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Uncertainty-dependent Effects of Monetary Policy Shocks: A New Keynesian Interpretation

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Abstract

We estimate a nonlinear VAR model to study the real effects of monetary policy shocks in regimes characterized by high vs. low macroeconomic uncertainty. We find unexpected monetary policy moves to exert a substantially milder impact in presence of high uncertainty. We then exploit the set of impulse responses coming from the nonlinear VAR framework to estimate a medium-scale new-Keynesian DSGE model with a minimum-distance approach. The DSGE model is shown to be able to replicate the VAR evidence in both regimes thanks to different estimates of some crucial structural parameters. In particular, we identify a steeper new-Keynesian Phillips curve as the key factor behind the DSGE model's ability to replicate the milder macroeconomic responses to a monetary policy shock estimated with our VAR in presence of high uncertainty. A version of the model featuring firm-specific capital is shown to be associated to estimates of the price frequency which are in line with some recent evidence based on micro data.

JEL-Codes: C220, E320, E520.

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

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1 Introduction

Two of the main facts of the global financial crises are the dramatic increase in uncertainty occurred starting in 2007 and the spectacular drop in the federal funds rate engineered by the Federal Reserve in the attempt of slowing down the fall of real GDP in the United States. According to Jurado, Ludvigson, and Ng (2015), the 2007-09 recession represents the most striking episode of heightened uncertainty in the post-WWII period. The Federal Reserve slashed the effective federal funds rate by more than 500 basis points in the period July 2007-December 2008 before hitting the zero lower bound and moving to unconventional policies. But how effective is expansionary monetary policy in presence of high uncertainty?

A recent strand of the empirical literature points to a weak impact of monetary policy shocks on real activity in presence of high uncertainty (see, among others, Eickmeier, Metiu, and Prieto (2016), Aastveit, Natvik, and Sola (2017), and Pellegrino (2017a,b)).[1] This paper's contribution to the literature is twofold. First, it offers fresh empirical estimates on the nonlinear macroeconomic effects of monetary policy shocks in presence of high uncertainty by estimating a medium-scale Threshold VAR (TVAR) model. High and low uncertainty states are identified by appealing to the macroeconomic uncertainty indicator recently proposed by Jurado, Ludvigson, and Ng (2015). Such indicator, constructed via a data-rich strategy involving more than 130 time-series, can be interpreted as a broad measure of macroeconomic uncertainty that is likely to proxy the type of uncertainty that households and firms consider when determining their optimal consumption, investment, and pricing plans. Second, and more importantly, we offer a new-Keynesian interpretation of the impulse responses produced by our TVAR. We do so by estimating key-structural parameters of the state-of-the-art medium-scale new-Keynesian model by Altig, Christiano, Eichenbaum, and Lindé (2011) in a state-contingent fashion to replicate the impulse responses of the "data", i.e., those coming from the TVAR model. The estimation of the Altig, Christiano, Eichenbaum, and Lindé (2011) model, which is an evolution of the Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007) workhorse frameworks, is conducted

[1] A related paper is Tillmann (2017), who shows that monetary policy shocks lead to a significantly smaller increase in long-term bond yields in presence of high policy uncertainty. This literature focuses on uncertainty as a conditioning element. A different literature scrutinizes the effects of monetary policy shocks and the role of systematic monetary policy in recessions and expansions - see, e.g., Mumtaz and Surico (2015), Tenreyro and Thwaites (2016), and Caggiano, Castelnuovo, and Nodari (2017). For an empirical paper dealing with uncertainty shocks in different monetary policy regimes, see Caggiano, Castelnuovo, and Pellegrino (2017).

by appealing to the Bayesian minimum-distance estimator recently proposed by Christiano, Trabandt, and Walentin (2011). This empirical step is implemented to unveil changes in the values of structural parameters which are crucial for the medium-scale DSGE model to replicate our state-dependent TVAR impulse responses. Importantly, the Altig, Christiano, Eichenbaum, and Lindé (2011) nests two cases. In the first one firms' capital is homogeneous and, therefore, immediately transferrable from a firm to another in response to a shock. This case is very standard in the literature. The second one is a case in which capital is firm-specific and, therefore, firms cannot adjust their level of capital in the short-run. As shown by Altig, Christiano, Eichenbaum, and Lindé (2011), firm-specific capital helps their estimated DSGE model to match the persistence of aggregate inflation without imposing an implausibly high degree of price stickiness (see also Eichenbaum and Fisher (2007)).[2]

Our results are the following. First, we find monetary policy shocks to exert a statistically and economically weaker effect on output and other real activity indicators when uncertainty is high. This result, which is obtained with a medium-scale VAR and the use of Jurado et al.'s (2015) state-of-the-art macroeconomic uncertainty indicator, confirms the ones previously put forth by Eickmeier, Metiu, and Prieto (2016), Aastveit, Natvik, and Sola (2017), and Pellegrino (2017a,b) on the weak influence of unexpected policy easings in periods of heightened uncertainty. With respect to these contributions, we use a larger scale VAR model, which is informationally richer and, therefore, less likely to deliver inconsistent responses due to informational insufficiency (Forni and Gambetti (2014)). Moreover, the use of the uncertainty indicator constructed by Jurado et al. (2015), which is based on a large set of macroeconomic and financial indicators, ensures that the definition of uncertainty we consider is a broad one, and therefore captures different types of uncertainty considered by agents in the economic system (say, the one surrounding future technological evolutions, fiscal and monetary policy, the stock market, and so on). Finally, the identification assumptions behind the estimation of the effects of monetary policy shocks in our VAR - i.e., those behind a triangular

[2]The key contribution of firm-specific capital in this set up is that it implies strong effects on output by monetary policy shocks in presence of a reasonable frequency with which firms -reoptimize prices. While sticking to firm-specific capital for comparability reasons with Altig et al. (2011), it is important to stress that alternative mechanisms are able to generate a similar result. A non-exhaustive list includes firm- and sector-specific labor, strategic complementarities due to an elasticity of firm demand that is increasing in the firm's price, sector-specific frequency of price changes, intermediate inputs, rational inattention, and state-dependent pricing. In general, any mechanism that causes a firm's marginal cost to increase with its output would be able to deliver the result delivered by firm-specific capital. For a discussion, see Altig et al. (2011).

economy - are fully consistent with the structure of Altig et al.'s DSGE model, something which is clearly desirable for our exercise. Going back to our impulse responses, we find the response of inflation to be positive and statistically significant only in presence of high uncertainty. This result, coupled with the one on the response of output, points to a trickier inflation-output trade-off to deal with when uncertainty is high.

Second, we find the model developed by Altig, Christiano, Eichenbaum, and Lindé (2011) to possess a remarkably good ability to fit our state-contingent responses no matter what the level of uncertainty is. This is due to the flexibility of our estimation strategy, which allows the structural parameters of the DSGE model to take state-contingent values in the estimation phase. In particular, our results point to a steeper new-Keynesian Phillips curve (NKPC) as the key ingredient to match the TVAR impulse responses in uncertainty times. This result, which is obtained with a full-system estimation of a medium-scale DSGE model, echoes the one in Vavra (2014b), who focuses on a single equation estimation of a battery of new-Keynesian Phillips curves. In his paper, the slope of the supply curve is influenced by a Calvo parameter whose value may depend on the level of uncertainty. With respect to Vavra (2014b), we show that a purely macro-related approach dealing with a DSGE model that features firm-specific capital is able to generate a worsening of the inflation-output trade-off in uncertain times. Importantly, we find that the change in this trade-off occurs for state-contingent estimates of the Calvo parameter whose values are close to the recent evidence on price duration based on micro data (see Nakamura and Steinsson (2008), Eichenbaum, Jaimovich, and Rebelo (2011), and Kehoe and Midrigan (2015)). This is due to the connection between the value of the Calvo parameter and that of the slope of the Phillips curve. Such connection is much tighter in models with homogeneous capital than in models with firm specific capital. The latter ones are able to generate a flatter slope of the Phillips curve conditional on the same calibration of the Calvo parameter, a flexibility which is picked up by the data when it comes to replicating impulse responses to a monetary policy shocks in presence of high and low uncertainty.

Our empirical findings are important from a modeling standpoint. First, empirically credible DSGE models are often used to perform policy exercises which aim at understanding the role of monetary policy for the stabilization of the business cycle. Our results point to the need of using different calibrations to study the effects of monetary policy shocks in normal times vs. periods of heightened uncertainty. Second, Vavra (2014b) estimates a battery of new-Keynesian Phillips curves whose structural parameters depend on the level of uncertainty present in the economic system. He shows that firm-level volatility may importantly influence the role played by macroeconomic shocks to the inflation-output trade-off faced by policymakers by affecting the slope of the new Keynesian Phillips curve. Our state-dependent estimates of the medium-scale DSGE model we work with supports this view, therefore stressing the relevance of modeling the interaction between uncertainty and price setting decisions when it comes to understanding the role of the former for the evolution of inflation and real activity. This mechanism adds to precautionary savings and real-option effects for the transmission of uncertainty shocks (see Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015) and Basu and Bundick (2017) for the former channel, Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2016) for the latter). Our paper, which is admittedly silent as regards these two channels, points to a state-contingent calibration of the Calvo parameter and, therefore, a different price flexibility at a macroeconomic level as an important mechanism to understand the different effects of monetary policy shocks in presence of high/low uncertainty. Our findings are also important from a policy perspective, in that they point to a different ability of exploiting the inflation-output trade-off in periods of high vs. low uncertainty by monetary policy makers.

The paper develops as follows. Section 2 discusses the relation with the literature. Section 3 presents the non-linear VAR model employed and documents our results on the uncertainty-dependent consequences of monetary policy shocks from this relatively unrestricted framework. Section 4 briefly presents the Altig et al. (2011) model, describes the econometric strategy adopted to estimate the DSGE model, and discusses the regime-dependent estimation results. Section 5 investigates the sources of the different monetary transmission mechanism during uncertain times via counterfactual exercises. Section 6 concludes. Our Appendix documents the robustness of our empirical results.

2 Connections with the literature

Our paper connects to recent contributions in the literature on the interrelations between uncertainty and monetary policy. Various alternative theoretical mechanisms could be at play when it comes to understanding how uncertainty can affect monetary policy's effectiveness. One advocates the real option effect originating in presence of fixed costs or partial irreversibilities. Bloom's (2009) and Bloom et al.'s (2016) (respectively) partial and general equilibrium real firm-level models feature non-convex adjustment costs in capital and labor and a time-varying second moment of the technology process. They find that during phases of heightened uncertainty firms' inaction regions expand as the real-option value of waiting increases. As a result, firms and, on aggregate, the economic system become less responsive to stimulus policies. As pointed out by Bloom (2014), higher precautionary savings in response to a spike in uncertainty could also make aggregate demand less sensitive to variations in policy variables. Another way to model the interaction between uncertainty and policy has to do with the uncertainty-dependent firm-price setting behavior in presence of either menu costs of changing prices or information frictions as in Vavra (2014a) and Baley and Blanco (2015). Both papers work with 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. In the same model, the price level reacts 36% more on impact at the 90th percentile. Our contribution adds to this literature by focusing on the interaction between uncertainty and price stickiness at a macroeconomic level with an estimated medium-scale model of the business cycle of the type employed by central banks.

The closest paper to ours is probably Bachmann, Born, Elstner, and Grimme (2013). They investigate whether uncertainty can reduce the effectiveness of monetary policy shocks through a greater frequency of price adjustments in a small-scale New Keynesian business cycle model. 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 differs from theirs mainly along two dimensions. First, we estimate the DSGE model we work with to match the different dynamic responses in the data during uncertain and tranquil times as captured by an unrestricted VAR model. This is important to understand what parts of the model one should tweak to replicate the empirical facts, something which is of obvious relevance when it comes to employing this model to conduct policy analysis in presence of different levels of uncertainty. For instance, we find that a lower degree of policy inertia in uncertain times plays a non-negligible role in shaping such responses. Second, we work with a medium-scale new-Keynesian model featuring the bells and whistles that one needs to generate hump-shaped responses of real variables and an inertial response of inflation to the monetary policy shock (Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), Altig, Christiano, Eichenbaum, and Lindé (2011)). In particular, Altig, Christiano, Eichenbaum, and Lindé (2011) show that the presence of firm specific capital can reconcile inflation inertia with a reasonable calibration of the Calvo parameter, something which is not possible in presence of homogeneous capital.

Another study closely related to ours is Vavra (2014b). He estimates a state-dependent new-Keynesian Phillips curve (NKPC) à la Galì and Gertler (1999) and shows that its slope is increasing in uncertainty, particularly with microeconomic uncertainty. He also finds that when his estimation is interpreted structurally through the lens of the Calvo new-Keynesian model, it implies an implausible 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 effect on frequency are likely to provide a lower bound on the actual importance of uncertainty in the data. Our empirical strategy tackles these issues. First, as pointed out above, we allow uncertainty to influence the calibration of the economy in a broader manner than just via pricing decisions. Second, we show that the firm-specific capital version of the Altig et al. (2011) model is empirically relevant in breaking the tight link between aggregate price flexibility and the frequency of adjustment which forces models with homogeneous capital to assume an implausibly high degree of price stickiness to replicate inflation persistence at a macroeconomic level.

To the best of our knowledge, this work is the first paper employing a nonlinear VAR framework to estimate a new-Keynesian model with a minimum-distance approach in a state-dependent fashion. We see this approach as a natural extension of the minimum distance approach implemented by, among others, Christiano, Eichenbaum, and Evans (2005), Boivin and Giannoni (2006), DiCecio (2009), Altig, Christiano, Eichenbaum, and Lindé (2011), and Cecioni and Neri (2011). Given that our analysis delivers a regime-contingent estimation of a DSGE model, our methodological approach naturally relates to the Markov-Switching DSGE approach empirical literature that has developed over the past few years - see, among others, Liu, Waggoner, and Zha (2011), Bianchi (2012), Bianchi (2013), Bianchi (2016), Foerster, Rubio-Ramírez, Waggoner, and Zha (2016), and Bianchi and Melosi (2017). Our approach is computationally easy and fast to implement. Moreover, it enables a researcher to identify the regimes of interest by focusing on an observable transition indicator - in our application, macroeconomic uncertainty as estimated by Jurado, Ludvigson, and Ng (2015). Hence, our application facilitates the identification of the relationship between our regime-specific empirical results and the predictions coming from the theory. Admittedly, our approach assumes that agents believe the state they are in to be absorbing, something which can be questioned in presence of past realizations of different regimes. Moreover, it is worth stressing that agents in our framework are rational regarding their policy functions, but are myopic as far as future regimes are concerned. This modeling assumption is tantamount to that of anticipated utility à la Kreps (1998) often entertained by the learning literature as regards agents dealing with Markov decision problems with unknown probabilities. Interestingly, Cogley and Sargent (2008) study several consumption-smoothing examples and show that the anticipated-utility approximation outperforms the rational expectations one.

More broadly, our paper is related to other recent approaches that estimate DSGE models by allowing for parameters instabilities. Hofmann, Peersman, and Straub (2012) and Giraitis, Kapetanios, Theodoridis, and Yates (2014) estimate New Keynesian DSGE models via an impulse response matching procedure which appeals to a time-varying coefficient-VAR.[3] Consequently, they can obtain time-varying estimate of each of the structural parameters of the model. A related strategy is that of identifying subsamples on the basis of statistical or economic criteria (e.g., a break in a policy regime) and allow for subsample-specific estimates of the DSGE model. Contributions following this strategy are Boivin and Giannoni (2006) and Inoue and Rossi (2011). A direct approach to estimate time-varying structural parameters is that of estimating nonlinear models via the particle filter approach as in Villaverde and Rubio-Ramírez (2007, 2008). Another strategy is that of estimating DSGE models with likelihood-based techniques and rolling (or recursive) windows. Canova (2009), Canova and Ferroni (2012), Castelnuovo (2012a), and Doko-Tchatoka, Haque, Groshenny, and Weder (2017) are examples of this approach. The main difference between our approach and the ones in the papers cited above is that ours relates the instability of the structural parameters to the pre-identified source of interest, which is, movements in uncertainty.

Before moving to the rest of the paper, it is worth stressing the following. The structural model by Altig et al. (2011) we use in our analysis is solved up to a first

[3] Notice that Giraitis, Kapetanios, Theodoridis, and Yates (2014) use indirect inference to estimate the DSGE model parameters, i.e., they match the impulse responses of the VAR estimated with actual data with those of the VAR estimated with pseudo-data generated with the DSGE model itself. This strategy requires the DSGE model to have a number of structural shocks at least as large as the number of endogenous variables modeled with the auxiliary VAR. This is a necessary condition to avoid stochastic singularity when estimating the VAR. Our application prevents us to use indirect inference because the number of modeled variables with the VAR (ten) is larger than the number of shocks in Altig et al.'s (2011) DSGE model (three).

order approximation. Hence, by construction, uncertainty plays no role, because it cannot influence agents' behavior. One would need to work with (at least) a third order approximation of the model for time-varying uncertainty to enter agents' policy functions and affect the transmission of monetary policy shocks (see, e.g., Andreasen (2012) and the literature cited therein).[4] Andreasen, Fernández-Villaverde, and Rubio-Ramírez (2017) show the stability of the pruned approximation up to a third order approximation and provide closed-form expressions for first and second unconditional moments and impulse response functions. This result implies that GMM estimation and impulse-response matching for DSGE models approximated up to third order becomes feasible. Andreasen, Fernández-Villaverde, and Rubio-Ramírez (2017) provide a foundation for indirect inference and simulated-method of moments. By conditioning on the first-approximation of the model, our investigation provides a first exploration on the ability of a state-of-the-art, widely employed DSGE framework like Altig et al. (2011) to match impulse responses in two different states of the economy (uncertain and tranquil times), and on the parametric instabilities required by this very same model to achieve this goal. We believe this analysis to be important in light of the wide number of linearized models which are still used in a variety of central banks around the world (Lindé, Smets, and Wouters (2016)). We leave the estimation of the third order approximated version of the model and the investigation on the role of the Phillips curve and other structural parameters in matching the TVAR impulse responses in such a version of the model to future research.

[4] With second order solutions, uncertainty would affect the steady states with no impact on the transmission of shocks. This statement is conditional on approximations in which the exogenous state variables are treated as the endogenous ones. Benigno, Benigno, and Nisticò (2013) follow a different strategy and approximate the exogenous state variables with conditionally-linear stochastic processes where either variances or standard deviations of the primitive shocks are modelled through stochastic linear processes. They show that a second-order approximation of the policy rules is sufficient for time-varying volatility to affect the endogenous variables of the system. A trade-off between generality of the solution and computational complexity is in place here. For a discussion, see Benigno, Benigno, and Nisticò (2013).

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

3.1 Nonlinear empirical methodology

3.1.1 The Threshold VAR

We investigate the uncertainty-conditional impact of monetary policy shocks by working with a two-regimes Threshold VAR model. Following Tsay (1998), the reduced form nonlinear VAR model we estimate is the following:

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

$$E(\mathbf{u}_t^j) = 0, E(\mathbf{u}_t^j \mathbf{u}_t^{j\prime}) = \boldsymbol{\Omega}^j, j \in \{U, T\} \tag{2}$$

where $\mathbf{Y}_t$ is a set of endogenous variables, $\boldsymbol{\alpha}$ is a vector of constants, $\mathbf{B}_j$ is a matrix of coefficients, $\mathbf{u}_t$ is a vector of residuals whose variance-covariance matrix is $\boldsymbol{\Omega}$, and the super-scripts U and T indicate the uncertain and tranquil times regimes, respectively. The two regimes are identified on the basis of the threshold variable z, which is a stationary proxy for uncertainty. A value of the threshold variable greater than or equal to (smaller than) the threshold value Γ implies that the economy behaves according to the uncertain (tranquil) times regime. This model allows, without requiring, for different dynamics of the economy in the two regimes.

The vector of endogenous variables $\mathbf{Y}_t$ embeds the same variables as in Altig et al.'s (2011) VAR, i.e., $\mathbf{Y}_t = [\triangle p_{It}, \triangle y_t - \triangle h_t, \pi_t, h_t, cu_t, y_t - h_t - w_t, c_t - y_t, i_t - y_t, r_t, p_t + y_t - m_t]'$, where $\triangle p_{It}$ stands for the growth rate of the relative price of investment, $\triangle y_t - \triangle h$ for the difference between the growth rate of real GDP per capita and the growth rate of hours worked per capita, which is, the growth rate of productivity, π_t is the GDP deflator quarterly inflation rate, cu_t stands for capacity utilization, $y_t - w_t$ represents the difference between log-real GDP per capita and the per capita real wage, c_t and i_t respectively stand for per-capita consumption and investment, r_t is the net nominal interest rate, and $p_t + y_t - m_t$ is the log of money velocity, m_t being the log of the nominal stock of money. We use an updated version of the original dataset by Altig et al. (2011). As in their paper, all data were taken from the FRED Database available through the Federal Reserve Bank of St. Louis's website. Data transformations in the VAR were performed to ensure stationarity of the modeled variable.

Uncertainty, which is the threshold variable dictating the switch from a regime to another, is not modeled in our VAR. This means that uncertainty cannot react to monetary policy shocks, an assumption that enables us to compute impulse responses to a monetary policy shock in a conditionally-linear fashion, therefore retaining all the properties associated to impulse responses in linear VARs. Hence, one could associate our baseline responses to "deep regimes", i.e., regimes the economic system is very unlikely to escape.[5] These responses, which do not allow for an endogenous response of uncertainty to monetary policy shocks, provide an upper bound for the difference in the real effectiveness of a monetary policy shock between uncertain and tranquil times (for a discussion, see Pellegrino (2017a)). Importantly, the decision to focus on this approach is justified by its consistency with the linearized DSGE model by Altig et al. (2011), which we will use to capture the TVAR state-contingent impulse responses by admitting for different estimates of key structural parameters. Our Appendix shows that computing Generalized IRFs à la Koop, Pesaran, and Potter (1996) - which take into account the endogeneity of the threshold variable - deliver qualitatively similar dynamics to those produced by the conditionally linear approach. As discussed in Section 2, an alternative would be to model different dynamics conditional on a time-varying endogenous process for uncertainty in DSGE model approximated at a third-order. We do not entertain this alternative here for two reasons. First, a nonlinear framework featuring endogenous uncertainty would be complicated to solve and estimate. Second, as pointed out by Christiano (2004), firm-specific capital - which is useful for us because of our intention of matching inflation dynamics without forcing the Calvo parameter to take implausibly large values - substantially complicates the computation of the equilibrium values of the endogenous variables of the system. This is due to the fact that, given that the capital stock is a state variable for an individual firm, the distribution of capital across firms matters for determining aggregate equilibrium outcomes. Hence, in a nonlinear framework, one should keep track of the evolution of that distribution over time. The choice of sticking to a linearized framework enables us to avoid facing the problem of computing such distribution and keeping track of its evolution. Finally, given that our goal here is to investigate the ability of a state-of-the-art model like Altig et al.'s to fit the data in two distinct regimes, our assumption is that rational agents here do not take into account the distribution over future regimes and, therefore, do not form

[5] For studies entertaining this assumption in the context of fiscal spending shocks and uncertainty shocks, see - respectively - Auerbach and Gorodnichenko (2012) and Caggiano, Castelnuovo, and Groshenny (2014).

expectations accordingly. One can interpret rational agents in our models as facing a degenerate distribution of realizations of future regimes pointing to absorbing states, i.e., agents assume the regime they find themselves in to be in place forever. This assumption is entertained in order to facilitate the estimation of the key parameters of the model.[6]

3.1.2 Empirical model: Specification

We study U.S. quarterly data, period: 1960Q3-2008Q2. The construction of the data closely follows Altig et al. (2011).[7] The proxy for uncertainty is the macroeconomic uncertainty index recently developed by Jurado, Ludvigson, and Ng (2015). This index measures uncertainty by computing 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 based on information contained in 132 macroeconomic and 147 financial indicators. Hence, it is informative on the unpredictable component of the economy as a whole, something which is likely to proxy well the uncertainty that agents in the economic system consider when determining their plans.[8] The beginning of the sample is due to the availability of the index, while the end of the sample is justified by our willingness to avoid dealing with the acceleration of the financial crisis occurred in September 2008 with Lehman Brothers' bankruptcy, which would probably require modeling a third regime. This choice also enables us to avoid dealing with the identifi-

[6] Admittedly, our regimes alternate at regular intervals and, in some cases, are characterized by relatively short spells. This implies that a formally more consistent approach would be that of using a Markov-switching DSGE approach as in Liu, Waggoner, and Zha (2011), Bianchi (2012), Bianchi (2013), Bianchi (2016), Foerster, Rubio-Ramírez, Waggoner, and Zha (2016), and Bianchi and Melosi (2017). However, this would render the estimation of the medium scale model we work with computationally challenging. Moreover, Markov-switching models typically feature a latent switching factor. Differently, we focus on an "observable" proxy of uncertainty. An alternative would be to tweak the definition of regimes to render the switches less frequent. Still, even if switches were low probability events, one would need to estimate the model by allowing for expectations to account for future changes in regimes. For earlier attempts along this line, see Cagliarini and Kulish (2013), Kulish and Pagan (2017), and Kulish, Morley, and Robinson (2017). Moreover, tweaking the definition of regimes would add a degree of arbitrariness to the empirical analysis. We leave this step to future research.

[7] 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 Altig et al. (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)).

[8] We use the JLN index referring to a forecasting horizon equal to three months, which is consistent with a one-quarter-ahead forecast. We take quarterly averages of the monthly series.

cation of unconventional monetary policy shocks.

Our TVAR is estimated by conditional least squares as in Tsay (1998). We use two lags.[9] Restrictions are required to identify the monetary policy shock. As suggested by Altig et al. (2011), the presence of a source of long-run growth in the DSGE model we will use to interpret our TVAR responses makes it desirable to sharpen the identification of monetary policy shocks by contemporaneously identifying neutral technology and capital embodied shocks (for a discussion, see Christiano, Trabandt, and Walentin (2011)). To do so, we use the following mix of long-run and short-run 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 in the long run; 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). Our Appendix documents the robustness of our impulse responses to monetary policy shocks identified with a standard Cholesky decomposition of the covariance matrix of the estimated VAR residuals.

A crucial choice is that of the value of the threshold Γ. To maximize the precision of the estimates in the two regimes and, at the same time, minimize the probability of finding different dynamics due to small-sample issues in one of the two regimes, we choose the value of the threshold Γ to be the median of the uncertainty proxy in our sample.[10] Figure 1 depicts the uncertain and tranquil regimes conditional on this choice. Much (but not all) of the periods identified as uncertain times (periods represented by grey vertical bars and characterized by a level of uncertainty above the threshold, which is identified by the horizontal line in the Figure) coincide with recessionary times. This is in line with Jurado et al.'s (2015) finding that the economy is less predictable in recessions than it is in normal times.

It is important to investigate whether our nonlinear specification is supported by the data. To this end, we provide the results from two nonlinear tests for threshold behavior at the multivariate level. Given that our baseline Threshold-VAR features a regime-dependent VCV matrix, we follow Galvão (2006) and Metiu, Hilberg, and

[9] Akaike, Hannan-Quinn and Schwartz criteria support a choice of $L = 3, 1, 1$, respectively for a standard linear VAR based on the same data (up to a maximum lag equal to 8). We choose to use two lags. Christiano, Trabandt, and Walentin (2011) adopt the same lag order for their quarterly sample similar to ours.

[10] Our results are robust to estimating the threshold value as in Tsay (1998) with a trimming equal to 20% and the correction proposed by Balke (2000). This evidence is available in our Appendix.

Grill (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:

$$BLM = \frac{1}{2ln(ln(n))}\left[\sup_{\Gamma_L \leq \Gamma \leq \Gamma_U} n\left(\frac{SSR^{lin} - SSR^{nlin}(\Gamma)}{SSR^{lin}}\right)\right]^{\frac{1}{2}} \text{ and} \tag{3}$$

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

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 TVAR alternative hypothesis.[11] The TVAR 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 $BLM(= 1.65) > 1$ and $BW(= 1.80) > 1$. This evidence supports the choice of working with a nonlinear model for modeling the data belonging to the vector $\mathbf{Y}_t$.

3.2 Empirical results

Figures 2 and 3 depict the state-conditional impulse responses to an unexpected one percentage point reduction of the federal funds rate and the corresponding 90% confidence bands.[12] The left column shows the response of the economy during uncertain times, while the right one the response during tranquil times.[13] The imposition of the same reduction of the federal funds rate in the two states of interest is justified by our willingness of computing macroeconomic responses to the very same policy move across states. The transmission of monetary policy shocks turns out to be state- specific along

[11] The values of Γ used are the actual values of the threshold variable inside the non-trimmed region. Our choice of the trimming is 20%.

[12] Our bootstrapped confidence bands are based over $1,000$ bootstrap realizations for the impulse responses, which are used to compute the bootstrapped estimate of the standard errors of the impulse response functions. As in Altig, Christiano, Eichenbaum, and Lindé (2011), the confidence bands are constructed by considering the point estimates of the impulse response ± 1.64 times the bootstrapped estimate of the standard errors.

[13] Following Altig et al. (2011), the set of impulse responses recovered on the basis of the vector $\mathbf{Y}_t$ are transformed in a different set that matches the DSGE model-consistent objects. In particular, we recover the following ten variables: output, MZM growth, inflation, federal funds rate, capacity utilization, average hours, real wage, consumption, investment, and velocity.

six dimensions. First, real activity indicators such as real GDP, consumption, investment, and hours worked display a lower peak response and persistence in uncertain times. Second, inflation raises quicker in uncertain times. This is signalled by a significant increase in inflation after roughly one year from the shock when uncertainty is high, while no significant response of inflation in tranquil times is detected.[14] Third, the interest rate drop is less persistent during uncertain times. Fourth, capacity utilization experiences a bigger (and significant) increase during uncertain times. Fifth, both the increase in the growth rate of money, which points to the presence of a liquidity effect, and the fall in money velocity are less persistent during uncertain times. Sixth, the increase in real wage is more sustained during tranquil times (even though its response is not precisely estimated).[15] Our Appendix documents the outcome of a formal test which points to statistically relevant differences between state-conditional responses.[16] As regards the confidence bands, notice that those associated to uncertain times are narrower for two reasons. First, uncertain times are characterized by a higher volatility of the macroeconomic indicators modeled with our VAR, something which brings relevant information and works in favor of augmenting the precision of our estimates. Second, our exercise contrasts the effects of an equally-sized reduction of the federal funds rate in the two different regimes. This reduction is equivalent to a shock of 1.25 standard deviations in uncertain times, and of 3.90 standard deviations in normal times, whose computation is possible thanks to the fact that the covariance matrix of our model is regime-specific and, therefore, accommodates shocks featuring regime-specific sizes. Hence, the impact of the normalization of the size of the shock in the two regimes works in favor of narrowing the bands relatively more in uncertain times.[17] When experimenting with a fixed variance-covariance matrix, which controls

[14] If anything, tranquil times are associated to the price puzzle (Eichenbaum (1992)). As far as we know, ours is the first paper to notice the absence of a price puzzle in uncertain times and its presence in tranquil times. We plan to investigate the structural drivers of this fact in future research.

[15] The response of the relative price of investment is not shown because it is unimportant to match model-based responses to a monetary policy shock. According to our VAR, its response is insignificant in both regimes.

[16] 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: $t - stat = (IRF_{t,i}^{U} - IRF_{t,i}^{T})/(\sqrt{(st.dev.(IRF_{t,i}^{U}))^2 + (st.dev.(IRF_{t,i}^{T}))^2})$, where $IRF_{t,i}^{regime}$ represents the point estimated IRF for regime U or T. $t = 0, ..., 19$ represents the horizon ahead to which the response is referred and $i = 1, ..., 10$ denotes the variable whose IRFs are referred.

[17] Notice that, given that we compute conditionally-linear impulse responses, the normalization of the size of the shock does not alter the moments associated to such responses.

for the latter reason behind the narrower bands in uncertain times, we still find that such bands are narrower than in tranquil times.

Our evidence, which is obtained with the medium-scale VAR à la Altig, Christiano, Eichenbaum, and Lindé (2011) and it is conditional on a state-of-the-art indicator of macroeconomic uncertainty recently proposed by Jurado, Ludvigson, and Ng (2015), corroborates that put forth in previous contributions such as Eickmeier, Metiu, and Prieto (2016), Aastveit, Natvik, and Sola (2017), and Pellegrino (2017a,b). It also corroborates the theoretical predictions by Vavra (2014a) and Baley and Blanco (2015) about the lower real effectiveness of monetary policy shocks induced by the higher price flexibility in presence of high uncertainty. About this latter point, our empirical contribution suggests that Vavra's and Baley and Blanco's theoretical predictions, which hinge upon microeconomic indicators of uncertainty, hold true even when using a macroeconomic indicator of uncertainty. Hence, what our empirical results suggest is that Vavra's and Baley and Blanco's models pass also a test conducted with macroeconomic data.

The stylized fact identified in our TVAR empirical analysis is robust to a variety of perturbations of our baseline model. The list includes: i) monetary policy shocks identified via a standard recursive identification scheme à la Christiano, Eichenbaum, and Evans (1999); ii) a constant covariance matrix of the estimated residuals; iii) a different proxy for uncertainty, i.e., the interquartile range of sales growth as in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2016); iv) the use of the Jurado, Ludvigson, and Ng (2015) index computed at a longer forecasting horizon, i.e., one-year ahead; v) a version of the model in which the threshold is estimated; vi) the computation of GIRFs à la Koop, Pesaran, and Potter (1996), which endogenize both uncertainty and its evolution in response to a monetary policy shock. For the sake of brevity, the documentation of these checks is confined in our Appendix.

An important note regards the response of inflation in this VAR. As mentioned above, the response of inflation in tranquil times is found to be statistically insignificant. However, looking at the point estimates, tranquil times are actually associated to the price puzzle (Eichenbaum (1992)). As far as we know, ours is the first paper to notice the absence of a price puzzle in uncertain times and its presence in tranquil times. However, it is well known that standard DSGE frameworks relying on a "demand channel" for the transmission of monetary policy shocks have hard times in replicating the positive response of inflation to a monetary policy shock (Boivin and Giannoni (2006), Rabanal (2007), Castelnuovo (2012b)). In fact, more than a genuine fact, the price puzzle could indeed be interpreted as a signal pointing to VAR misspecification. If the true data-generating process is not consistent with the model of Altig et al. (2011), the identifying assumptions in this stage of the analysis are called into question. A possible consequence is that the estimated impulse response functions are inconsistent, which, in turn, implies that the minimum distance estimation we conduct in the next Section of this paper could produce inconsistent parameters estimates. To tackle this issue, we follow Sims (1992) and add commodity prices to the vector of variables modeled by Altig et al. (2011).[18] Our Appendix shows that our impulse responses are robust to the inclusion of commodity prices in the vector.

4 New Keynesian interpretation of the stylized facts

4.1 The Altig et al. (2011) framework

The impulse responses presented in the previous Section point to different macroeconomic effects of uncertainty shocks in uncertain vs. tranquil times. This Section aims at interpreting such state-conditional responses through the lens of the state-of-the-art new-Keynesian DSGE model by Altig, Christiano, Eichenbaum, and Lindé (2011). This model, which builds on the previous medium-scale DSGE frameworks proposed by Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007), is particularly suited for our purposes for two reasons. First, its timing restrictions are consistent with those imposed on our TVAR to identify monetary policy shocks. This implies that its impulse responses to a monetary policy shock can legitimately be compared with the state-conditional responses produced with our TVAR, something that enables us to estimate the structural parameters of the DSGE model via direct inference.[19] Second,

[18]We add commodity prices in growth rates to line up with the modeling choice by Altig et al. (2011), who work with stationarized variables in their VAR. Our results are unchanged when we model commodity prices in log-levels. An alternative would be to add data on inflation expectations coming from the Survey of Professional Forecasters or Greenbook data, as done by Castelnuovo and Surico (2010). However, this would imply a loss of 10 years of observations, which is the reason why we stick to the more common commodity prices modeling solution.

[19]Notice that VAR and DSGE-based responses are fully comparable since we match the responses of the linearized version of our microfounded model to the conditionally-linear responses of each regime of our VAR. This is feasible for two reasons. First, the variable we employ to determine the regimes of our TVAR, i.e., uncertainty, is modeled neither in our TVAR nor in the DSGE model we work with. Second, since the Altig et al. (2011) model admits a Structural VAR representation (see Section 9 of Altig et al.'s (2011) Appendix), our Structural TVAR can be seen, for each regime, as a finite-lag VAR representation for the DSGE model describing that particular regime. Conditional on state-specific linear responses, the size/sign of the shock does not matter for the shape of responses and hence for DSGE estimation purposes.

this model features firm-specific capital. As shown by Altig, Christiano, Eichenbaum, and Lindé (2011), firm-specific capital is a crucial ingredient to reconcile the micro evidence on the frequency of price adjustment and the macro one on inflation persistence. As we will see later, this ingredient turns out to be crucial also to explain the relationship between uncertainty and the slope of the Phillips curve without appealing to implausible calibrations of the Calvo parameter.

Altig. et al. (2011) is a dynamic, stochastic general equilibrium one-sector model featuring both nominal and real rigidities. The list of rigidities include Calvo-type sticky prices and wages, backward dynamic indexation, habit formation in consumption, investment adjustment costs, variable capital utilization, and a cost channel of monetary policy due to working capital, i.e., firms must borrow to pay wages to workers before the goods market opens. The model features three shocks, i.e., a monetary policy shock, a neutral technology shock, and an investment-specific technology shock. The monetary policy shock exerts a temporary effect on the level of output, while the two technology shocks have a permanent impact on the level of productivity. The model rationalizes liquidity holding (cash balances) via a transaction cost function which is decreasing in the amount of cash balances held. Given that the model is well-known, we refer the reader to the original article by Altig et al. (2011) for details, and we present here just the parts that are crucial for our analysis.

This model features equilibrium linearized expressions which are identical for two different versions of the way in which capital is modeled, i.e., homogeneous vs. firm-specific. However, the slope of the Phillips curve is characterized by different convolutions depending on the way capital is treated. Consider the following expression for aggregate inflation dynamics:

$$\Delta\hat{\pi}_t = E[\beta\Delta\hat{\pi}_{t+1} + \gamma\hat{s}_t \mid \Omega_t] \tag{5}$$

where $\widehat{x} \equiv (x - \overline{x})/\overline{x}$, x is a generic variable whose steady-state value is $\overline{x}$, π_t denotes inflation, s_t identifies the economy-wide average marginal cost of production in units of the final good, Ω_t represents the information set including the current realization of the technology shocks but - given the recursive structure of the economic system - not the monetary policy shock, and β stands for households' discount factor. In this expression, the slope of the Phillips curve γ is a reduced-form coefficient whose convolution of structural parameters reads:

$$\gamma = \frac{(1-\xi_p)(1-\beta\xi_p)}{\xi_p}\chi \qquad (6)$$

where ξ_p denotes the Calvo-probability for a firm to not reoptimize its price in a period, and χ is the parameter that dictates the influence of the way in which capital is modeled on the slope of the Phillips curve.

As shown by Altig et al. (2011), if capital is homogeneous, eq. (6) features $\chi = 1$. In this case, γ coincides with the slope of the New Keynesian Phillips Curve in standard new Keynesian models.[20] If instead capital is firm-specific, χ turns out to be a nonlinear function of the parameters of the model, i.e., $\chi = \chi(\sigma_a, \lambda_f) < 1$, where σ_a regulates the curvature of the capacity utilization adjustments costs function, and λ_f stands for the elasticity of substitution among intermediate goods in the production process. The dependence of χ on these structural parameters is due to the fact that, in the firm-specific version of the model, a firm's marginal costs depends positively on its own output level. To fix ideas, suppose an expansionary monetary policy shock hits the economic system. After the shock, firms' demand increases. As a consequence, marginal costs go up. Optimizing firms, which react to this shock by increasing their price, experience a fall in demand, which goes to sticky price firms. Hence, flexible price firms aim at getting rid of capital, which should be reallocated to sticky price firms. Capital reallocation does occur in the homogenous capital world. Differently, in the firm-specific version of the model, capital is not tradable. Hence, the only way for an optimizing firm (that is losing demand) to deal with the shock is by reducing the capital utilization rate, which reduces the firm's marginal costs of production. Assume that capital utilization does not adjust much due to adjustments costs. Then, the shadow value of capital related to optimizing firms drops. This implies that future expected marginal costs will decrease, something which puts a downward pressure on optimizing firms's prices. In equilibrium, prices (and, therefore, inflation) do not move much even if marginal costs and output move around. This is the reason why inflation moves around less in presence of firm-specific capital, something which renders inflation more persistent all else being equal (Calvo stickiness included). Hence, γ is low, and the model is able to replicate the mild relationship between changes in inflation and marginal costs documented in Altig et al. (2011). This mechanism is stronger the more

[20] To be sure, eq. (5) 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 that between $\hat{\pi}_t - \beta E \hat{\pi}_{t+1}$ and $\hat{s}_t$. Hence, γ represents the sensitivity of the change in inflation to marginal cost. Notice that eq. (5) can be rewritten as $\hat{\pi}_t = \frac{1}{1+\beta}\hat{\pi}_{t-1} + E[\frac{\beta}{1+\beta}\hat{\pi}_{t+1} + \frac{\gamma}{1+\beta}\hat{s}_t \mid \Omega_t]$.

elastic firms' demand curve is (i.e., the lower λ_f is) and the more costly it is for a firm to vary capital utilization (i.e., the larger σ_a is). 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 estimated γ implies a bigger ξ_p.

Going back to expression (5), notice that the different convolutions of the slope parameter γ do not affect the rational expectations solution of the model. Given that the two versions of the model are observationally equivalent, their impulse responses to identified shocks are exactly the same. However, the consequences of the very same impulse responses for the estimation of the Calvo parameter, which one can obtain by backing out its value conditional on the estimation of the slope of the Phillips curve and the estimation/calibration of σ_a and λ_f, can be very different. We discuss the implications of the state-conditional estimation of this model in the next Section.

The model is closed by assuming that the central bank sets the policy rate as suggested by the following Taylor rule:[21]

$$\widehat{R}_t = \rho_r \widehat{R}_{t-1} + (1-\rho_R)(\phi_\pi E_t \widehat{\pi}_{t+1} + \phi_{\Delta y} \Delta \widehat{y}_t) + \varepsilon_{Rt} \tag{7}$$

where $\hat{R}_t$ denotes the deviation in percentage points of the nominal interest rate from its steady state value, $E_t\widehat{\pi}_{t+1}$ and $\Delta\widehat{y}_t$ denote percentage deviations of expected inflation and the growth rate of output from their steady state values, and ε_{Rt} represents the i.i.d. monetary policy shock. The choice of modeling the systematic relationship between the policy rate and the growth rate of output is justified by the fact that this variable is observable, which does not require the estimation of latent factors as the output gap. Moreover, Ascari, Castelnuovo, and Rossi (2011) estimate different version of a small-scale new-Keynesian model and show that a Taylor rule similar to the one used here fits the U.S. data better than a battery of alternative rules. Christiano, Trabandt, and Walentin (2011) postulate a Taylor rule according to which policymakers systematically respond to output. Our results are robust to the employment of an alternative policy rule in which the systematic response to output is modeled.

[21] Altig et al. (2011) close their model by assuming a process for the money growth rate which is shocked to simulate the effects of a monetary policy shock. An unexpected increase in the growth rate leads to an excess of liquidity which brings the nominal interest rate down and, therefore, stimulates consumption and investment decisions and has a temporary effect on aggregate output and inflation. Our results are robust to employing a money growth rule as in Altig et al. (2011).

4.2 Minimum-distance estimation strategy

We estimate Altig et al.'s (2011) model by IRFs matching, i.e., by choosing the values of the structural parameters of the DSGE model that minimize a measure of the distance between our TVAR impulse responses and the DSGE model-based ones. With respect to Altig et al. (2011), who employ a classical approach, we employ the Bayesian IRFs matching estimation approach recently proposed by Christiano, Trabandt, and Walentin (2011). This enables us to impose economically sensible prior densities on the structural parameters while asking the data to shape the posterior density of the estimated model. Our application represents a twist of Christiano et al.'s (2011) methodological proposal, in that we rely on a nonlinear TVAR model and conduct a state-dependent Bayesian estimation of the DSGE model we are interested in.

Our state-dependent Bayesian minimum distance estimator works as follows. Denote by $\widehat{\boldsymbol{\psi}^i}$ the vector in which we stack the TVAR estimated impulse responses over a 20-quarter horizon to a monetary policy shock for regime $i = U, T$.[22] When the number of observations per each regime n^i is large, standard asymptotic theory suggests that:

$$\widehat{\boldsymbol{\psi}^i} \overset{a}{\sim} N(\boldsymbol{\psi}\left(\boldsymbol{\zeta}_0^i\right), \mathbf{V}^i(\boldsymbol{\zeta}_0^i, n^i)), \text{ for } i = U, T \tag{8}$$

where $\boldsymbol{\zeta}_0^i$ denotes the true vector of structural parameters that we estimate ($i = U, T$) and $\boldsymbol{\psi}\left(\boldsymbol{\zeta}^i\right)$ denotes the model-implied mapping from a vector of parameters to the analog impulse responses in $\widehat{\boldsymbol{\psi}^i}$. We treat $\widehat{\boldsymbol{\psi}^i}$ as our observed data.[23] To compute the posterior density for $\boldsymbol{\zeta}^i$ given $\widehat{\boldsymbol{\psi}^i}$ using Bayes' rule, we first need to compute the likelihood of $\widehat{\boldsymbol{\psi}^i}$ conditional on $\boldsymbol{\zeta}^i$. Given (8), the approximate likelihood of $\widehat{\boldsymbol{\psi}^i}$ as a function of $\boldsymbol{\zeta}^i$ reads as follows:

$$f(\widehat{\boldsymbol{\psi}^i}|\boldsymbol{\zeta}^i) = \left(\frac{1}{2\pi}\right)^{\frac{N^i}{2}} \left|\mathbf{V}^i(\boldsymbol{\zeta}_0^i, n^i)\right|^{-\frac{1}{2}} \times \exp\left[-\frac{1}{2}\left(\widehat{\boldsymbol{\psi}^i} - \boldsymbol{\psi}\left(\boldsymbol{\zeta}^i\right)\right)' \mathbf{V}^i(\boldsymbol{\zeta}_0^i, n^i)^{-1}\left(\widehat{\boldsymbol{\psi}^i} - \boldsymbol{\psi}\left(\boldsymbol{\zeta}^i\right)\right)\right] \tag{9}$$

where N^i denotes the number of elements in $\widehat{\boldsymbol{\psi}^i}$ and $\mathbf{V}^i(\boldsymbol{\zeta}_0^i, n^i)$ is treated as a fixed

[22] For a paper proposing information criteria to select the responses that produce consistent estimates of the true but unknown structural parameters and those that are most informative about DSGE model parameters, see Hall, Inoue, Nason, and Rossi (2012).

[23] Notice that, given that the "data" are represented solely by impulse responses to selected shocks, this is a limited-information approximate likelihood approach. As the DSGE model assumes that a monetary policy shock has no effects on the relative price of investment, the vector $\widehat{\boldsymbol{\psi}^i}$ includes 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).

value.[24] We use a consistent estimator of $\mathbf{V}^i$. Because of small sample-related considerations, such estimator features only diagonal elements (see Christiano, Trabandt, and Walentin (2011) and Guerron-Quintana, Inoue, and Kilian (2017)). In our case, $\mathbf{V}^i$ is a regime-dependent diagonal matrix with the variances of the $\widehat{\boldsymbol{\psi}^i}$'s along the main diagonal.[25] This choice is widely adopted in the literature and allows one to put more weight in replicating VAR-based responses with relatively smaller confidence bands. Treating eq. (9) as the likelihood function of $\widehat{\boldsymbol{\psi}^i}$, it follows that the Bayesian posterior of $\boldsymbol{\zeta}^i$ conditional on $\widehat{\boldsymbol{\psi}^i}$ and $\mathbf{V}^i$ is:

$$f(\boldsymbol{\zeta}^i|\widehat{\boldsymbol{\psi}^i}) = \frac{f(\widehat{\boldsymbol{\psi}^i}|\boldsymbol{\zeta}^i)p(\boldsymbol{\zeta}^i)}{f(\widehat{\boldsymbol{\psi}^i})} \tag{10}$$

where $p(\boldsymbol{\zeta}^i)$ denotes the priors on $\boldsymbol{\zeta}^i$ and $f(\widehat{\boldsymbol{\psi}^i})$ is the marginal density of $\widehat{\boldsymbol{\psi}^i}$. The mode of the posterior distribution of $\boldsymbol{\zeta}^i$ is computed by maximizing the value of the numerator in (10). The posterior distribution of $\boldsymbol{\zeta}^i$ is computed using a standard Markov Chain Monte Carlo (MCMC) algorithm.

We estimate 9 structural parameters per each regime i, i.e., $\boldsymbol{\zeta}^i = \left[\gamma, \sigma_L, b, \epsilon, \sigma_a, S'', \phi_\pi, \phi_{\Delta y}, \rho_R\right]$. These parameters are the slope of the NKPC γ, the inverse of the labor supply elasticity σ_L, the degree of habit formation b, the interest rate semi-elasticity ϵ, the parameter regulating the curvature of the capacity adjustment costs function σ_a, the parameter regulating the investment adjustment cost function S'', and the parameters of the Taylor rule ϕ_π, $\phi_{\Delta y}$, and ρ_R which - respectively - capture the systematic response to inflation and output growth and the degree of interest rate smoothing. Following Altig et al. (2011), we calibrate the price markup to a value that works in favor of solving the micro–macro pricing puzzle in their model ($\lambda_f = 1.01$). Moreover, we follow Christiano, Trabandt, and Walentin (2011) and estimate the inverse labor supply elasticity, σ_L, rather than the Calvo parameter controlling for the degree of wage stickiness (which as the authors we fix to $\xi_w = 0.75$).[26]

Our priors are reported in Table 1. When available, we use the same priors as in Christiano et al. (2011) for comparability reasons. For the parameters γ and ϵ, we

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[24] To be sure, the likelihood function is regime-specific.

[25] Denoting by $\hat{\mathbf{W}}^i$ the bootstrapped variance-covariance matrix of VAR-based impulse responses $\widehat{\boldsymbol{\psi}}^i$ for regime i, i.e., $\frac{1}{M}\sum_{j=1}^{M}(\boldsymbol{\psi}_j^i - \bar{\boldsymbol{\psi}}^i)(\boldsymbol{\psi}_j^i - \bar{\boldsymbol{\psi}}^i)'$ (where $\boldsymbol{\psi}_j^i$ denotes the realization of $\widehat{\boldsymbol{\psi}}^i$ in the j^{th} - out of $M = 1,000$ bootstrap replications - and $\bar{\boldsymbol{\psi}}^i$ denotes the mean of $\boldsymbol{\psi}_j^i$), $\mathbf{V}^i$ is based on the diagonal of the matrix $\hat{\mathbf{W}}^i$.

[26] This choice allows us to indirectly capture the influence of uncertainty on the precautionary labor supply of individuals.

take as prior means the values estimated by Altig et al. (2011) conditional on impulse responses to a monetary policy shock, and we use diffuse priors. Regarding the output growth parameter in the Taylor rule, we borrow the prior from Ascari, Castelnuovo, and Rossi (2011), which estimate a Taylor rule similar to ours in a small-scale DSGE framework. The remaining parameters of the model are calibrated as in Altig et al. (2005, 2011), again for comparability reasons.[27]

Notice that the use of the same priors for both regimes clearly works against finding regime-dependent parameter estimates. In general, the use of priors can hide identification issues even in population, which tend to be severe for a IRFs matching approach (see Canova and Sala (2009)). However, in our case, lack of identification would work against us and return parameter estimates which are similar between regimes. We anticipate that our results point to different sets of estimates between the two regimes, an evidence that speaks in favor of identification in our exercise.

4.3 Regime-specific estimation results

Overall fit of the model. Our regime-dependent model-based responses are reported in Figures 2 and 3 along with the VAR-based responses. The model captures remarkably well the unrestricted dynamics of the economy in both regimes. Most of the DSGE impulse responses lie within the 90% confidence bands of the TVAR impulse responses. The model is able to replicate the smaller peak reactions of real variables during uncertain times as well as the fact that they are shorter-lived than responses in tranquil times. Moreover, the model is able to capture the faster increase in inflation during uncertain times as well as the lower persistence of the interest rate drop, the behavior of money growth and the behavior of real wages. One exception is the response of capacity utilization, which is clearly underestimated by the DSGE model in uncertain times, while it is much better captured by the model in normal times. The difficulty of the model of replicating the facts mimics the finding in Altig et al. (2011) in their linearized analysis.[28] Interestingly, the model perfectly replicates the response of inflation in uncertain times. Overall, however, the model appears to assign a different macroeconomic power to monetary policy shocks in the two regimes.

[27] A short description of these parameters as well as their fixed values can be found in Table A2 in the Appendix.

[28] As pointed out by Christiano et al. (2011), the capacity utilization numbers processed by the VAR are for the manufacturing sector. Hence, these data are likely to be influenced by the durable part of manufacturing, which may overstate the response of capacity utilization in general in the economic system after a monetary policy shock.

Structural parameters between uncertain and tranquil times. Table 1 (last two columns) presents the parameters estimates for both regimes.[29] In spite of the use of common priors, the estimated parameters appear to be different between regimes. Turning to the estimated parameters, the slope of the Phillips curve γ is increasing in uncertainty, a result fully consistent with the empirical results by Vavra (2014b). This means that, in presence of heightened uncertainty, the trade-off between output and inflation worsens, as prices rise faster after a monetary policy shock during uncertain times. The microeconomic implication for pricing behavior are postponed to the next Section.

The inverse labor supply elasticity σ_L is estimated to be lower during uncertain times, implying a consumption-compensated labor supply elasticity for the household higher during uncertain times. Following Christiano, Trabandt, and Walentin (2011) we interpret σ_L as dictating the elasticity with which different members of the households enter or leave employment in response to shocks.[30] Under this interpretation, when σ_L is low it means that there is a large number of household members close to indifferent between working and not working, so that a small change in the real wage is followed by a large labor supply response. Under the same interpretation, the disutility of working for a household member is lower during uncertain times. This result may be indirectly capturing a higher precautionary labor supply in place due to high uncertainty (see Basu and Bundick (2017)). Furthermore, these estimates also imply a higher slope of the wage inflation NKPC during uncertain times (see Christiano, Trabandt, and Walentin (2011)). The interest semielasticity of money demand ϵ is higher during uncertain times. This parameter helps matching the different responses of money velocity to a monetary policy shock. The elasticity of capital utilization with respect to the rental rate of capital $1/\sigma_a$ is higher during uncertain times, meaning that it is less costly to vary capital utilization in uncertain times. This parameter is trying to capture the bigger response of capacity utilization observed in our VAR during uncertain times, but it is unable to properly fit it and the model-implied response is far below the lower

[29] Allowing private sector parameters to differ across regimes is in line with the literature. For instance, Canova (2009) and Inoue and Rossi (2011) find that changes in the private sectors' coefficients is a possible driver of the Great Moderation, while Canova and Menz (2011) and Castelnuovo (2012a) find such changes to be relevant as regards the role of money in the post-WWII sample.

[30] Christiano et al. (2011) interpret hours worked in the model as capturing the number of people working in the economy. Accordingly, $1/\sigma_L$ has not to be interpreted as the Frisch elasticity, which instead captures the percent change in a person's labor supply in response to a change in the real wage holding the marginal utility of consumption fixed. As stressed by Christiano et al. (2011), the Frisch elasticity in the micro data and the labor supply elasticity in the macro data are two different concepts.

bound of the confidence bound for the the VAR-response. The elasticity of investment with respect to a 1 percent temporary increase in the current price of installed capital $1/S''$is counter-intuitively higher during uncertain times. 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)). 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. Finally, not all estimated parameters are found to be state-dependent. The degree of habits in consumption is found to be basically the same in the two regimes. Given the difference between the prior mean on the parameter b (0.75) and its posterior means, which read 0.82 and 0.86 in the uncertain and tranquil regime, this result does not seem to be driven by an identification issue. We see this evidence as pointing to the differences commented above as being facts and not artifacts due to our estimation strategy.

Moving to the estimated policy rule, we find that the uncertainty regime is associated with a weaker response to inflation, a more aggressive response to output growth, and a lower degree of interest rate smoothing. This result squares well with the findings recently documented by Gnabo and Moccero (2015). They estimate a Taylor rule with real time data in which the policy parameters are allowed to take different values depending on the level of risk associated with the inflation outlook and the evolution of financial markets. They also find a stronger response to real activity and a lower degree of interest rate smoothing in presence of high uncertainty, while their response to inflation is found to be less dependent to uncertainty than ours. Overall, their uni-equational approach with real time data produces results which are quite in line with those obtained by our multivariate framework, something which we see as reassuring as regards the sensibility of our novel empirical approach.

Our findings are robust to the following list of checks, all referring to estimated models: i) a price mark-up determined by the data; ii) an estimated degree of price indexation; iii) a Taylor rule featuring output in levels instead of in growth rates; iv) a Taylor rule featuring a degree of interest rate smoothing of order two as in Coibion and Gorodnichenko (2012); v) a money growth rule replacing our baseline Taylor rule. These robustness checks are discussed and documented in our online Appendix.[31]

[31] A warning is in order here. Suppose the true DGP is a non-linear model in which uncertainty plays

Model microeconomic implications. We expect that a higher estimate of the slope of the NKPC for the uncertain time regime 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 the Calvo probability ξ_p. Although this happens by construction in the homogenous capital version of the model (see equation 6), this is not necessarily true as regards the firm-specific capital model. Interestingly, from Table 2 we can observe that also for the firm-specific capital model our estimates imply a lower ξ_p during uncertain times. The average time between price re-adjustment predicted by the estimated model varies from 3.5 quarters in uncertain times to 29.6 quarters in tranquil times for the homogenous capital model, and from 2.2 to 6 quarters for the firm-specific capital model.

Altig et al. (2011) exploit micro-data evidence to discriminate between the homogeneous capital model and the firm-specific one. They find that the latter is the one matching the frequencies of price adjustment coming from firm-level data. How does our state-contingent evidence square with the one coming from studies relying on micro data? Bils and Klenow (2004) find evidence in favor of frequent price changes - once every 4.3 months - once sales are left out of the data. However, as shown by Nakamura and Steinsson (2008), the same data point to adjustments every 7-11 months once price cuts are removed. Eichenbaum, Jaimovich, and Rebelo (2011) show that, while prices change in general every two weeks, modal prices are much more inertial and change about every year. Kehoe and Midrigan (2015) focus on regular price changes, i.e., the slow-moving trend which one can identify by controlling for temporary price increases and decreases. They find that regular prices are updated every 14.5 months, which is, about every 5 quarters. These papers provide a range between slightly more than a quarter and almost five quarters. Interestingly, this micro evidence is of help to discriminate between the homogeneous capital model and the firm-specific capital one even when a state-dependent estimation like ours is undertaken. The homogeneous capital model returns an implied price duration in uncertain times equal to three quarters, an evidence in line with the micro data. However, the same model-based moment in tranquil times reads 30 quarters, a duration which is just at odds with the micro evidence cited above. Differently, the firm-specific capital model implies price durations of about

a role per se because it affects the function relating states at time t to states at time $t+1$. In a world like this, one would like to disentangle the role of structural parameters in matching the asymmetric transmission of monetary policy shocks accounting for the role played by variations in uncertainty. This can be done by using the techniques recently developed by Andreasen, Fernández-Villaverde, and Rubio-Ramírez (2017). We see this investigation as material for future research.

two quarters (uncertain times) and six quarters (tranquil times). This figures are much more in line with the extant micro evidence. Indeed, the average of the price durations in the firm-specific model - four quarters - is very close to that proposed by Nakamura and Steinsson (2008), who find it to range between 3 and 4 quarters, Eichenbaum, Jaimovich, and Rebelo (2011), who find it to be about one year, and Kehoe and Midrigan (2015), who find it to be of about 5 quarters. Hence, a state-dependent analysis like ours confirms that firm-specific capital is essential to get the frequency of price adjustment right in a medium-scale DSGE model featuring Calvo prices.[32] Importantly, our nonlinear analysis unveils that the failure of models with homogeneous capital to get such frequency right comes from tranquil times, i.e., periods characterized by low uncertainty which are associated with a slope of the NKPC which implies absurdly large values of the Calvo parameters. Differently, a model with homogeneous capital performs much better in uncertainty times - according to our empirical estimates, the price duration in uncertain times is slightly larger than three quarters. It is important to notice that, in uncertain times, prices are found to be more flexible conditional on the firm-specific capital model.

A note is in order here. As shown above, firm-specific capital helps us to obtain state-specific estimates of the Calvo probabilities that are, when taken on average between regimes, closer to those coming from studies using microeconomic data. However, it would be interesting to know whether the implications on our state-contingent estimates are close to state-contingent estimates at a microeconomic level. Unfortunately, state-dependent micro evidence is scarce. Vavra (2014b) and Bachmann et al. (2013) provide preliminary evidence which points to a moderate decrease in stickiness in uncertain times. If this evidence is correct, our model - while working in the right direction - probably overestimates the impact of the change in the frequency of price adjustment driven by an increase in uncertainty.

[32] Of course, one should bear in mind that the comparison between the estimate values of the Calvo parameter in these frameworks and the information coming from micro data should be drawn carefully. In fact, the DSGE model we work with features full dynamic indexation of prices to past inflation, 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. Hence, even if firms change prices, this does not mean that they are re-optimimizers. Indeed, they could be re-setters.

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

This Section aims at identifying what the most important drivers are behind the state-specific macroeconomic impact of monetary policy shocks. To this aim, we propose a counterfactual exercise that replaces, for each structural parameter we focus on, the estimated parameters values for uncertain times with the ones for tranquil times. To be sure, the way in which the exercise is designed is such that, if we replaced all estimated parameters contemporaneously, by construction we would move from the DSGE model-consistent responses estimated under uncertainty to those estimated under tranquil times.[33]

Figures 4 and 5 report results focusing on the responses of output, inflation and the policy rate. Three comments are in order. First, the higher slope of the NKPC during uncertain times is important in explaining much of the reduced effectiveness of monetary shocks during these times. If uncertain times were characterized by the same slope estimated for tranquil times, output would experience a bigger and more persistent response to monetary policy shocks in combination with a flatter response of inflation and a more persistent fall of the nominal interest rate. Second, households-related parameters (σ, b, ε) during uncertain times do not influence, if not marginally, the effectiveness of monetary policy with respect to tranquil times, while firms-related parameters - i.e., σ_a and S'' - positively affects it. Third, systematic monetary policy during uncertain times works in favor of reducing the impact of monetary policy shocks on real activity. In contrast, the central bank controls inflation more effectively. The lower degree of interest rate smoothing during uncertain times plays a big role as regards the lower policy effectiveness in the short run.

Our counterfactual simulations point to the higher slope of the NKPC γ as the crucial parameter behind the different power of monetary policy shocks in influencing inflation and output in the two uncertainty regimes. Since the slope of the NKPC determines the inflation-output volatility trade-off faced by central banks and affects the *relative* response of inflation and output to an unanticipated monetary policy shock, this means that the policy trade-off worsens during uncertain times. In other words, a given percent increase in output due to a monetary policy shock has to be accompanied

[33] To be sure, given that firm-specific capital in this framework implies a link between structural parameters (mostly, γ, λ_f and σ_a) and the Calvo parameter ξ_p, it is technically not correct to say that we change one parameter at a time "all else being equal", because when we change the value of one of the parameters listed above we implicitely allow for a change in the value of ξ_p.

by a higher inflation rate, something that the monetary authority may not be willing to tolerate. This may be the rationale for the less gradual and more active conduct of monetary policy we find during uncertain times.

6 Conclusion

This paper estimates a nonlinear VAR model and documents that monetary policy shocks have milder real effects and stronger inflationary ones in periods of high macroeconomic uncertainty than in normal times. Then, it exploits this evidence to estimate a medium-scale DSGE model featuring firm-specific capital via a Bayesian direct inference approach. The DSGE model is shown to possess enough flexibility - due to a state-specific set of estimates of some key-structural parameters - to capture the macroeconomic dynamics generated by a monetary policy shock. In particular, a steeper slope of the Phillips curve is shown to be the main driver of the state-contingent responses generated by the model. The relevance of firm-specific capital arises when contrasting the estimates of the Calvo parameter and the implied price durations to recent findings based on micro data. Firm-specific capital enables the model to return reasonable estimates in uncertain times and tranquil times. Differently, a version of the model with homogeneous capital returns an implausibly long price duration in tranquil times.

From a modeling standpoint, our findings point to the need of working out mechanisms which can explain a positive relation between the level of uncertainty and the slope of the Phillips curve. Given the role played by such a slope in influencing the inflation-output volatility trade-off, our results open the way to studies aiming at understanding optimal monetary policy in regimes characterized by different levels of uncertainty.

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		Priors		Posteriors	
				Uncertain times	Tranquil times
Parameter	*Interpretation*	Distribution [bounds]	Mean, std.dev.	Mean, std.dev. [5% and 95%]	Mean, std.dev. [5% and 95%]
γ	Slope of the NKPC	Gamma	0.106, 0.09	0.12, 0.04	0.001, 0^+
		[0,∞]		[0.05, 0.18]	[0^+, 0.003]
σ_L	Inverse of the labor supply elasticity	Gamma	0.300, 0.20	0.19, 0.08	0.49, 0.25
		[0,∞]		[0.07, 0.30]	[0.12, 0.86]
b	Consumption habit	Beta	0.750, 0.15	0.82, 0.02	0.86, 0.02
		[0,1]		[0.79, 0.85]	[0.82, 0.89]
ϵ	Interest rate semi-elasticity	Gamma	0.820, 0.70	1.19, 0.12	1, 0.12
		[0,∞]		[1, 1.39]	[0.81, 1.20]
σ_a	Capacity adj. costs, curvature	Gamma	1.000, 0.75	0.07, 0.04	1.17, 0.81
		[0,∞]		[0.003, 0.13]	[0.02, 2.27]
S''	Investment adj. costs, curvature	Gamma	12.00, 8.00	4.63, 0.71	15.89, 3.92
		[0,∞]		[3.47, 5.76]	[9.57, 21.78]
ϕ_π	Taylor rule param., inflation	Gamma	1.600, 0.15	1.27, 0.11	1.61, 0.15
		[1.01,4]		[1.09, 1.44]	[1.37, 1.85]
$\phi_{\Delta y}$	Taylor rule param., output growth	Gamma	0.125, 0.05	0.22, 0.07	0.115, 0.04
		[0,∞]		[0.10, 0.33]	[0.04, 0.18]
ρ_R	Taylor rule param., lagged int. rate	Beta	0.800, 0.10	0.80, 0.02	0.89, 0.01
		[0,1]		[0.77, 0.82]	[0.87, 0.91]

Table 1: **Regime-dependent estimated parameter values.** Posteriors computed via MCMC with a random walk metropolis algorithm. 600 000 draws, 20 percent for burn-in. Acceptance rates: 31 percent for uncertain times, 30 percent for tranquil times.

	Uncertain times	Tranquil times
Calvo probability (ξ_p)		
Homogenous capital model	0.71	0.97
Firm-specific capital model	0.54	0.83
Price duration ($\frac{1}{1-\xi_p}$)		
Homogenous capital model	3.47	29.62
Firm-specific capital model	2.19	5.95

Table 2: **Regime-dependent implied Calvo parameter and average time (quarters) between reoptimization.**

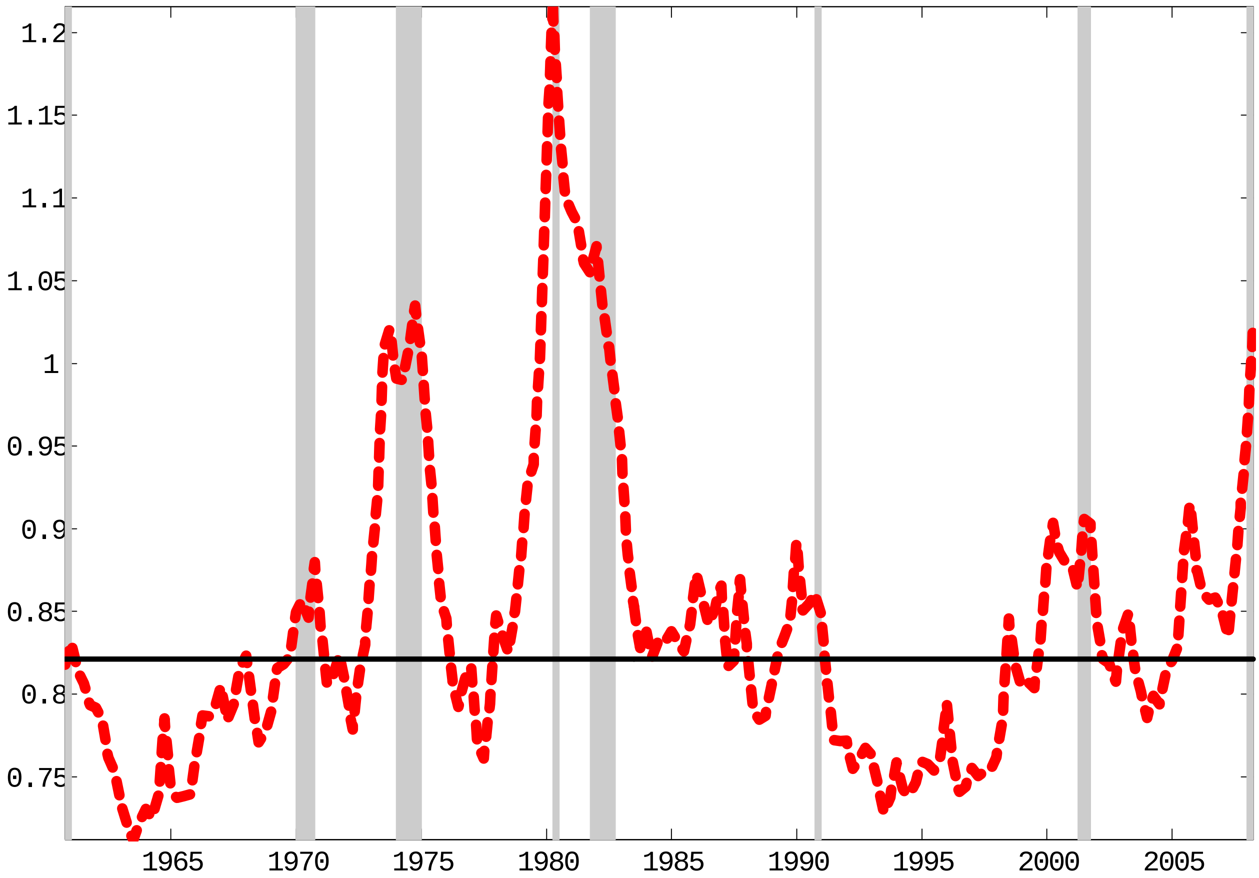

Figure 1: **Uncertain and tranquil times**. Red dashed line: Uncertainty indicator by Jurado, Ludvigson, and Ng (2015). Black solid horizontal line: Threshold value. Grey vertical bars: NBER recessions.

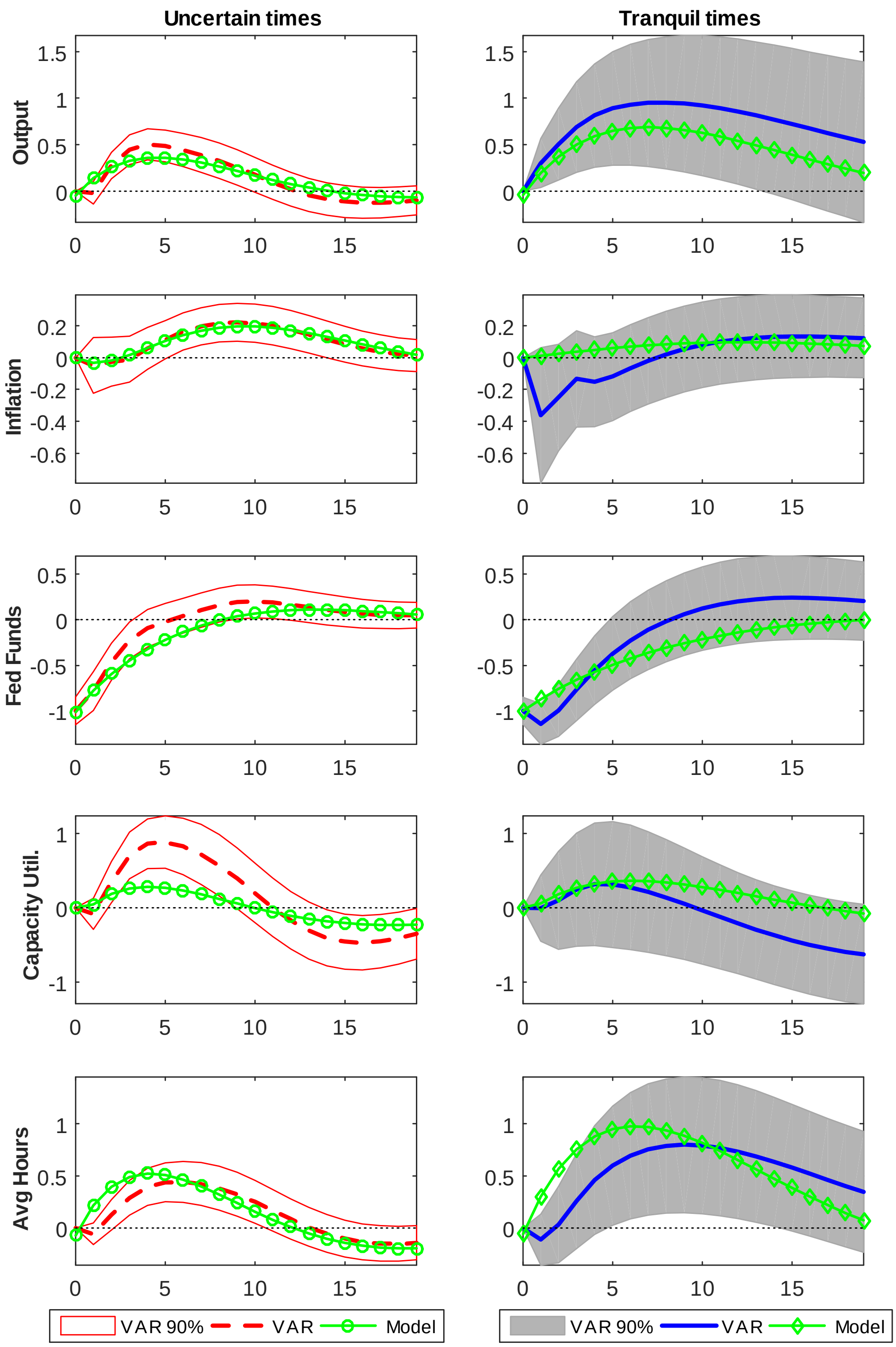

Figure 2: **TVAR-based regime-dependent responses for the uncertain and tranquil times regimes (first set of parameters).** Red dotted and solid lines: Point estimates and 90 percent bootstrapped confidence bands for the IRFs conditional to a uncertain times regime. Blue solid lines and grey areas: Point estimates and 90 percent bootstrapped confidence bands for the IRFs conditional to a tranquil times regime. DSGE model estimates conditional on the estimated parameter values.

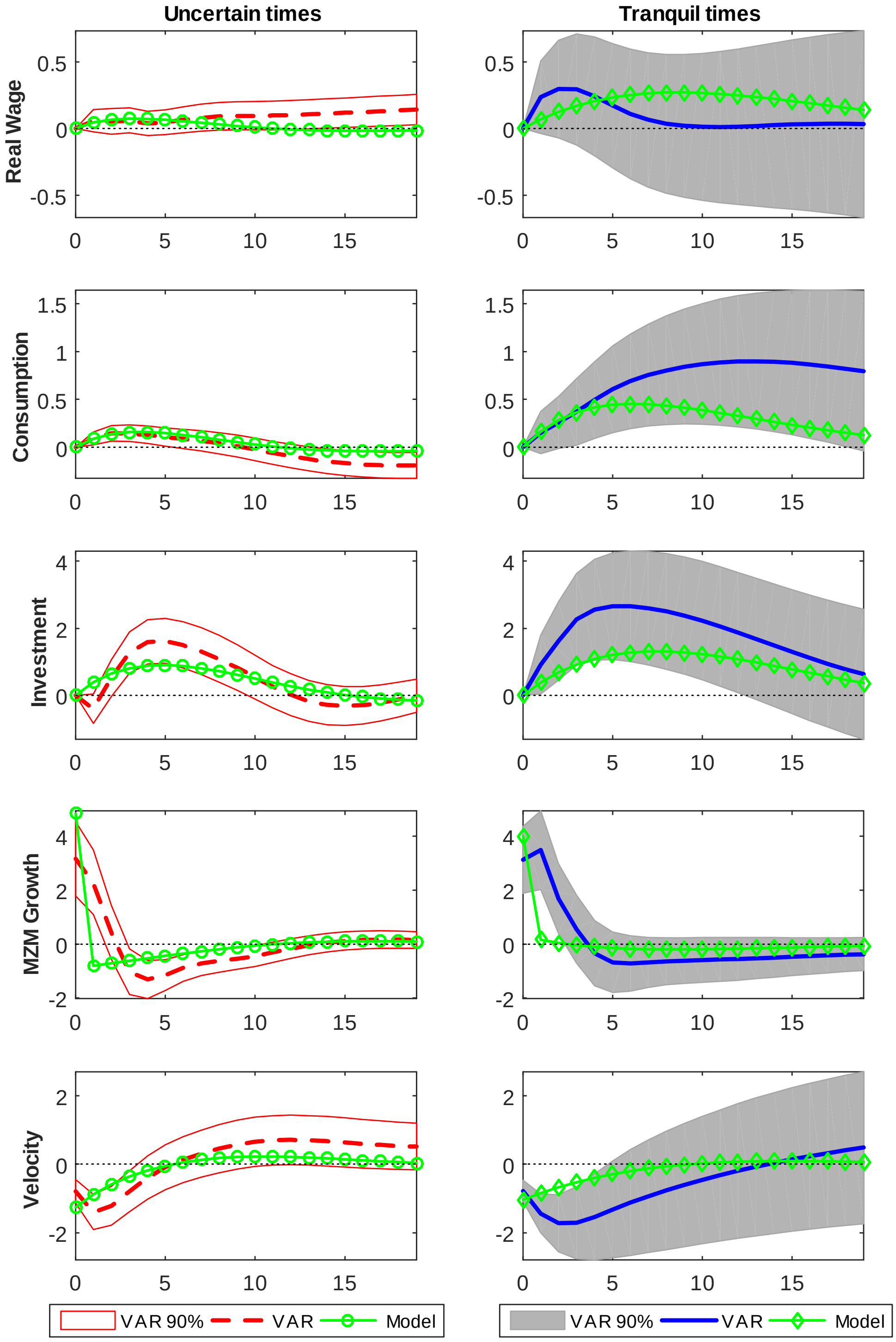

Figure 3: **TVAR-based regime-dependent responses for the uncertain and tranquil times regimes (second set of parameters).** Red dotted and solid lines: Point estimates and 90 percent bootstrapped confidence bands for the IRFs conditional to a uncertain times regime. Blue solid lines and grey areas: Point estimates and 90 percent bootstrapped confidence bands for the IRFs conditional to a tranquil times regime. DSGE model estimates conditional on the estimated parameter values.

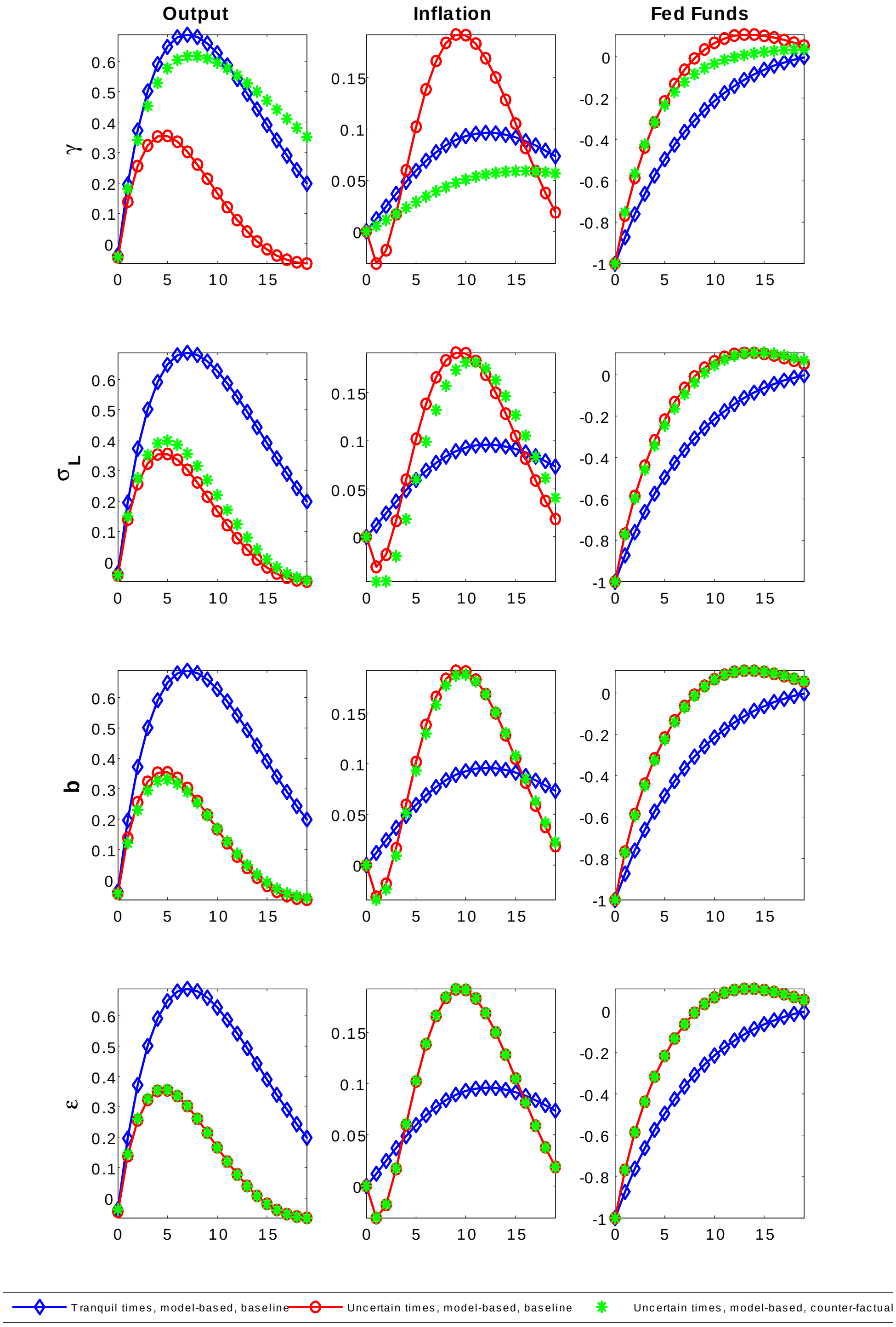

Figure 4: **Role of structural parameters for the state-contingent IRFs produced by the DSGE model (first set of parameters).** Red solid lines with circles: Baseline DSGE-based IRFs conditional to a uncertain times regime. Blue solid lines with diamonds: Baseline DSGE-based IRFs conditional to a tranquil times regime. Magenta dashed-dotted lines: Counterfactual DSGE-based IRFs conditional to the uncertain times regime.

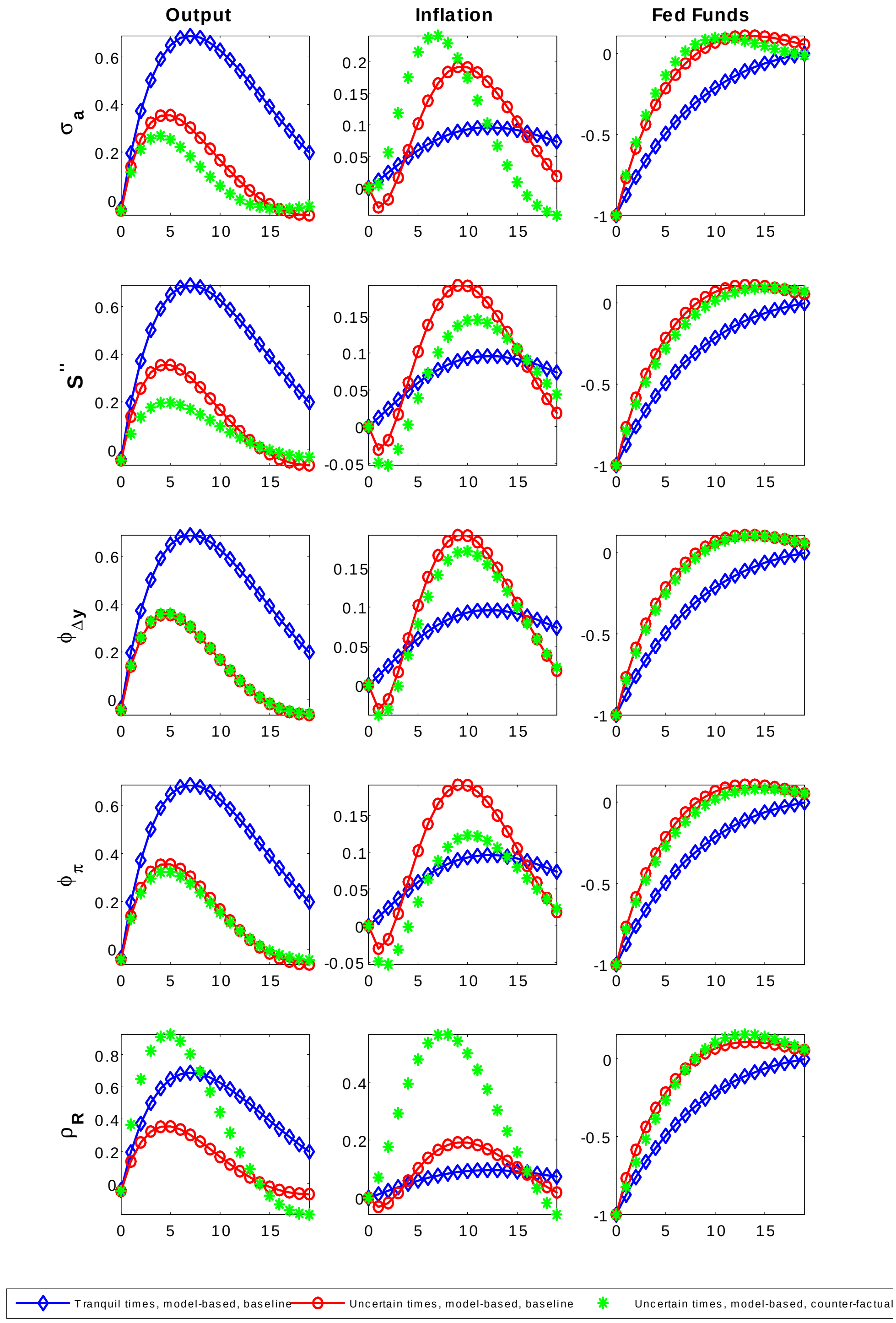

Figure 5: **Role of structural parameters for the state-contingent IRFs produced by the DSGE model (first set of parameters).** Red solid lines with circles: Baseline DSGE-based IRFs conditional to a uncertain times regime. Blue solid lines with diamonds: Baseline DSGE-based IRFs conditional to a tranquil times regime. Magenta dashed-dotted lines: Counterfactual DSGE-based IRFs conditional to the uncertain times regime.

Appendix of the paper "Uncertainty-dependent Effects of Monetary Policy Shock: A New Keynesian Interpretation" by Efrem Castelnuovo and Giovanni Pellegrino

This Appendix is structured as follows. First, we document the robustness of our nonlinear VAR evidence to a variety of perturbations. Second, we offers detail on the algorithm to compute the Generalized Impulse Response Functions (GIRFs). Third, we formally show that our state-conditional impulse responses are different between states. Finally, we document the robustness of the change of the slope of the new-Keynesian Phillips curve (NKPC) to a battery of changes of the estimated DSGE model.

TVAR evidence: Robustness

Recursive identification. Our baseline analysis employs the identification strategy followed by Altig, Christiano, Eichenbaum, and Lindé (2011), i.e., a mix of long- and short-run restrictions from which monetary policy shocks are derived. A popular alternative is that of imposing the short-run restrictions implied by the Cholesky decomposition of the variance-covariance (VCV) matrix of the estimated residuals. This identification relies on exclusion restrictions, i.e., monetary policy shocks do not contemporaneously affect inflation and real activity indicators. At the same time, such aggregates are allowed to contemporaneously influence the policy rate. Notice that these restrictions are consistent with the recursive DSGE model by Altig et al. (2011). Figure A1 shows the impulse response functions of a TVAR where shocks were recovered according to this assumption. For the sake of brevity, we focus on the responses of output, inflation, and the federal funds rate. As shown by the Figure, the responses of this check lay well inside the confidence bands associated to our baseline case.

Constant VCV matrix. Our baseline Threshold-VAR models a regime-dependent VCV matrix. One could think that this favors differences between regimes because of the possibility of a state-contingent impulse vector. We check for this possibility by adopting a constant VCV matrix. Again, Figure A1 shows that our baseline results are robust.

Alternative proxy for uncertainty: IQR of sales growth. In the baseline analysis we use the macroeconomic uncertainty indicator proposed by Jurado, Ludvigson, and Ng (2015). Our choice is justified by the way in which this indicator is constructed, i.e., by employing a large number of macroeconomic and financial indicators whose future realizations, which are uncertain, are likely to affect households' and firms' decisions. Of course, different measures of uncertainty may lead to different results. It is then of interest to check if our results are specific to the employment of the Jurado et al. (2015) measure or if, instead, are robust to sensible alternatives. To this end, we run a check with a micro-level measure of uncertainty, 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, and Terry (2016).[1] The choice of this measure is motivated by its connection with idiosyncratic (i.e., firm-specific) shocks, which are likely to be relevant for understanding price setting decisions at a micro-level (see, e.g., Vavra (2014) and the literature cited therein). Given that price-setting behavior may be behind the different slope of the NKPC found in our baseline exercise, it would be reassuring to know that our results are robust to the employment of this measure of uncertainty. The IRFs documented in Figure A1 confirm that our results are robust to the identification of uncertainty and tranquil times operated via the IQR of sales growth.

JLN index conditional on a one-year forecast horizon. The JLN index used in our analysis refers is constructed by referring to a three-month forecast horizon. Agents' decisions may be determined on the basis of a different horizon. We then recompute our impulse responses by conditioning on the version of the JLN index computed by considering a one-year horizon. Figure A1 shows that our results are robust to this variation of the baseline exercise.

Estimated threshold. The threshold value of the uncertainty index used in our baseline exercise to separate uncertain and tranquil times is the median value of the (JLN) uncertainty measure. The idea was to minimize the probability of finding different dynamics due to small-sample issues in one of the two regimes. Of course, one could wonder how robust our results are to estimating the threshold value. Figure A1 shows that results are robust when the threshold value is estimated by minimizing the AIC as in Tsay (1998). Following Balke (2000), the possible threshold values were restricted so that at least 20% of the observations plus the number of parameters of a standard linear VAR (for an individual equation) were present in each regime.

Generalized Impulse Response Functions. Our baseline TVAR analysis as-

[1] This measure is constructed on the basis of data regarding 2,465 publicly quoted firms spanning all the sectors of the economy. This uncertainty measure, which can be downloaded from the website http://www.stanford.edu/~nbloom/RUBC.zip, is available starting from 1962Q1. We Hodrick-Prescott filter this uncertainty index (lambda=1,600) to remove its low-frequency component.

sumes that uncertainty does not respond to monetary policy shocks at all times. This assumption makes our TVAR consistent with the linearized DSGE model we estimate (in a regime-specific manner) in the second part of the paper. However, Pellegrino (2017a) finds that uncertainty can indeed respond to monetary policy shocks (for a similar result obtained with European data, see Pellegrino (2017b)). We then present a check in which uncertainty is modeled as an endogenous variable in the vector. Specifically, we include our threshold variable, i.e., the JLN uncertainty indicator, among the endogenous variables of the TVAR and order it last in $\mathbf{Y}$. Technically, the result is a Self Exciting (SE-) TVAR model in which the regime is allowed to change after the shock to the extent that uncertainty reacts to the monetary shock. This is a fully nonlinear model that implies the computation of Generalized IRFs (GIRFs) à la Koop, Pesaran, and Potter (1996). GIRFs allow responses to depend on the starting condition (or initial history) at the time of the shock, in addition to the size and sign of the shock. The point estimates for the regime-dependent GIRFs are computed as the average of all the history-conditional GIRFs referring to a particular regime. In the figure regimes are defined on the basis of initial histories with uncertainty in its top or bottom decile and hence correspond to an "extreme events" logic (see, e.g., Auerbach and Gorodnichenko (2012) and Caggiano, Castelnuovo, and Groshenny (2014)). The following Section of this Appendix offers details on the algorithm employed to compute our GIRFs.

Figure A1 reports the estimated GIRFs. When we acknowledge for the endogenous role of uncertainty, the regime-dependent responses for uncertain and tranquil times become closer between them, consistently with what found by Pellegrino (2017a,b). However, we still find a clear difference in the GIRFs corresponding to deep regimes, which is exactly the point of our TVAR analysis.

Commodity prices. The possibility of a misspecified VAR not containing enough information as regards future inflationary pressures is investigated by adding commodity prices to the VAR as suggested by Sims (1992). This is an important check, in light of the price puzzle evidence we find in tranquil times. We then add commodity prices to the Altig et al.'s (2011) vector and order it first.[2] We model commodity prices in growth rates to line up with Altig et al. (2011), who model the variables in their VAR as I(0) processes. However, our results are unchanged when modeling commodity prices in log-levels. Figure A2 shows that our results are robust to the inclusion of commodity prices in our vector.

[2] We employ the Producer Price Index for All Commodities (PPIACO) downloadable from the Federal Reserve Bank of St. Louis' website.

Generalized Impulse Response Functions for the SE-TVAR

The algorithm employed to compute the GIRFs and their confidence intervals is a modified version of the one proposed Koop, Pesaran, and Potter (1996). In particular, we consider orthogonalized residuals and give them an interpretation as structural shocks as in Kilian and Vigfusson (2011) and Fazzari, Morley, and Panovska (2014).

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

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

where $E[\cdot]$ stands for the expectation operator. The algorithm to estimate the state-conditional GIRFs follows the steps described below:

1. we pick an initial condition $\varpi_{t-1} = \{\mathbf{Y}_{t-1}, ..., \mathbf{Y}_{t-L}\}$, i.e., the historical values for the lagged endogenous variables at a particular date $t = L + 1, \ldots, T$. The lagged value of the threshold variable y_{t-1}^{thres}, which belongs to the vector $\mathbf{Y}_{t-1}$, determines the starting regime $i = 1, 2$ of the model;

2. we randomly draw (with repetition) two sequences of (n-dimensional) residuals $\{\boldsymbol{\varepsilon}_{t+h}^i\}$, $h = 0, 1, ..H = 19$, from the empirical distributions $d(\mathbf{0}, \widehat{\boldsymbol{\Omega}}^i)$, where $\widehat{\boldsymbol{\Omega}}^i$ is the estimated VCV matrix for regime $i = 1, 2$. In order to preserve the contemporaneous structural relationships among variables, residuals are assumed to be jointly distributed, so that if a date t' s residual is drawn, all n residuals for such date are collected. The sequence s of residuals $\{\boldsymbol{\varepsilon}_{t+h}\}^s$ employed to iterate the system will be a combination of the two previous sequences (see the following point);

3. conditional on ϖ_{t-1} and on the estimated nonlinear VAR model, we employ $\{\boldsymbol{\varepsilon}_{t+h}\}^s$ to simulate the evolution of the vector of endogenous variables over the following H periods when a structural shock δ_t is imposed to ε_t^s. In particular, depending on the regime $i = 1, 2$ in which the system starts the iteration, we Cholesky-decompose $\widehat{\boldsymbol{\Omega}}^i = \mathbf{C}_i\mathbf{C}_i'$, where $\mathbf{C}_i$ is a regime-dependent lower-triangular matrix. Then, we recover the structural innovation associated to $\boldsymbol{\varepsilon}_t^s$ via the system $\mathbf{u}_t^s = \mathbf{C}_i^{-1}\varepsilon_t^s$, and add a quantity $\delta < 0$ to the scalar element of $\mathbf{u}_t^s$ that refers to the variable we want to shock (the federal funds rate), i.e. $u_{t,ffr}^s$, to simulate an expansionary shock. We then move again to the residual associated with the

structural shock $\boldsymbol{\varepsilon}_t^{s,\delta} = \mathbf{C}_i \mathbf{u}_t^{s,\delta}$ to proceed with the iteration. We account for the possibility of a switch in regime during the iteration by selecting, per each future period h, $\boldsymbol{\varepsilon}_{t+h}^s$ from $\{\varepsilon_{t+h}^i\}$, $t+h$, $h = 1, ..H$, according to the regime $i = 1, 2$ in which the resulting path finds itself at time $t+h$. The so obtained path, which is influenced by the shock δ, is termed $\mathbf{Y}_{t+h}^{s,\delta}$;

4. conditional on ϖ_{t-1} , on the estimated nonlinear VAR model, and on the very same $\{\boldsymbol{\varepsilon}_{t+h}\}^s$ employed in the previous step, we simulate the evolution of the vector of endogenous variables over the following H periods to obtain the path $\mathbf{Y}_{t+h}^s$ for $h = 0, 1 \ldots H$. Notice that, in this simulation, $\delta = 0$. Hence, in iterating the system, the two paths $\mathbf{Y}_{t+h}^s$ and $\mathbf{Y}_{t+h}^{s,\delta}$ are different because of the absence of the shock at this step vs. its presence in the previous step;

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

6. we repeat steps 2-5 for a number $S = 500$ of different extractions for the residuals, then take the average values across s. Notice that this computation is performed by sticking to the same starting quarter $t-1$. This enables us to obtain a consistent point estimate of the GIRFs for each given starting quarter in our sample , i.e. $\widehat{GIRF}_{Y,t}(\delta_t, \varpi_{t-1}) = \left\{ \widehat{E}\left[\mathbf{Y}_{t+h} \mid \delta_t, \varpi_{t-1}\right] - \widehat{E}\left[\mathbf{Y}_{t+h} \mid \varpi_{t-1}\right] \right\}_{h=0}^{19}$. If a given initial condition ϖ_{t-1} leads to an explosive response - namely, if such response is explosive for most of the sequences of residuals drawn $\{\boldsymbol{\varepsilon}_{t+h}\}^s$, in the sense that the response of the shocked variable diverges instead than reverting to zero -, such response is discarded and not considered for state-conditional responses at the next step;[3]

7. these history-dependent GIRFs are then averaged over a particular subset of initial conditions of interest to produce our state-dependent GIRFs. To do so, an initial condition $\varpi_{t-1} = \{Y_{t-1}, ..., Y_{t-L}\}$ is classified to belong to the "uncertain times" state if $y_{t-1}^{thres} > \Gamma_1$, and to the "tranquil times" state if $y_{t-1}^{thres} < \Gamma_2$, where $\Gamma_2 < \Gamma_1$ are threshold values identifying the first and ninth deciles of the empirical density of uncertainty in our sample, and $t = L+1, \ldots, T$. In this way we obtain our $\widehat{GIRF}_{Y,t}(\delta_t, uncertain\ times)$ and $\widehat{GIRF}_{Y,t}(\delta_t, tranquil\ times)$.

[3] This is a theoretical case. We verified that, as regards our empirical application, this case does not apply.

Statistical evidence on the difference between state-dependent IRFs

The test is based on a t-statistic for the statistical difference between regime-dependent responses, taken to be independent (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: $t-stat = (IRF^U_{t,i} - IRF^T_{t,i})/(\sqrt{(st.dev.(IRF^U_{t,i}))^2 + (st.dev.(IRF^T_{t,i}))^2})$, 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 $i = 1, ..., 10$ denotes the variable whose IRFs are referred.

Figure A3 depicts the outcome of this test. As it is evident, the state-dependent IRFs are different between regimes.

DSGE evidence: Robustness

We perform two variations as regards the price setting-related parameters in the DSGE models, and two related to the way in which we model the systematic monetary policy conduct.

Estimated markup. Our baseline results point to changes in the slope of the NKPC as crucial to replicate the reduced impact on real activity and the larger one on prices during uncertain times. The variation of such slope is determined by a reduction in price stickiness as captured by the Calvo parameter. However, this parameter is the only price-setting parameter that we allowed to differ between regimes (the other parameters being calibrated as in Altig et al., 2011). In the attempt of checking other price setting-related parameters, we take to the data a version of the model in which the markup is also estimated. Allowing this parameter to vary between regimes allows for the price elasticity of demand to be regime-specific. For instance, Eichenbaum and Fisher (2007) argue that departing from the assumption that monopolistically competitive firms face a constant elasticity of demand is important in order to obtain plausible degrees of inflation inertia with models featuring a Calvo-type of friction. Table A1 documents our results.[4] In particular, we find a lower desired price markup during uncertain times. However, this additional estimated parameter hardly influences our estimates of the slope of the NKPC in the two regimes under scrutiny.

[4]The slight discrepancy between the moments reported in this Table as regards the baseline case and those reported in Table 1 in the text are due to the fact that, for our robustness checks, we decided to work with the Laplace approximation of the posterior density in order to save computational time.

Estimated price indexation. Another robustness check regards the estimation of the fraction of firms that index to past inflation. We find that this fraction is higher during uncertain times, when, according to our model, firms optimally change prices also more frequently. Interestingly, Fernández-Villaverde and Rubio-Ramírez (2008) find that periods of high price rigidities are also periods of low indexation, and vice-versa. Our regime-dependent estimation enables us to extend this reasoning to periods characterized by high vs. low uncertainty.

Taylor rule with a richer smoothing structure. Our baseline Taylor rule specification features a lag of the policy rate. This has been shown to be relevant to capture the policy gradualism by the Federal Reserve (English, Nelson, and Sack (2003), Castelnuovo (2003)). However, recent research conducted by Coibion and Gorodnichenko (2012) and Ascari, Castelnuovo, and Rossi (2011) points to the empirical relevance of a richer dynamic structure for the federal funds rate. To this end, we re-estimate our model by replacing our baseline policy rule the following specification:

$$\hat{R}_t = \rho_{1,R}\hat{R}_{t-1} + \rho_{2,R}\hat{R}_{t-2} + (1 - \rho_{1,R} - \rho_{2,R})(\phi_\pi E_t\hat{\pi}_{t+1} + \phi_{\Delta y}\Delta\hat{y}_t) + \varepsilon_{Rt} \tag{1}$$

which features an interest rate smoothing structure of order two. Table A1 shows the implications for the estimation of the DSGE model of using a rule like this. The monetary authority is still found to govern the interest rate with much less inertia during uncertain times (the sum of the interest smoothing parameters is smaller during uncertain times than in tranquil times, 0.79 versus 0.89). Further, the monetary authority is still found to react less aggressively to expected inflation and to output growth during uncertain times than tranquil times. Again, our main result on a steeper slope of the NKPC survives this modification of the baseline set up.

Money growth rate rule. Finally, we estimate a different version of the model featuring a money growth rule instead of a Taylor rule (a similar exercise can be found in Altig et al., 2011). We work with the following rule:

$$\hat{x}_{M,t} = \rho_M\hat{x}_{M,t-1} + \sigma_M\varepsilon_{M,t},\ \sigma_M > 0, \tag{2}$$

where $\hat{x}_{M,t}$ denotes the percentage deviation of the growth rate of money, $x_{M,t} = M_t/M_{t-1}$, from its steady state value and where $\varepsilon_{M,t}$ represents the i.i.d. monetary policy shock with unitary variance. In this case, the VAR-based responses $\widehat{\psi}^i$ that we use in the estimation procedure are the responses to a one standard deviation shock to the federal funds rate. Then, after the estimation, we rescale the DSGE model-based responses to obtain a comparable 1% expansionary shock to the federal funds rate in both regimes.[5] We find the transmission of monetary policy shocks to be very similar to the one found in the baseline estimation. The corresponding parameters estimates are shown in Table A1. Our baseline results are robust also to this alternative specification of the policy rule.

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[5] These responses are produced with a conditionally-linear framework. Hence, the shape of the responses does not depend on the size of the shock.

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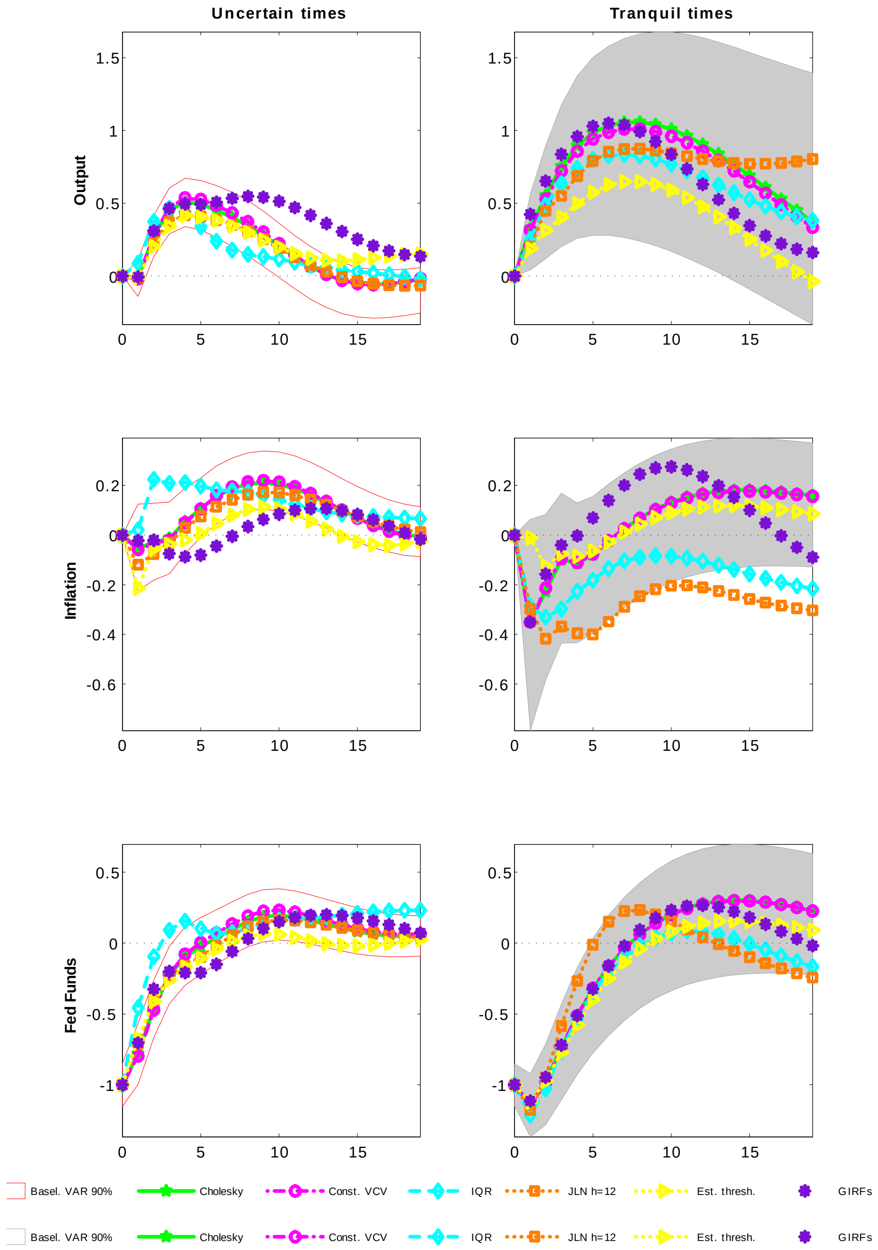

Figure A1: **TVAR: Robustness checks.** Areas within red solid lines (grey areas): 90% bootstrapped confidence bands for the baseline VAR-based IRFs conditional to uncertain times (tranquil times). Red (blue) lines with different markers: VAR-based IRFs conditional to a uncertain times (tranquil times) regime for several alternative TVAR specifications.

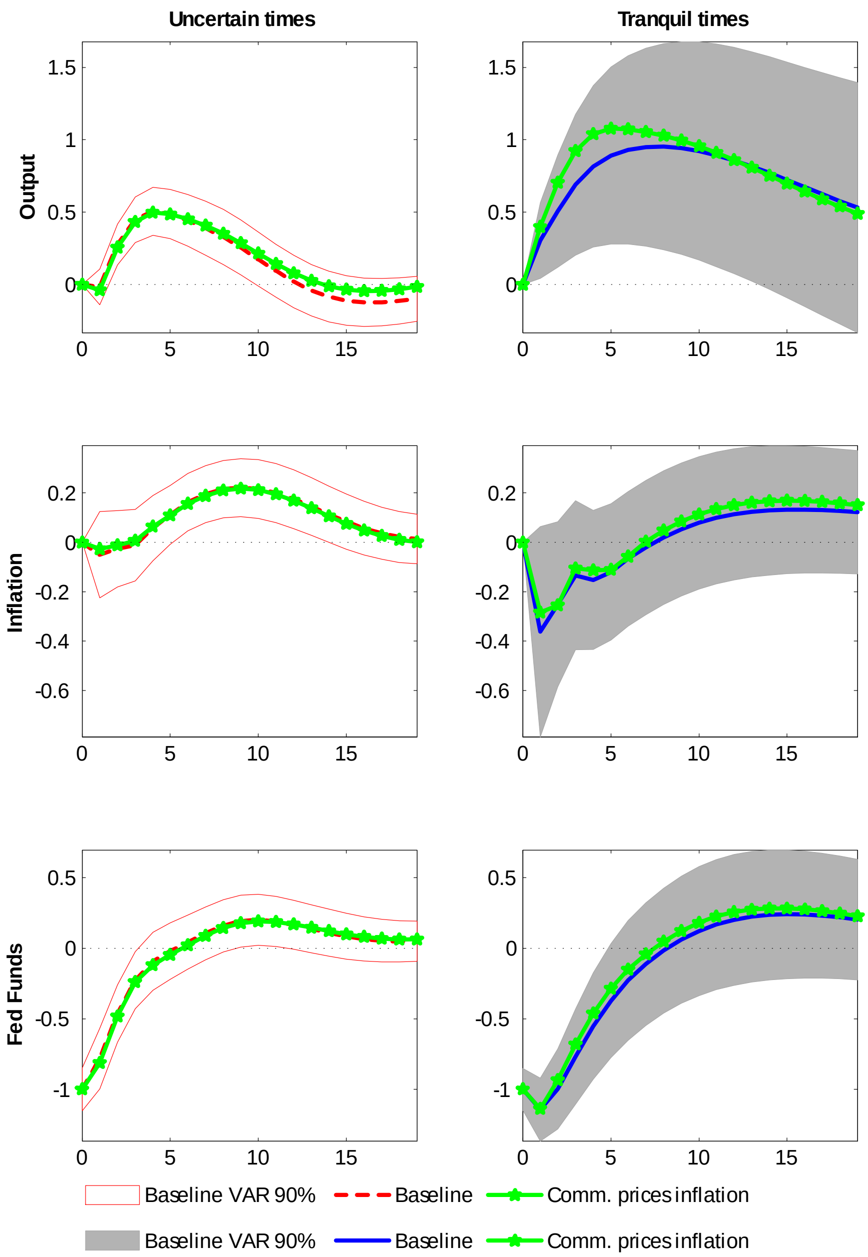

Figure A2: **TVAR: Role of commodity prices.** Areas within red solid lines (grey areas): 90% bootstrapped confidence bands for the baseline VAR-based IRFs conditional to uncertain times (tranquil times). Red dashed (blue continuous) lines: VAR-based IRFs conditional to a uncertain times (tranquil times) regime. Green lines with circles: Responses obtained with the VAR embedding commodity prices.

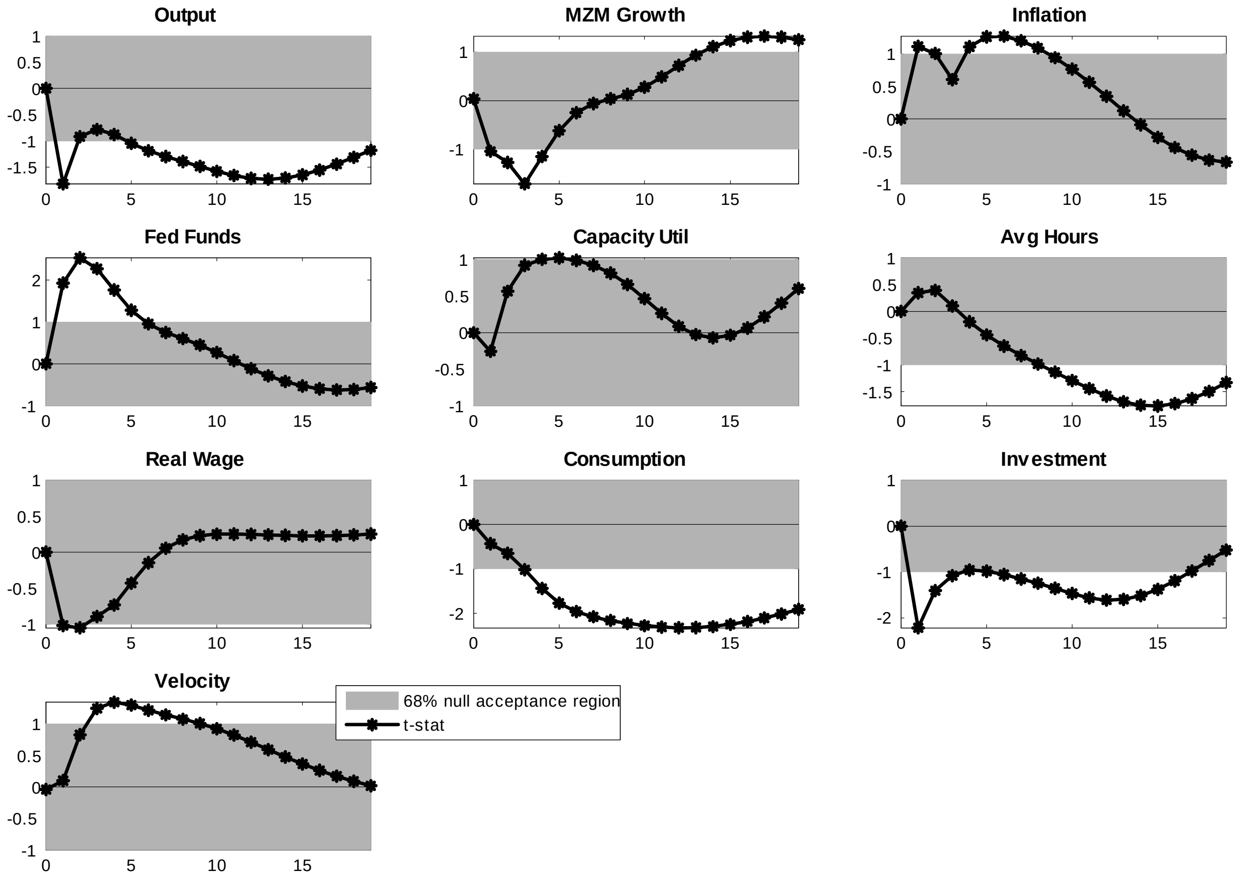

Figure A3: **Nonlinearity test**. Test-statistic (black-circled line) computed as explained in the text. Gray areas identify the 68% band of the null hypothesis of no difference between responses.

γ	σ_L	b	ϵ	σ_a	S''	ϕ_π	$\phi_{\Delta y}$	ρ_R	λ_f	i_p	ρ_M	σ_M	$\rho_{1,R}$	$\rho_{2,R}$
G(0.106, 0.09)	G(0.3,0.2)	B(0.75,0.15)	G(0.82,0.7)	G(1,0.75)	G(12,8)	G(1.6,0.15)	G(0.125,0.05)	B(0.8,0.1)	G(1.2,0.15)	B(0.5,0.15)	N(-0.04,0.5)	IG(0.33,0.2)	N(1.1,0.5)	N(-0.2,0.5)
Uncertain times														
Benchmark														
0.10	0.13	0.82	1.20	0.03	4.56	1.24	0.19	0.80	[1.01]	[1]	-	-	-	-
(0.04)	(0.05)	(0.02)	(0.12)	(0.03)	(0.68)	0.11	(0.07)	(0.02)						
Estimated markup (a)														
0.11	0.12	0.81	1.19	0.03	3.84	1.26	0.20	0.80	1.26	[1]	-	-	-	-
(0.05)	(0.04)	(0.02)	(0.12)	(0.03)	(0.58)	(0.11)	(0.07)	(0.02)	(0.09)					
Estimated indexation														
0.16	0.23	0.83	1.21	0.02	4.60	1.29	0.17	0.80	[1.01]	0.77	-	-	-	-
(0.05)	(0.08)	(0.02)	(0.12)	(0.02)	(0.67)	(0.11)	(0.06)	(0.02)		(0.09)				
Taylor rule à la Coibion and Gorodnichenko (2012)														
0.07	0.11	0.81	1.22	0.04	3.84	1.13	0.26	-	[1.01]	[1]	-	-	0.95	-0.16
(0.03)	(0.05)	(0.02)	(0.11)	(0.03)	(0.67)	(0.10)	(0.08)						(0.07)	(0.07)
Money growth rate rule														
0.05	0.13	0.81	0.65	0.06	5.42	-	-	-	[1.01]	[1]	0.06	0.33	-	-
(0.02)	(0.06)	(0.02)	(0.11)	(0.05)	(0.89)						(0.09)	(0.04)		
Tranquil times														
Benchmark														
0.001	0.34	0.86	1.00	0.83	14.29	1.59	0.10	0.89	[1.01]	[1]	-	-	-	-
(0.001)	(0.20)	(0.02)	(0.12)	(0.73)	(3.55)	(0.15)	(0.04)	(0.01)						
Estimated markup (a)														
0.002	0.43	0.83	1.01	0.25	11.87	1.59	0.09	0.90	1.57	[1]	-	-	-	-
0.001	(0.23)	(0.02)	(0.12)	(0.22)	(2.65)	(0.15)	(0.04)	(0.01)	(0.12)					
Estimated indexation														
0.0004	0.25	0.84	0.97	1.38	12.89	1.58	0.08	0.86	[1.01]	0.50	-	-	-	-
(0.0006)	(0.18)	(0.02)	(0.12)	(0.77)	(3.37)	(0.15)	(0.04)	(0.01)		(0.18)				
Taylor rule à la Coibion and Gorodnichenko (2012) (b)														
0.0007	0.19	0.86	1.04	0.25	9.68	1.55	0.13	-	[1.01]	[1]	-	-	1.22	-0.33
(0.0007)	(0.17)	(0.02)	(0.11)	(0.34)	(2.34)	(0.15)	(0.06)						(n.a.)	(n.a.)
Money growth rate rule														
0.001	0.54	0.89	0.87	1.99	19.21	-	-	-	[1.01]	[1]	0.37	0.16	-	-
0.0005	(0.24)	(0.02)	(0.10)	(0.93)	(4.65)						(0.06)	(0.02)		

Table A1: **Regime-dependent estimated parameter values for alternative specifications of the DSGE model.** Posterior mode values of the parameters computed by Chris Sims' csminwel. Standard deviations reported in parentheses. Figures based on Laplace approximations. Numbers in squared brackets denote calibrated parameters. Second raw: Priors densities (mean, st.dev). (a): Nelder-Mead simplex based optimization routine used here because in one regime the csminwel returns a non-positive definite hessian matrix at the mode. (b): csminwel and Nelder-Mead simplex based optimizers fail to return a positive st. dev. for the AR(2) smoothing parameters, possibly because of a ridge.

Parameters in ζ_{cal}	Description	Calibration	Source
β	Discount factor	$1.03^{-0.25}$	ACEL(2005,2011)
α	Capital share	0.36	ACEL(2005,2011)
δ	Depreciation rate	0.025	ACEL(2005,2011)
ψ_L	Labor disutility	1	ACEL(2005,2011)
λ_w	Wage markup	1.05	ACEL(2005,2011)
μ_Υ	SS Gross investment technology growth	1.0042	ACEL(2005,2011)
μ_z	SS Gross neutral technology growth	1.00013	ACEL(2005,2011)
x	SS Gross growth rate of money	1.017	ACEL(2005,2011)
ν	SS Velocity	0.45	ACEL(2005,2011)
η	SS transactions technology value	0.036	ACEL(2005,2011)
ξ_w	Wage stickiness	0.75	CTW(2011)
λ_f	Price markup	1.01	ACEL(2011)

Table A2: **DSGE model: Calibrated parameters.** Values borrowed from Altig et al. (2005, 2011). SS stands for steady state. ACEL stands for Altig, Christiano, Eichenbaum, and Lindé. CTW stands for Christiano, Trabandt, and Walentin.