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 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.

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

JEL codes: C22, E32, E52.

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1 Introduction

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, Aastveit, Natvik, and Sola (2013), Eickmeier, Metiu, and Prieto (2016), and Pellegrino (2017a,b)). 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) 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 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. The Altig, Christiano, Eichenbaum, and Lindé (2011) nests two cases, one in which firms’ capital is homogeneous - and, therefore, immediately trans-
ferrable from a firm to another in response of a shock - and another 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.

Our results are the following. First, we find monetary policy shocks to exert a statistically and economically weaker effect on output 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 Aastveit, Natvik, and Sola (2013), Eickmeier, Metiu, and Prieto (2016), and Pellegrino (2017a,b) on the weak influence of unexpected policy tightenings in periods of heightened uncertainty. The response of inflation is 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 of fitting 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. We find the parameters regulating price stickiness and monetary policy persistence to be crucial for matching the different macroeconomic responses to an equally sized unexpected change in the federal funds rate. In particular, state-contingent estimates of the Calvo parameter 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, 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) 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 along a number of dimensions. 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 macroeconomics 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 interactions 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 (2016) for the former channel, Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014) 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 standpoint, 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. Hence, policy exercises conducted by appealing to state-of-the-art DSGE models should ideally consider mechanisms able to generate different effects of monetary policy shocks conditional on different levels of uncertainty, or they should at least consider state-contingent calibrations of such DSGE models.

The paper develops as follows. Section 2 discusses the relation with the literature. Section 3 presents the non-linear VAR model employed and presents results on the uncertainty-dependent consequences of monetary policy shocks from this relatively un-
restricted framework. Section 4 briefly presents the Altig et al. (2011) model, describes the econometric strategy adopted to estimate the DSGE model and discuss the regime-dependent estimation results found. Section 5 investigates the sources of the different monetary transmission mechanism during uncertain times via counterfactual exercises. Section 6 concludes. An Appendix available upon request 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 (2014) (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 micro-economic analysis. Their results suggest that uncertainty influences the real effects of monetary policy shocks only to a negligible extent. Our study differs from theirs along a number of 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 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. 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. Our empirical investigation shows that firm specific capital is crucial to replicate the persistent response of inflation and output to a monetary policy shock in our regimes conditional on a reasonable value of the Calvo parameter. This result complements the one of Vavra (2014b), who shows the limitations of a NKPC whose marginal costs are related to the presence of homogeneous capital when it comes to obtaining a steeper curve in uncertain times. Third, our empirical approach allows uncertainty to influence the estimation of different structural parameters that, in principle, could play an important role in influencing the response of inflation and output in the two states we investigate. For instance, we find that a lower degree of policy inertia in uncertain times plays a non-negligible role in shaping such responses.

Another study closely related to ours is Vavra (2014b). He estimates a state-dependent new-Keynesian Phillips curve (NKPC) à la Galí 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. 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), 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 assume 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. Most closely related to our approach, 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. 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), and Castelnuovo (2012) 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.

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

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

\[
Y_t = \begin{cases} 
\alpha^U + \sum_{j=1}^L B_j^U Y_{t-j} + u^U_t & \text{if } z_{t-1} \geq \Gamma \\
\alpha^T + \sum_{j=1}^L B_j^T Y_{t-j} + u^T_t & \text{if } z_{t-1} < \Gamma 
\end{cases} 
\]

(1)

\[
E(u^U_t) = 0, E(u^U_t u^U_s) = \Omega^U, j \in \{U, T\}
\]

(2)

where \(Y_t\) is a set of endogenous variables, \(\alpha\) is a vector of constants, \(B_j\) is a matrix of coefficients, \(u_t\) is a vector of residuals whose variance-covariance matrix is \(\Omega\), 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 \(\Gamma\) 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 \(Y_t\) embeds the same variables as in Altig et al.’s (2011) VAR, i.e., \(Y_t = [\Delta p_t, \Delta y_t - \Delta h_t, \pi_t, h_t, c_u, y_t - h_t - w_t, c_t - y_t, i_t - y_t, r_t, p_t + y_t - m_t]^\prime\), where \(\Delta p_t\) stands for the growth rate of the relative price of investment, \(\Delta y_t - \Delta h_t\) 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, \(\pi_t\) is the GDP deflator quarterly inflation rate, \(c_u\) 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 update 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.\footnote{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).} 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)). 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 quantitatively similar dynamics to those produced by the conditionally linear approach. Importantly, the decision to focus on the latter approach is justified by the 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. 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 the computationally burdensome problem of computing such distribution and keeping track of its evolution.

3.1.2 Empirical model: Specification

We study US quarterly data, period: 1960Q3-2008Q2. The construction of the data closely follows Altig et al. (2011).\footnote{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 preferred 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)).} 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 extracted on the 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. The beginning of the sample is justified by 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 identification of unconventional monetary policy shocks.

Our TVAR is estimated by conditional least squares as in Tsay (1998). We use two lags. 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 $\Gamma$. 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

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4We 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.

5Akaike, 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.
choose the value of the threshold $\Gamma$ to be the median of the uncertainty proxy in our sample.\textsuperscript{6} 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 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:

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

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

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.\textsuperscript{7} 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 $Y_t$.

\textsuperscript{6}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).

\textsuperscript{7}The values of $\Gamma$ used are the actual values of the threshold variable inside the non-trimmed region. Our choice of the trimming is 20%.
3.2 Empirical results

Figures 2 and 3 depict the state-conditional impulse responses to an unexpected 1% reduction of the federal funds rate and the corresponding 90% confidence bands. The left column shows the response of the economy during uncertain times, while the right one the response during tranquil times. 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 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. 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).

Our Appendix documents the outcome of a formal test which points to statistically relevant differences between state-conditional responses. These findings are robust to

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8Our 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 Lindén (2011), the confidence bands are constructed by considering the point estimates of the impulse response $\pm 1.64$ times the bootstrapped estimate of the standard errors.

9Following 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.

10If 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.

11The 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.

12The 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: $t_{stat} = (IRF_{t,i}^{U} - IRF_{t,i}^{T})/\sqrt{(st.dev.(IRF_{t,i}^{U}))^2 + (st.dev.(IRF_{t,i}^{T}))^2}$, where $IRF_{t,i}^{regime}$ represents the point estimated
a variety of perturbations of our baseline VAR framework, which are documented in our Appendix.

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 Aastveit, Natvik, and Sola (2013), Eickmeier, Metiu, and Prieto (2016), 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 (2014); 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 endogeneize 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 available upon request.

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.\textsuperscript{13} Second, 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 our Appendix and 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

\textsuperscript{13}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 (for a similar approach see Hofmann et al. (2012)). 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.
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:

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

where \( \hat{x} \equiv (x-\bar{x})/\bar{x} \), \( x \) is a generic variable whose steady-state value is \( \bar{x} \), \( \pi_t \) denotes inflation, \( s_t \) denotes the economy-wide average marginal cost of production in units of the final good, \( \Omega_t \) denotes 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 \( \beta \) identifies households’ discount factor. In this expression, the slope of the Phillips curve \( \gamma \) is a reduced-form coefficient whose convolution of structural parameters reads:

\[ \gamma = \frac{(1 - \xi_p)(1 - \beta \xi_p)}{\xi_p} \chi \quad (6) \]

where \( \xi_p \) denotes the Calvo-probability for a firm to not reoptimize its price in a period, and \( \chi \) is the parameter that dictates the impact of capital 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, \( \gamma \) coincides with the slope of the New Keynesian Phillips Curve in standard new Keynesian models.\(^{14}\) If instead capital is firm-specific, \( \chi \) turns out to be a nonlinear function of the parameters of the model, i.e., \( \chi = \chi(\sigma_a, \lambda_f) < 1 \), where \( \sigma_a \) regulates the curvature of the capacity utilization adjustments costs function, and \( \lambda_f \) stands for the elasticity of substitution among intermediate goods in the production process. The dependence of \( \chi \) 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

\(^{14}\)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, \( \gamma \) represents the sensitivity of the change in inflation to marginal cost. Notice that eq. (5) can be rewritten as \( \hat{\pi}_t = \frac{1}{1+\beta} \hat{\pi}_{t-1} + E[\frac{\beta}{1+\beta} \hat{\pi}_{t+1} + \frac{\gamma}{1+\beta} \hat{s}_t \mid \Omega_t] \).
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 loosing 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 (Calvo stickiness included) being equal. As an implication, \( \gamma \) is
low, something which well replicate the mild relationship between changes in inflation
and marginal costs documented in Altig et al. (2011). This mechanism is stronger the
more elastic firms’ demand curve is (i.e., the lower is \( \lambda_f \)) and the more costly it is for
a firm to vary capital utilization (i.e., the larger \( \sigma_a \) is). Wrapping up, \( \gamma \) is the smaller
the larger is \( \sigma_a \) and the lower is \( \lambda_f \). Notice, finally, that other things equal, a smaller
estimated \( \gamma \) implies a bigger \( \xi_p \).

Going back to expression (5), notice that the different convolutions of the slope
parameter \( \gamma \) 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 \( \sigma_a \) and \( \lambda_f \), 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 sug-
gested by the following Taylor rule:\footnote{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).}

\[
\hat{R}_t = \rho_r \hat{R}_{t-1} + (1 - \rho_R)(\phi_x E_t \hat{\pi}_{t+1} + \phi_{\Delta y} \Delta \hat{y}_t) + \varepsilon_R, \tag{7}
\]

where \( \hat{R}_t \) denotes the deviation in percentage points of the nominal interest rate from
its steady state value, \( E_t \hat{\pi}_{t+1} \) and \( \Delta \hat{y}_t \) denote percentage deviations of expected inflation
and the growth rate of output from their steady state values, and $\varepsilon_R$ 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.

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 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 $\tilde{\psi}^i$ the vector in which we stack the TVAR estimated impulse responses over a 20-quarter horizon to a monetary policy shock for regime $i = U, T$.\footnote{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).} When the number of observations per each regime $n^i$ is large, standard asymptotic theory suggests that:

$$\tilde{\psi}^i \sim N(\psi(\zeta_0^i), V^i(\zeta_0^i, n^i)), \text{ for } i = U, T$$  \hspace{1cm} (8)

where $\zeta_0^i$ denotes the true vector of structural parameters that we estimate ($i = U, T$) and $\psi(\zeta^i)$ denotes the model-implied mapping from a vector of parameters to the analog impulse responses in $\tilde{\psi}^i$. We treat $\tilde{\psi}^i$ as our observed data.\footnote{As the DSGE model assumes that a monetary policy shock has no effects on the relative price}

\[\]
the posterior density for $\zeta^i$ given $\hat{\psi}^i$ using Bayes’ rule, we first need to compute the likelihood of $\hat{\psi}^i$ conditional on $\zeta^i$. Given (8), the approximate likelihood of $\hat{\psi}^i$ as a function of $\zeta^i$ reads as follows:

$$f(\hat{\psi}^j | \zeta^i) = \left( \frac{1}{2\pi} \right)^{\frac{N^i}{2}} |V^i(\zeta_0^i, n^i)|^{-\frac{1}{2}} \exp \left[ -\frac{1}{2} \left( \hat{\psi}^j - \psi^i(\zeta^i) \right)' V^i(\zeta_0^i, n^i)^{-1} \left( \hat{\psi}^j - \psi^i(\zeta^i) \right) \right]$$

where $N^i$ denotes the number of elements in $\hat{\psi}^j$ and $V^i(\zeta_0^i, n^i)$ is treated as a fixed value. We use a consistent estimator of $V^i$. 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, $V^i$ is a regime-dependent diagonal matrix with the variances of the $\hat{\psi}^j$’s along the main diagonal.\footnote{Denoting by $W^i$ the bootstrapped variance-covariance matrix of VAR-based impulse responses $\hat{\psi}^i$ for regime $i$, i.e., $\frac{1}{M} \sum_{j=1}^{M} (\psi^i_j - \hat{\psi}^i)(\psi^i_j - \hat{\psi}^i)'$ (where $\psi^i_j$ denotes the realization of $\hat{\psi}^i$ in the $j$th - out of $M = 1,000$ bootstrap replications - and $\hat{\psi}^i$ denotes the mean of $\psi^i_j$), $V^i$ is based on the diagonal of the matrix $W^i$.}

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 $\hat{\psi}^j$, it follows that the Bayesian posterior of $\zeta^i$ conditional on $\hat{\psi}^j$ and $V^i$ is:

$$f(\zeta^i | \hat{\psi}^j) = \frac{f(\hat{\psi}^j | \zeta^i)p(\zeta^i)}{f(\hat{\psi}^j)}$$

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

We estimate 9 structural parameters per each regime $i$, i.e., $\zeta^i = [\gamma, \sigma_L, b, \epsilon, \sigma_a, S''_y, \phi_\pi, \phi_{\Delta y}, \rho_R]$. These parameters are the slope of the NKPC $\gamma$, the inverse of the labor supply elasticity $\sigma_L$, the degree of habit formation $b$, the interest rate semi-elasticity $\epsilon$, the parameter regulating the curvature of the capacity adjustment costs function $\sigma_a$, the parameter regulating the investment adjustment cost function $S''_y$, and the parameters of the Taylor rule $\phi_\pi, \phi_{\Delta y}$, and $\rho_R$ which - respectively - capture the systematic response of investment, the vector $\psi^j$ 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).
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, $\sigma_L$, rather than the Calvo parameter controlling for the degree of wage stickiness (which as the authors we fix to $\xi_w = 0.75$).\textsuperscript{19}

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 $\gamma$ and $\epsilon$, we 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.\textsuperscript{20}

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

\textbf{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

\textsuperscript{19}This choice allows us to indirectly capture the influence of uncertainty on the precautionary labor supply of individuals.

\textsuperscript{20}A short description of these parameters as well as their fixed values can be found in Table A1 in the Appendix.
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 the two states, an evidence that mimics the one by Altig et al. (2011) in their linearized analysis. Overall, however, the model appears to assign a different macroeconomic power to monetary policy shocks in the two regimes.

**Structural parameters between uncertain and tranquil times.** Table 1 (last two columns) presents the parameters estimates for both regimes. 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, $\gamma$, 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, $\sigma_L$, 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 $\sigma_L$ as dictating the elasticity with which different members of the households enter or leave employment in response to shocks. Under this interpretation, when $\sigma_L$ 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 (2016)). 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, $\epsilon$, 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

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21 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 (2012) find such changes to be relevant as regards the role of money in the post-WWII sample.

22 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 a Frisch elasticity, which is instead assumed to be 0 (see Section 2.3 in their paper).
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 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, \( \frac{1}{S^0} \), 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 un-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 Appendix, which is available upon request.

**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 $\xi_p$. 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 $\xi_p$ 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 microdata 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. 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 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, 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. 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.

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

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23 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 $\xi_p$ 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.

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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.24

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 of tranquil times, the output would experience a bigger and more persistent response, due to a flatter response of inflation and a more persistent fall of the nominal interest rate. Second, households-related parameters \((\sigma, b, \varepsilon)\) 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., \(\sigma_a\) and \(S''\) - increase it (think to a more reactive capital utilization). Third, the different reaction of the monetary authority during uncertain times reduces the real effectiveness of monetary policy shock but it safeguards the economy from more inflation. Among policy parameters, the lower degree of interest rate smoothing during uncertain times explains the biggest fraction of lower effectiveness in the short run. However, given the monetary authority systematic reaction parameters, adopting such a smaller smoothing parameter would imply a too big reaction of inflation to the monetary shock relative to the bigger increase in output.

Our counterfactual simulations point to the higher slope of the NKPC \(\gamma\) as the crucial parameter behind the different power of monetary policy shocks in influencing output and inflation in the two uncertainty regimes. Since the slope of the NKPC determines the output-inflation trade-off faced by central banks and affects the relative response of output and inflation in response to an unanticipated monetary policy shock, this means that the output-inflation trade-off worsens during uncertain times. Hence a given percent increase in output due to a monetary policy shock has to be accompanied 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, which further deteriorates the real effectiveness of monetary policy shocks.

24To be sure, given that in the firms-specific capital model we use here features a link between structural parameters (mostly, \(\gamma, \lambda_f\) and \(\sigma_a\)) and the Calvo parameter \(\xi_p\), 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 implicitly allow for a change in the value of \(\xi_p\).
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.

References


<table>
<thead>
<tr>
<th>Parameter</th>
<th>Interpretation</th>
<th>Distribution</th>
<th>Mean, std.dev.</th>
<th>Uncertain times</th>
<th>Tranquil times</th>
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Table 1: Regime-dependent estimated parameter values. Posterior 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.
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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 an 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.