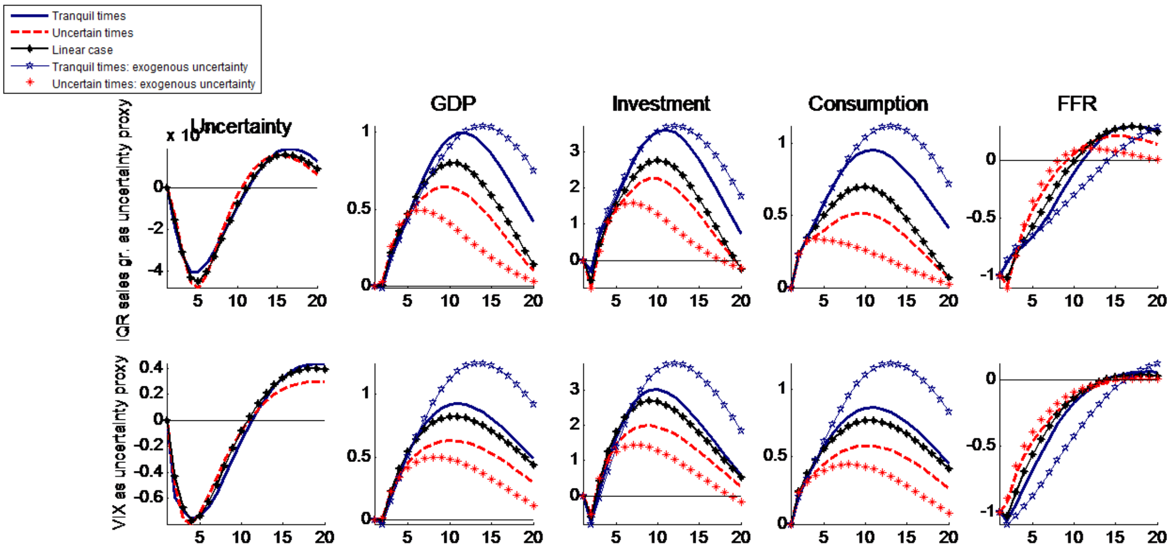

Figure A1: **Comparison among several state-conditional GIRFs: baseline, linear and exogenous uncertainty cases (shock: one percent unexpected decrease in the FFR)**. Upper row: IQR of sales growth as uncertainty proxy. Lower row: VIX as uncertainty proxy. Blue solid and red dashed lines: baseline GIRFs conditional to a tranquil and uncertain times state respectively. Black diamond line: point estimated IRFs from the nested linear VAR model. Starred blue lines and starred red points: point estimated GIRFs conditional respectively to a Tranquil and Uncertain times state respectively for the case uncertainty is not endogenously modeled.