Understanding Fluctuations in Uncertainty: A New Keynesian Interpretation*

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Preliminary

Abstract

Is monetary policy less effective during periods characterized by high uncertainty? To tackle this question, we estimate a Threshold VAR model designed to isolate "uncertain" and "tranquil" times and compute state-dependent impulse responses to a monetary policy shock. This empirical framework points to a lower effectiveness of monetary policy shocks during uncertain times. Then, we use the nonlinear VAR as auxiliary model to estimate the state-of-the-art medium scale DSGE model proposed by Altig et al. (2011) with a minimum-distance approach. We find this model to be remarkably able to match our VAR impulse responses, particularly in tranquil times. This performance is driven by very different estimated values for some key-structural parameters in the two states. A higher slope of the new-Keynesian Phillips curve, a higher cost of the variation in capital utilization, and a lower degree of habit formation in consumption are shown to be behind the model ability to predict the lower real effects of monetary policy shocks in periods of high uncertainty.

Keywords: Monetary policy shocks, uncertainty, Threshold VAR, medium scale DSGE framework, minimum-distance estimation.

JEL codes: C22, E32, E52.

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1 Introduction

Does uncertainty affect the transmission mechanism of monetary policy shocks? Some recent theoretical studies suggest that its influence on the economy can be pervasive and operating through several channels[1]. On the more empirical side, although some recent analyses argue that uncertainty importantly affects the effectiveness of monetary policy shocks, no study has so far disentangled empirically the sources of its influence on aggregate economic behavior and ascertained the relative importance of these sources in affecting the propagation mechanism of monetary shocks. To this end, this paper proposes a *regime-dependent* structural estimation of a workhorse New-Keynesian model, namely the one by Altig, Christiano, Eichenbaum and Lindè (ACEL) (2011), an extended version of Christiano, Eichenbaum and Evans's (CEE) (2005) well known model[2]. The idea is to capture the influence of uncertainty on the overall economy by means of an empirical methodology which is flexible enough to capture a different economic behavior and possibly unmodelled mechanisms through regime-specific estimates of structural parameters[3].

Our aim is threefold. First, re-assess empirically with a medium-scale non-linear VAR what has been found by some recent empirical studies as regards a less effective monetary policy during uncertain times (see Aastveit, Natvik and Sola (2013), Caggiano, Castelnuovo and Nodari (2015), Pellegrino (2015)). Our medium-scale VAR can handle more information than small-scale VARs with the purpose of digging more on the way the transmission mechanism of monetary shocks is influenced by uncertainty. Second, evaluate whether a workhorse New Keynesian model can fit reasonably well the state-conditional evidence found and tell a sensible story for it (through parameters instabilities). This is important given that, even if these models have proven effective in fitting the "normal" dynamics of the economics, it is not said a priori that they can explain equally well its dynamics during uncertain phases. Third, working with an estimated model allows us to understand which, if any, workhorse theoretical construct seems most able to explain the different transmission mechanism between uncertain and tranquil times. A structural model allows us to perform sensible counterfactuals

[1]The reader is referred below for references.

[2]Several papers in the literature use a model based on, or similar to, ACEL's one. Some examples are Christiano, Eichenbaum and Vigfusson (2007), DiCecio (2009), Christiano, Eichenbaum and Rebelo (2011), Christiano, Trabandt, and Walentin (2011).

[3]For some arguments on the reasons why instabilities in parameters may be thought as capturing an omitted mechanism see Fernandez-Villaverde and Rubio-Ramirez (2008) and Schorfheide (2008). Below more on this.

exercises which are helpful for such an investigation.

Answering these research questions would be important from a policy standpoint. It would allow us to assess the degree of practical importance of instabilities in the structural parameters of models typically employed to conduct policy analysis in central banks. In addition, it would allow us to investigate the way in which these structural instabilities depend on the state of the economy. This could be a first step in designing state-conditional policies aimed to deal optimally with such instabilities.

On the basis of the theoretical literature, several explanations are thought to be able to influence the effectiveness of monetary policy or policy stimuli during uncertain times. One advocates the real option effect originating in the presence of fixed costs or partial irreversibilities[4]. Another one has to do with the state-dependent firm-price setting behavior in presence of either menu costs of changing prices or information frictions[5]. In addition, higher precautionary savings during uncertain times could also play a role (see Bloom's survey (2014) and references therein). Uncertainty could hence influence aggregate price flexibility, as well as consumers' and firms' behavior, so that to play a potential important role in the core channels of policy transmission[6]. Notwithstanding a similar interest in the literature, we are not aware of previous attempts that enquire the influence of uncertainty in the monetary policy transmission mechanism by employing New-Keynesian models or that assess their ability to fit uncertainty-conditional evidence[7]. One exception is Bachmann, Born, Elstner and Grimme (2013) who inves-

[4]See Bloom's (2009) and Bloom et al.'s (2014) respectively partial and general equilibrium real models featuring time-varying volatility, non-convex adjustment costs in both capital and labor and firm-level idiosyncratic shocks. They find that during phases of heightened uncertainty firms' inaction regions expand as the real-option value of waiting increases with uncertainty. As a result the economy will be particularly unresponsive to stimulus policies (for an exercize showing this see section 7 in Bloom et al. (2014)).

[5]See Vavra's (2014a) and Baley and Blanco's (2015) price-setting calibrated general equilibrium menu cost models. For example, Vavra's (2014a) model suggests that greater uncertainty induces firms to change prices more frequently, hence lowering the real effects of monetary shocks . In the most realistically calibrated version of his model, he 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. In the same model, the price level reacts 36% more on impact at the 90th percentile.

[6]Boivin, Kiley and Mishkin (2010) review the channels through which monetary policy operates in a number of macroeconometric models, including DSGE models. They name the channels mentioned in the text as the core channels of policy transmission or neoclassical channels, where price stickiness, consumers' IES and firms' Tobin's q are the key ingredients. Notice that our standard model instead is not allowed to capture non-neoclassical channels, such as credit-based channels, whose analysis is left to future research.

[7]Instead, New Keynesian models have typically been used to study the impact of uncertainty shocks on the economy, something which require a III-order approximated solution of the model. A non exhaustive list of the channels through which uncertainty shocks may propagate throughout the economy includes precautionary behavior (Basu and Bundick (2014)), contractionary bias at the zero lower

tigate whether uncertainty can reduce the effectiveness of monetary policy through a greater frequency of price adjustments. They set up a small-scale New Keynesian business cycle model as in Galì (2008), in which they capture the change in the frequency of price adjustments via a one-off change in the Calvo parameter, calibrated on the basis of their microeconomic analysis. Their results suggest that uncertainty influences the real effects of monetary policy shocks only to a negligible extent. Our study is linked to theirs in the intent, but differs methodologically along a number of dimensions. First, we permit uncertainty to influence many parameters regarding the structure of the economy besides the Calvo parameter. Second, we adopt a medium-scale NK model able to generate an hump-shaped response of real variables and an inertial response of inflation to the monetary policy shock. Third, we estimate the DSGE model employed, with the aim of matching the different dynamic patterns in the data during uncertain and tranquil times as suggested by an unrestricted VAR model[8].

Another study assessing empirically the relevance of uncertainty for policy trade-offs is Vavra (2014b). He estimates a state-dependent New Keynesian Phillips curve à la Galì and Gertler (1999) and shows that its slope its increasing in uncertainty, particularly with microeconomic uncertainty. He also finds that when his estimation is interpreted structurally through the lens of the Calvo NK model, it implies an irrealistically large difference of the frequency of price adjustment between uncertain and tranquil times (something required in order to match the variation in aggregate price flexibility). He therefore argues that models where uncertainty is just allowed to affect aggregate price flexibility through its affect on frequency are likely to provide a lower bound on the actual importance of uncertainty in the data. Importantly, our methodology overcomes these issues. Firstly, and again, we allow uncertainty to play a role on the structure of the economy not just through its influence on aggregate price flexibility and pricing decisions because this would be just one channel. Secondly, the firm-specific capital version of the ACEL model, i.e., one of the two observationally equivalent versions nested in the ACEL model (the other one being the homogenous capital version), allows us to break the tight link, present in standard NK models, between aggregate price flexibility and the frequency of adjustment. In particular, given the frequency of price changes, the aggregate price flexibility is endogenous in this version of the model and

bound (Basu and Bundick (2015)), credit frictions (Cesa Bianchi and Fernandez-Corugedo (2014)) and upward pricing bias leading to higher markups (Born and Pfeifer (2014) and Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015).

[8] VARs are the type of models typically employed to uncover the impact of monetary policy shocks (Christiano, Eichenbaum and Evans (1999)).

is influenced by several parameters related to the structure of the economy.

Our econometric strategy hinges on a non-linear VAR model on the empirical side, and on a regime-dependent DSGE minimum distance (MD) estimator on the more structural side. More specifically, we employ a two-regimes Threshold VAR (TVAR) model with the aim of identifying a high uncertainty regime and a tranquil times regime[9]. On the basis of the TVAR regime-dependent responses, then, we, for each regime, estimate the parameters of the model to match as closely as possible the formers with model-based responses. These regime-dependent parameter estimates will inform us on the structure of the economy in case the latter stays in a particular regime.

To the best of our knowledge, this work is the first one employing such a econometric strategy. Interestingly, however, it nests another strategy employed in the literature, i.e. the widely adopted DSGE estimation based on two different sub-sample periods (see, among others, Boivin and Giannoni (2006), who document a break date in their standard VAR model and investigate the effectiveness of monetary policy shocks in two different samples, i.e. the pre- and post-1980 periods, through a impulse response matching procedure). A structural break VAR is just a TVAR where the threshold variable chosen is time. Our TVAR instead uses an uncertainty proxy as threshold variable (i.e. Jurado, Ludvingson and Ng (2015) macroeconomic uncertainty indicator). Our strategy is also linked to other related recent approaches that estimate DSGE models by allowing for parameters instabilities. Most closely related to our approach, Hofmann, Peersman and Straub (2012) and Giraitis, Kapetanios, Theodoris and Yates (2014) estimate a New Keynesian DSGE model on the basis of a time varying parameter (TVP) VAR via a impulse response matching procedure[10]. The first study estimates the DSGE model on the basis of three selected IRFs that for the authors represent the three regimes they want to investigate (i.e., the period before the start of the "Great Inflation", the "Great Inflation" and the Volcker–Greenspan era), whereas the second study estimates the DSGE in a time-varying fashion (i.e. for each given response of their TVP VAR in their sample) and hence obtain a time-varying estimate of each of the structural parameters of the model. My strategy differs from these studies inasmuch it is based just on two regimes (returning abrupt changes in parameters), which are though identified and justified on the basis of the data. Another related data-driven estimation approach is the one recently proposed by Bacchiocchi, Castelnuovo and Fanelli (2014),

[9] For a recent review of Threshold VAR models see Tong (2011).

[10] Giraitis et al. (2014) use indirect inference (rather than direct inference) in order to estimate Smets and Wouters's (2007) model.

who employ an impulse response matching approach to estimate a NK model on the basis of the responses obtained through a novel non-recursive identification scheme based on two different heteroskedasticity regimes detected in the data.

The first study we are aware of that estimates a NK DSGE model allowing for drifting parameters is the one by Fernandez-Villaverde and Rubio-Ramirez (2008). They allow model parameters to drift according to a AR(1) in a model where agents are aware about drifts. Their model is approximated with second-order perturbation techniques and estimated by means of a particle-filtering algorithm, which is though particularly computationally intensive to allow all parameters to vary at the same time. They therefore allow parameters to vary a group at a time, and focus on the two groups of policy parameters, and wage and price rigidities parameters. Less closely related to my approach are the studies estimating a Markow switching DSGE model (see Liu, Waggoner, and Zha (2011), Bianchi (2013), Maih (2015), among others). Differently from these approaches, my approach assumes non-communicant regimes, it does not consider a specific parametric form of time variation for parameters, and it is not computationally burdensome so that to allow all relevant parameters to change across regimes (see Cogley (2008) for the importance of allowing for this) . Canova (2009), Canova and Ferroni (2011) and Castelnuovo (2012) reach time-varying parameters estimates for a NK DSGE model by means of rolling samples and full information Bayesian methods. Differently, we adopt limited information classical methods and use only one sample period for estimation. All-in-one, we believe that the novelty of our approach consists in the employment of an observed threshold variable which allows as to identify trasparently two regimes from the data consistently with our purposes. In this sense, our empirical strategy returns an educated model that allows us to link parameters instability to the state of the economy under investigation.[11] We believe that the development of econometric methodologies able to estimate DSGEs models in a state-conditional manner is something strictly necessary provided the flourishing empirical literature estimating

[11] For Fernandez-Villaverde and Rubio-Ramirez (2008) instabilities in structural parameters estimates may indicate misspecification in the micro-founded model. For example, by finding evidence of a time-varying Calvo parameter, and in particular in a way positively related to trend inflation (see their figure 2.20), they suggest that is worth conducting more research on the state-dependent structure of pricing where the changing duration of prices is endogenous. Even though this is not one of the points of the present paper, just notice that our regime-dependent estimation strategy may represent a way to improve the fit of the DGSE model to different states of the economy given its ability to capture possibly unmodelled mechanisms through different estimates of structural parameters between regimes.

state-conditional Structural VAR models, that in a way "naturally" calls for a more structural, empirical counterpart[12].

Our main results can be briefly summarized as follows. First, consistently with several theoretical and empirical studies, our medium-scale nonlinear VAR finds evidence pointing to a lower effectiveness of monetary policy shocks during uncertain times. It points to shape- and not only level-differencies in the monetary transmission mechanism. Second, the ACEL model is found remarkably able to match uncertainty-conditional facts, although its fit is poorer for uncertain times and particularly for investment and capital utilization dynamics, which may be a symptom of some misspecification along this dimension of the model[13]. Third, the regime-dependent parameters estimates imply overall a reasonable difference in the structure of the economy between uncertain and tranquil times. In particular, different private-sector parameters estimates between regimes let the model tell a story for a different monetary transmission mechanism that touches very closely the channels identified by the theoretical literature[14]. Further, parameters estimates nicely square with the results from studies on time-varying structural estimation of NK models, but it is difficult to empirically assess the model microeconomic predictions about price changes. Forth, counter-factual exercises suggest that the most important drivers behind the lower effectiveness of monetary policy shocks on output during uncertain times are, in order of relevance on real output, a steeper NKPC, a higher cost to vary capital utilization and a lower degree of habits in consumption. Interestingly, the less persistent drop of the interest rate found by the VAR during uncertain times is explained endogenously by the model and, overall, the exogenous shock parameters have not a big role in explaining it. Fifth, the results are robust to several perturbations of baseline specification, included the use of different uncertainty proxies in the VAR or the shutdown of the working capital channel.

The paper develops as follows. Section 2 presents the non-linear VAR model employed and presents results on the uncertainty-dependent consequences of monetary policy shocks from this relatively unrestricted framework. Section 3 presents briefly the

[12] Some recent examples of studies performing a state-conditional estimation of an empirical model are Auerback and Gorodnichenko (2012), Owyang, Ramey and Zubairy (2013), Caggiano, Castelnuovo and Grosshenny (2014), Alessandri and Mumtaz (2014), Caggiano, Castelnuovo and Pellegrino (2015).

[13] This might be due to the fact that, as suggested by several studies (eg. Bloom (2009), Bloom et al. (2014)), non-convex investment adjustment costs, not modelled in the workhorse NK model, are instead important in practice, especially during uncertain times.

[14] Allowing private sector parameters to differ across regimes is something fully in line with the literature. Inoue and Rossi (2011), for example, find that the change in private sector coefficients was a further and neglected explanation of the well studied Great Moderation period.

ACEL model, describes the econometric strategy adopted to estimate the DSGE model and discuss the regime-dependent estimation results found. Section 4 investigates the sources of the different monetary transmission mechanism during uncertain times. Section 5 checks the solidity of our main results. Section 6 concludes. The appendix briefly summarize ACEL's model and relevant results.

2 Empirical evidence on the uncertainty-dependent consequences of monetary policy shocks

2.1 Nonlinear empirical methodology

2.1.1 The Threshold VAR

In order to investigate the state-conditional impact of monetary policy shocks we adopt a two-regimes Threshold VAR model. Following Tsay (1998), the reduced form nonlinear VAR model we estimate is the following[15]:

$$\mathbf{Y}_t = \begin{cases} \alpha^U + \sum_{j=1}^{L} \mathbf{B}_j^U \mathbf{Y}_{t-j} + \mathbf{u}_t^U \quad , & \text{if } z_{t-1} \geq \Gamma \\ \alpha^T + \sum_{j=1}^{L} \mathbf{B}_j^T \mathbf{Y}_{t-j} + \mathbf{u}_t^T \quad , & \text{if } z_{t-1} < \Gamma \end{cases} \tag{1}$$

$$\mathbf{u}_t^U \sim N(0, \mathbf{\Omega}^U) \;\; , \;\; \mathbf{u}_t^L \sim N(0, \mathbf{\Omega}^L) \tag{2}$$

where the usual notation has been used. Notice that the super-scripts U and T indicates the two uncertainty states, i.e. the uncertain and tranquil times state, respectively. The two uncertainty regimes are identified on the basis of the threshold variable z, a stationary uncertainty proxy, which is not modeled in the VAR consistently with both ACEL's (2011) VAR and model (where uncertainty is not a modelled variable, neither endogenously nor exogenously). Whenever the lagged value of the threshold variable is greater or equal than a certain threshold value, Γ, the economy is supposed to transit in the uncertain times state, which is allowed, but not imposed, to capture a different dynamics of the economy with respect to the tranquil times state.

The vector of endogenous variables Y_t is composed of the same variables as in ACEL's (2011) VAR, i.e.

[15] The model is estimated as in Tsay's (1998) by conditional least squares (see equation preceding equation 18 in Tsay's paper).

$$\mathbf{Y}_t = \begin{pmatrix} \triangle \ln(relative\ price\ of\ investment_t) \\ \triangle \ln(GDP_t/Hours_t) \\ \triangle \ln(GDP\ deflator) \\ Capacity\ Utilization_t \\ \ln(Hours_t) \\ \ln(GDP_t/Hours_t) - \ln(W_t/P_t) \\ \ln(C_t/GDP_t) \\ \ln(I_t/GDP_t) \\ Federal\ Funds\ Rate_t \\ \ln(GDP\ deflator_t) + \ln(GDP_t) - \ln(MZM_t) \end{pmatrix} \tag{3}$$

Since uncertainty is not modeled in the VAR, and hence uncertainty is assumed to not react to monetary policy shocks, we compute IRFs conditional on the regime prevailing at the time of the disturbance and throughout the duration of the response (see Ehrmann, Ellison and Valla (2003)). In this way, each regime has a conditionally-linear dynamics. The necessity to adopt conditionally-linear IRFs in order to perform a IRFs matching estimation procedure is noticed in Hofmann et al. (2012, p.777) on the ground that we want to estimate the structural parameters of the model associated with the VAR-based impulse responses in a specific point in time without any influence of future time variation in the structure of the economy. In sub-section 3.1, we will provide a further, formal argument on the reasons why conditionally-linear responses are used[16].

2.1.2 Specifying the empirical model

With the aim of being consistent with ACEL's (2011) theoretical model, we identify the monetary policy shocks along with neutral technology and capital embodied shocks on

[16] For an empirical study that endogenizes uncertainty and that aims at empirically quantifying the difference of the effects of monetary policy shocks between uncertain and tranquil times see Pellegrino (2015). Recent empirical investigations point to a decrease of uncertainty after a monetary policy shock (Bekaert, Hoerova and Lo Duca (2013), Pellegrino (2015)) and, as shown by Pellegrino (2015), who computes Generalized IRFs à la Koop et al. (1996), considering for that can be important in order to better estimate the proper uncertainty-dependent effects of monetary policy shocks. The aim of the present study instead is to assess structurally what can explain the difference across the transmission of monetary policy shocks in uncertain vs. tranquil times. Answering this question with a regime-dependent IRFs matching DSGE estimation is feasible in the setup we are considering in this work (see reasons in section 3.1). On top of that, to my knowledge, still any structural model has identified a transmission mechanism through which uncertainty can react to monetary policy shocks. Hence here we prefer to be consistent with the general workhorse micro-founded model studying the effects of monetay policy shocks). A robustness check in case uncertainty is modelled in the VAR is anyway provided in section 5.

the basis of the following restrictions: (i) neutral and capital embodied shocks are the only shocks that affect productivity in the long run; (ii) the capital embodied shock is the only shock that affects the price of investment goods; and (iii) monetary policy shocks do not contemporaneously affect aggregate quantities and prices. In order to deal with this mix of long-run and short-run restrictions we adopt the instrumental variable (IV) approach proposed by Shapiro and Watson (1988) (for details see the technical appendix to ACEL (2011), i.e., ACEL (2004)). The shocks on which this work focuses are monetary disturbances[17].

We work with the same quarterly data and sample used in ACEL (2005) , i.e. 1959II - 2001IV [18]. We measure uncertainty with the macroeconomic uncertainty indicator proposed by Jurado, Ludvingson and Ng (JLN) (2015), who measure uncertainty on the basis of the common factor of the time-varying volatility of the estimated h-steps-ahead forecast errors of a large number of economic time series. The index is extracted on the information contained in 132 macroeconomic and financial indicators, and hence is likely to bring information on the unpredictable component of the economy, what is generally believed to represent uncertainty[19]. The index is available since the second part of 1960 and hence forces us to start the sample from 1960IV (i.e., $n = 165$)[20]. On the basis of the restricted sample availability and the employment of a two-regime TVAR featuring a regime-specific estimation, we use two lags ($L = 2$) to be parsimonious and obtain stable IRFs[21].

The threshold value Γ is chosen on the basis of the minimum AIC, as proposed by Tsay (1998)[22]. A trimming percentage equal to 30% has been used to avoid too little

[17] Even though here we focus on monetary policy shocks only, we prefer to adopt the same identification restrictions as in ACEL (2005, 2011) in order to obtain results easily comparable with theirs. Indeed, adopting just a Cholesky decomposition for recovering monetary policy shocks would restitutes a different impulse response function to a monetary disturbance (see also Christiano, Trabandt and Walentin (2011, footnote 54)). In addition, in this way our baseline specification is fully consistent with the ACEL's model structure. Anyway, in section 5 we will provide a robustness check for the case a Cholesky identification strategy is employed.

[18] The ACEL's replication code only furnishes this sample at most, which correspond to the same sample period used in ACEL (2005). This notwithstanding, in section 5 we will provide a robustness check involving an updated sample. Main results do not change across the two.

[19] The use of Jurado et al. (2015) index allow us to use a threshold variable that limit its degree of endogeneity in the VAR, which is important considering our conditionally-linear responses.

[20] We use the JLN index referring to a forecasting horizon equal to three months, which is consistent with a one-quarter-ahead forecast.

[21] Christiano, Trabandt and Walentin (2011) adopt the same lag order for their long quarterly sample for variables similar to ours. ACEL (2005) prefer to go with 4 lags, even if they notice that the Akaike, Hannan-Quinn and Schwartz criteria support a choice of L = 2, 2, 1, respectively. Anyway we will show that the parameters estimates based a linear VAR with 2 lags restitutes results similar to theirs.

[22] Notice that each regime has its AIC. We then, following Tsay, compute the AIC of the TVAR as

observations in a regime. Figure 1 the threshold variable employed. The threshold value identified by the minimization of the AIC is 0.85 which allows us to distinguish between uncertain versus tranquil times (respectively given by periods with the JLN indicator above or below the red dashed line). Notice that, much (but not all) of the periods identified as uncertain times coincide with recessionary times (represented by grey vertical bars). This is in line with Jurado et al.'s (2015) finding that, on the basis of their indicator, the economy is objectively less predictable in recessions than it is in normal times. Pellegrino (2015) discerns between the role of uncertainty and the role of recessions in driving the effectiveness of monetary policy shocks. His findings suggest that high uncertainty periods rather than recessionary ones reduces it most.

Before to proceed with our nonlinear specification it is important to investigate whether it is supported by the data. To this end we provide the results from some nonlinear tests for threshold behavior at the multivariate level. Acknowledging that our baseline Threshold-VAR features a regime-dependent VCV matrix, we follow Galvão (2006) and Metiu et al. (2015) in using the bounded supLM (BLM) and supWald (BW) statistics. These statistics uses asymptotic bounds ($1/2ln(ln(n))$) and the maximum value of a Wald and LM statistic over a grid of possible values for the threshold value as proposed by Altissimo and Corradi (2002). The BLM and BW statistics are respectively given by:

$$BLM = \frac{1}{2ln(ln(n))}\left[\sup_{\Gamma_L \leq \Gamma \leq \Gamma_U} n\left(\frac{SSR^{lin} - SSR^{nlin}(\Gamma)}{SSR^{lin}}\right)\right]^{\frac{1}{2}} \tag{4}$$

$$BW = \frac{1}{2ln(ln(n))}\left[\sup_{\Gamma_L \leq \Gamma \leq \Gamma_U} n\left(\frac{SSR^{lin} - SSR^{nlin}(\Gamma)}{SSR^{nlin}(\Gamma)}\right)\right]^{\frac{1}{2}}, \tag{5}$$

where SSR^{lin} is the total sum of squared residuals (SSR), computed as in Tsay (1998), under the null of a nested linear VAR , and $SSR^{nlin}(\Gamma)$ is the SSR under the T-VAR alternative hypothesis[23]. The T-VAR is chosen over the Linear VAR whenever $BLM > 1$ ($BW > 1$). This model selection rule ensures that type I and type II errors are asymptotically zero. In our case, we have both $BLM(= 2.068) > 1$ and $BW(= 2.43) > 1$, which suggest us we can proceed.

$AIC = n_U * AIC_U + n_T * AIC_T$.

[23] The values of Γ used are the actual values of the threshold variable inside the non-trimmed region.

2.2 Empirical results

Figure 2 shows the state-conditional effects of monetary policy shocks as found by our TVAR model[24]. The dashed red and solid blue lines are used for the point estimates of the regime-specific responses to a 1% unexpected decrease in the federal funds rate (FFR) for the uncertain and tranquil times, respectively. Bootstrapped bands corresponding to a 90% confidence level are also shown[25]. Briefly, four are the main differences across regimes:

1. real variables, i.e. GDP, consumption, investment, and hours worked react more and faster during tranquil times. That is, as suggested theoretically by Vavra (2014) and Baley and Blanco (2015), and as found empirically by Aastveit, Natvik and Sola (2013) and Pellegrino (2015), monetary policy shocks appear less effective in uncertain times. This is also consistent with Bloom (2009) , Bloom et al. (2014) and Bloom (2014);

2. inflation is found to raise quicker in the immediate aftermath of the shock during uncertain times. This is consistent with the theoretical predictions by Vavra (2014) and Baley and Blanco (2015), and with the empirical findings in Pellegrino (2015);

3. the interest rate drop is less persistent during uncertain times;

4. capacity utilization appears to increase initially mildly faster after the shock during uncertain times, even if the shock has overall still very transitory and weak effects.

Figure 3 presents more evidence on these results in terms of the statistical difference between state-conditional responses[26]. The results of the test support previous considerations.

[24] We, as in ACEL, transform the set of impulse responses recovered on the basis of the vector Y_t in equation (3) in another set. In particular, they recover responses for the following 11 variables: output, MZM growth, Inflation, federal funds rate, capacity utilization, average hours, real wage, consumption, investment, velocity, and price of investment.

[25] A set of $M = 1000$ bootstrap realizations for the impulse responses are obtained. As in ACEL (2011) the confidence interval is defined by the point estimate of the impulse response, ± 1.64 times the bootstrapped estimate of the standard errors of the impulse response functions.

[26] The test is based on a t-statistic for the statistical difference between regime-dependent responses, taken to be indipendent (as estimated on two different samples). In particular, following ACEL, we can compute bootstrapped standard deviations of the IRFs, for each variable and for each horizons ahead. Then the test-statistic is as follow: $t - stat = (IRF^U_{t,i} -$

Overall, the empirical evidence found seems in line with the channels identified by the theoretical literature through which heightened uncertainty can influence the economy. The unrestricted nonlinear VAR is likely to capture the role played by three of these channels, i.e. (i) real option theory effects in labor and investment, (ii) precautionary savings and precautionary labor supply, (iii) firms price-setting behavior. Respectively, these are likely to be important in presence of non-convex adjustment costs for investment or hiring, in presence of risk-averse consumers, or in presence of non-convex costs of adjusting prices and/or information frictions. Again, with this medium-scale VAR we are able to capture in a unrestricted way the dynamics of several important variables to monetary policy shocks and the comovements they display in responding to it[27]. However, based just on the empirical evidence we have no clues on which channel is the most relevant in the data.

The next step is to employ ACEL's model with the purpose of assessing qualitatively the ability of this workhorse model to replicate the state conditional behavior of the economy through parameter estimation. To the extent that the model fit is sufficiently good - as it turns out -, we can employ it as a device to detect the structural differences between uncertain and tranquil times through the lenses of a NK model. Even though the structural model of ACEL (2011) does not allow us to assess directly the relevance of each of the previous channels (as, to the best of my knowledge, no existing model would do)[28], we can investigate indirectly their role provided that the estimation of structural and behavioral parameters differs between uncertainty times[29]. To the extent that the model is able to provide a reasonable explanation for the different effects of monetary policy shocks between times - as it also turns out - , we can then be sufficiently encouraged to employ it as a laboratory in which to investigate through counterfactuals exercises the most relevant drivers of such a different monetary transmission mechanism. This constitutes the roadmap of the remaining part of the paper.

$IRF^{T}_{t,i})/(\sqrt{(st.dev.(IRF^{U}_{t,i}))^2 + (st.dev.(IRF^{T}_{t,i}))^2})$, where $IRF^{regime}_{t,i}$ represents the point estimated IRF for regime U or T. $t = 0, ..., 19$ represents the horizon ahead to which the response is referred and $i = 1, ..., 11$ denotes the variable whose IRFs are referred.

[27] Several robustness checks for the specification of the TVAR model are presented in section 5.

[28] Notice indeed that the model features convex adjustment costs in investing, a Calvo-style exogenous probability of changing prices and wages, and it is linearized and with a risk aversion coefficient fixed to 1.

[29] As noticed in the Introduction, notice that our proposed regime-dependent estimation approach may capture possibly unmodelled mechanisms through different estimates of structural parameters between regimes.

3 Structural assessment of the influence of uncertainty in the monetary transmission mechanism

3.1 Brief description of the ACEL structural model

We chose to estimate Altig et al.'s (ACEL) (2011) linearized model for three reasons. (i) It can be seen as representing the workhorse medium-scale New Keynesian model, (ii) it interestingly nests two alternative versions of the model useful for our purposes, and, (iii) it allows us to be fully consistent with our non-linear empirical VAR model.

First, ACEL (2011) model is an example of the workhorse medium-scale New Keynesian model. It is a dynamic, stochastic general equilibrium one-sector model whose equations are derived from the first-order conditions of optimizing representative firms and households behaving according to rational expectations. It features both nominal rigidities (in the form of Calvo-type sticky prices and wages allowing for backward dynamic indexation), and real frictions (in the form of habit formation in consumption, investment adjustment costs, variable capital utilization and a cost channel of monetary policy, as firms must borrow working capital to finance their wage bill). The model represents an extension of the very well known model by CEE (2005) in that it adds two additional exogenous economic shocks to the monetary policy innovation present in the original CEE model. These two additional shocks are a neutral and an investment-specific technology shock, which exhibit serial correlation and have permanent effects on the level of productivity. More details on the ACEL model are presented in the Appendix to this paper. Notice that the ACEL model does not feature an interest rate feedback rule but a money growth rule. The monetary authority shocks the economy through an unexpected increase in the growth rate of money which is then transmitted to the interest rate, something useful to the aim of explaining endogenously the less persistent interest rate drop during uncertain times. Avoiding an interest rate rule appears useful also because, on the basis of the claims of the theoretical literature, we could expect changes in private sector parameters between uncertain and tranquil times to be more important than changes in the systematic conduct of monetary policy.

Second, the reduced-form of the ACEL model that we estimate nests two alternative versions of the model. In one, capital is homogeneous and can be instantly and costlessy transferred across firms (as in standard equilibrium business cycles models), whereas in the other, capital is completely firm-specific and the only way a firm can change its capital stock is by varying the rate of investment (i.e. a firm's capital stock is predetermined). The two models differ just as regards the equation relating inflation to marginal costs, i.e. :

$$\Delta\hat{\pi}_t = E[\beta\Delta\hat{\pi}_{t+1} + \gamma\hat{s}_t \mid \Omega_t], \tag{6}$$

where π_t denotes inflation, s_t denotes the economy-wide average marginal cost of production in units of the final good, $\hat{\ }$ denotes the percent deviation of a variable from its steady state value, β denotes the households' discount factor, Ω_t denotes the information set including the current realization of the technology shocks, and where the reduced form coefficient γ is:

$$\gamma = \frac{(1-\xi_p)(1-\beta\xi_p)}{\xi_p}\chi, \tag{7}$$

where ξ_p denotes the constant probability that a firm faces, in each period, of being able to not re-optimize optimally its nominal price. In the technical appendix to ACEL paper (section 7), they show that χ differs between the two versions of the model. In the homogenous capital version of their model, $\chi = 1$ (and hence γ coincides with the slope of the New Keynesian Phillips Curve in standard New Keynesian models with a Calvo environment[30]), whereas in the firm-specific capital version χ is a particular nonlinear function of the parameters of the model[31]. Despite this difference, the way equation (6) is parametrized let the two models be observationally equivalent (up to a linear

[30] See Galì and Gertler (1999) and Vavra (2014b). Notice though that equation (6) represents the NKPC in presence of full backward indexation, i.e., it models the relation between $\Delta\hat{\pi}_t - \beta E\Delta\hat{\pi}_{t+1}$ and $\hat{s}_t$, rather than between $\hat{\pi}_t - \beta E\hat{\pi}_{t+1}$ and $\hat{s}_t$. Hence, γ represents the sensitivity of the growth rate of inflation to marginal cost changes (i.e., the percent change in the inflation rate due to a temporary one percent change in marginal cost). Notice that equation (6) could be rewritten as $\hat{\pi}_t = \frac{1}{1+\beta}\hat{\pi}_{t-1} + E[\frac{\beta}{1+\beta}\hat{\pi}_{t+1} + \frac{\gamma}{1+\beta}\hat{s}_t \mid \Omega_t]$.

[31] As regards the dependence on estimated parameters, essentially we have $\chi = \chi(\sigma_a,\lambda_f,\xi_p) < 1$ (see the first equation at page 77 of ACEL technical appendix). ACEL (2011) stress the dependence of χ , and hence γ, from σ_a and λ_f. This dependence is due to the fact that, in the firm-specific version of the model, a firm's marginal cost curve depends positively on its own output level, and that the steepness of this curve changes with these two parameters. This is because of the assumption that firms cannot trade phisical capital among them. To fix ideas, suppose an expansionary monetary policy shock. After the shock, optimizing firms (answering by increasing their price) would experience a *decrease in demand*, that would go toward sticky price firms which would require therefore more phisical capital. But since capital is not tradable, the only way for an optimizing firm (that is loosing demand) to deal with the shock is by *reducing the capital utilization rate,* which would reduce the firm's marginal cost. However, this reduction in marginal costs would reduce the incentive of flexible firms to raise prices. This mechanism is enhanced the more elastic is the firm's demand curve (i.e. the lower is λ_f) and the more costly it is for a firm to vary capital utilization (i.e., the larger is σ_a). Wrapping up, γ is the smaller the larger is σ_a and the lower is λ_f. Notice, finally, that other things equal, a smaller γ implies a bigger ξ_p.

approximation as our case), hence permitting to estimate the model on macro data in terms of γ without taking a stand on whether capital is firm-specific or homogeneous. This is useful for us for two reasons. Firstly, ACEL argue that the firm-specific capital version, which they show to be supported in its predictions by micro data, provides a way to overcome the apparent conflict between macro and micro evidence on pricing behavior (related to aggregate price stickiness and the firms' frequency of price changes, respectively). Aggregate price stickiness is indeed endogenous to the firm-specific model and not depending just on the frequency of price adjustments. This is important for us in order to overcome Vavra's (2014b) criticisms on the use of NK models (mentioned in the Introduction) and hence to validate in a better way the ability of workhorse New Keynesian models in fitting uncertainty-dependent fact. Secondly, by drawing results on both versions of the model we can be more general in our conclusions. This is important in order to understand whether we can obtain general and model-free policy suggestions.

Third, both the timing assumptions in ACEL model and the strategy for approximating the solution adopted by the authors allow us to be fully consistent with our non-linear empirical VAR model. To be more precise, our Structural Threshold VAR can be seen, for each regime, as a finite-lag VAR representation for the DSGE model describing that particular regime. Timing assumptions are described in details in the Appendix, but just notice that these imply that wages, prices and real quantities are predetermined relative to the monetary policy shock. As regards the strategy for approximating the solution, ACEL first take a log-linear approximation of various equations of the model around the non-stochastic steady state of the economy and then use the solution methods discussed in Anderson and Moore (1985) and Christiano (2002). In this way, the linearized DSGE model can be written in State Space form as follows:

$$\mathbf{Y}_t = \mathbf{\Xi}(\zeta)\mathbf{X}_t \tag{8}$$

$$\mathbf{X}_t = \mathbf{\Phi}(\zeta)\mathbf{X}_{t-1} + \mathbf{\Lambda}(\zeta)\varepsilon_t \ , \tag{9}$$

where equation (9) describes the evolution of the state vector, $\mathbf{X}_t$, equation (8) relates the vector of observable variables, $\mathbf{Y}_t$, with the state vector, and ε_t denotes the vector of the structural errors, which are i.i.d. distributed with zero mean and identity covariance matrix ($E\varepsilon_t\varepsilon_t' = I$). Notice that the elements of matrices $\mathbf{\Xi}$, $\mathbf{\Phi}$, and $\mathbf{\Lambda}$ are nonlinear functions of the vector of structural parameters, ζ. ACEL show in the technical appendix to their paper (ACEL, 2004, section 9) that the same can be written in a infinite order Structural VAR form as follows:

$$\mathbf{Y}_t = \alpha(\zeta) + \sum_{j=1}^{\infty} \mathbf{B}_j(\zeta)\mathbf{Y}_{t-j} + \mathbf{u}_t \ , \tag{10}$$

where $\mathbf{u}_t = \mathbf{C}(\zeta)\varepsilon_t$ are the residuals of the system[32]. Equation (10) is nothing more than the infinite order version of the conditionally-linear Structural VAR that we estimate for each regime of our T-VAR model. Hence, to the extent that we have enough evidence from the data that the economy behaves differently among regimes, we can fit ACEL model to each of our regime-dependent VAR models and hence obtain a regime-dependent estimate of the vector of parameters ζ.[33] Notice that this is clearly feasible given that the variable we employ to define the regimes of our T–VAR, i.e., uncertainty, is not a modelled variable (neither endogenously nor exogenously) of both the adopted empirical and micro-founded models. This means that the two regimes are assumed to be non-communicant among them so that we can estimate each regime neglecting the other and obtain conditionally-linear responses. Our analysis will inform us on which is the response to a monetary policy shock provided the economy stays in the particular regime in which the shock hits.

3.2 Minimum-distance estimation strategy

We estimate the ACEL's (2011) model by IRFs matching, i.e. by choosing the parameters values that minimize a measure of the distance between VAR-based responses and model-based responses. This is the same estimation approach used by ACEL. Previous contributions in the literature that used this approach are, among others, Rotemberg and Woodford (1997), Christiano, Eichenbaum and Evans (2005), Iacoviello (2005), Boivin and Giannoni (2006), DiCecio (2009), Theodoris (2011). Jordà and Kozicki (2011) proposes IRFs matching estimation based on local projections. Recently Christiano, Trabandt and Walentin (2011) have proposed a bayesian IRFs matching estima-

[32] ACEL (2004) show how to approach the issue that the number of fundamental shocks in their model is smaller than the number of observable variables. For a general invertibility condition in case there are equal numbers of VAR and economic shocks see Fernandez-Villaverde, Rubio-Ramirez, Sargent and Watson (2007) and Christiano, Eichenbaum and Vigfusson (2006).

[33] Clearly, in applications, a truncated version of the VAR in (10) can be estimated, which could lead to a truncation bias (see Ravenna (2007)). Theodoris (2011, chart 2) employs the medium-scale Smets and Wouters (2007)'s model to perform an exercise showing how VAR-based responses converge to model-based responses as the lag order of the VAR increases. From this exercise, the truncation bias appears acceptable for commonly used lag orders involving the state-of-the-art New Keynesian models.

tion, an approach followed by Hofmann et al. (2012) and Christiano, Eichenbaum and Trabandt (2015). Differently from these works, we here perform a regime-dependent IRFs matching, something nesting the approach followed by Boivin and Giannoni (2006) with their structural break VAR model.

As in ACEL, we use the IRFs to a monetary policy shock to estimate 9 structural parameters. Seven of these pertain to the "non-stochastic part" of the model $\zeta_{ns} = [\lambda_f, \xi_w, \gamma, \sigma_a, b, S'', \epsilon]$ while two refer to the "stochastic part" of the model and in particular to the monetary policy shock process, i.e. $\zeta_s = [\rho_{xM}, \sigma_M]$. The remained parameters of the model, ζ_{cal}, are instead fixed and calibrated as in ACEL (2005, 2011)[34].

We are looking for a regime-dependent estimation of the vector of parameters $\zeta^i = [\zeta^i_s, \zeta^i_{ns}]$, where $i = U, T$. The estimates of our vectors of parameters ζ^i solves

$$\zeta^i = \arg\min_{\zeta^i} \left[\widehat{\psi}^i - \psi\left(\zeta^i\right)\right]' \left(\mathbf{V}^i\right)^{-1} \left[\widehat{\psi}^i - \psi\left(\zeta^i\right)\right] \quad , \quad i = U, T \tag{11}$$

where $\psi\left(\zeta^i\right)$ denotes the model-based IRFs to a monetary policy shock in regime $i = U, T$ (depending on ζ^i), and $\widehat{\psi}^i$ denotes the corresponding TVAR-based state-conditional responses. We consider, as in ACEL (2011), the response for the first 20 quarters ahead from the shock hit (even though ideally the horizon should be determined statistically as proposed by Hall et al. (2012)).[35] $\mathbf{V}^i$ is a regime-dependent diagonal matrix with the variances of the $\widehat{\psi}^i$'s (i.e. the same variances at the basis of the confidence intervals in figure 2) along the diagonal[36] . Notwithstanding this is not the efficient weighting matrix, this choice is widely adopted in the literature and allows us to obtain consistent estimates which let model-based responses to lie as much as possible inside the VAR confidence intervals (see CEE (2005))[37]. To be sure that just the data are driving the difference across state-conditional estimation we adopt the same starting values for the

[34] A short description of parameters as well as the fixed values for ζ_{cal} can be found in table A1 in the Appendix.

[35] As the ACEL's structural model assumes that a monetary policy shock has no effects on the relative price of investment, the vector $\widehat{\psi}^i$ will include 193 elements, namely 10 (i.e. the number of variables except the price of investment) times 20 (number of responses) minus 7 (contemporaneous responses to the monetary policy shock that are required to be zero by our identification assumption).

[36] Denoting by $\hat{\mathbf{W}}^i$ the bootstrapped variance-covariance matrix of VAR-based impulse responses $\widehat{\psi}^i$ for regime i, i.e. $\frac{1}{M-1}\sum_{j=1}^{M}(\psi^i_j - \bar{\psi}^i)(\psi^i_j - \bar{\psi}^i)'$ (where ψ^i_j denotes the realization of $\widehat{\psi}^i$ in the j^{th} (out of M) bootstrap replication and $\bar{\psi}^i$ denotes the mean of ψ^i_j), $\mathbf{V}^i$ is based on the diagonal of this matrix.

[37] In particular, with this choice, the estimation criterion is is less concerned about reproducing VAR-based responses with larger confidence bands (Christiano Trabandt, and Walentin (2011)).

minimization algorithm used[38][39]. In both regimes the algorithm converges to a solution.

The VAR-based responses $\widehat{\psi}^i$ we use in the computational procedure are the responses to a one standard deviation shock in the FFR in each regime. The purpose is to estimate properly also the stochastic component of the monetary policy shock process referring to the volatility of the shock, i.e. σ_M. These responses however are not directly comparable to study the effectiveness of monetary policy shocks, since the initial impulse in the FFR might change across states provided our regime-dependent VCV matrix. To this end we show instead a scaled version of both VAR-based and model-based responses so that to have a 1% expansionary shock in the FFR[40].

Here, some reasons why we find this limited information estimation approach appealing. First of all, and in line with Boivin and Giannoni (2006), since we are interested in explaining the sources of the observed changes in the responses to a monetary policy shock across uncertain and tranquil times, it is natural to estimate the structural parameters on the basis of the correspondent impulse response functions. Furthermore, the IRFs matching approach is transparent as its estimation strategy tries to fit in the best way possible a small number of features of the data, it does not require to assume that the underlying data are realizations from a Normal distribution, and it is computationally fast (see Christiano, Trabandt and Walentin's (2011) survey for details). Finally, we think that limited information estimation strategies increase their potential in presence of a nonlinear approach like ours. In particular, in our situation, we can estimate without any computational issues an abrupt-change nonlinear model at the

[38]In particular, as starting values, we use the parameter estimates in ACEL (2005) for the monetary policy shocks only case (see table A1 in the Appendix to this paper to have a look to them). As in ACEL we employ a simplex algorithm, although we increase the maximum number of iterations to 10000. Notice that parameter estimates are almost insensitive if we use instead a Newton-Raphson type algorithm as in Hall et al. (2012).

[39] Standard errors for point estimates are computed as in ACEL (2011) by the Delta Method (see ACEL(2005)). When the number of observations in a regime, n^i, is large, for standard asymptotic theory we have that $\zeta^i \overset{a}{\sim} \mathbf{N}(\zeta_0^i, \mathbf{\Omega}(\zeta_0^i, n^i))$, where ζ_0^i represents true values of the parameters that we estimate and $\mathbf{\Omega}$ represents the asymptotic variance-covariance matrix of the parameters that we estimate (which depends on the variance-covariance matrix of VAR-based impulse responses for regime i^{th}, $\mathbf{W}^i$) (see ACEL (2005, footnote 14) and Hamilton (1994, chapter 14)).

[40]In particular, we scale both VAR-based and model-based responses by the regime-specific standard deviation of the FFR shock of the VAR (this produces an approximated 1% decrease in the model-based IRFs, depending on the way the MD estimation matches the impact decrease in the FFR). This can be done without any problems since we are dealing with a linearized DSGE and with a TVAR conditionally-linear in each regime, and hence the shape of the responses will not depend at all on the size of the shock (see Koop, Pesaran and Potter (1996)). Notice, furthermore, that the parameter estimates are particularly robust to this transformation. In case the computational procedure would be used on a 1% FFR shock in both states just the parameter σ_M would sensibly change (but its estimate would be counter-intutitive).

same time being fully consistent with the structural model employed. More in general, Andreasen et al. (2014) work on the use of limited information estimation strategies for the estimation of nonlinear(ized) DSGE models (e.g. III order approximated, smoothly nonlinear, DSGE models). They study the pruned state-space system for second- and third-order approximated solutions of DSGE models, for which they derive the statistical properties as well as closed-form expressions for unconditional moments and impulse response functions. As a results, they argue how various limited information methods used in linearized DSGE models, including GMM (or SMM) estimation and IRFs matching estimation, now can be applied easily to non-linear approximations with the advantage of a greatly simplified computational burden. Notice, however, that a drawback of the IRFs matching estimation procedure is that it may be prone to several identification issues (see Canova and Sala (2009))[41].

As in ACEL (2005, 2011) we adopt a classical IRFs matching estimation procedure rather than the bayesian equivalent recently proposed in Christiano, Trabandt and Walentin (2011). We preferred the first one for three reasons. Firstly, to remain close to ACEL for an easy comparison. Secondly, since there is not available literature suggesting us how priors should be chosen across regimes. Even if we chose to employ a similar prior mean between regimes, the choice of prior variances would be equally difficult and may influence results. Thirdly, to allow an higher degree of flexibility in the estimation[42].

3.3 Regime-specific estimation results

Overall fit of the model. Before to discuss the differences in parameters estimates we briefly discuss their consequences for the fit of model-based responses to VAR-based regime-dependent responses.

[41] We disregard here from these issues, even though we admit that some diagnostic exercises aimed to detect the existence of identification problems would be necessary (the reader is referred to Canova and Sala (2009) that study a medium-scale model similar to the one employed in this work and have several exercises focusing on the monetary policy shock as in this work). We are confident that identification problems in our procedure are not more relevant than in ACEL's work since many of their estimated parameters lie inside our regime-dependent parameters estimates. Instead, ACEL's (2005, Appendix A) and Christano, Eichenbaum and Vigfusson (2007) present Monte Carlo exercises proving the good performance in terms of bias and sampling uncertainty of VAR methods when applied to the ACEL model.

[42] However, this comes at the cost that the numerical procedure may bring their estimates close to their bounds (available in table A in the Appendix). In addition, the numerical algorithm may drive also parameters inside an indeterminacy region of the model. However, fortunately, we do not encouter these problems in our baseline estimation as the algorithm converges to parameters estimates that are inside their bounds and inside the model determinacy region. The are further in line with existing studies on parameters instabilities in NK DSGE models.

Figures 4 and 5 compare VAR-based responses and model-based responses for the uncertain times and tranquil times regimes, respectively. The model captures remarkably well the unrestricted dynamics of the economy in both regimes. A part from few exceptions for some horizons ahead, model-based responses are well inside the 90% confidence bands for TVAR hump-shaped responses and also respect quite well the timing of most peak reactions[43]. However, the fit of the model is less satisfactory in matching the uncertain times dynamics of the economy, in particular as regards the inflation spike, capacity utilization reaction and investment dynamics.

Figure 6, which compares model-based responses for both regimes, confirms previous thoughts. A part from a poorer performance as regards uncertain times, overall, the model ability to replicate regime-conditional evidence is impressive. The model is able to replicate the smaller peak reactions of real variables during uncertain times as well as the anticipate timing of their peak reactions, the short-run faster increase in inflation during uncertain times as well as the lower persistence in the interest rate drop, the behavior of money growth as well as the behavior of real wages. Capacity utilization response is instead very poorly captured. Overall the model, in line with the empirical evidence, is suggesting that tranquil times and uncertain times feature a different transmission mechanism of monetary policy shocks.

Structural parameters between uncertain and tranquil times. Table 1 presents the parameters estimates and their standard errors for both regimes[44]. Six coefficients out of nine are statistically significant for both regimes at standard significance levels, and the same three, i.e. S'', σ_a and γ are not statistically significant for both regimes. The latter two are neither statistically significant in the estimation based on the impulse responses coming from a linear VAR model (see the last column)[45].

[43] The model responses do a little job in replicating the response of the relative price of investment. In the model there is the assumption that the latter does not respond to monetary policy shocks, which though seems to be particularly stringent in tranquil times. Christiano, Trabandt and Walentin (2011) find a similar result in normal times (i.e., the times mostly captured by a linear VAR) and argue that, in order to try to fix it, it would be worth exploring technologies for producing investment goods involving a nonlinear trade-off between consumption and investment, something which we leave to future research.

[44] Notice that the table reports also standard errors for ξ_p. As ξ_p is a nonlinear function of parameters estimates, we rely on the Delta Method (see Greene (2003, p. 914)). In particular, calling $c(\cdot)$ this nonlinear function, standard errors were computed as the square root of the diagonal of $\mathbf{C}(\zeta)\boldsymbol{\Omega}\mathbf{C}(\zeta)'$, where $\boldsymbol{\Omega}$ is the variance-covariance matrix of our vector of parameters estimates ζ, and $\mathbf{C}(\zeta)$ is the vector of partial derivatives of $c(\cdot)$ with respect to the parameters estimates, $\partial c(\zeta)/\partial\zeta'$, which is computed numerically (using symmetric differentiation).

[45] We find it is coherent to compare our regime-dependent results with the results as coming from the linear VAR nested to our TVAR model, rather than with ACEL's (2005) results. Notice, however, that notwithstanding differences in the sample period (due to the JLN index availability), lags adopted,

Many of the parameters referring to normal times (represented by the linear VAR responses) are inside the values estimated for the tranquil and uncertain times regimes. S'', however, is estimated to be particularly large when compared to the corresponding estimate for normal times, even if it is still consistent with what found by the literature when sampling variability into account[46]. It is worth testing whether the vector of parameters overall statistically differs across regimes. To this end, a Wald test rejects the null hypothesis of no difference at any conventional significance level[47].

Drawing upon the parameters interpretation (see the description to table 1), the estimated parameters are signalling what following regarding the structural difference between tranquil and uncertain times. The slope of the Phillips curve, γ, is increasing in uncertainty, a result fully consistent with the empirical results by Vavra (2014b) (presented in the Introduction). This means that, in presence of heightened uncertainty, the trade-off between output and inflation worsens, as prices are rising faster after a monetary policy shock during uncertain times. Pellegrino (2015) provides empirical evidence to the latter respect. We expect that part of this result should depend on a higher frequency of price adjustments during uncertain times (Vavra (2014a) and Baley and Blanco (2015)), which in our model should be reflected in a lower estimate of ξ_p. Although this happens by construction in the homogenous capital version of the model (see equation 7), this is not said for the firm-specific capital model[48]. Interestingly, also for the firm-specific model our estimates imply a lower ξ_p during uncertain times, which is a result per se. The average time between price re-adjustment predicted by the estimated model varies from 2.41 quarters in uncertain times to 10.77 quarters in tranquil times for the homogenous capital model, and from 1.1 to 8.93 in tranquil times for the firm-specific capital model. A rather important difference. In the next section we will dig in much deeper on this large difference between regimes and compare it with existing, although scarse, empirical evidence available.

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and maximum number of iterations (that we fix to 10000), results are very close to ACEL's ones (see table A1 in the Appendix to this paper).

[46] For example, Christiano, Trabandt and Walentin (2011) estimate S'' equal to 14.30 by matching a variant of ACEL model to VAR-based responses.

[47] As detailed in footnote 39 we have that $\zeta^i \overset{a}{\sim} \mathbf{N}(\zeta_0^i, \mathbf{\Omega}^i(\zeta_0^i, n^i))$ for $i = U, T$. Since the two vectors of parameters are asymptotically independent we can construct a Wald test as follows: $\Lambda_T = (\zeta^U - \zeta^T)'(\mathbf{\Omega}^U - \mathbf{\Omega}^T)^{-1}(\zeta^U - \zeta^T)$. Treating the threshold value as known we have that $\Lambda_T \overset{a}{\sim} \chi(9)$ (see Andrews and Fair (1988) for a proof, Hamilton (1994 pp. 424-425) for a textbook-like coverage, and Ireland (2004) for an application in case of a Structural break). We have that $\Lambda_T = 42.11$ with associated $p - value = 0.000003$ (notice, however, that this very low p-value could reflect the fact that we actually searched for the optimal threshold value).

[48] Just to show that it is not said even with sensible estimates, and given γ, consider the following ad-hoc example. We would have that $\xi_p^U(\gamma_p^U, \lambda_f^T, \sigma_a^{ACEL2005}) = 0.583 > \xi_p^T(\gamma_p^T, \lambda_f^U, \sigma_a^U) = 0.577$

The degree of habits in consumption, b , is pretty lower during uncertain times than tranquil times[49]. This might signal both the fact that (i) higher precautionary savings are in place, and that (ii) lower consumption smoothing is achievable perhaps due to financial distress in place (see Caggiano, Castelnuovo and Nodari (2015) and references therein). This result is consistent with results in Sule, Crossley and Low (2012). They provide evidence on the spike in households savings rates that happens usually at onset of a recession and build a life-cycle model to explain why households save on a "rainy day" (which is captured in their model by a mix of fall in income, increase in uncertainty, reduction in the supply of credit and sharp decline in asset prices).

The steady state price elasticity of demand, $\lambda_f/(\lambda_f - 1)$, is higher during uncertain times, perhaps due to the fact that consumers, who are saving more, become more sensitive to prices when buying goods. Letting this parameter to vary between regimes acknowledge for the fact that the elasticity of demand is not constant, but rather time-varying and differing across times. For example Eichenbaum and Fisher (2007) argue that departing from the assumption that monopolistically competitive firms face a constant elasticity of demand it is important in order for a Calvo-type model to generate plausible degrees of inertia in price setting behavior by firms[50].

The monetary policy shock is found to be less persistent (lower ρ_M) and more volatile (higher σ_M) during uncertain times, and this may be an important explanation behind the results obtained (its role needs to be evaluated through counterfactuals exercises). In addition, the interest semielasticity of money demand, ϵ , is lower during uncertain times, and it is consistent with the fact that consumers want to save more (and consequently need less money for transactional motives).

The elasticity of capital utilization with respect to the rental rate of capital, $1/\sigma_a$, is lower during uncertain times, meaning that it is more costly to vary capital utilization in uncertain times. The higher estimate of σ_a during uncertain times is somehow needed in order to match well output and inflation empirical responses. Indeed, an higher σ_a allow to obtain both a smaller reaction of output and a bigger reaction of inflation to the shock, which is exactly what the VAR evidence suggests is happening during uncertain times[51].

[49] Notice that we can conclude statistically at the 10% significance level that $b^H < b^T$ (even if not that $b^H \neq b^T$), as $(b^H - b^T)/(\sqrt{SE^2_{b^H} + SE^2_{b^T}}) < -1.28$ (notice that the two parameters estimates are treated as indipendent as estimated on different sub-samples).

[50] In particular, they use Kimball's (2005) specification allowing for the possibility that the elasticity of demand is increasing in a firm's price. Our regime-dependent estimation just allows, in reduced form, the elasticity to differ across tranquil and uncertain times.

[51] See figure 6 in Christiano et al. (2005) for an exercise showing this.

This is because, everything else equal, less elastic capital services imply, through a large increase in the rental rate of capital, a larger increase in marginal costs after an expansionary monetary policy shocks, which is then transmitted to higher prices. On the other side, an higher σ_a implies a flat model-based response for capital utilization, that is though at odds with capacity utilization VAR-based response, particularly with its faster short-run reaction during uncertain times. Notice furthermore that, given ξ_p, the higher estimate for σ_a and the lower for λ_f during uncertain times avoid an irrealistically large γ[52].

The elasticity of investment with respect to a 1 percent temporary increase in the current price of installed capita, $1/S''$, is counter-intuituively higher during uncertain times, although one must consider that S'' is very imprecisely estimated. Notice that the model underestimates the response of investment to the shock during uncertain times and it is unable to match its lagged reaction (see again figures 4 and 5). A reason why the model fits particularly poorly investment and capital utilization in uncertain times might be given by the neglected modelling of investment non-convex adjustment costs, which are more relevant in presence of high uncertainty and which may influence the aggregate level dynamics of investment (Bloom (2009))[53]. The VAR-based responses may indeed capture the fact that, during uncertain times, due to non-convex and irreversible adjustment costs in investment, firms prefer to meet a surge in demand throughout an increase in capital services, rather than an increase in investment.

Wages appear stickier during uncertain times (higher ξ_w) although the difference is minimum when considering sampling variability. The fact that wages are stickier during uncertain times might be due to more precautionary labor supply in place which the VAR might capture by the missed reaction of wages to the monetary shock (see Basu and Bundick (2014)). This may also reflect that for firms it becomes optimal to postpone labor hiring during uncertain times due to larger inaction regions (see Bloom (2009)).

Still on the transmission mechanism of monetary policy shocks. It is clear how these differences in parameters estimates between regimes imply a different transmission mechanism of monetary shocks between uncertain and tranquil times. It

[52] Just as an example, consider that $\gamma^U(\xi_p^U, \lambda_f^T, \sigma_a^T) = 6.15$.

[53] Notice that the optimal behavior of the generic firm changes substantially between the case of convex or non-convex adjustment costs. In the first case for the firm it is optimal to invest very frequently and with very little movements in the capital stock, while in the second case for the firms it is optimal to invest less frequently and by large amounts (see, e.g., Dixit (1993)).

seems also interesting to discuss the way the model can explain in a general equilibrium framework the different persistence of the interest rate drop between regimes. First of all notice that ACEL assumptions imply that a money injection policy shock must be fully absorbed by household cash holdings. This depends from the money market–clearing condition (equations A.2 in the online Appendix) and from the fact that the nominal wage and hours worked are predetermined. Since prices are also predetermined to the policy shock, it follows that real cash balances increases and hence that a reduction in the interest rate is required to induce households to increase their cash holdings. Then, the different persistence of the interest rate drop between regimes reflects several things (as it can be seen from the household's first-order condition for cash balances, equation A.1 in the Appendix)[54]. A part from the persistence of the money growth shock, it depends from the reaction of prices, the reaction of wages, the reaction of hours worked and the reaction of consumption, which all together shape the reaction of velocity to the shock. From another look to figure 6, it is interesting to notice that the responses of these variables imply a less persistent drop in velocity that is reflected in the less persistent interest rate drop in the uncertain times regime.

Discussion of model micro implications. As seen, the differences between regimes in parameters referring to macro and micro price behavior are of the expected sign and consistent with theoretical and empirical studies on the price setting behavior between uncertain and tranquil times. However, it seems worthwhile discussing whether the magnitude of model micro implications are also both (i) in line with existing studies on parameters instabilities and (ii) empirically justifiable.

Regarding (i) we can easily compare the range of the Calvo probability (ξ_p) between uncertain and tranquil times that we have found to the one that other studies have found. For example, both Fernandez-Villaverde et al. (2008) and Giraitis et al. (2014) obtain a time-varying estimate of the Calvo probability in a model comparable to the homogenous capital version of the ACEL model. Both of them obtain that the estimated Calvo probability is between 0.5 and 0.95, hence very close to the values that we estimated for the uncertain times and tranquil times states, respectively. Their Calvo probabilities imply that the price duration is between around 2 and 20 quarters.

Regarding empirical justifiability, (ii), it is difficult to establish. One could follow two paths here. One is to avoid comparing the model micro implications with microeconomic evidence on the average duration of prices (Bils and Klenow 2004, or Nakamura and

[54] Notice that, as explained in section 3.2, model-based responses are scaled so that to have a 1% shock in the interest rate in both regimes.

Steinsson 2006), as Fernandez-Villaverde et al. (2008) do. The reason is that such a comparison is difficult because we use a model with full dynamic indexation, i.e. prices change every quarters for each producers, a fraction ξ_p because producers reoptimize and a fraction $(1-\xi_p)$ because of indexation. This means that even if firms are changing prices, this does not mean that they have re-optimized those prices. A subset of firms is changing prices just for some kind of time-dependent price updating rule.

The second option is to bear this in mind, but anyway to find it tempting and somehow useful to compare the model micro implications with the findings on price stickiness based on microeconomic data, as Eichembaum and Fisher (2007) do. In this case, however, it is worth noting that there is still scarce available evidence on the frequency of price adjustments between uncertain and tranquil times. Vavra (2014b) provides some. As mentioned, he estimates structurally an uncertainty-dependent, otherwise standard, NKPC à la Galì and Gertler (1999) (i.e. without dynamic indexation). Interestingly, in the homogenous capital model (the one producing a NKPC mostly comparable with Vavra's estimated one), we find that the difference in the frequency of price adjustments between uncertain and tranquil times, $(1-\xi_p)^U - (1-\xi_p)^T$, roughly equal to 30 percentage points, is very close to the one found by Vavra (2014b, table 6)[55][56]. Vavra argues that this difference is not a good description of reality, but rather something required in order to rationalize an higher slope of a standard NK Phillips curve during uncertain times: when he defines regimes on the basis of the interquartile range of price changes there is evidence of just a 3 percentage points higher frequency of adjustment during uncertain times than during tranquil ones (i.e., during uncertain times roughly 3% more firms are resetting their price each quarter than during tranquil times)[57]. What he concludes is that the variation in aggregate price flexibility between uncertain and tranquil times cannot be explained solely by variation in the frequency of adjustment - as it is the case in a NK DSGE model with a standard NKPC - and that results are instead consistent with Ss models of price-setting (where, as predicted by Vavra's (2014a) theoretical model, the extensive margin, i.e. the change in the mix of adjusters, can be the most important determinant).

[55] We can conclude statistically that $\xi_p^H < \xi_p^T$ at the 10% significance level.

[56] We cannot directly compare our estimates to Vavra's one because his NKPC assumes no indexation. However, Eichenbaum and Fisher (2007, p. 2040) show that estimates are comparable in presence of an highly inertial $\hat{\pi}_t$ and for values of β close to one.

[57] This is in line with what Bachmann et al. (2013) find on German data, i.e., that during the 08/09-recession, the average share of firms adjusting their price in a given quarter increased by 7 percentage points. Of this change, they attribute just a small amount to heightened uncertainty (which they measure with their index named absolute quantitative forecast error, $\text{ABSFE}^{\text{quan}}$).

As already mentioned, our methodology could solve these criticisms, firstly, as we allow uncertainty to influence the structure of the economy besides from its influence on aggregate price flexibility and pricing decisions and, secondly, through the firm-specific capital version of the ACEL model (the reader is referred to the Introduction and to section 3.1 for the reasons why)[58]. However, our results do not allow us to take a stand on whether the model produces empirically justifiable microeconomic implications. Unfortunately, the firm-specific capital model returns an imprecise estimate of the difference in frequency of price adjustments between uncertain and tranquil times (the difference is even larger than in the homogenous capital version, but now the parameter ξ_p estimated for uncertain times is very imprecisely estimated). However, one has to admit that, differently from Vavra's (2014b) analysis, the assumption of full dynamic indexation makes it conceptually difficult to make comparisons[59] [60].

4 The main drivers behind the difference between uncertain and tranquil times

The mian aim of this section is to investigate what are the most important drivers behind the lower effectiveness of monetary policy shocks on output during uncertain times according to our workhorse New Keynesian model. To this aim, we perform some counter-factual exercises.

We begin with a counterfactual exercise that splits estimated parameters into four groups and asks which group appears the most important in reducing the difference

[58] To understand the increase in flexibility allowed by the firm-specific capital model, just consider that the homogenous capital model would need an irrealistically large $\gamma^H = 9.06$ in order to generate the ξ_p^H of the firm-specific capital model.

[59] Notice that if one instead would not care that much to this conceptually difficult comparison, a possible conclusion could be the following. Even though the firm-specific capital model is generally found succeding in reconciling macro vs. micro evidence in average (i.e., during normal times) (see ACEL (2011) and Eichembaum and Fisher (2007)), it seems not able to do the same between uncertain and tranquil times. This result may point to a inner deficiency of NK models. That is, although the Calvo-type restrictions can be thought as useful reduced form tool for a parsimonious modelling of firms price setting decisions in normal times, the same tool has a smaller potential when uncertainty-conditional facts have to be explained, where extensive margin decisions (i.e. regarding the change in the mix of adjusters) by firms may be an important driver behind the difference in aggregate price flexibility between uncertain and tranquil times.

[60] Provided that most New Keynesian models fail to fit micro evidence on the frequency of price adjustement equally well as they fit aggregate price dynamics, and given that this generally does not have important shortcomings on the way the model can explain macro data – our objective - , we do not see a fail of the model along this line as an impediment against the use of the model in order to investigate, through counterfactual experiments, which seem to be the most important drivers behind the difference between uncertain and tranquil times.

between regimes in model-based responses. In particular, we obtain model-based responses on the basis of a counter-factual exercise that replaces, for each group at a time, the estimated parameters values for uncertain times with the ones for tranquil times. The four groups in which we split parameters are the following: a "monetary policy shock" parameters group, including ρ_M and σ_M, a "price-setting" parameters group, including γ and λ_f, a "consumers" parameters group, including b and ϵ, and a "firm-side" parameters group, including σ_a and S''[61].

Figure 7 reports results focusing on the responses of output, inflation and the policy rate[62]. Two comments are in order. First, the most important parameters group in driving the difference between regimes is the price-setting group. That is, by replacing uncertain times price-setting parameters with tranquil times ones we obtain that output response during uncertain times get the closest to tranquil times response. The more persistent response of output seems due to a flatter response of inflation. Second, the parameters group less important in explaining the difference is the monetary policy shock group. This suggests that the model is able to explain internally the difference between uncertain and tranquil times. Indeed, as the reader may see, the monetary shock parameters taken together do not influence much the different response of the policy rate between regimes, meaning that it is in large part explained internally by the model.

It is now important to assess the role of each given parameter inside each group. We do that with a counter-factual exercise that replaces one uncertain times parameter value at a time with the correspondent estimated value for tranquil times. Figure 8 in its first 3 rows presents results for each of the parameters inside the price-setting parameters group, consumers parameters group and firm-side parameters group. The focus is on real activity variables (a figure showing the model-based responses of each variable is available on request). Interestingly, each parameters group has one parameter which matters more in explaining the difference between regimes for real activity variables. In particular, the parameters driving most the difference are the slope of the NKPC,

[61] Price-setting parameters group is as in Christiano, Trabandt and Walentin (2011, table 3). The firm-side parameters group includes parameters referring to variables that are object of choice by firms in the firm-specific capital model. In general, parameters inside this group can be referred to as the supply-side of the economy. We do not include the parameter ξ_w in any groups, but including it in the consumers parameters group would not influence importantly results.

[62] Notice that this counterfactual can be interpreted easily for the homogenous capital model. Instead, a clarification is needed for the firm-specific capital model. In this case one has to remember that when parameters change (mostly γ, λ_f or σ_a) also the implied ξ_p is changing (and hence it cannot be said that exactly everything else is equal).

γ, the degree of habits in consumption, b, and the capacity adjustment costs curvature, σ_a. Therefore, on the basis of the model employed, we can conclude that what reduces most the effectiveness of monetary policy shocks on output during uncertain times is a mix of three things: (i) a steeper NKPC (e.g., because of firms incentives to re-adjust prices more frequently), (ii) an higher cost to vary capital utilization , and (iii) a less care by consumers to previous consumption levels in order to decide the current one (both because of more precautionary savings in place and a reduced "subsistence" level of consumption required[63]) . The last row of figure 8 presents a check for such a claim. It shows a counter-factual exercise where all the previous three parameters are varied in once. It turns out that the difference in these estimated parameters between regimes explains most of the difference in output response between uncertain and tranquil times.

Wrapping up, the workhorse NK model shows itself as being remarkably able to fit uncertainty-conditional unrestricted evidence, to provide sensible parameters estimates accounting for the difference between uncertain and tranquil times, and to give reasonable insights on the main drivers of the difference among uncertainty times.

5 Robustness checks

In this section, we perturb, one at a time, the baseline specification of both the TVAR and ACEL DSGE model, in order to check the robustness of our results along several dimensions. As regards the TVAR model it is important to check whether results are robust to the most common identification scheme used in the literature to identify monetary policy shocks (i.e., Cholesky), to a longer and updated sample period, and to the employment of different uncertainty proxies. As regards the DSGE model, it seems foremost important to check whether the assumption about the working capital channel plays a crucial role in obtaining results.

5.1 TVAR specification

Recursive identification. Our baseline analysis has used the identification scheme as in ACEL (2005, 2011), i.e. a mix of long- and short-run restrictions from which the monetary policy shocks were obtained. However, the most common way to identify monetary policy shocks in the literature is through the short-run restrictions implied by the Cholesky decomposition of the VCV matrix of VAR residuals. Figure 9 shows

[63] Regarding the latter interpretation, notice that, defined $H_t = bC_{t-1}$, it has to be $C_t - H_t > 0$ in order to have a well defined utility function (see Dennis (2009) for this interpretation).

the impulse response functions (and relative confidence bands) of a TVAR where shocks were recovered according to this assumption[64]. The figure (as also the following ones shown in this sub-section) plots also baseline model-based responses in order to check whether they are still able to explain the alternative empirical evidence found. As it is clear from the figure, most IRFs are still well inside VAR confidence bands and the same conclusions as in the baseline analysis can be drawn.

Updated sample period. The baseline analysis is conducted over the quarterly sample period 1960IV-2001IV in order to remain as close as possible to ACEL (2005) (whose data are available in the ACEL's (2011) replication file). It is though important to show that results do not depend on the particular sample period employed. To this end, we update the data in the sample following ACEL (2011, footnote 16)[65]. Figure 10 plots the results based on the sample period 1960IV - 2008III[66]. Again, results are very robust.

A firm-level uncertainty proxy: IQR of sales growth. In the baseline analysis we used the macroeconomic uncertainty indicator proposed by Jurado et al. (JLN) (2015). We believe it represents a good baseline choice, because, as this index is constructed on the basis of whether the whole economy has become more or less predictable - rather than whether particular economic indicators have become more or less variable or disperse per se -, it is likely to be relevant for economic decision making. However, even though not questioning the ability of the JLN index in capturing the degree of uncertainty in the economy, it is important to check whether our results are robust to the employment of other dispersion/volatility indicators adopted in the literature. To this end, we now present a check where uncertainty is proxied with a micro-level measure, i.e., the interquartile range (IQR) of sales growth. This is a cross sectional firm-level measure of uncertainty constructed by Bloom, Floetotto, Jaimovich, Saporta-Eksten

[64] A part from Cholesky identification, all the other choices are as in baseline: ACEL's sample, regime-dependent VCV matrix, 2 lags, estimated threshold (the same one as in the baseline analysis is chosen). There is evidence of nonlinearity too (BLM = 2.07, Bwald = 2.44).

[65] All the data are downloaded from the FRED Database available through the Federal Reserve Bank of St. Louis. The mnemonic names of the series downloaded and used are the following: GDP, GDPC96, PCDG, GPDI, PCND, PCESV, GCE, MZMSL, CNP16OV, CUMFNS, FEDFUNDS, HOANBS, COMPNFB and CONSDEF. Notice that, differently from ACEL (2011, footnote 16), we preferreed CUMFNS to CUMFN (as the latter is available from 1972 only). We use the relative price of investment goods available on FRED Database (mnemonic: PIRIC, for more details see DiCecio (2009)).

[66] A part from the extended sample period going all the rest is as in the baseline spefication (here, again, the estimated threshold, 0.851, is at the top of the distribution). There is still evidence of nonlinearity (BLM = 1.82, Bwald = 2.02). The longer sample period allow us also to use more lags (e.g., results, available on request, are similar using 3 lags).

and Terry (2014)[67]. Regarding its motivation, notice that this disaggregate indicator is likely to also capture idiosyncratic (i.e., firm-specific) shocks. These, it is suggested by several studies, constitute 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)). Provided that, according to our results in section 4, price setting behavior constitutes one of the most important driver behind the structural difference between uncertain and tranquil times, it is therefore important to check whether our conclusions based on the baseline nonlinear VAR are robust to the adoption of the IQR of sales growth. This is also important as several studies have found results based on this variable (e.g., Vavra (2014b) and Pellegrino (2015))[68]. Figure 11 presents results based on this uncertainty proxy. As it is clear, most of baseline model-based IRFs still lie inside the confidence bands for the IRFs of this alternative VAR specification.

Uncertainty modelled in the VAR. In our baseline analysis we have excluded uncertainty from our nonlinear VAR in order to be consistent between the TVAR model and the DSGE model. This was a choice motivated by the purpose of estimating the ACEL model. Once we have estimated it, it is though important to assess whether VAR-based responses would be significantly affected by the endogenous modelling of uncertainty in (each regime of) the TVAR. To this end we present a check where we include the baseline JLN uncertainty indicator as the last ordered variable in the VAR[69]. Figure 12 presents the results based on the conditionally-linear responses obtained from the TVAR model[70]. As it clear, VAR-based responses can be still reliably represented

[67] 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 .

[68] Vavra (2014b) uses this measure as an alternative measure to his baseline one, i.e. the IQR of plant-level TFP from Bloom et al. (2014), which is though annual. Pellegrino (2015) instead uses this measure as baseline and finds empirical evidence in favor of a reduced effectiveness of monetary policy shocks during firm-level uncertain times. Here, we start the sample period in 1971Q1 (as in Pellegrino (2015)), instead than from 1962Q1 (i.e., since when uncertainty is available) since this measure is increasing initially and hence the estimated threshold in the latter case would divide the sample in two temporal sub-samples rather than identifying phases of high vs. low uncertainty. In addition, in order to avoid imprecisely estimated IRFs in the uncertain regime we increase the trimming percentage to 35%. Notice that the estimated threshold is again in the upper part of the distribution and there is evidence of nonlinearity as well. We adopt a Cholesky decomposition (but results, available on requests, are very similar in case we adopted the baseline identification strategy).

[69] Jurado, Ludvingson and Ng (2015) use a VAR similar to that studied in Christiano, Eichenbaum, and Evans (2005) and ACEL (2011) and order their uncertainty measure as last too. We use a Cholesky decomposition we identify the monetary policy shocks.

[70] That is, in obtaining responses, we do not acknoledge for the possible feedback effect that the monetary policy shock could have on the uncertainty regime. What one can expect to obtain are responses for a deep uncertain times regime and a deep tranquil times regime. Many recent papers share this assumption with us (see Mittnik and Semmler (2012), Auerbach and Gorodnichenko (2012),

by baseline model-based responses[71]. It seems worthy noticing also the bigger inflation spike that the TVAR estimates for the uncertain times regime.

5.2 DSGE specification

Working capital channel. The ACEL model assumes that firms must borrow the wage bill in advance at the gross nominal interest rate. In this case, a decline in the interest rate lowers firms' marginal costs, which helps to explain an inertial reaction of inflation to the monetary shock. This assumption can be empirically justified on the basis that monetary VARs usually display a "price puzzle" (i.e., a temporary decrease in prices following a monetary policy expansionary shock), although this justification is questionable as it is not clear whether the price response represents a fact or an artifact (see Sims (1992), Uhlig (2005), and Castelnuovo and Surico (2010)). As most NK models do not use such an assumption, it seems hence useful to check whether it is crucial for our results[72]. Figure 13 shows the model-based responses recovered in absence of the working capital assumption and put them in comparison with baseline VAR-based responses. A part from a bigger inflation response, main conclusions remain unaltered.

6 Conclusion

This study, after reassessing with a traditional nonlinear VAR model recent findings in the literature suggesting a lower effectiveness of monetary policy shocks during uncertain times, assesses the ability of a workhorse New Keynesian model to replicate the uncertainty-conditional empirical facts found and to identify their sources. This analysis is made possible by employing a novel regime-dependent IRFs matching estimation approach. This approach may be a way to improve the fit of the DGSE model to different states of the economy given its ability to capture possibly unmodelled mechanisms through regime-specific estimates of structural parameters (see Schorfheide (2008)).

The findings point to an encouraging overall fit of the employed model, reached

Berger and Vavra (2014), and Caggiano, Castelnuovo, and Groshenny (2014)).

[71] This result is in line with Jurado et al. (2015, fn. 20) as the authors find that adding their uncertainty indicator to a linear VAR model does not influence importantly, neither qualitatively nor quantitatively, the effects of monetary policy shocks.

[72] For example, a more persistent drop in the interest rate could be at the basis, through the working capital channel, of the more inertial response of inflation during tranquil times, and hence at the basis of the bigger reaction of output too.

mostly through changes in private sectors structural parameters between regimes, which touch closely several theoretical channels proposed in the literature. Among these, the model suggests that the most important drivers behind the lower effectiveness of monetary policy shocks on output during uncertain times are a steeper NKPC, a higher cost to vary capital utilization and a lower degree of habits in consumption.

Still some modelling (as well as estimation) advancements are needed to approach in the best way the kind of questions that here we answer through the lenses of the currently workhorse New Keynesian model[73]. Theoretically, the ideal model for such a purpose, to our knowledge, is not available yet. The influence of uncertainty on the effectiveness of monetary policy shocks or policy stimuli in general has been studied separately either in price-setting general equilibrium menu cost models or real models embedding non-convex investment and hiring adjustment costs (see Vavra (2014a) and Baley and Blanco (2015) as examples of the first type of models, and Bloom (2009) and Bloom et al. (2014) as examples of the second type). Our data-driven results just scratch the surface and suggest that developing a DSGE model embedding more than just a channel at a time among those identified by the literature would be a particularly fruitful avenue to follow for research.

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Parameters	Uncertain times Parameter Estimates	Tranquil times Parameter Estimates	Linear VAR Parameter Estimates
ρ_M	-0.355*** (0.098)	0.237* (0.123)	-0.008 (0.080)
σ_M	0.333*** (0.076)	0.216*** (0.058)	0.341*** (0.072)
ϵ	0.665*** (0.161)	0.838*** (0.229)	0.756*** (0.173)
S''	7.151 (14.739)	20.263 (30.611)	4.698*** (2.359)
ξ_w	0.801*** (0.271)	0.753*** (0.212)	0.607**** (0.090)
b	0.652*** (0.126)	0.848*** (0.031)	0.777*** (0.035)
λ_f	1.010*** (0.347)	1.163*** (0.308)	1.043*** (0.109)
σ_a	1.750 (5.828)	0.248 (0.416)	0.047 (0.049)
γ	0.295 (0.400)	0.010 (0.021)	0.065 (0.053)
Implied ξ_p:			
-homogenous capital	0.586*** (0.209)	0.907*** (0.095)	0.778*** (0.080)
-firm-specific capital	0.091 (2.572)	0.888*** (0.131)	0.744*** (0.122)
Price duration:			
-homogenous capital	2.417	10.765	4.507
-firm-specific capital	1.100	8.931	3.912

Table 1: **Regime-dependent estimation results.** The estimated parameters are: Autocorr. monetary policy shock (ρ_M), St. dev. monetary shock (σ_M), SS Interest rate semi-elasticity (ϵ), Investment adjustment costs curv. (S''), Wage stickiness (ξ_w), Consumption habit (b), Price markup (λ_f), Capacity adjustment costs curv. (σ_a), Slope NKPC (γ).

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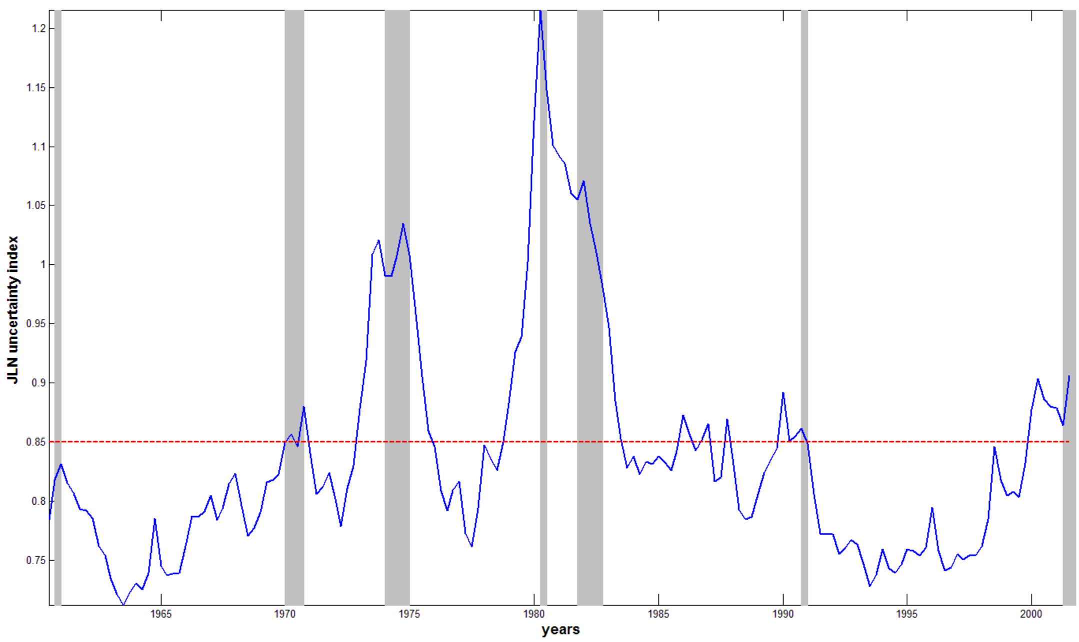

Figure 1: **Threshold variable between uncertainty regimes.** Blue solid line: Jurado, Ludvingson and Ng (JLN) uncertainty index (sample: 1960Q4-2001Q4). Grey areas: NBER recessionary quarters. Red dotted line: estimated threshold value.

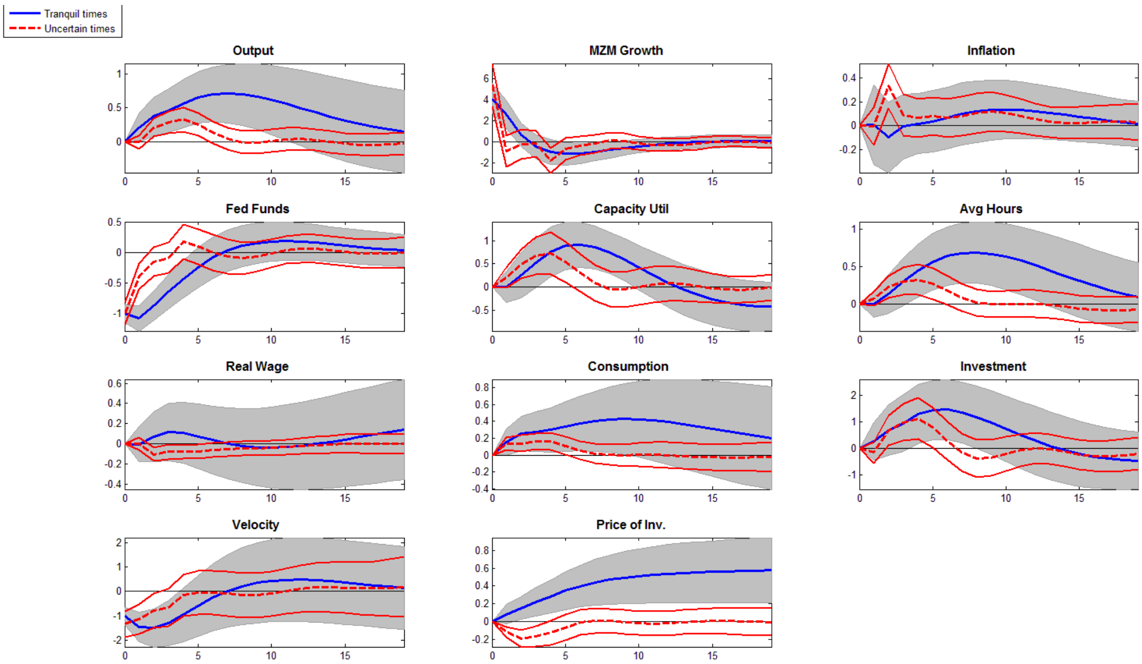

Figure 2: **TVAR-based regime-dependent responses for the uncertain times and tranquil times regime.** Red dotted and solid lines: point estimates and 90% bootstrapped confidence bands for the IRFs conditional to a uncertain times regime. Blue solid lines and grey areas: point estimates and 90% bootstrapped confidence bands for the IRFs conditional to a tranquil times regime.

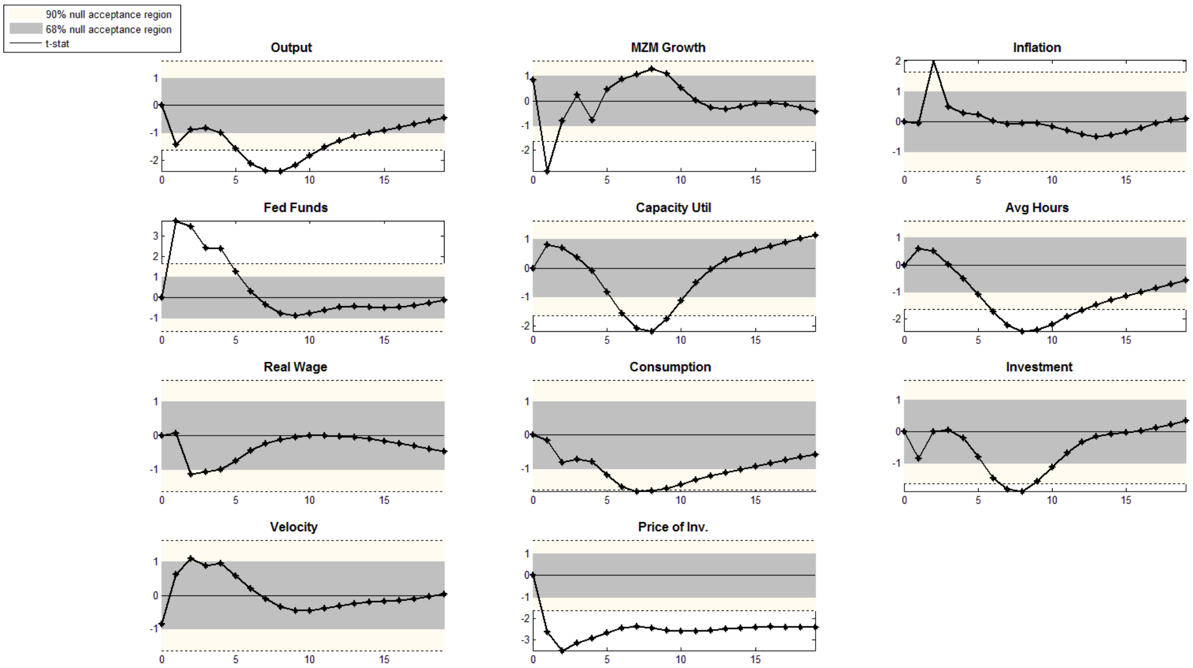

Figure 3: **Test for the difference between regime-dependent IRFs.** Solid black line: t-stat for the difference of the IRFs between uncertain and tranquil times. Interior dark grey and exterior light grey areas: 68% and 90% two-sided acceptance regions for the null hypothesis of no difference.

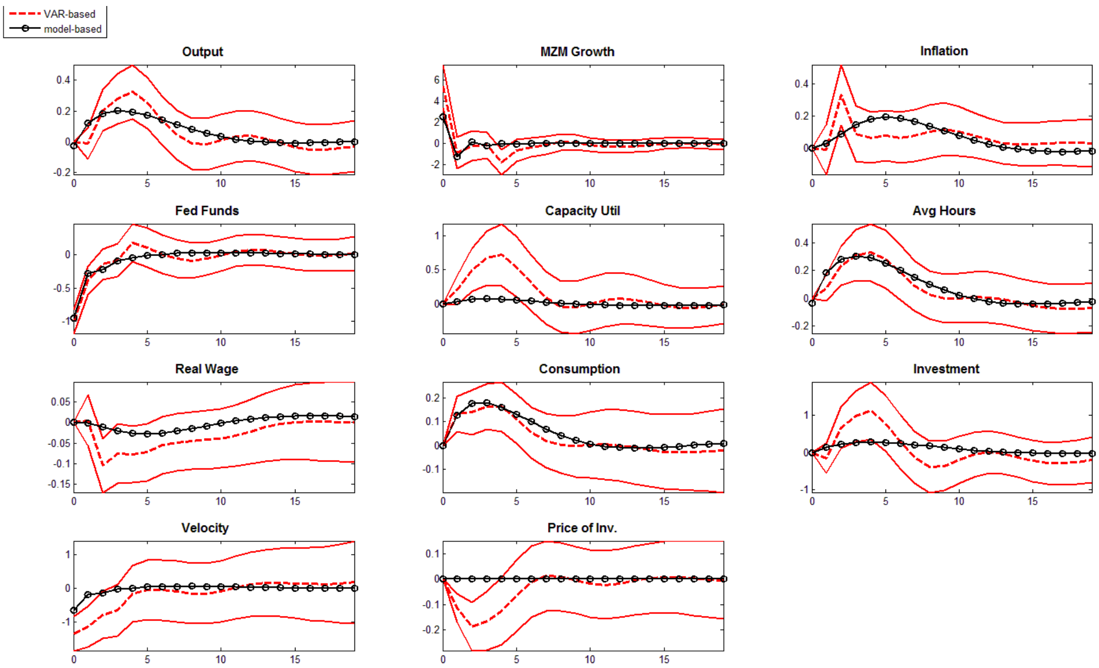

Figure 4: **Comparison between TVAR-based and DSGE-based regime-dependent responses for the uncertain times regime.** Red dotted and solid lines: point estimates and 90% bootstrapped confidence bands for the VAR-based IRFs conditional to a uncertain times regime. Black solid lines: DSGE-based IRFs conditional to a uncertain times regime.

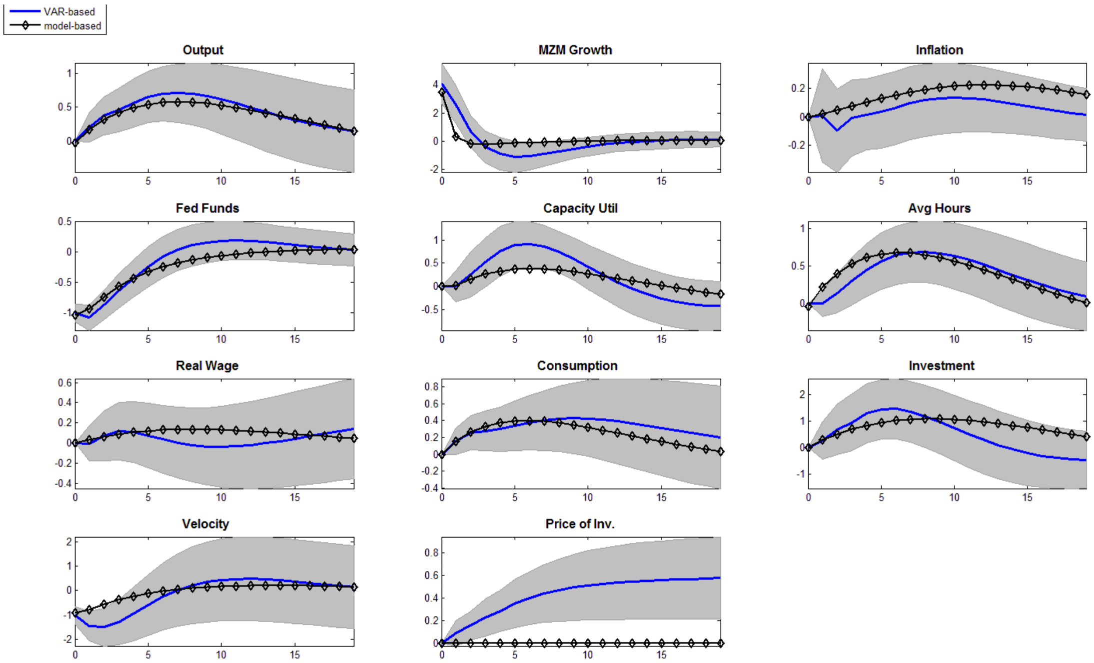

Figure 5: **Comparison between TVAR-based and DSGE-based regime-dependent responses for the tranquil times regime.** Blue solid lines and grey areas: point estimates and 90% bootstrapped confidence bands for the VAR-based IRFs conditional to a tranquil times regime. Balck solid lines: DSGE-based IRFs conditional to a tranquil times regime

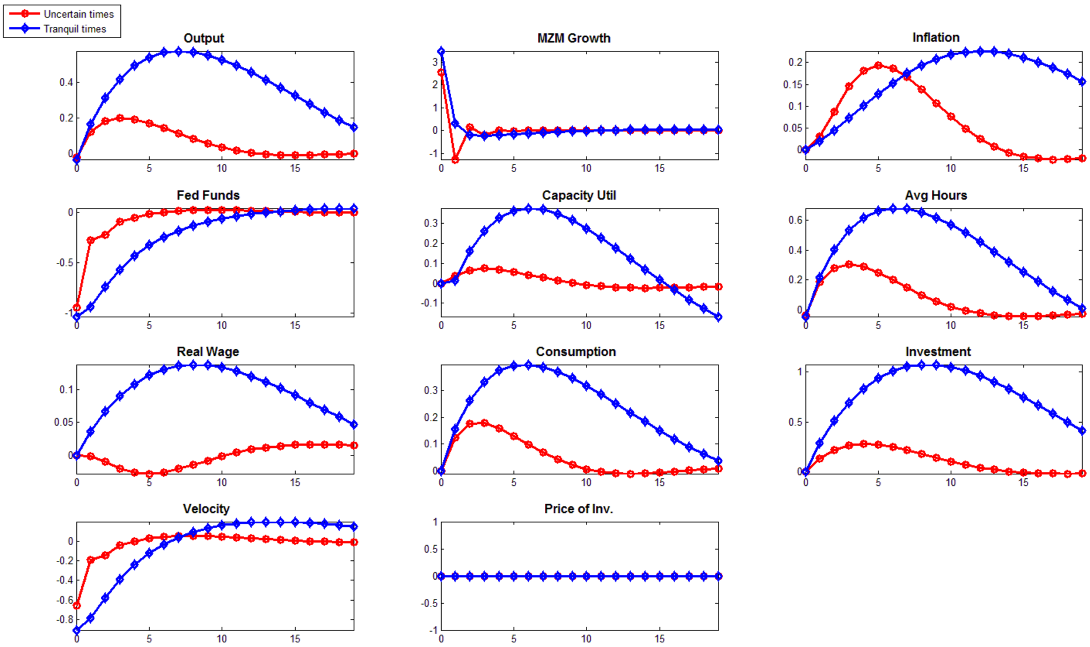

Figure 6: **Comparison between DSGE-based regime-dependent responses for the uncertain times and tranquil times regimes**. Red dashed lines: DSGE-based IRFs conditional to a uncertain times regime. Blue dashed lines: DSGE-based IRFs conditional to a tranquil times regime.

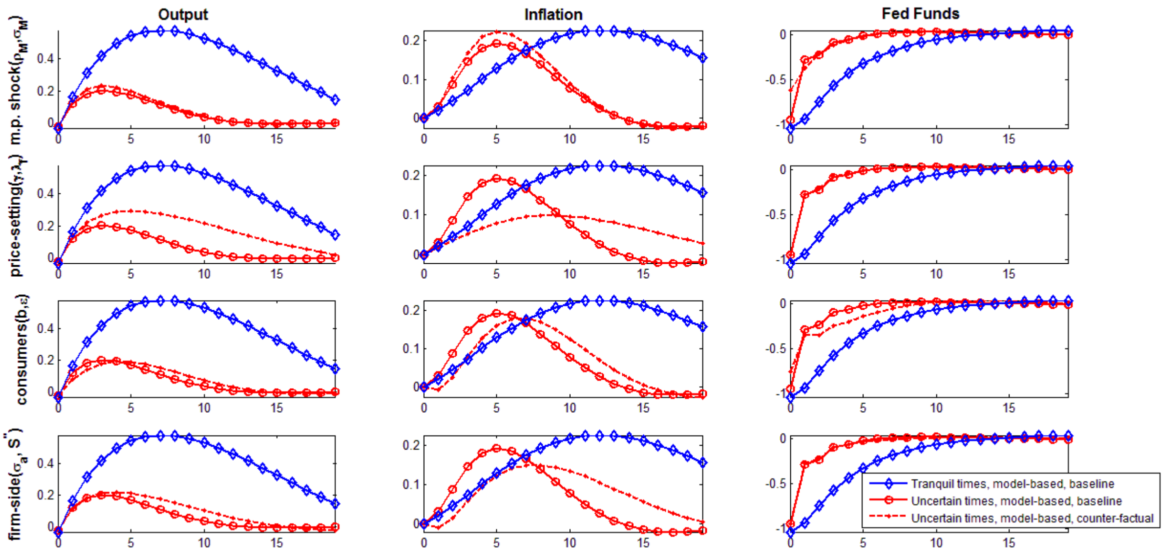

Figure 7: **Counter-factual exercise 1: the parameters groups as a driver of the difference between uncertain and tranquil times.** Red solid lines: baseline DSGE-based IRFs conditional to a uncertain times regime. Blue solid lines: baseline DSGE-based IRFs conditional to a tranquil times regime. Red dashed lines: counter-factual DSGE-based IRFs conditional to a uncertain times regime.

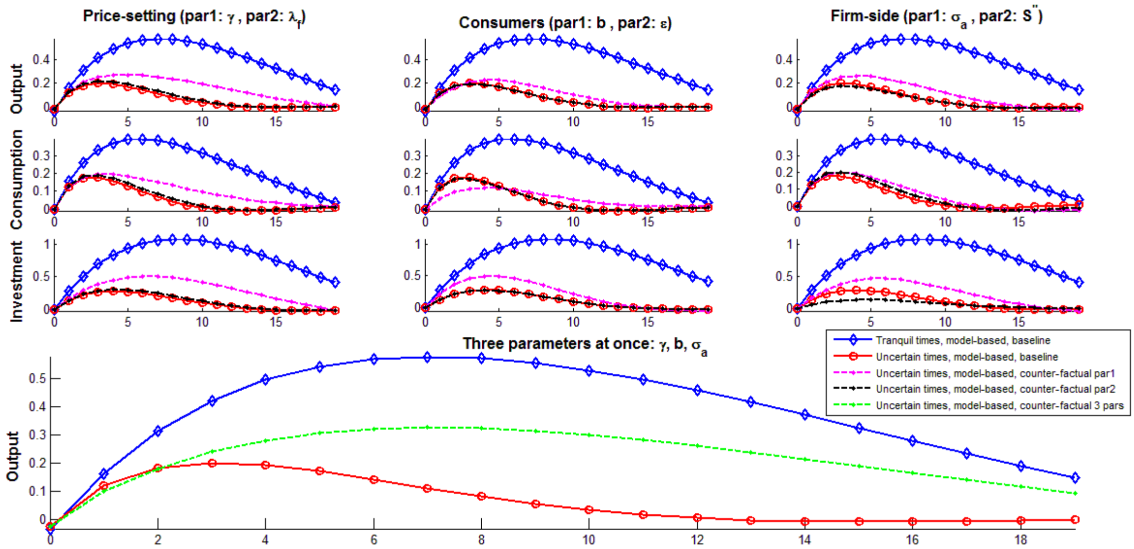

Figure 8: **Counter-factual exercise 2: the parameters driving most the difference between uncertain and tranquil times.** Red solid lines: baseline DSGE-based IRFs conditional to a uncertain times regime. Blue solid lines: baseline DSGE-based IRFs conditional to a tranquil times regime. Magenta, black and green dashed lines: counterfactual DSGE-based IRFs conditional to a uncertain times regime.

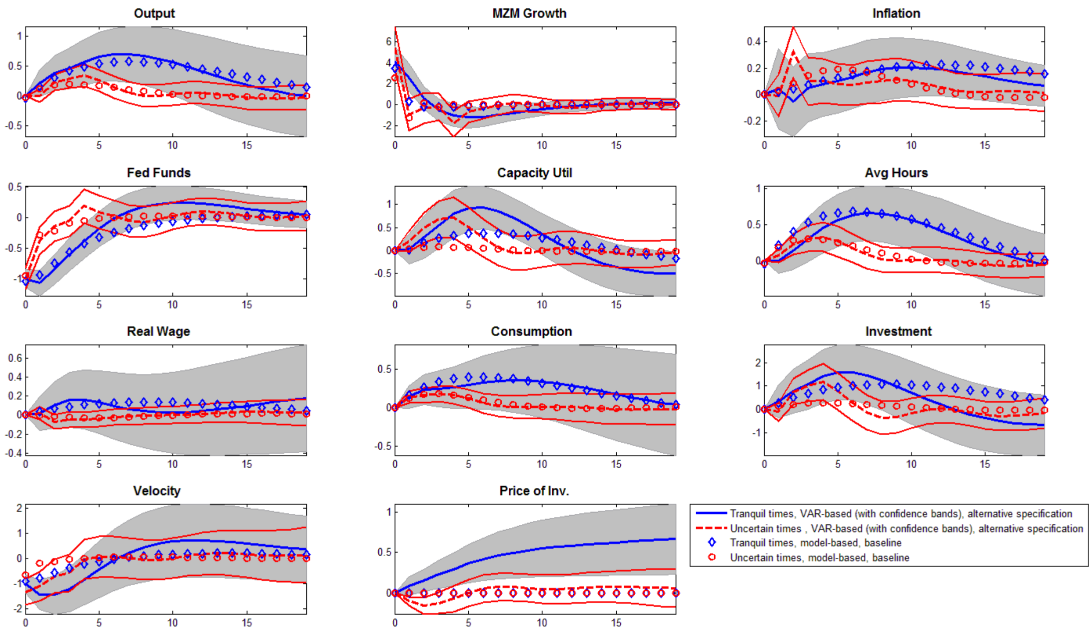

Figure 9: **VAR robustness check 1: Cholesky identification.** Red dotted and solid lines (blue solid lines and grey areas): point estimates and 90% bootstrapped confidence bands for the VAR-based IRFs conditional to a uncertain times (tranquil times) regime for the alternative TVAR specification. Red circles (blue diamonds): baseline DSGE-based IRFs conditional to a uncertain times (tranquil times) regime .

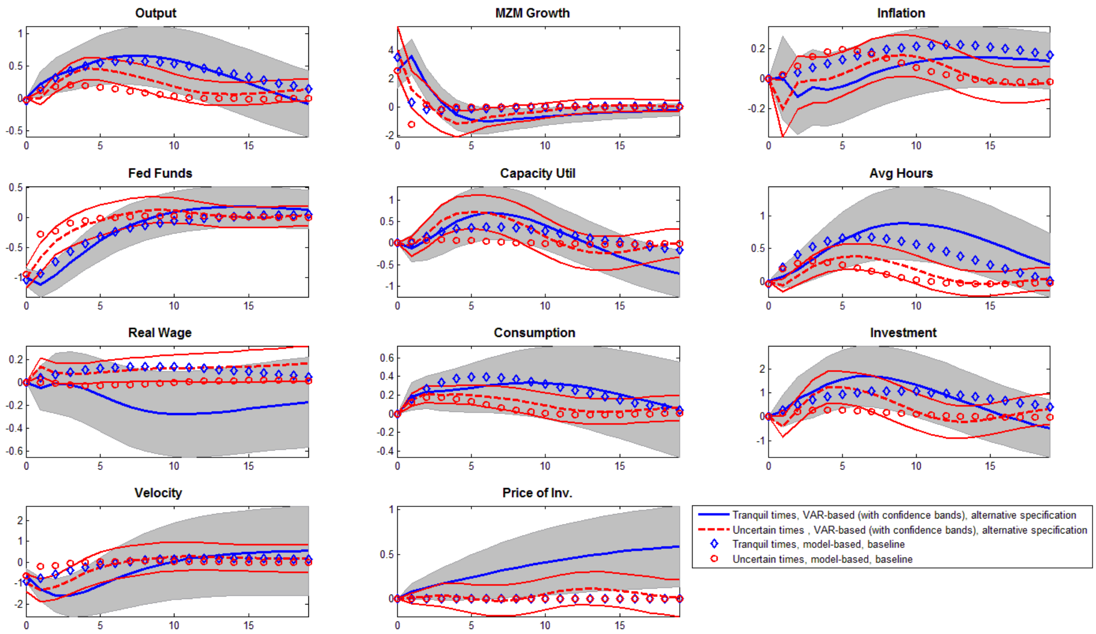

Figure 10: **VAR robustness check 2: longer and updated sample period.** Red dotted and solid lines (blue solid lines and grey areas): point estimates and 90% bootstrapped confidence bands for the VAR-based IRFs conditional to a uncertain times (tranquil times) regime for the alternative TVAR specification. Red circles (blue diamonds): baseline DSGE-based IRFs conditional to a uncertain times (tranquil times) regime .

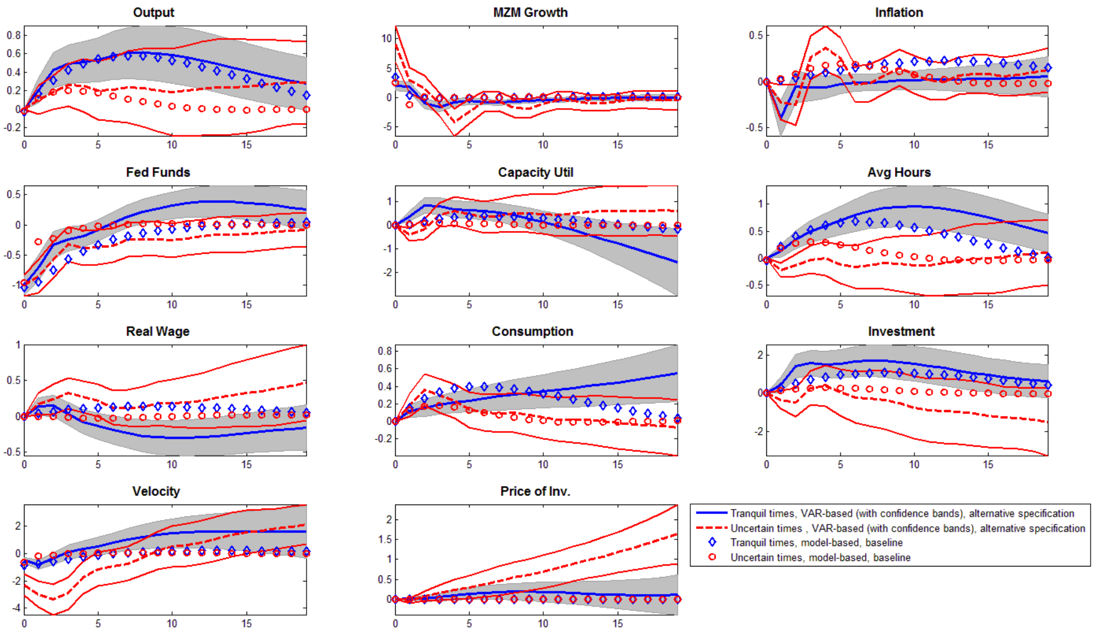

Figure 11: **VAR robustness check 3: IQR of sales growth as an alternative uncertainty proxy.** Red dotted and solid lines (blue solid lines and grey areas): point estimates and 90% bootstrapped confidence bands for the VAR-based IRFs conditional to a uncertain times (tranquil times) regime for the alternative TVAR specification. Red circles (blue diamonds): baseline DSGE-based IRFs conditional to a uncertain times (tranquil times) regime .

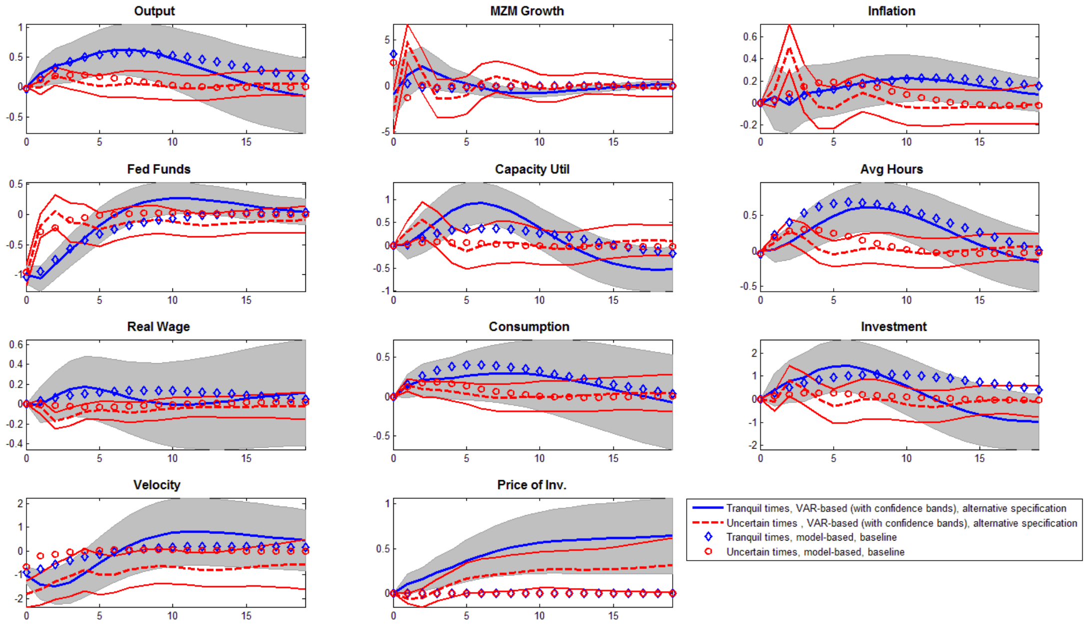

Figure 12: **VAR robustness check 4: JLN uncertainty modeled in the VAR.** Red dotted and solid lines (blue solid lines and grey areas): point estimates and 90% bootstrapped confidence bands for the VAR-based IRFs conditional to a uncertain times (tranquil times) regime for the alternative TVAR specification. Red circles (blue diamonds): baseline DSGE-based IRFs conditional to a uncertain times (tranquil times) regime .

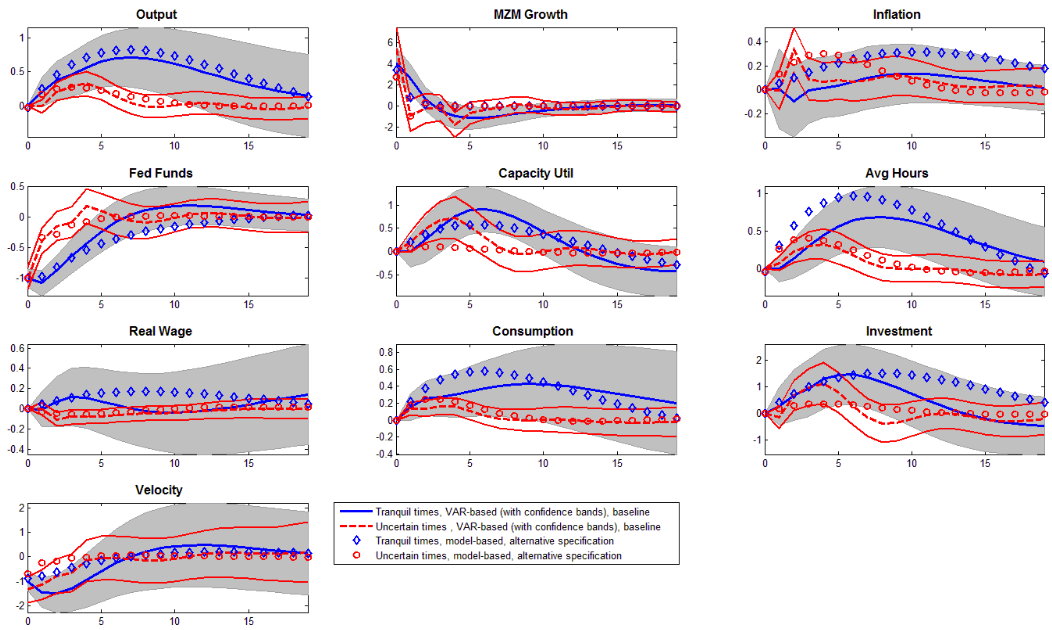

Figure 13: **DSGE robustness check 1: no working capital channel.** Red dotted and solid lines (blue solid lines and grey areas): point estimates and 90% bootstrapped confidence bands for the baseline VAR-based IRFs conditional to a uncertain times (tranquil times) regime. Red circles (blue diamonds): DSGE-based IRFs conditional to a uncertain times (tranquil times) regime for the alternative DSGE specification .