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UNCERTAINTY AND MONETARY POLICY IN GOOD AND BAD TIMES

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Uncertainty and Monetary Policy in Good and Bad Times*

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Abstract

We employ a nonlinear VAR to document the asymmetric reaction of real economic activity to uncertainty shocks. An uncertainty shock occurring in recessions triggers an abrupt and deep drop followed by a quick rebound and a temporary overshoot. The same shock hitting in expansions induces a milder slowdown, a longer-lasting recovery, and no overshoot. The employment of linear models is shown to offer a distorted picture of the timing and the severity of heightened uncertainty. Monetary policy responds quite aggressively during bad times, and more mildly during booms. Counterfactual simulations point to monetary policy ineffectiveness during the first months after the shock, especially in recessions, and to policy effectiveness in the medium-term, especially during expansions. This holds true considering as policy tools both the federal funds rate and a long-term interest rate. Our results call for microfounded models admitting nonlinear effects of uncertainty shocks.

Keywords: Uncertainty shocks, nonlinear Smooth Transition Vector AutoRegressions, Generalized Impulse Response Functions, systematic monetary policy, forward guidance.

JEL codes: C32, E32.

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1 Introduction

Bloom's (2009) seminal contribution on the impact of uncertainty shocks has revamped the attention on the role that uncertainty plays for macroeconomic fluctuations. Using a linear VAR, he provides empirical evidence that uncertainty shocks in the U.S., proxied by large stock-market volatility jumps, generate a quick "drop and rebound" in output and employment in the short-run followed by a temporary "overshoot" in the medium run. The effects of uncertainty shocks are substantial, e.g., industrial production rapidly falls of about 1% within four months. A variety of theoretical models further examine the role of uncertainty in affecting agents' decisions and triggering macroeconomic dynamics (see, e.g., Gilchrist and Williams (2005), Bloom (2009), Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011), Basu and Bundick (2012), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), Leduc and Liu (2013), Johannsen (2013), Christiano, Motto, and Rostagno (2014), and the review by Bloom, Fernández-Villaverde, and Schneider (2013)). From an empirical perspective, several contributions have assessed the importance of uncertainty as a driver of the business cycle and as an obstacle to stabilization policy. A non-exhaustive list includes Alexopoulos and Cohen (2009), Baker, Bloom, and Davis (2013), Bloom (2009), Gilchrist, Sim, and Zakrajsek (2013), Leduc and Liu (2013), Mumtaz and Theodoridis (2012), Stock and Watson (2012), Colombo (2013), Aastveit, Natvik, and Sola (2013), Mumtaz and Surico (2013), Nodari (2014), Pellegrino (2014), Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2014), and Furlanetto, Ravazzolo, and Sarferaz (2014).[1]

This recent empirical literature has provided lots of insights on the macroeconomic effects of uncertainty shocks. A modeling assumption shared by these contributions is that of symmetric effects of uncertainty shocks across different phases of the business cycle. However, some recent contributions provide evidence challenging this assumption. First, many macroeconomic aggregates of interest for policymakers display an asymmetric behavior over the business cycle (see, among others, Caggiano and Castelnuovo (2011), Morley and Piger (2012), Abadir, Caggiano, and Talmain (2013), Morley, Piger, and Tien (2013)). Second, uncertainty appears to rise sharply in recessions, much more sharply than in good times. Micro- and macro-evidence of countercyclical uncer-

[1] Some recent papers have pointed out that reverse causality going from recessions to uncertainty may be at play (Bachmann and Moscarini (2012), Bachmann and Bayer (2013)), or that the real effects of uncertainty shocks may in fact be modest (Bachmann and Bayer (2014), Born and Pfeifer (2014)). Baker and Bloom (2012) use disasters as natural experiments to identify first and second moment shocks in a panel of 60 countries. They find second moment shocks to account for at least a half of the variation of these countries' real growth.

tainty with abrupt increases in recessions is documented by Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), Jurado, Ludvigson, and Ng (2013), Bloom (2014) and Orlik and Veldkamp (2014).[2] Different indicators of realized volatility, often taken as a proxy for expected volatility in empirical analysis, are documented to be higher and more volatile in recessions (Bloom (2014)). Moreover, recent theoretical contributions give hints on why uncertainty shocks may exert more severe effects if hitting during bad times. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) show that resource reallocation among differently-productive firms and consumption smoothing are likely to play a major role in the transmission of uncertainty shocks to the real economy. However, during economic downturns entrepreneurs and consumers are more likely to face harsher financial conditions, which can impede the implementation of optimal allocation plans by firms and households (Canzoneri, Collard, Dellas, and Diba (2011), Bonciani and van Roye (2013)). Consequently, the economic effects of uncertainty shocks may very well be different in good and bad times.

To empirically scrutinize this potential asymmetry, we model Bloom's (2009) set of macroeconomic indicators with a Smooth Transition Vector AutoRegression (STVAR) framework, which allows us to jointly model economic good and bad times. Following Bloom (2009), we proxy uncertainty with the VXO index, a measure of implied volatility.[3] The dynamic responses of the variables of interest to an uncertainty shock are obtained by computing Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran, and Potter (1996) and Ehrmann, Ellison, and Valla (2003). This modeling choice enables us to endogenously account for possible regime-switches due to uncertainty shocks. This is important because i) uncertainty shocks occurring in expansions are likely to drive the economy into a recessionary state, and ii) uncertainty shocks occurring in recessions may lead the economy to a temporary expansion in the medium term due the "volatility effect" documented by Bloom (2009).[4]

[2]Spikes in uncertainty indicators may occur also in good times. For instance, the VXO registered a substantial increment after the Black Monday (October 19, 1987), during a period classified as expansionary by the NBER. In general, however, increases in uncertainty during bad times are much more abrupt that those occurring in good times.

[3]As recalled by Bloom (2014), Knight (1921) defined uncertainty as people's inability to form a probability distribution over future outcomes. Differently, he defined risk as people's inability to predict which outcome will be drawn from a known probability distribution. Following most of the empirical literature, we do not distinguish between the two concepts, and use the VIX as a proxy for uncertainty, though we acknowledge it is a mixture of both risk and uncertainty. For an analysis that disentangles the effects of risk and uncertainty, see Bekaert, Hoerova, and Duca (2013).

[4]In Bloom's (2009) model, the "volatility effect" is due to an increase in aggregate uncertainty

Our results point to clearly asymmetric effects of uncertainty shocks over the business cycle. We find the drop, rebound, and overshoot response of industrial production and employment to an uncertainty shock to be present only in recessions. Quite differently, the response of real activity in expansions is gradual, with a milder drop followed by quite a prolonged recovery, and no overshoot. Moving to the reaction of nominal variables, uncertainty shocks are found to drive inflation and interest rates down, a result that (combined with the one on the responses of industrial production and employment) is in line with the effects of a typical "demand" shock as in Basu and Bundick (2012) and Leduc and Liu (2013). Consistently with the evidence on the real effects of volatility shocks, the response of the policy rate is found to be substantially more marked during economic downturns, i.e., the reaction of the federal funds rate is estimated to follow a drop, rebound, and overshoot pattern in recessions only. The deflationary effects of volatility shocks occurring in expansions are mild at best. Importantly, these results are robust to a variety of perturbations of our baseline empirical model, including different definitions of extreme uncertainty events, different calibrations of the speed of transition from an economic phase to another, an alternative indicator of the business cycle to model recessions and expansions (the unemployment rate, as an alternative to our baseline growth rate of industrial production), the inclusion of measures of financial strain to control for the financial transmission channel of uncertainty shocks as in Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2014), and the inclusion of house prices, which enables us to account for housing shock as in Furlanetto, Ravazzolo, and Sarferaz (2014).

We then run counterfactual exercises to understand how effective the systematic component of monetary policy is in tackling the real effects of uncertainty shocks in good and bad times. In particular, we simulate a scenario in which systematic monetary policy is not allowed to react to uncertainty shocks. Under recessions, the short-run response of real activity is found to be virtually unchanged, and the medium-run response of real activity is just partly affected. This is consistent with the predictions of the theoretical models by Bloom (2009) and Bloom et al. (2012). In presence of labor and capital adjustment costs, such models predict a weak impact of monetary policy

which translates into an increase in the realized volatility of business conditions across firms. This implies that some firms enjoy a better technology, and they then decide to optimally invest/hire. Other firms, instead, feature a worse technology after the shock, which leads them to disinvest/fire or stay still. Given that the bulk of the business condition density is located close to the inaction/hiring-inaction/investing region, a temporary increase in aggregate production and employment occurs. A detailed discussion of the transmission mechanism of uncertainty shocks in Bloom's (2009) model and its relevance for our empirical analysis is provided in the next Section.

when uncertainty is high due to the relevance of "wait-and-see" effects. Our result is also consistent with Vavra (2014), whose model predicts a link between greater volatility and higher aggregate price flexibility, with the latter harming a central bank's ability to influence aggregate demand. Interestingly, we also find no overshoot in the medium run, possibly because of the higher borrowing costs implied by this counterfactual scenario. Differently, our simulations suggest that a muted (i.e., non expansionary) monetary policy in a low-uncertainty scenario would induce a deeper and longer-lasting recession following an uncertainty shock. The same message is found to be supported when a long-term interest rate, an empirical proxy to capture the role of forward guidance, is considered as an alternative policy instrument.

Our findings are important from a policymakers' standpoint. Blanchard (2009) calls for policies designed to remove tail risks, channel funds towards the private sector, and undo the "wait-and-see" attitudes by creating incentives to spend. Bloom (2014) suggests that stimulus policies should be more aggressive during periods of higher uncertainty. Baker, Bloom, and Davis (2013) find that policies that are unclear, hyperactive, or both, may raise uncertainty. Bekaert, Hoerova, and Duca (2013) find that monetary policy shocks have short and medium-term effects on risk aversion and uncertainty. Our results suggest that policymakers could very well be called to design state-dependent optimal policy responses, possibly closer to first-moment policies in expansions, but clearly different from them in recessions.

From a modeling standpoint, our evidence supports the development and use of micro-founded nonlinear frameworks able to replicate our VAR evidence (see Cacciatore and Ravenna (2014) for a recent example). As for existing frameworks, the facts established with our analysis are of help to discriminate among competing theoretical models in favor of those pointing to the recessionary effects (see, among others, Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), Basu and Bundick (2012), Johannsen (2013) and Leduc and Liu (2013)). Importantly, given the difference we find as for the dynamics of production and employment in good and bad economic times, our results point to the possibility of state-dependent capital and labor adjustment costs and/or countercyclical financial frictions in models à la Bloom (2009) and Bloom et al. (2012). Bloom's (2009) partial equilibrium analysis shows that aggregate uncertainty shocks cause a drop and rebound in real activity followed by an overshoot due to increased realized volatility at micro-level (units, firms, and industries). The general equilibrium analysis by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) shows that, even in presence of capital and labor adjustment costs, there is no real activity overshoot if consumers can optimally smooth consumption via intertemporal reallocation of resources. Intuitively, the overshoot in real activity may occur if financial markets do not allow for consumption smoothing, a situation which is more likely to realize when the economy is in a recession. In presence of a bust, financial markets freeze, and a less efficient reallocation of resources across households realize. In turn, large swings in aggregate consumption may realize, consistently with a drop, rebound, and overshoot path of real variables as in Bloom (2009). This type of behavior in real activity is exactly what our VAR model predicts. Differently, consumption smoothing in the Bloom et al. (2012) model predicts a milder exit from an uncertainty-induced recession, which is what we find when estimating the effects of uncertainty shocks in good times in which financial constraints are less tight. More generally, our findings support a research agenda aiming at identifying state-dependent relevant frictions able to induce different dynamic responses to structural shocks in good and bad times.

The paper develops as follows. Section 2 presents our non-linear framework and the data employed in the empirical analysis. Section 3 documents our main results and a number of robustness checks. Section 4 provides counterfactual analysis about the effects of monetary policy in recessions and expansions. Section 5 relates our work to the broader literature. Section 6 concludes.

2 Linear and nonlinear estimates of the impact of uncertainty shocks

We estimate the impact of uncertainty shocks on real economic outcomes via a nonlinear version of the eight variable-VAR model proposed by Bloom (2009). The vector $\boldsymbol{X}_t$ collects the following variables (from the top to the bottom of the vector): the S&P500 stock market index, a stock-market volatility indicator based on the VXO, the federal funds rate, a measure of average hourly earnings, the consumer price index, hours, employment, and industrial production. As in Bloom (2009), all variables are in logs, except the volatility indicator, the policy rate, and hours.[5] The volatility indicator is

[5] Unlike Bloom (2009), we do not filter these variables with the Hodrick-Prescott (HP) procedure. The reason for not detrending the data is twofold. First, as shown by Cogley and Nason (1995), HP-filtering may induce spurious cyclical fluctuations, which may bias our results. Second, the computation of the GIRFs requires the inclusion of the transition variable z_t, calculated as a moving average of the growth rate of (unfiltered) industrial production in the STVAR. We notice, however, that the choice of not detrending the variables employed in our analysis does not qualitatively affect our results.

a dummy variable that takes the value of 1 when the HP-detrended VXO level rises 1.65 standard deviations above the mean, and 0 otherwise. Following Bloom (2009), this indicator function is employed to ensure that identification comes from large, and likely to be exogenous, volatility shocks and not from smaller, business-cycle related, fluctuations. To ease the comparison of our results with Bloom's (2009), we use the same data frequency and time span, i.e., monthly data from July 1962 to June 2008. Figure 1 reports the VXO series used to construct the dummy variable as in Bloom (2009) along with the NBER recessions dates. The sixteen episodes which Bloom identifies as uncertainty shocks are equally split between recessions and expansions. Noticeably, all recessions are associated with significant spikes in the volatility series.

The vector of endogenous variables $\boldsymbol{X}_t$ is modeled with the following STVAR (for a detailed presentation, see Teräsvirta, Tjøstheim, and Granger (2010)):

$$\boldsymbol{X}_t = F(z_{t-1})\boldsymbol{\Pi}_R(L)\boldsymbol{X}_t + (1 - F(z_{t-1}))\boldsymbol{\Pi}_E(L)\boldsymbol{X}_t + \boldsymbol{\varepsilon}_t, \quad (1)$$

$$\boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{\Omega}_t), \quad (2)$$

$$\boldsymbol{\Omega}_t = F(z_{t-1})\boldsymbol{\Omega}_R + (1 - F(z_{t-1}))\boldsymbol{\Omega}_E, \quad (3)$$

$$F(z_t) = \exp(-\gamma z_t)/(1 + \exp(-\gamma z_t)), \gamma > 0, z_t \sim N(0, 1). \quad (4)$$

In this model, $F(z_{t-1})$ is a logistic transition function which captures the probability of being in a recession, γ is the smoothness parameter, z_t is a transition indicator, $\boldsymbol{\Pi}_R$ and $\boldsymbol{\Pi}_E$ are the VAR coefficients capturing the dynamics in recessions and expansions respectively, $\boldsymbol{\varepsilon}_t$ is the vector of reduced-form residuals with zero-mean and whose time-varying, state-contingent variance-covariance matrix is $\boldsymbol{\Omega}_t$, where $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$ are covariance matrices of the reduced-form residuals computed during recessions and non-recessions, respectively. Recent applications of this STVAR framework to analyze the U.S. economy include Auerbach and Gorodnichenko (2012), Bachmann and Sims (2012), Berger and Vavra (2014), and Caggiano, Castelnuovo, Colombo, and Nodari (2014), who employ it to study the effects of fiscal spending shocks in good and bad times, and Caggiano, Castelnuovo, and Groshenny (2014), who focus on the effects of uncertainty shocks on unemployment in recessions.

In short, the STVAR model assumes that the vector of endogenous variables can be described as a combination of two linear VARs, i.e., one suited to describe the economy

Some exercises conducted with HP-detrended variables as in Bloom (2009) and based on conditionally linear IRFs computed with our STVAR framework returned results qualitatively in line with those documented in this paper. These results are available upon request and are consistent with the robustness check in Bloom (2009), Fig. A3, p. 679.

during recessions and the other to be interpreted as a vector modeling the expansionary phase. Conditional on the standardized transition variable z_t, the logistic function $F(z_t)$ indicates the probability of being in a recessionary phase. The transition from a regime to another is regulated by the smoothness parameter γ. Large values of γ imply abrupt switches, whereas small values of γ enable the economic system to spend some time in each regime before switching to the alternative one. The linear model is a special case of the STVAR, where $\mathbf{\Pi}_R = \mathbf{\Pi}_E = \mathbf{\Pi}$ and $\mathbf{\Omega}_R = \mathbf{\Omega}_E = \mathbf{\Omega}$. Following Bloom (2009), the identification of exogenous variations of the uncertainty index is achieved via a Cholesky-decomposition of the covariance matrix of the residuals. Hence, the ordering of the variables admits an immediate response of the business cycle to uncertainty shocks. Therefore, the STVAR model can be interpreted as a generalization of Bloom's (2009) linear approach, which is included as a special case. The model is suited to examine the role played by nonlinearities in the transmission of uncertainty shocks, since it discriminates between different phases of the business cycle while retaining enough information to estimate a richly parametrized VAR framework.

A key-role is played by the transition variable z_t (see eq. (4)). Auerbach and Gorodnichenko (2012), Bachmann and Sims (2012), Berger and Vavra (2014), Caggiano, Castelnuovo, and Groshenny (2014), and Caggiano, Castelnuovo, Colombo, and Nodari (2014) construct their transition indicator using a standardized moving-average of the quarterly real GDP growth rate. Similarly, we employ a standardized backward-looking moving average involving twelve realizations of the month-to-month growth rate of industrial production.[6] Another important feature of the STVAR model is the choice of the smoothness parameter γ. We exploit the dating of recessionary phases produced by the National Bureau of Economic Research (NBER) and calibrate the smoothness parameter γ to match the frequency and duration of the U.S. recessions, which amounts to 14% in our sample. Consistently, we define as "recession" a period in which $F(z_t) \geqslant 0.86$, and calibrate γ to obtain $\Pr(F(z_t) \geqslant 0.86) \approx 0.14$.[7] This metric implies $\gamma = 1.8$. Figure 2 plots the transition function and superimposes the resulting probability of being

[6] Section 4 shows that our results are robust to the employment of the unemployment rate as transition indicator.

[7] This choice is consistent with a threshold value $\overline{z}^{std}$ equal to -1.01%, which corresponds to a threshold value for the non-standardized moving average of the growth rate of industrial production equal to to 0.13%. This last figure is obtained by considering the sample mean of the non-standardized growth rate of industrial production (in moving average terms), which is equal to 0.40, and its standard deviation, which reads 0.27. Then, its corresponding threshold value is obtained by "inverting" the formula we employed to obtain the standardized transition indicator z, i.e., $\overline{z}^{nonstd} = (\overline{z}^{std}\sigma_z + \overline{z}) = (-1.01 \times 0.27 + 0.40) \approx 0.13\%$.

in a recession on the U.S. post-WWII recessions as documented by the NBER. As one can see, our transition probability tracks well the downturns of the U.S. economy.[8]

Since any smooth transition regression model is not identified if the true data generating process is linear, we test for the null hypothesis of linearity vs. the alternative of logistic STVAR for our vector of endogenous variables. We employ two tests proposed by Teräsvirta and Yang (2014). The first is a LM-type test, which compares the residual sum of squares of the linear model with that of a third-order approximation of the STVAR framework. The second is a rescaled version of the previous test, which accounts for size distortion in small samples. Both test statistics lead to strongly reject the null hypothesis of linearity at any conventional significance level. A detailed description of the tests is provided in our Appendix.

We estimate both the linear VAR model and the nonlinear STVAR framework with six lags, a choice supported by standard information criteria. Given the high nonlinearity of the model, we estimate it by employing the Markov-Chain Monte Carlo simulation method proposed by Chernozhukov and Hong (2003).[9] The estimated model is then employed to compute GIRFs to an uncertainty shock. Details on their computation are provided in our Appendix.

We interpret our impulse responses as the reaction of economic variables to an uncertainty shock. It is, in principle, difficult to rule out the possibility that uncertainty shocks are caused by first-moment shocks like, e.g., aggregate TFP shocks (see, e.g., Bachmann and Bayer (2013)), and are therefore endogenous to the economic system. We check the exogeneity of our uncertainty shocks by running bivariate VARs modeling the vectors $[sp500, VXO]'$, $[indpro, VXO]'$, and $[empl, VXO]'$, where $sp500$, VXO, $indpro$, and $empl$ stand for (respectively) the log of S&P500, the VXO index, the log of industrial production, and the log of employment. All these bivariate VARs point to i)

[8] The slight delay which with our transition probability peaks in occurrence of a recession with respect to the NBER dating is due to the choice of using a backward-looking transition indicator. Such choice enables us to compute the probability $F(z)$ by appealing to realizations of industrial production (as opposed to predicted values) due to uncertainty shocks. As one can notice, the volatility of the F(z) function visibly drops when entering the Great Moderation period, i.e., 1984-2008. This might suggest the need of re-optimizing the calibration of our slope parameter to better account for differences in regime switches in the 1962-1983 vs. 1984-2008 periods. The calibrations for the two periods read, respectively, 1.62 and 1.72 (for capturing the 19.6% and 8% frequencies of NBER recessions in the two subsamples). Such calibrations are quite close to the one we employ in our baseline exercise, i.e., 1.8. Estimations conducted with these two alternative values of γ lead to virtually unaltered results.

[9] In principle, one could estimate the STVAR model we deal with via maximum likelihood. However, since the model is highly non-linear and has many parameters, using standard optimization routines is problematic. Under standard conditions, the algorithm put forth by Chernozhukov and Hong (2003) finds a global optimum in terms of fit as well as distributions of parameter estimates.

a strong evidence (at any conventional level) against the null hypothesis that the VXO does not Granger-cause the other variables, and ii) no evidence (at any conventional level) against the null hypothesis that each of the other variables does not Granger-cause the VXO. These results, based on macroeconomic aggregates, complement those by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), who work with industry-level data and find no significant impact of first-moments shocks on measures of TFP dispersions.

3 Results

3.1 Responses of real aggregates

Are the real effects of uncertainty shocks state-dependent? Figure 3 plots the estimated dynamic responses of employment and industrial production to an uncertainty shock obtained with the linear VAR as well as those conditional on recessions and expansions as described by our STVAR model.[10] The linear model replicates well the drop, rebound, and overshoot of industrial production and employment documented by Bloom (2009). In particular, the peak short-run response of industrial production is about -1.5%, while that of employment reads -1%. Hence, a one-standard deviation shock in uncertainty triggers quantitatively important real effects. Importantly, however, the contractionary effects of uncertainty shocks appear to be mainly driven by what happens in recessions. The short-run responses of industrial production and employment conditional on recessions are larger than what predicted by a linear VAR model. The peak short-run response of industrial production is below -2%, while that of employment is about -1.5% Interestingly, the rebound in industrial production is quicker in recessions than what a linear model would suggest, and the volatility overshoot is larger as well. Overall, a linear model provides a distorted picture of the real effects of uncertainty shocks in terms of: i) the magnitude of the impact over the business cycle, ii) the magnitude of the medium-run overshoot, and iii) the timing of the overshoot.[11]

[10]Following Koop, Pesaran, and Potter (1996), we compute our impulse responses by integrating over a large number of different sets of initial conditions. Hence, these responses are to be interpreted as median responses in recessions/expansions, and not as responses conditional to a given recession/expansion. The size of the standard deviation of the shock is normalized to one in both states. This is done to simulate the effects of the same shock in the linear case vs. the nonlinear scenarios. Simulations based on shocks with different magnitudes suggest a negligible role of the "size effect" of the shocks in recession and expansions before normalization.

[11]Interestingly, the same holds for hours worked, suggesting that firms are likely to adjust their demand for labor after an uncertainty shock both on the intensive and the extensive margin. The

How relevant is this result from a statistical standpoint? Figure 4 contrasts the responses of industrial production and employment obtained in recessions vs. expansions by considering two different confidence levels, i.e., 68% (areas identified with dashed and dotted lines) and 95% (grey areas). The abrupt drop-and-rebound reaction of industrial production in recessions, followed by a persistent overshoot, turns out to be clearly significant by our empirical analysis even at a 5% significance level. Quite differently, uncertainty shocks in expansions trigger a hump-shaped, delayed reaction of industrial production, with no evidence of overshoot. Very similar results hold for employment, whose rebound and overshoot is estimated to be slower than that of industrial production, but clearly significant at the 68% confidence level, in recessions. Again, expansions suggest a different conditional path for employment characterized by a much slower return to its trend level and no overshoot.

3.2 A possible interpretation

Our GIRFs suggest a drop, rebound, and overshoot type of response of industrial production and employment in recessions only. Differently, uncertainty shocks occurring in good times induce a hump-shaped response of these variables, and no medium term overshoot. What drives such a different dynamic path? Some recent theoretical models on the real effects of uncertainty shocks suggest there might be two mechanisms at work here. The first comes from Bloom (2009)'s partial equilibrium analysis, and it refers to the "volatility effect". The overshoot in real activity is driven by increased micro-level realized volatility after a macro-uncertainty shock. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) provide compelling empirical evidence in favor of the countercyclicality of different measures of realized micro-volatility at different levels of disaggregation (unit, firm, and industry level). We corroborate their evidence by regressing the within-quarter cross-sectional spread of profit growth rates normalized by average sales (a measure of cross-sectional unit-level volatility in Bloom (2009)) against different measures of business conditions, i.e., the annual real GDP growth rate and the business cycle indicator employed by Caggiano, Castelnuovo and Groshenny (2014).[12]

figure about the response of hours and all the remaining variables included in the VAR is included in the Appendix.

[12] The measure of unit-level volatility constructed by Bloom (2009) is the standard deviation of firm profit growth, defined as $(profits_t - profits_{t-1}) / (0.5 \times sales_t \times sales_{t-1})$, using firms with 150+ quarters of data in Compustat quarterly accounts. The NBER recession dating is a dummy variable, which takes the value of -1 when the economy is officially in a recession, 0 otherwise. The transition variable in Caggiano, Castelnuovo and Groshenny (2014) is the standardized moving average involving seven realizations of the quarter-on-quarter real GDP growth. Data are quarterly, and cover the

We find a negative and statistically significant coefficient for both measures, an evidence consistent with a countercyclical behavior of micro-level volatility.[13] A second mechanism that can explain the different dynamics in recessions and expansions comes from the general equilibrium model in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), in which the volatility effect is dominated by the consumption smoothing effect. This is so because the overshoot in Bloom's (2009) partial equilibrium economy requires big variations in investment, which imply large changes in consumption. Once consumption smoothing is allowed to play a role, the overshoot in real activity disappears. However, consumption smoothing is intuitively possible if agents can easily access financial markets. But credit conditions are typically tighter in recessions. Hence, one could expect the consumption smoothing effect to be more important, and its relative importance with respect to the volatility effect to be higher, during good times, which could then be associated to a hump-shaped response of real activity to an uncertainty shock. Binding credit constraints in recessions could instead prevent consumption smoothing, therefore leading to a quicker rebound and an overshoot in real activity, which is exactly what our impulse responses predict.[14]

3.3 Robustness analysis

Exogenous uncertainty shocks. Following Bloom (2009), our baseline analysis is conducted by working with 16 extreme realizations of uncertainty. Some of them, however, might be related to changes in the business cycle, e.g., the 1987 black Monday, or the 1982 economic recession. Hence, endogeneity may be at work and affect our impulse responses. To control for this possible endogeneity, we define an alternative volatility dummy by focusing on just 10 out of 16 extreme realizations of uncertainty, i.e., those which are associated to terror, war, or oil events by Bloom (2009).[15] Figure 5

1966Q1-2008Q4 period.

[13] The estimated coefficients, and the associated p-values, are equal to -0.30 (-4.15) and -0.36 (-4.26), respectively.

[14] Consistently with this interpretation, Carrière-Swallow and Céspedes (2013) find the real effects of uncertainty shocks to be stronger in emerging economies than in developed countries, and show that this heterogeneity largely due to the different depth of financial markets. In a different but related context, Canzoneri, Collard, Dellas, and Diba (2011) show the importance of countercyclical financial frictions in a DSGE model to explain the nonlinear dynamics of real activity indicators after fiscal policy shocks.

[15] The Terror shocks are: the Cuban Missile Crisis (October 1962), the Assassination of JFK (November 1963), the 9/11 Terrorist Attack (September 2001). The War shocks are: the Vietnam buildup (August 1966), the Cambodian and Kent State (May 1970), the Afghanistan, Iran hostages (March 1980), the Gulf War I (October 1990), the Gulf War II (February 2003). The Oil shocks are dated December 1973 and November 1978.

reports the estimated GIRFs for industrial production and employment to this possibly more "exogenous" shock, along with the 68% and 95% confidence bands. As in the baseline case, our results show that the drop, rebound and overshoot path is present only when uncertainty shocks hits during recessions (though it is only marginally significant for employment).

Different calibration of the slope parameter. One potential drawback of our STVAR model is that the slope parameter γ, which drives the smoothness with which the economy switches from one regime to another, is calibrated. Our baseline estimation uses a value of $\gamma = 1.8$, selected so that the economy spends 14% of the time in recessions, which is the frequency observed in our sample according to the NBER definition of recessions. To check the robustness of the baseline results to different values of γ, we have re-estimated the model using values of γ between 1.4 and 2.2, which imply a frequency of recessionary periods in the sample equal to 10% and 25%, respectively. Following Hansen (1999), we set to 10% the frequency corresponding to the minimum amount of observations each regime should contain to be identified. Our results are reported in Figure 6, which plots our baseline GIRFs along with the GIRFs obtained with our alternative calibration values for γ. This robustness check clearly confirms our baseline results.

Unemployment as transition indicator. In our baseline exercise, the transition indicator z, which regulates the probability of being in a recession, is a twelve terms moving average of the month-by-month growth rate of the industrial production index. An alternative indicator of the business cycle often considered by policymakers and academics is the unemployment rate. We then estimate a version of our STVAR model in which our baseline vector is augmented with the unemployment rate (ordered after the uncertainty dummy). Following some recent announcements by U.S. policymakers and the modeling choice in Ramey and Zubairy (2014), we classify periods in which the unemployment rate is over (under) 6.5% as recessionary (expansionary).[16] Figure 7 documents our GIRFs, which deliver the same stylized facts as in our baseline analysis, i.e., a marked drop followed by a quick rebound and a temporary overshoot in industrial production and employment when uncertainty shocks occur in recessions, and a hump-shaped response of real activity in good times.

[16] On December 12, 2012, the Federal Open Market Committee decided to tie the target range of the federal funds rate at 0 to 1/4 percent and maintain it as such exceptionally low levels *"[...] at least as long as the unemployment rate remains above 6-1/2 percent, inflation between one and two years ahead is projected to be no more than a half percentage point above the Committee's 2 percent longer-run goal, and longer-term inflation expectations continue to be well anchored."*

Uncertainty and financial risk. Stock and Watson (2012) point out that financial strains lead to higher uncertainty, which in turn increases financial risk. An implication of this relationship for our analysis is that the transmission of uncertainty shocks to the real economy might not be due to uncertainty *per se* but it might rather be driven by the level of financial stress in the economy. Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2014) provide empirical evidence in favor of larger real effects of uncertainty shocks in periods of high financial stress. A way to control for the presence of time-varying financial risk is to include a measure of credit spread in our VAR. Gilchrist and Zakrajsek (2012) propose a micro-founded measure of excess bond premium, i.e., a measure of credit spread cleaned by the systematic movements in default risk on individual firms. Such a measure has the attractive feature of isolating the cyclical changes in the relationship between measured default risk and credit spreads. Unfortunately, it is unavailable prior to 1973. Hence, its employment would considerably shorten our sample size, and this would be particularly problematic for the estimation of a richly-parameterized nonlinear VAR like ours. To circumvent this issue, we consider a large set of credit spread measures available for our full sample, as in Stock and Watson (2012), and choose the one which correlates the most with Gilchrist and Zakrajsek's measure of excess bond premium in the sample 1973-2008. The selected credit spread measure is the difference between the Baa corporate bonds and the 10-year Treasury yield, whose correlation with Gilchrist and Zakrajsek's excess bond premium reads 0.67. We then add the Baa-10yr spread to our 8-variate VAR. Figure 8 reports the response of industrial production and employment to an uncertainty shock in recessions and expansion for a nine-variate STVAR embedding the selected credit spread. Two alternative orderings are considered. In one, the credit spread is ordered before uncertainty, implying that uncertainty responds contemporaneously to credit spread but not viceversa. In the other one, credit spread is ordered after uncertainty, so to admit a contemporaneous reaction of credit spread to changes in uncertainty. Our results broadly confirm those of our baseline scenario, i.e., uncertainty shocks occurring in recessions generate a drop and rebound in real activity in the short-run, followed by a medium-run, temporary overshoot (which is less clearly evident for employment, though). These results are consistent with the findings by Bekaert, Hoerova, and Duca (2013), who show that uncertainty shocks induce business cycle fluctuations even when controlling for indicators of time-varying risk aversion. Our results are also consistent with those in Caldara et al. (2014), who show that uncertainty shocks working via credit frictions may lead to a persistent decline in real and financial variables.

Uncertainty and housing. Since Iacoviello (2005) paper and the 2007-2009 financial and real crisis, there has been a revamped attention toward the relationship between housing market dynamics and the business cycle. The housing market is particularly important for us in the light of a recent paper by Furlanetto, Ravazzolo, and Sarferaz (2014), who show that uncertainty shocks may play a minor role if one controls for housing shocks. We then add the real home price index computed by Robert Shiller to our baseline vector.[17] As before, two alternative orderings are considered, one in which the house price index is ordered just before uncertainty, and the other one in which such index is ordered after uncertainty. Figure 9 depicts our median responses. Quite interestingly, the presence of house prices does not appear to quantitatively affect the drop and rebound part of the response of industrial production and employment in bad times. However, it clearly dampens the overshoot of the former variable, and it implies no overshoot as for the latter. As for the response of these variables in expansions, house prices do appear to moderate the response of real activity also in the short-run. These results are consistent with those in with Furlanetto, Ravazzolo, and Sarferaz (2014), who show that part of the effects often attributed to uncertainty shocks may be an artifact due to the omission of house prices from VAR analysis. However, even when controlling for house prices, we find asymmetric responses of industrial production and employment (in terms of severity of the recession, speed of the recovery, and overall dynamics) over the business cycle.

Wrapping up, our findings are robust to the inclusion of a different uncertainty indicators, calibration of the slope parameter of the logistic function, business cycle indicators to detect the transition from a state to another, a measure of credit spread, and an indicator of real house prices. In the next Section, we turn to the analysis of monetary policy effectiveness after uncertainty shocks.

4 Uncertainty shocks and monetary policy

4.1 Baseline responses

We now turn to the dynamics of prices and the federal funds rate, the latter being the indicator of monetary policy stance in our vector. As before, Figure 10 focuses on the differences between recessions and expansions, and plots 68% and 95% confidence bands

[17] The index is available here: http://www.econ.yale.edu/~shiller/data/Fig2-1.xls. This index is quarterly. We moved to monthly frequencies via a cubic interpolation of the quarterly series. Our VAR models the log of such interpolated index.

around the estimated generalized impulse responses. An uncertainty shock triggers a significant negative reaction of prices only in recessions. Inflation goes down and then gradually returns to its initial value. As both quantities and prices fall after an uncertainty shock, and much more markedly in recessions, a central bank following a Taylor-type rule would lower the interest rate. Our GIRFs show that, in line with a Taylor-type behavior, the interest rate goes down significantly, both in recessions and expansions. However, in terms of dynamics and quantitative response, the difference is remarkable. When the uncertainty shock hits the economy during an expansion, the interest rate goes down by about 0.5 percentage points at its peak, and the reaction is short-lived. When the uncertainty shock hits in recessions, the policy rate goes down up to about two percentage points, and remains statistically significant for a prolonged period of time. These results support the view put forward by Basu and Bundick (2012) and Leduc and Liu (2013) that uncertainty shocks are demand shocks, and show again that they have different effects over the business cycle.

Our VAR estimates policy easings to occur even when uncertainty shocks hit in expansions. A look at some events of recent U.S. economic history suggests that high peaks of uncertainty in expansions did not necessarily lead to recessions. An example is the "Black Monday" in October 1987, which is associated to the highest increase of the volatility index in our sample. While possibly being the responsible of the downturn in industrial production and employment in the following months, this uncertainty shock did not drive the U.S. economy into a recession. However, this "missing recession" may be due to the response of the Federal Reserve, which implemented open market operations that pushed the federal funds rate down to around 7 percent on Tuesday from over 7.5 percent on Monday. The path followed by these variables after the black Monday is consistent with the prediction of our VAR models in expansions.

4.2 Counterfactual scenarios

This evidence shows that monetary authorities react to uncertainty shocks in both phases of the business cycle. But what would have happened if the Federal Reserve had not reacted to the macroeconomic fluctuations induced by volatility shocks? Would the recessionary effects of uncertainty shocks have been magnified? If so, to what extent? Answering these questions is key to understand the role that can be played by conventional monetary policy, a first-moment tool, in presence of second-moment shocks.

We employ our STVAR and run a counterfactual simulation designed to answer these questions. Our counterfactual assumes the central bank to stay still after an uncertainty shock, i.e., we shut down the systematic response of the federal funds rate to movements in the economic system due to uncertainty shocks.[18] Given that the federal funds rate is bound to stay fixed to its pre-shock level, the responses we obtain are informative as for the costs of "doing nothing" by policymakers.

Figure 11 superimposes the dynamic reactions of real activity obtained by muting the systematic policy response to uncertainty shocks to our baseline GIRFs (a scenario identified by the label "muted systematic policy"). Noticeably, the short-run effects of this counterfactual policy response are negligible in recessions. In other words, the recession is estimated to be as severe as the one that realizes when policymakers are allowed to lower the policy rate. The short-run recessionary effect is exactly the same in the two scenarios, and a gap between the baseline responses and those produced with our counterfactual experiment begins realizing just after one year. Noticeably, this difference mainly regards the speed with which real activity recovers and overshoots before going back to the steady state. A different picture emerges when our counterfactual monetary policy is planted in good times. As Figure 11 shows, when the policy rate is kept fixed, industrial production goes down markedly (about -3% at its peak) and persistently, remaining statistically below zero for a prolonged period of time (for all 20 quarters according to 68% confidence bands). The same holds when looking at the response of employment, i.e., the gap between the baseline response and the one associated to our counterfactual exercise is quantitatively substantial.

Interestingly, what makes the difference between the two scenarios is not necessarily the different systematic response to fluctuations in uncertainty *per se*. Indeed, when only the systematic component related to uncertainty in the federal funds rate equation is switched off, uncertainty shocks are found to induce a response in real activity which is barely unchanged with respect to the baseline one (see Figure 11, scenario: "muted pol. react. to uncertainty"). Hence, uncertainty shocks trigger significant monetary policy responses mainly via the effects they exert on the macroeconomic indicators embedded in our vector. This finding point to a Taylor rule not featuring uncertainty among the variables policymakers directly respond to as a possible interpretative model

[18] As in Sims and Zha (2006), we do so by zeroing the coefficients of the federal funds rate equation in our VAR. Alternatively, one could create fictitious monetary policy shocks to keep the federal funds rate fixed to its pre-shock level. We follow the former strategy to line up with counterfactuals typically played by macroeconomists who work by perturbing the values of policy parameters directly. In this sense, we interpret our federal funds rate equation as a "monetary policy equation".

of the U.S. monetary policy.

Are the impulse responses depicted in Figure 11 statistically different? Figure 12 plots the distribution of the difference between the GIRFs obtained with our "muted systematic policy" scenario and our baseline one. In line with what commented above, such difference is hardly significant in recessions according to the 95% confidence bands, while it is significant in expansions when the same confidence level is considered. The 68% confidence bands tell a somewhat different story, and suggest that the short-run effect of different systematic monetary policies may be at work also in recessions. However, it is so for just a few months, while in expansions such effect is present and significant for more than four years after the shock.

4.3 Interpreting policy (in)effectiveness

How can one interpret the state-dependence of monetary policy effectiveness? These results might find a rationale in the real option value theory. When uncertainty is high, firms's inaction region expands. Hence, the "wait-and-see" behaviour becomes the optimal strategy for a larger number of firms, compared to normal times. These firms become quite insensitive to the rate of return of capital, which explains why the peak recessionary effect is virtually identical. When uncertainty starts to drop down, firms become more willing to invest to face their pent-up demand. However, when monetary policy does not react as in our counterfactual scenario, they also consider the higher (with respect to the baseline) cost of borrowing in place. Hence, they re-start investing at a lower pace with respect to what happens in our baseline scenario (which is characterized by a strong temporary drop in the nominal interest rate). In equilibrium, firms do invest less than in the baseline case in the medium-run, and the overshoot just does not realize. A similar reasoning can be done as for labor demand and, therefore, employment. Quite differently, higher realizations of the interest rate (at least in the short-run) are found to importantly concur to the downturn triggered by uncertainty shocks in expansions. If the option value of waiting due to uncertainty is less important in expansions, firms are more reactive to stimulus policy. Hence, in presence of a higher nominal interest rate, firms are more likely to invest less and demand a lower quantity of labor. Consequently, a stronger recessionary effect realizes.

Our empirical findings, which highlight the role of the systematic component of monetary policy, are consistent with those by Aastveit, Natvik, and Sola (2013), Tenreyro and Thwaites (2013), Pellegrino (2014), and Mumtaz and Surico (2014), who also find monetary policy to be less powerful in periods of high uncertainty or, more generally, during recessions. In particular, Mumtaz and Surico (2014) show that the reduced-form coefficients of the U.S. aggregate demand schedule are state dependent, i.e., when real activity is above its conditional average, the degree of forward-lookingness and the interest rate semi-elasticity are significantly larger than the values estimated when real activity is below average. This implies that, all else being equal, monetary policy is more powerful in good than in bad times. Again, given the tight link between the IS curve schedule and the structure and features of the financial markets, we speculate that our results might be seen as consistent with the different role played by financial frictions in economic booms and busts.

4.4 Contemporaneous policy and forward guidance

It is of interest to understand if the differences documented in Figures 11 and 12 are mainly due to movements of the federal funds rate *per se* or to agents' expectations over future policy moves. If movements in the federal funds rate *per se* are the only element that matters to stabilize real activity, policymakers should implement aggressive and timely changes in the federal funds rate to tackle the effects of an uncertainty shocks, above all in recessions. Differently, if expectations over future policy moves matter, policymakers are called to choose the optimal mix involving variations in the federal funds rate and forward guidance to influence market beliefs about the expected path of short term rates. Gurkaynak, Sack, and Swanson (2005) argue that the Fed has increasingly relied on communication to affect agents's expectations over future policy moves. Kuttner (2001) proposes to use federal funds rate futures to capture financial markets' expectations over future policy moves. Gertler and Karadi (2014) employ such measures of expectations to investigate the empirical relevance of forward guidance by the Federal Reserve. Unfortunately, federal funds rate futures are available from 1989 only. Hence, their use in our context would imply a substantial loss in degrees of freedom for the econometric analysis. Interestingly, Gurkaynak, Sack, and Swanson (2007) find the predictive power of a variety of financial instruments, including federal funds rate futures and short-term Treasury maturity rates, to be very similar when horizons over six months are considered. Following Bagliano and Favero (1998), we then enrich our VAR with the 10-year Treasury constant maturity rate (ordered after the uncertainty dummy), which is likely to carry information over future, expected policy moves, and it can therefore be relevant to capture the link between changes in the policy instrument and target variables (Kulish (2007)). We then produce two sets of GIRFs. The first one refers to the unconstrained nine-variate STVAR modeling all baseline variables plus the long-term interest rate. The second one focuses on the counterfactual response of real activity conditional on a fixed federal funds rate. As before, we conduct this counterfactual to assess the role of systematic monetary policy in this context. The third one simulates the responses to an uncertainty shock conditional on a fixed long-term interest rate. This exercise is conducted to capture the role that expectations over future monetary policy may play in transmitting the effects of uncertainty shocks.

Figure 13 plots these sets of GIRFs over our baseline ones (obtained with our baseline eight-variate STVAR). Three results stand out. First, the presence of the long-term interest rate *per se* does not exert any appreciable impact on our baseline GIRFs. Second, a counterfactually still monetary policy is confirmed to deliver a deeper recession than the one predicted with our baseline exercise. However, with respect to Figure 11, such counterfactual recession is milder. This is so because of the role played by the long-term interest rate in this system. Indeed, the third message of this exercise is that shutting down the long-rate channel does also have an impact on our GIRFs. In particular, uncertainty shocks hitting in recessions are associated to a slower medium-run recovery. The effect is even more pronounced when one moves to uncertainty shocks hitting in good times. Indeed, the long-term interest rate also appears to represent an important bit to understand the effects of an unexpected increase in volatility when the economy experiences booms. The effects of shutting down the short vs. the long-term interest rates appear to be quite similar during the first eighteen months as for industrial production. Then, while the effects of these two counterfactual policies remain similar in recessions, a difference can be notice as for expansions, with the federal funds rate playing a bigger role. The opposite holds as for employment, which turns out to be mainly affected by the long-term interest rate. Interestingly, the effects of these counterfactual policies are again larger, above all as for expansions, in the medium run, but remain weak in the short run, particularly during recessions.[19]

[19] Obviously, caution should be used in interpreting these results, which come from exercises that are subject to the Lucas critique. Ideally, one should build up a model which meaningfully features uncertainty shocks, financial frictions, short- and long-term interest rates, and mechanisms inducing a nonlinear response of real aggregates to uncertainty shocks. We see our results as supporting this research agenda.

5 Relation to the literature

The theoretical and empirical literature about the real effects of uncertainty shocks has blossomed in the aftermath of the recent crisis and the following deep and long-lasting recession. Several policy makers and academics alike have stressed the role played by high uncertainty in prolonging the recession. We quickly recall here the models by Bloom (2009) and Bloom et al. (2012) (already presented in Section 3). Bloom (2009) works with a partial equilibrium model where uncertainty shocks are modeled as time-varying second-moment shocks. He shows that such shocks induce a drop, rebound, and overshoot of real variables such as output and employment. In short, in presence of nonconvex labor and capital adjustment costs, an increase in uncertainty raises the real-option value of waiting, thereby enlarging the region of optimal inaction faced by firms in the hiring and investment space. As uncertainty fades away, the inaction region becomes smaller, and firms optimally face their pent-up demand by investing and hiring. In the medium run, investment and employment (and, consequently, output) experience a (temporary) overshoot due to reallocation effects driven by a higher intra-industry realized volatility of business conditions. An important extension of Bloom's (2009) partial equilibrium framework is Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012). They model time-varying uncertainty in a dynamic stochastic general equilibrium framework with heterogeneous firms and non-convex capital and labor adjustment costs, in which households optimally choose their consumption paths. As in Bloom (2009), uncertainty shocks are found to be recessionary shocks. However, consumption smoothing is found to be key for understanding the gradual recovery, and the absence of any overshoot, occurring after a drop caused by an increase in the dispersion of TFP shocks.

A number of recent papers have further examined the transmission mechanism of uncertainty shocks to the economic system, and their impact on the effectiveness of stabilization policies. Using a DSGE model with sticky prices, Basu and Bundick (2012) show that an increase in uncertainty generates precautionary labor supply, which reduces the marginal cost of production. If prices adjust slowly, however, firms' mark-up increases over marginal costs. A higher mark-up reduces the demand for both consumption and investment goods, which in turn implies a fall in output and employment, consistent with business-cycle comovements. Since monetary authorities react to heightened uncertainty by lowering the interest rates, hitting the Zero Lower Bound (ZLB), by making conventional monetary policy ineffective, greatly amplifies the recessionary effects of uncertainty shocks. In a similar fashion, Benigno and Ricci (2011) and Cacciatore and Ravenna (2014) also show the importance of wage rigidities in magnifying the real effects of heightened volatility. Leduc and Liu (2013) get similar results in a model with sticky prices and search frictions in the labor market. Bonciani and van Roye (2013) investigate the role played by frictions in the banking sector for the transmission of uncertainty shocks. Sticky retail interest rates due to monopolistic power enjoyed by financial intermediaries imply an imperfect pass-through of the central bank interest rate to the private sector. An exogenous increase in uncertainty leads to a reduction in the policy rate which does not fully translate into lower borrowing costs for entrepreneurs. Hence, credit spreads augment in sync with economic downturns. According to Bonciani and van Roye's (2013) simulations, uncertainty shocks trigger particularly strong effects in distressed scenarios (which are simulated by considering big negative TFP shocks). Differently, they explain quite a modest fraction of the variance of output in normal times. As for emerging economies, Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011) show that variations in the volatility of the reference external real interest rate at which such economies borrow may exert important effects on a number of real activity indicators.

The consequences of increased uncertainty on the effectiveness of monetary policy have been examined by Vavra (2014). In a Ss model with second moment shocks that increase idiosyncratic volatility, he shows that greater uncertainty on the one hand pushes, ceteris paribus, more firms to adjust prices. On the other hand, however, it increases the option value of waiting, which widens the inaction region and lowers price adjustment. The first effect typically dominates the second, even with transitory increases in uncertainty. Therefore, in times of high volatility (uncertainty), aggregate prices become more responsive to nominal shocks. As a consequence, real output responds less, making the inflation-output trade-off worse and the real effects of monetary policy smaller.

From an empirical standpoint, a growing branch of the literature supports the claim that uncertainty is a major driver of the business cycle. Bloom (2009) finds empirical evidence in favor of the drop, rebound, and overshoot in real variables after large jumps in the VXO, a measure of stock-market volatility. In particular, he finds that uncertainty shocks cause a rapid decline in industrial production, of about 1% within four months, followed by rapid recovery and overshoot from about seven months after the shock. A similar drop, rebound, and overshoot is found for employment. Carriero, Mumtaz, Theodoridis, and Theophilopoulou (2013) employ a proxy-SVAR approach to study the effects of an uncertainty shock in a VAR à la Bloom (2009). Instead of modeling a measure of uncertainty directly in their VAR, they employ it as an instrument to estimate the impulse vector related to an uncertainty shock as well as the volatility of such a shock via an adequate number of moments. Their approach confirms the negative role played by exogenous increases in uncertainty as for the U.S. business cycle. However, they find the effects of such shocks to induce larger and longer-lasting recessions than in Bloom (2009). Moreover, no evidence of overshoot is found. Bekaert, Hoerova, and Duca (2013) use the VIX to disentangle the effects of uncertainty from those of risk aversion and show that it is uncertainty to play a major role in driving business cycle fluctuations. Leduc and Liu (2013) employ several measures of uncertainty in a parsimonious linear VAR to show that an increase in uncertainty causes a persistent increase in unemployment and a decrease in inflation. Baker, Bloom, and Davis (2013) develop a news-based index of economic policy uncertainty and show, using a linear VAR, that positive spikes in their index anticipate declines in real economic activity. Mumtaz and Surico (2013) use a SVAR with fixed-coefficients and stochastic volatility. They model a link from the second to the first moments of their VAR, i.e., the volatility of uncertainty shocks is allowed to exert an impact on the dynamics of the VAR. They find that the contribution of policy uncertainty to fluctuations in output, consumption and investment is about 30% to 40%. In particular, they show that uncertainty about long-run fiscal sustainability has the largest impact on real activity. A similar approach is followed by Mumtaz and Zanetti (2013), who estimate a smaller-scale VAR and show that monetary policy uncertainty shocks may have a non-trivial impact on the economy. Benati (2013) estimates a VAR featuring time-varying coefficients and stochastic volatility to model the economic policy uncertainty index developed by Baker, Bloom, and Davis (2013) jointly with a standard set of macroeconomic variables for the United States, the United Kingdom, the Euro area, and Canada. Depending on the identification scheme employed (short-run restrictions vs. maximum forecast error variance à la Uhlig, 2004), he finds economic policy uncertainty shocks to play a role in explaining industrial production in these countries ranging from marginal to important (20-30 percent of the one-year ahead forecast error variance). The real effects of economic policy uncertainty have been examined also by Johannsen (2013), who shows that the effects of short- and long-run fiscal policy uncertainty are large when the ZLB is binding, otherwise they are modest. Colombo (2013) studies the spillover effects due to an economic policy uncertainty shock originating in the United States as for the Euro area. She finds such a shock to be an important driver of the European policy rate.

Though this list is far from being exhaustive, the large majority of empirical analyses of uncertainty share one feature, i.e., they estimate the real effects of uncertainty shocks by appealing to a linear framework. As anticipated, we relax this assumption in order to investigate the potentially different macroeconomic effects of volatility shocks during recessions and expansions. A few studies have previously attempted to identify nonlinearities in this context. Grier, Ólan T. Henry, Olekalns, and Shields (2004) employ a bivariate VAR to model the first moment as well as the conditional volatility of output growth and inflation in the U.S. They find that an increase in growth uncertainty is associated with significantly lower average growth, while higher inflation uncertainty is associated to lower output growth and inflation. Enders and Jones (2013) work with a univariate nonlinear model to isolate potentially different effects of uncertainty shocks in presence of high vs. low uncertainty. Aastveit, Natvik, and Sola (2013), Tenreyro and Thwaites (2013), and Pellegrino (2014) focus on the potentially nonlinear effects of uncertainty on monetary policy effectiveness and find monetary policy shocks to be less powerful in stabilizing real activity in presence of high uncertainty. Given that uncertainty is typically high in bad times, related results are those provided by Mumtaz and Surico (2014), who find that periods of slack are associated to a lower impact on consumption by real interest rate movements due to the lower intertemporal elasticity of substitution and degree of foward-lookingness of the IS curve. These findings offer support to Vavra's (2014) previously mentioned theoretical model. Bijsterbosch and Guérin (2014) follow a two-step approach, i.e., they first identify episodes of high uncertainty in the U.S. modeling measures of uncertainty via a Markov-Switching approach, and then regress a number of macroeconomic and financial indicators on a "high uncertainty dummy" constructed via the first step. They find that high uncertainty is associated to weaker growth performance as well as sharp declines in stock prices. Differently, low uncertainty is found to be virtually unrelated to economic or financial downturns. Our paper deals with the real effects of uncertainty shocks in good and bad times, with a particular focus on the role played by systematic monetary policy in the context of the uncertainty transmission mechanism.

The paper closest to ours is probably Caggiano, Castelnuovo, and Groshenny (2014). They employ a small-scale nonlinear STVAR to study the effects of uncertainty shocks on U.S. unemployment in recessions, and find such effects to be stronger than those predicted by a standard linear VAR. We improve over their approach along three key dimensions. First, we endogenize the probability that the economic system might switch from one phase of the business cycle to another after an uncertainty shock by computing

GIRFs à la Koop, Pesaran, and Potter (1996) and Ehrmann, Ellison, and Valla (2003). This is particularly important when simulating the effects of uncertainty shocks in expansions, given that their real effects are very likely to drive the economy in a downturn and, possibly, in a recession. Second, we employ monthly data rather than quarterly, a choice that presents three non-negligible advantages in our context: i) it makes the identification of uncertainty shocks in expansions easier, since high uncertainty episodes during economic booms are less common than in recessions. Importantly, the superior information content of monthly data (as opposed to quarterly observations) for the identification of nonlinearities in the U.S. is also advocated by, among others, Sims (2012) and Ng and Wright (2013); ii) it makes the zero-restrictions due to the recursive structure of the VAR model more plausible; and iii) it makes our results comparable with those documented in Bloom (2009). As a third and last improvement over Caggiano, Castelnuovo and Groshenny (2014), we employ a larger scale VAR, which includes a higher number of nominal and real activity indicators. Such a choice reduces the relevance of the nonfundamentalness issue due to the "informational insufficiency" in VAR analysis (Forni and Gambetti (2014)).

6 Conclusions

We re-examine the "drop, rebound and overshoot" response of employment and output to uncertainty shocks in the U.S. documented by Bloom's (2009) seminal paper via the lenses of a nonlinear Smooth-Transition VAR framework. We show that real activity responds asymmetrically over the business cycle. Following an uncertainty shock, the drop in real activity is found to be much larger during recessions than what suggested by a linear VAR. Since uncertainty shocks hit the economy more often during recessions, our findings suggest that they may be substantially more costly than what linear frameworks suggest. Differently, the reaction of real activity in expansions is shown to be much more gradual and to display no overshoot. The different path of real activity in expansions may be due to the effect of consumption smoothing (see Bloom et al. 2012), which is likely to induce state-dependent effects on real activity due to the countercyclicality of financial frictions. Possibly, our results point to credit constraints and financial markets frictions as important drivers behind the different responses to uncertainty shocks in good and bad times. Finally, counterfactual simulations conducted to assess the role of systematic monetary policy in our framework points to policy ineffectiveness in the short run, above all when uncertainty shocks hit in bad times, and policy effectiveness in the medium run, above all in good times. This message holds true also when a long-term interest rate, an empirical proxy to capture the role of forward guidance, is considered as an alternative policy instrument.

Our results raise questions that are relevant both from a modeling standpoint and from a policy perspective. Bloom (2009) shows that uncertainty shocks imply a drop, rebound, and overshoot of real economic activity. This is due to nonconvex adjustment costs that imply the presence of a region of inaction in the hiring and investment space. Our findings suggest that adjustment costs may very well be countercyclical. Another possible interpretation of our results point to state-dependent frictions in the credit market, which may prevent consumption smoothing and, therefore, influence the exit path from a downturn (Bloom et al., 2012). In general, our findings support a research agenda aiming at identifying state-dependent relevant frictions able to induce different dynamic responses to structural shocks in recessions and expansions.

From a policy standpoint, high uncertainty is found to reduce the sensitivity of output to stimulus policies. Theoretical models like the one developed by Vavra (2014) and empirical investigations as those by Aastveit, Natvik, and Sola (2013), Tenreyro and Thwaites (2013), Mumtaz and Surico (2014), and Pellegrino (2014) also offer support to this view as for monetary policy interventions. Our results reinforce Blanchard's (2009) and Bloom's (2014) call for larger policy stimuli during recessions, as well as "second moment policies" like stabilization packages designed to reduce systemic risk. Also, in light of the link between unclear and hyperactive policies and policy uncertainty identified by Baker et al.'s (2013), our results lend support to policies which are clearly communicated and steadily implemented, above all during recessions. In general, our findings call for the design of state-dependent optimal policy responses, possibly closer to first-moment policies in expansions, but clearly different from them in recessions.

Appendix of "Uncertainty and Monetary Policy in Good and Bad Times" by Giovanni Caggiano, Efrem Castelnuovo, Gabriela Nodari

First, this Appendix documents statistical evidence in favor of a nonlinear relationship between the endogenous variables included in our STVAR. Next, it offers details on the estimation procedure of our non-linear VARs. Finally, it reports details on the computation of the GIRFs.

Statistical evidence in favor of non-linearities

To detect non-linear dynamics at a multivariate level, we apply the test proposed by Teräsvirta and Yang (2014). Their framework is particularly well suited for our analysis since it amounts to test the null hypothesis of linearity versus a specified nonlinear alternative, that of a (Vector Logistic) Smooth Transition Vector AutoRegression with a single transition variable.

Consider the following $p-$dimensional 2-regime approximate logistic STVAR model:

$$\mathbf{X}_t = \mathbf{\Theta}_0'\mathbf{Y}_t + \sum_{i=1}^{n} \mathbf{\Theta}_i'\mathbf{Y}_t z_t^i + \boldsymbol{\varepsilon}_t \tag{5}$$

where $\mathbf{X}_t$ is the $(p \times 1)$ vector of endogenous variables, $\mathbf{Y}_t = [\mathbf{X}_{t-1}| \dots |\mathbf{X}_{t-k}|\boldsymbol{\alpha}]$ is the $((k \times p + q) \times 1)$ vector of exogenous variables (including endogenous variables lagged k times and a column vector of constants $\boldsymbol{\alpha}$), z_t is the transition variable, and $\mathbf{\Theta}_0$ and $\mathbf{\Theta}_i$ are matrices of parameters. In our case, the number of endogenous variables is $p = 8$, the number of exogenous variables is $q = 1$, and the number of lags is $k = 6$. Under the null hypothesis of linearity, $\mathbf{\Theta}_i = \mathbf{0}\ \forall i$.

The Teräsvirta-Yang test for linearity versus the STVAR model can be performed as follows:

1. Estimate the restricted model $(\mathbf{\Theta}_i = \mathbf{0}, \forall i)$ by regressing $\mathbf{X}_t$ on $\mathbf{Y}_t$. Collect the residuals $\tilde{\mathbf{E}}$ and the matrix residual sum of squares $\mathbf{RSS}_0 = \tilde{\mathbf{E}}'\tilde{\mathbf{E}}$.

2. Run an auxiliary regression of $\tilde{\mathbf{E}}$ on $(\mathbf{Y}_t, \mathbf{Z}_n)$ where $\mathbf{Z}_n \equiv [\mathbf{Z}_1|\mathbf{Z}_2| \dots |\mathbf{Z}_n] = [\mathbf{Y}_t'z_t|\mathbf{Y}_t'z_t^2| \dots |\mathbf{Y}_t'z_t^n]$. Collect the residuals $\tilde{\mathbf{\Xi}}$ and compute the matrix residual sum of squares $\mathbf{RSS}_1 = \tilde{\mathbf{\Xi}}'\tilde{\mathbf{\Xi}}$.

3. Compute the test-statistic

$$
\begin{aligned}
LM &= Ttr\left\{\mathbf{RSS}_0^{-1}\left(\mathbf{RSS}_0-\mathbf{RSS}_1\right)\right\} \\
&= T\left(p-tr\left\{\mathbf{RSS}_0^{-1}\mathbf{RSS}_1\right\}\right)
\end{aligned}
$$

Under the null hypothesis, the test statistic is distributed as a χ^2 with $p\,(kp+q)$ degrees of freedom For our model, we get a value of $LM = 1992$ with a corresponding p-value equal to zero. The LM statistic has been computed by fixing the value of the order of the Taylor expansion n equal to three, as suggested by Luukkonen, Saikkonen, and Teräsvirta (1988). It should be noticed, however, that the null of linearity can be rejected also for $n = 2$.

4. As pointed out by Teräsvirta and Yang (2014), however, in small samples the LM-type test might suffer from positive size distortion, i.e., the empirical size of the test exceeds the true asymptotic size. We then employ also the following rescaled LM test statistic:

$$F = \frac{(pT-k)}{G \times pT} LM,$$

where G is the number of restrictions. The rescaled test statistic follows an $F\,(G, pT-k)$ distribution. In our case, we get $F = 13.54$, with p-value approximately equal to zero.

Estimation of the non-linear VARs

Our model (1)-(4) is estimated via maximum likelihood.[20] Its log-likelihood reads as follows:

$$\log L = const + \frac{1}{2}\sum\nolimits_{t=1}^{T} \log|\mathbf{\Omega}_t| - \frac{1}{2}\sum\nolimits_{t=1}^{T} \boldsymbol{u}_t'\mathbf{\Omega}_t^{-1}\boldsymbol{u}_t \tag{A1}$$

where the vector of residuals $\boldsymbol{u}_t = \boldsymbol{X}_t -\ (1-F(z_{t-1})\mathbf{\Pi}_E\boldsymbol{X}_{t-1} - F(z_{t-1})\mathbf{\Pi}_R\boldsymbol{X}_{t-1}$. Our goal is to estimate the parameters $\mathbf{\Psi} = \{\gamma, \mathbf{\Omega}_R, \mathbf{\Omega}_E, \mathbf{\Pi}_R(L), \mathbf{\Pi}_E(L)\}$, where $\mathbf{\Pi}_j(L) = \begin{bmatrix} \mathbf{\Pi}_{j,1} & \ldots & \mathbf{\Pi}_{j,p} \end{bmatrix}$, $j \in \{R, E\}$. The high-non linearity of the model and its many parameters make its estimation with standard optimization routines problematic. Following Auerbach and Gorodnichenko (2012), we employ the procedure described below.

Conditional on $\{\gamma, \mathbf{\Omega}_R, \mathbf{\Omega}_E\}$, the model is linear in $\{\mathbf{\Pi}_R(L), \mathbf{\Pi}_E(L)\}$. Then, for a given guess on $\{\gamma, \mathbf{\Omega}_R, \mathbf{\Omega}_E\}$, the coefficients $\{\mathbf{\Pi}_R(L), \mathbf{\Pi}_E(L)\}$ can be estimated by

[20] This Section heavily draws on Auerbach and Gorodnichenko's (2012) "Appendix: Estimation Procedure".

minimizing $\frac{1}{2}\sum_{t=1}^{T} \boldsymbol{u}_t'\boldsymbol{\Omega}_t^{-1}\boldsymbol{u}_t$. This can be seen by re-writing the regressors as follows. Let $\boldsymbol{W}_t = \left[\begin{array}{ccccc} F(z_{t-1})\boldsymbol{X}_{t-1} & (1-F(z_{t-1})\boldsymbol{X}_{t-1} & \ldots & F(z_{t-1})\boldsymbol{X}_{t-p} & 1-F(z_{t-1})\boldsymbol{X}_{t-p} \end{array}\right]$ be the extended vector of regressors, and $\boldsymbol{\Pi} = \left[\begin{array}{cc} \boldsymbol{\Pi}_R(L) & \boldsymbol{\Pi}_E(L) \end{array}\right]$. Then, we can write $\boldsymbol{u}_t = \boldsymbol{X}_t - \boldsymbol{\Pi}\boldsymbol{W}_t'$. Consequently, the objective function becomes

$$\frac{1}{2}\sum_{t=1}^{T} (\boldsymbol{X}_t - \boldsymbol{\Pi}\boldsymbol{W}_t')'\boldsymbol{\Omega}_t^{-1}(\boldsymbol{X}_t - \boldsymbol{\Pi}\boldsymbol{W}_t').$$

It can be shown that the first order condition with respect to $\boldsymbol{\Pi}$ is

$$vec\boldsymbol{\Pi}' = \left(\sum_{t=1}^{T} \left[\boldsymbol{\Omega}_t^{-1} \otimes \boldsymbol{W}_t'\boldsymbol{W}_t\right]\right)^{-1} vec\left(\sum_{t=1}^{T} \boldsymbol{W}_t'\boldsymbol{X}_t\boldsymbol{\Omega}_t^{-1}\right). \tag{A2}$$

This procedure iterates over different sets of values for $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$. For each set of values, $\boldsymbol{\Pi}$ is obtained and the $logL$ (A1) computed.

Given that the model is highly non-linear in its parameters, several local optima might be present. Hence, it is recommended to try different starting values for $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$. To ensure positive definiteness of the matrices $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$, we focus on the alternative vector of parameters $\boldsymbol{\Psi} = \{\gamma, chol(\boldsymbol{\Omega}_R), chol(\boldsymbol{\Omega}_E), \boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$, where $chol$ implements a Cholesky decomposition.

The construction of confidence intervals for the parameter estimates is complicated by, once again, the non-linear structure of the problem. We compute them by appealing to a Markov Chain Monte Carlo (MCMC) algorithm developed by Chernozhukov and Hong (2003) (CH hereafter). This method delivers both a global optimum and densities for the parameter estimates.

CH estimation is implemented via a Metropolis-Hastings algorithm. Given a starting value $\boldsymbol{\Psi}^{(0)}$, the procedure constructs chains of length N of the parameters of our model following these steps:

Step 1. Draw a candidate vector of parameter values $\boldsymbol{\Theta}^{(n)} = \boldsymbol{\Psi}^{(n)} + \boldsymbol{\psi}^{(n)}$ for the chain's $n+1$ state, where $\boldsymbol{\Psi}^{(n)}$ is the current state and $\boldsymbol{\psi}^{(n)}$ is a vector of i.i.d. shocks drawn from $N(0, \boldsymbol{\Omega}_\Psi)$, and $\boldsymbol{\Omega}_\Psi$ is a diagonal matrix.

Step 2. Set the $n+1$ state of the chain $\boldsymbol{\Psi}^{(n+1)} = \boldsymbol{\Theta}^{(n)}$ with probability $min\left\{1, L(\boldsymbol{\Theta}^{(n)})/L(\boldsymbol{\Psi}^{(n)})\right\}$, where $L(\boldsymbol{\Theta}^{(n)})$ is the value of the likelihood function conditional on the candidate vector of parameter values, and $L(\boldsymbol{\Psi}^{(n)})$ the value of the likelihood function conditional on the current state of the chain. Otherwise, set $\boldsymbol{\Psi}^{(n+1)} = \boldsymbol{\Psi}^{(n)}$.

The starting value $\boldsymbol{\Theta}^{(0)}$ is computed by working with a second-order Taylor approximation of the model (8)-(11), so that the model can be written as regressing $\boldsymbol{X}_t$ on lags of $\boldsymbol{X}_t$, $\boldsymbol{X}_t z_t$, and $\boldsymbol{X}_t z_t^2$. The residuals from this regression are employed to fit the expression for the reduced-form time-varying variance-covariance matrix of the VAR (see our paper) using maximum likelihood to estimate $\mathbf{\Omega}_R$ and $\mathbf{\Omega}_E$. Conditional on these estimates and given a calibration for γ, we can construct $\mathbf{\Omega}_t$. Conditional on $\mathbf{\Omega}_t$, we can get starting values for $\mathbf{\Pi}_R(L)$ and $\mathbf{\Pi}_E(L)$ via equation (A2).

The initial (diagonal matrix) $\mathbf{\Omega}_\Psi$ is calibrated to one percent of the parameter values. It is then adjusted "on the fly" for the first 20,000 draws to generate an acceptance rate close to 0.3, a typical choice for this kind of simulations (Canova (2007)). We employ $N = 50,000$ draws for our estimates, and retain the last 20% for inference.

As shown by CH, $\overline{\mathbf{\Psi}} = \frac{1}{N}\sum_{n=1}^{N}\mathbf{\Psi}^{(n)}$ is a consistent estimate of $\mathbf{\Psi}$ under standard regularity assumptions on maximum likelihood estimators. Moreover, the covariance matrix of $\mathbf{\Psi}$ is given by $\boldsymbol{V} = \frac{1}{N}\sum_{n=1}^{N}(\mathbf{\Psi}^{(n)} - \overline{\mathbf{\Psi}})^2 = var(\mathbf{\Psi}^{(n)})$, that is the variance of the estimates in the generated chain.

Generalized Impulse Response Functions

We compute the Generalized Impulse Response Functions from our STVAR model by following the approach proposed by Koop, Pesaran, and Potter (1996). The algorithm features the following steps.

1. Consider the entire available observations, with sample size $t = 1962M7, \ldots, 2008M6$, with $T = 552$, and construct the set of all possible histories $\mathbf{\Lambda}$ of length $p = 13$:[21] $\{\boldsymbol{\lambda}_i \in \mathbf{\Lambda}\}$. $\mathbf{\Lambda}$ will contain $T - p + 1$ histories $\boldsymbol{\lambda}_i$.

2. Separate the set of all recessionary histories from that of all expansionary histories. For each $\boldsymbol{\lambda}_i$ calculate the transition variable z_{λ_i}. If $z_{\lambda_i} \leq \overline{z} = -1.01\%$, then $\boldsymbol{\lambda}_i \in \mathbf{\Lambda}^R$, where $\mathbf{\Lambda}^R$ is the set of all recessionary histories; if $z_{\lambda_i} > -\overline{z} = -1.01\%$, then $\boldsymbol{\lambda}_i \in \mathbf{\Lambda}^E$, where $\mathbf{\Lambda}^E$ is the set of all expansionary histories.

3. Select at random one history $\boldsymbol{\lambda}_i$ from the set $\mathbf{\Lambda}^R$. For the selected history $\boldsymbol{\lambda}_i$, take $\widehat{\mathbf{\Omega}}_{\lambda_i}$ obtained as:
$$\widehat{\mathbf{\Omega}}_{\lambda_i} = F\left(z_{\lambda i}\right)\widehat{\mathbf{\Omega}}_R + \left(1 - F\left(z_{\lambda_i}\right)\right)\widehat{\mathbf{\Omega}}_E, \tag{6}$$
where $\widehat{\mathbf{\Omega}}_R$ and $\widehat{\mathbf{\Omega}}_E$ are obtained from the generated MCMC chain of parameter values during the estimation phase.[22] z_{λ_i} is the transition variable calculated for

[21] The choice $p = 13$ is due to the number of moving average terms (twelve) of our transition variable z_t and to the fact that such transition variable enters our ST-VAR model via the transition probability $F(z_{t-1})$ with one lag.

[22] We consider the distribution of parameters rather than their mean values to allow for parameter uncertainty, as suggested by Koop, Pesaran, and Potter (1996).

the selected history $\boldsymbol{\lambda}_i$.

4. Cholesky-decompose the estimated variance-covariance matrix $\widehat{\boldsymbol{\Omega}}_{\lambda_i}$:

$$\widehat{\boldsymbol{\Omega}}_{\lambda_i} = \widehat{\mathbf{C}}_{\lambda_i}\widehat{\mathbf{C}}'_{\lambda_i} \tag{7}$$

and orthogonalize the estimated residuals to get the structural shocks:

$$\mathbf{e}_{\lambda_i}^{(j)} = \widehat{\mathbf{C}}_{\lambda_i}^{-1}\widehat{\boldsymbol{\varepsilon}}. \tag{8}$$

5. From $\mathbf{e}_{\lambda_i}$ draw with replacement h eight-dimensional shocks and get the vector of bootstrapped shocks

$$\mathbf{e}_{\lambda_i}^{(j)*} = \left\{\mathbf{e}^*_{\lambda_i,t}, \mathbf{e}^*_{\lambda_i,t+1}, \ldots, \mathbf{e}^*_{\lambda_i,t+h}\right\}, \tag{9}$$

where h is the horizon for the IRFs we are interested in.

6. Form another set of bootstrapped shocks which will be equal to (9) except for the k_{th} shock in $\mathbf{e}_{\lambda_i,t}^{(j)*}$ which is the shock we want to perturbate by an amount equal to δ. Denote the vector of bootstrapped perturbated shocks by $\mathbf{e}_{\lambda_i}^{(j)\delta}$.

7. Transform back $\mathbf{e}_{\lambda_i}^{(j)*}$ and $\mathbf{e}_{\lambda_i}^{(j)\delta}$ as follows:

$$\widehat{\boldsymbol{\varepsilon}}_{\lambda_i}^{(j)*} = \widehat{\mathbf{C}}_{\lambda_i}\mathbf{e}_{\lambda_i}^{(j)*} \tag{10}$$

and

$$\widehat{\boldsymbol{\varepsilon}}_{\lambda_i}^{(j)\delta} = \widehat{\mathbf{C}}_{\lambda_i}\mathbf{e}_{\lambda_i}^{(j)\delta}. \tag{11}$$

8. Use (10) and (11) to simulate the evolution of $\mathbf{X}_{\lambda_i}^{(j)*}$ and $\mathbf{X}_{\lambda_i}^{(j)\delta}$ and construct the $GIRF^{(j)}(h, \delta, \lambda_i)$ as $\mathbf{X}_{\lambda_i}^{(j)*} - \mathbf{X}_{\lambda_i}^{(j)\delta}$.

9. Conditional on history λ_i, repeat for $j = 1, \ldots, B$ vectors of bootstrapped residuals and get $GIRF^{(1)}(h, \delta, \lambda_i), GIRF^{(2)}(h, \delta, \lambda_i), \ldots, GIRF^{(B)}(h, \delta, \lambda_i)$. Set $B = 500$.

10. Calculate the GIRF conditional on history λ_i as

$$\widehat{GIRF}^{(i)}(h, \delta, \lambda_i) = B^{-1}\sum_{j=1}^{B} GIRF^{(i,j)}(h, \delta, \lambda_i). \tag{12}$$

11. Repeat all previous steps for $i = 1, \ldots, 500$ histories belonging to the set of recessionary histories, $\boldsymbol{\lambda}_i \in \boldsymbol{\Lambda}^R$, and get $\widehat{GIRF}^{(1,R)}(h, \delta, \lambda_{1,R}), \widehat{GIRF}^{(2,R)}(h, \delta, \lambda_{2,R}), \ldots, \widehat{GIRF}^{(500,R)}(h, \delta, \lambda_{500,R})$, where now the subscript R denotes explicitly that we are *conditioning upon recessionary histories.*

12. Take the average and get $\widehat{GIRF}^{(R)}\left(h, \delta, \boldsymbol{\Lambda}^R\right)$, which is the average GIRF under recessions.

13. Repeat all previous steps - 3 to 12 - for 500 histories belonging to the set of all expansions and get $\widehat{GIRF}^{(E)}\left(h, \delta, \boldsymbol{\Lambda}^E\right)$.

14. The computation of the 95% confidence bands for our impulse responses is undertaken by picking up, per each horizon of each state, the 2.5th and 97.5th percentile of the densities $\widehat{GIRF}^{([1:500],R)}$ and $\widehat{GIRF}^{([1:500],E)}$.

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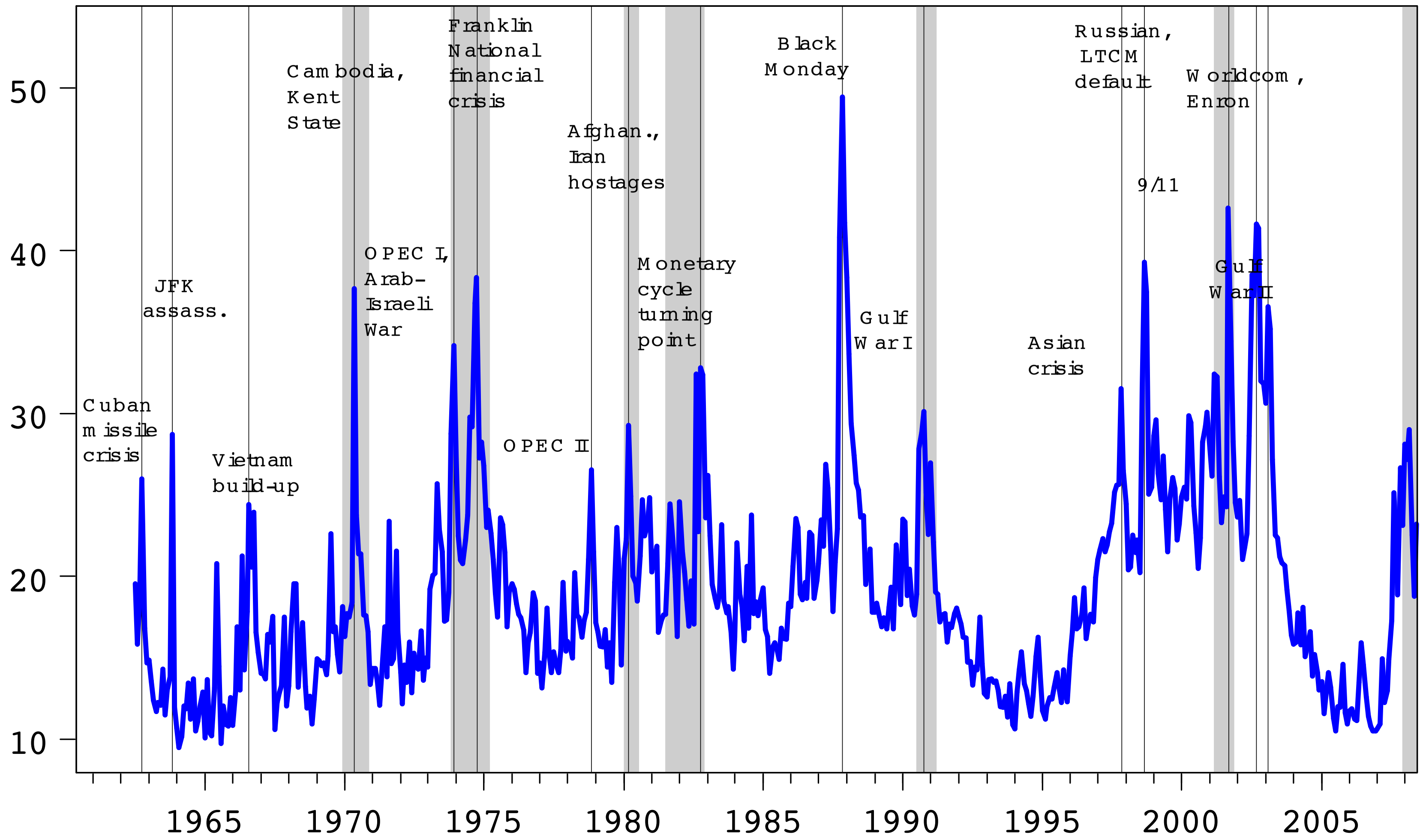

Figure 1: **Uncertainty shocks and the business cycle.** Sample: 1962M6-2008M6. Blue line: U.S. stock market volatility. Shaded areas: NBER recessions. U.S. stock market volatility: Chicago Board of Options Exchange VXO index of percentage implied volatility (on a hypothetical at the money Standard and Poor's 100 option 30 days to expiration) from 1986 onward. Pre-1986 returns volatilities obtained by computing the monthly standard deviation of the daily Standard and Poor's 500 index normalized to the same mean and variance as the VXO index when they overlap from 1986 onward. Uncertainty episodes identified as realizations over 1.65 time the standard deviation of the Hodrick-Prescott filtered VXO (smoothing weight: 129,600).

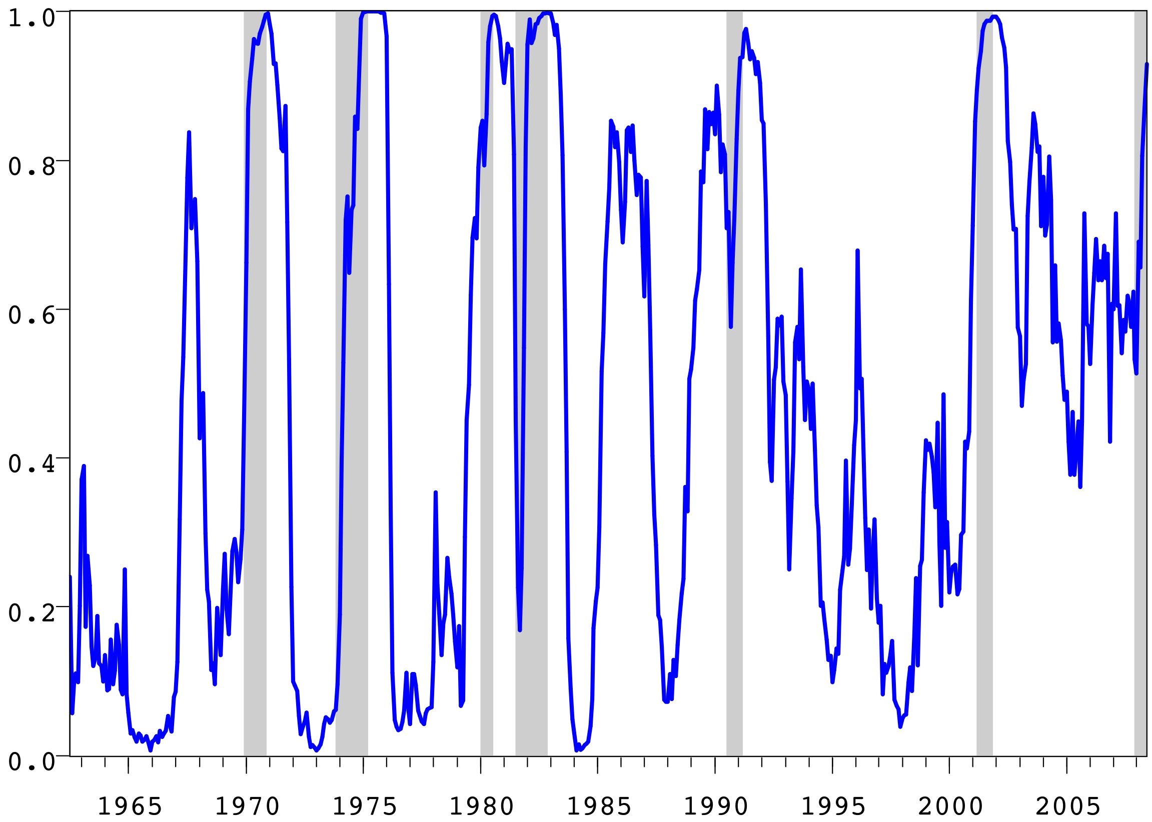

Figure 2: **Probability of being in a recessionary phase.** Blue line: Transition function F(z). Shaded columns: NBER recessions. Transition function computed by employing the standardized moving average (12 terms) of the month-on-month growth rate of industrial production.

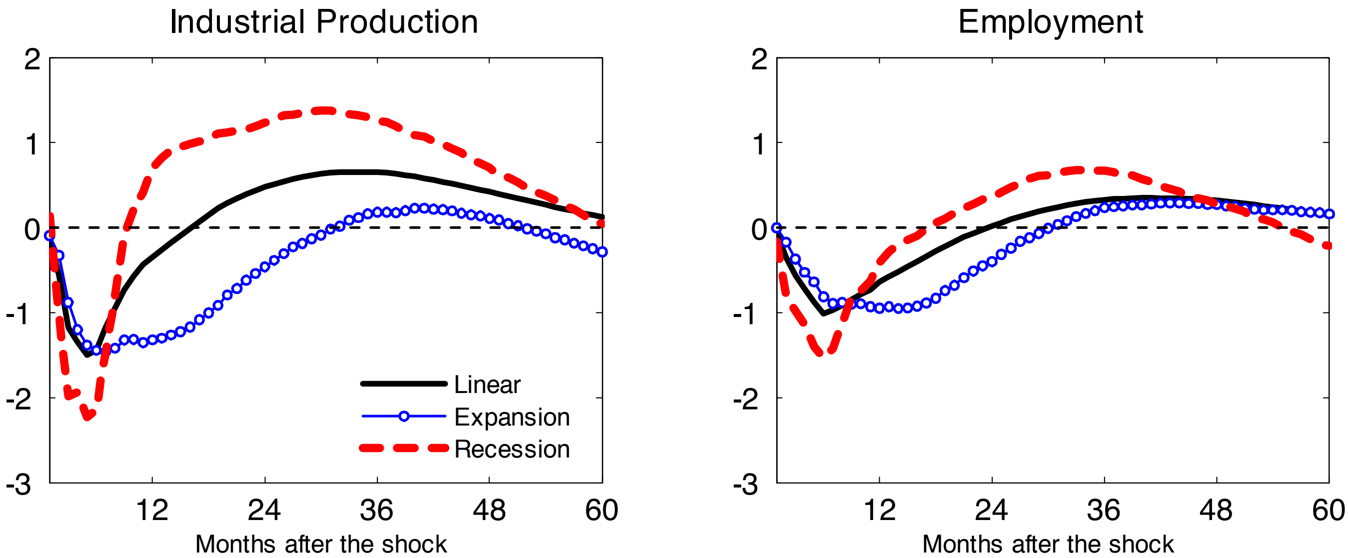

Figure 3: **Real Effects of Uncertainty Shocks: Linear vs. Nonlinear Frameworks.** Impulse responses (median values) to a one-standard deviation uncertainty shock identified as described in the paper. Solid black lines: Responses computed with the linear VAR. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions).

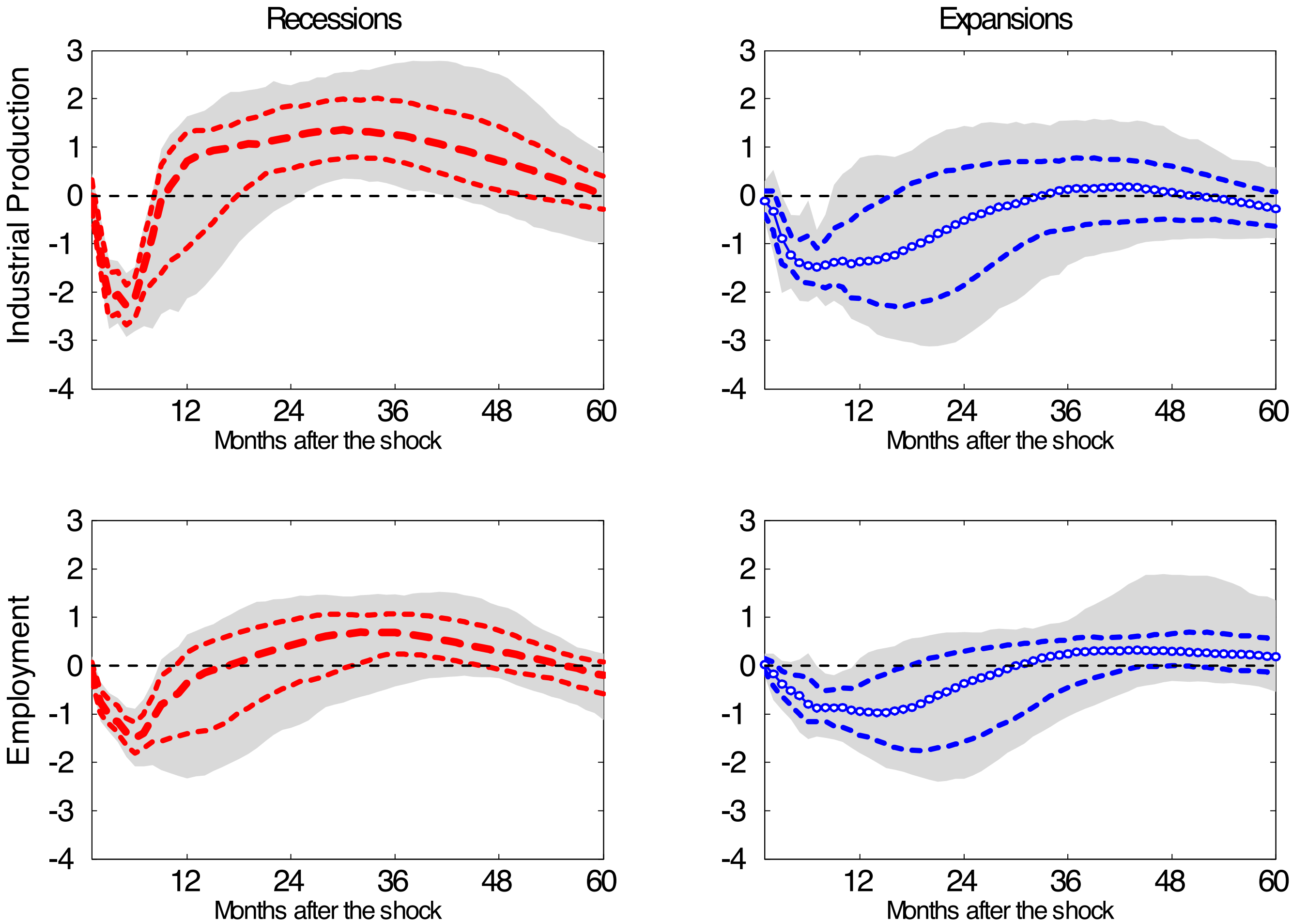

Figure 4: **Real Effects of Uncertainty Shocks: Good and Bad Times.** Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands. Gray areas: 95% confidence bands. Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.

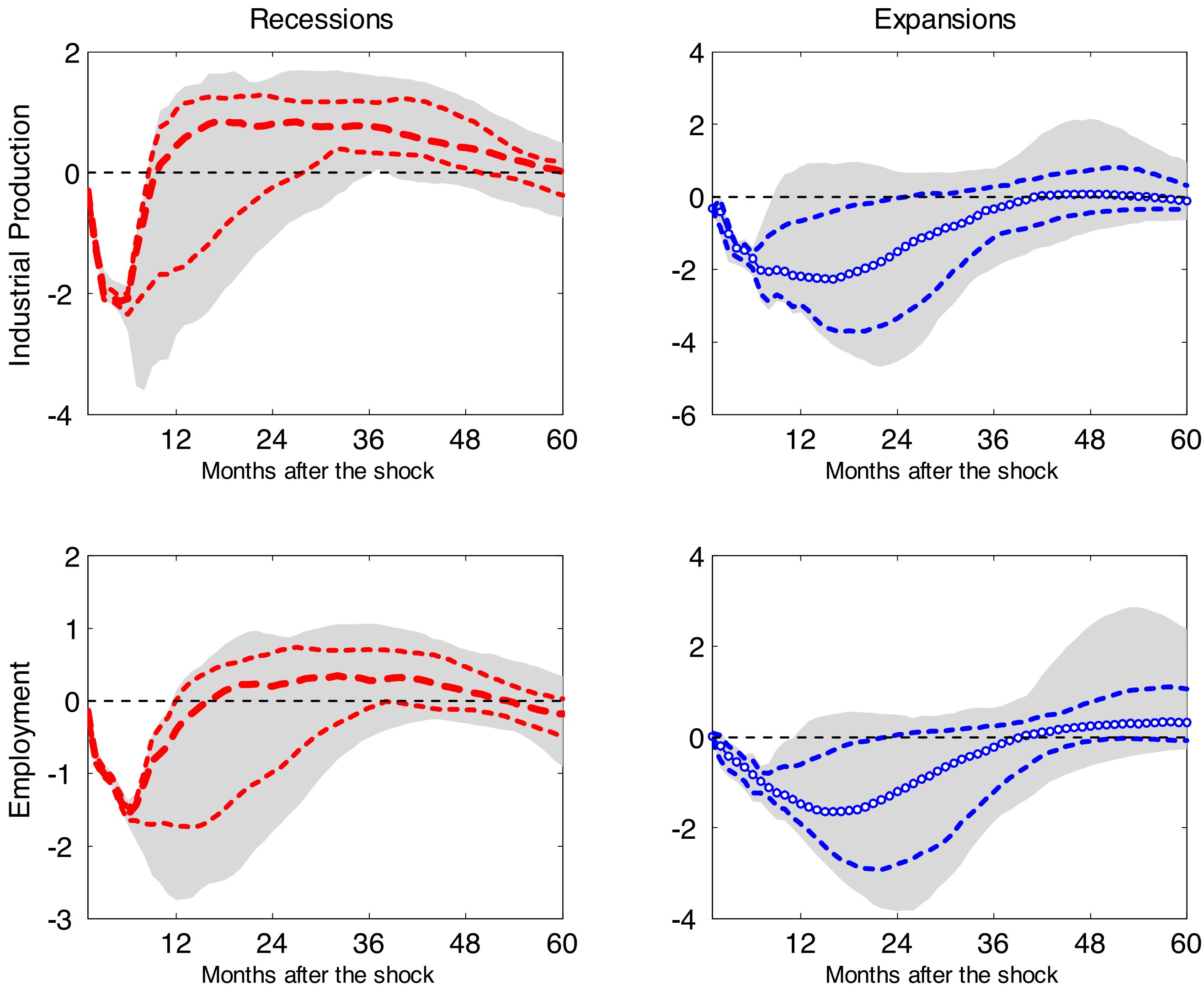

Figure 5: **Real Effects of Uncertainty Shocks: Exogenous dummy.** Uncertainty dummy constructed by considering extreme realizations of the VXO index related to terror, war, and oil events only. Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands. Gray areas: 95% confidence bands. Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.

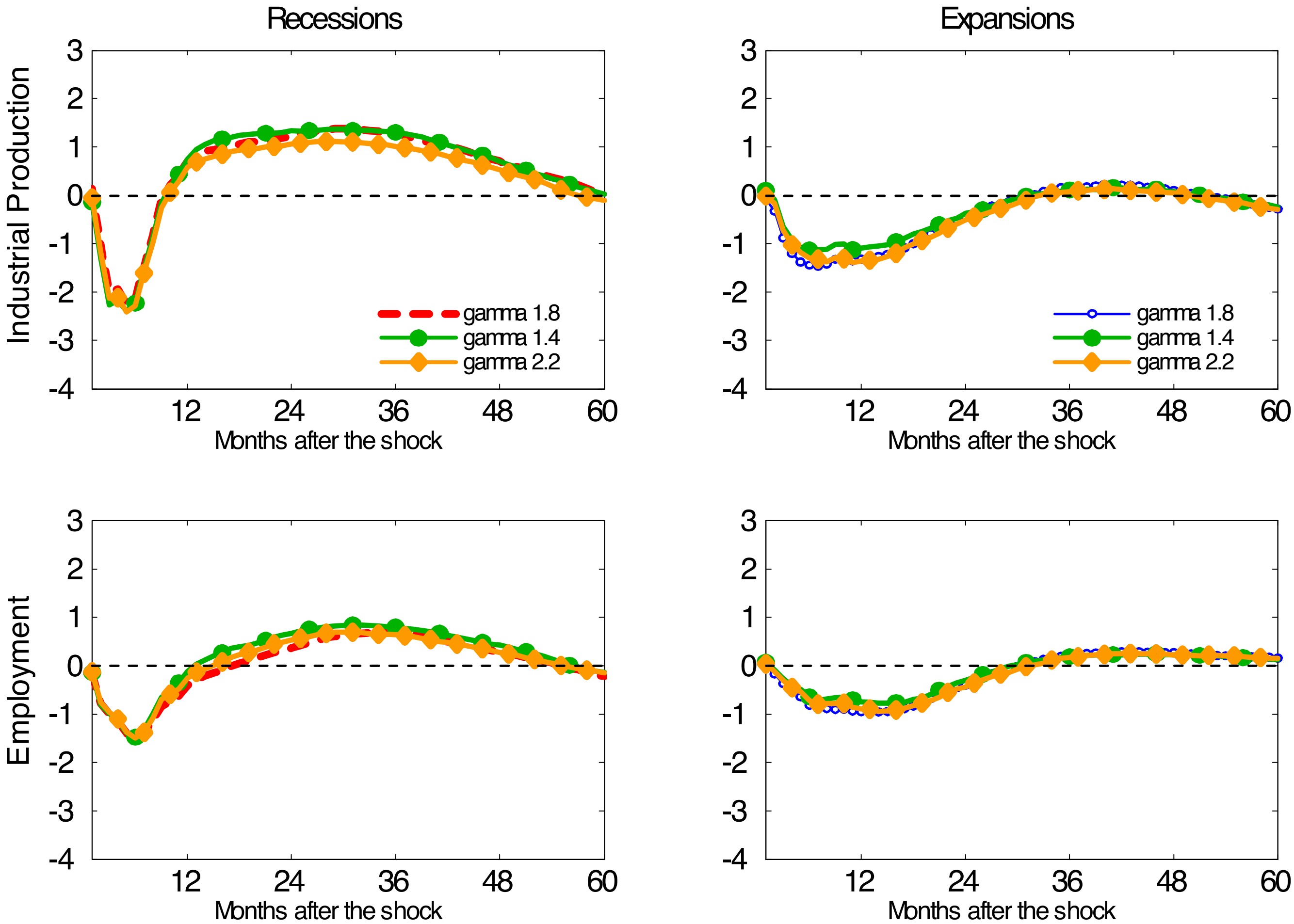

Figure 6: **Real Effects of Uncertainty Shocks: Different Calibrations of the Slope Parameters.** Impulse responses (median values) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed/blue dashed-circled lines: GIRFs conditional on $\gamma = 1.8$. Green lines: GIRFs conditional on $\gamma = 1.4$. Black lines: GIRFs conditional on $\gamma = 2.2$. Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.

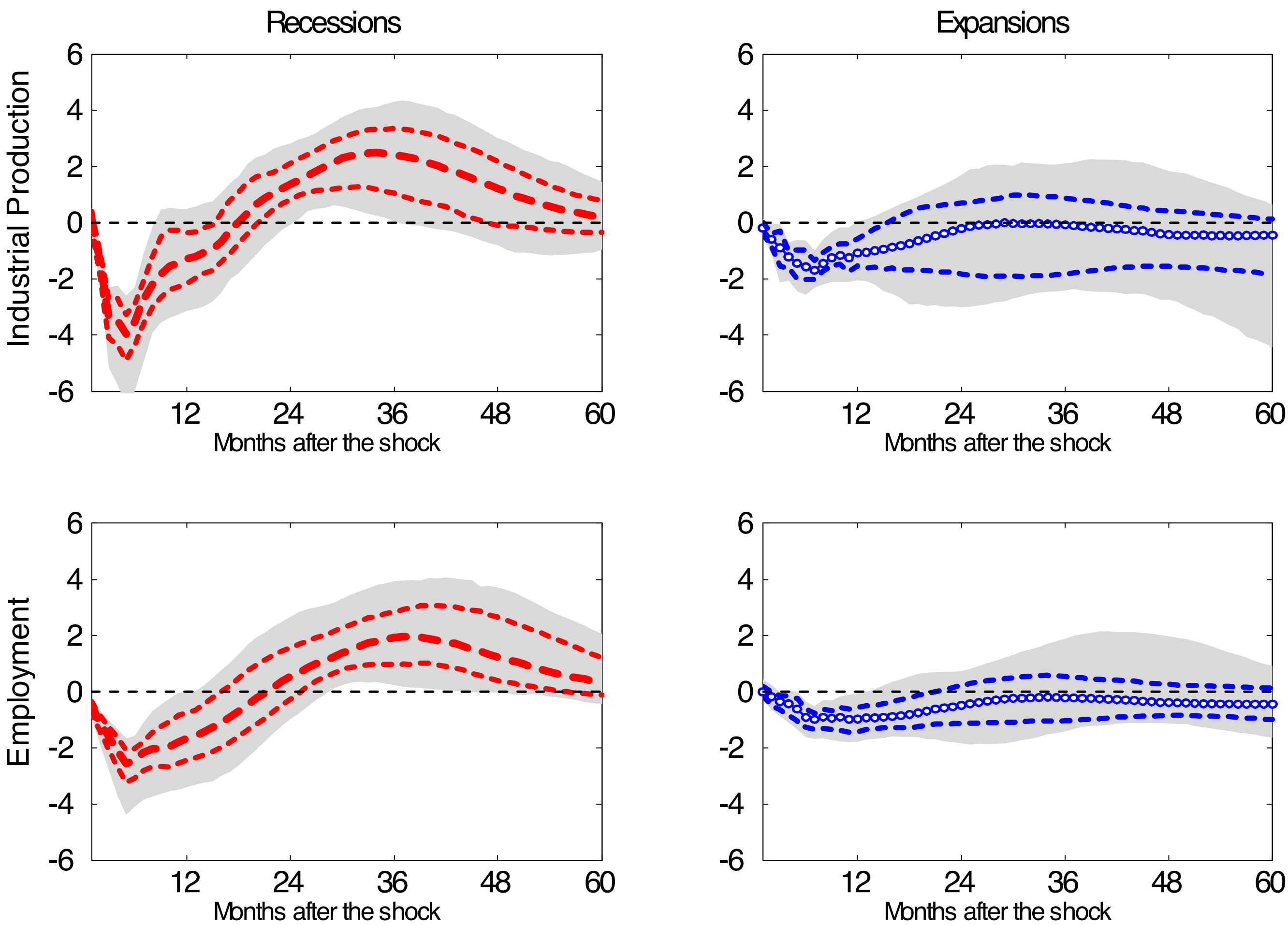

Figure 7: **Real Effects of Uncertainty Shocks: Unemployment as transition indicator.** Unemployment added to our baseline model and employed and transition indicator. Realizations of unemployment above (below) 6.5% are associated to recessions (expansions). Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands. Gray areas: 95% confidence bands. Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.

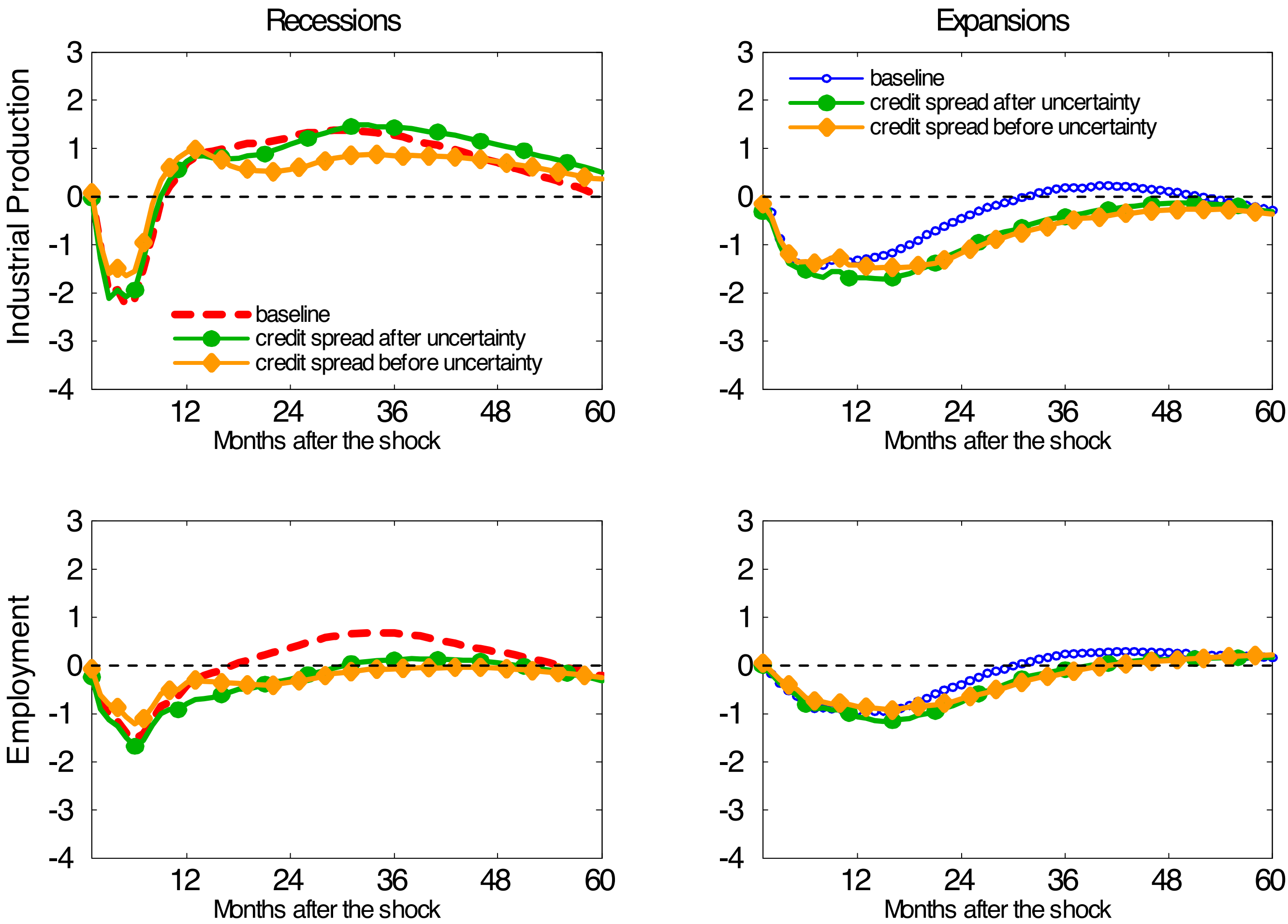

Figure 8: **Real Effects of Uncertainty Shocks: Role of Credit Spreads.** Median impulse responses to a one-standard deviation uncertainty in scenarios without/with credit spreads. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Responses of the models estimated with credit spreads are in green (when the spread is ordered after uncertainty) and orange (when the spread is ordered before uncertainty). Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.

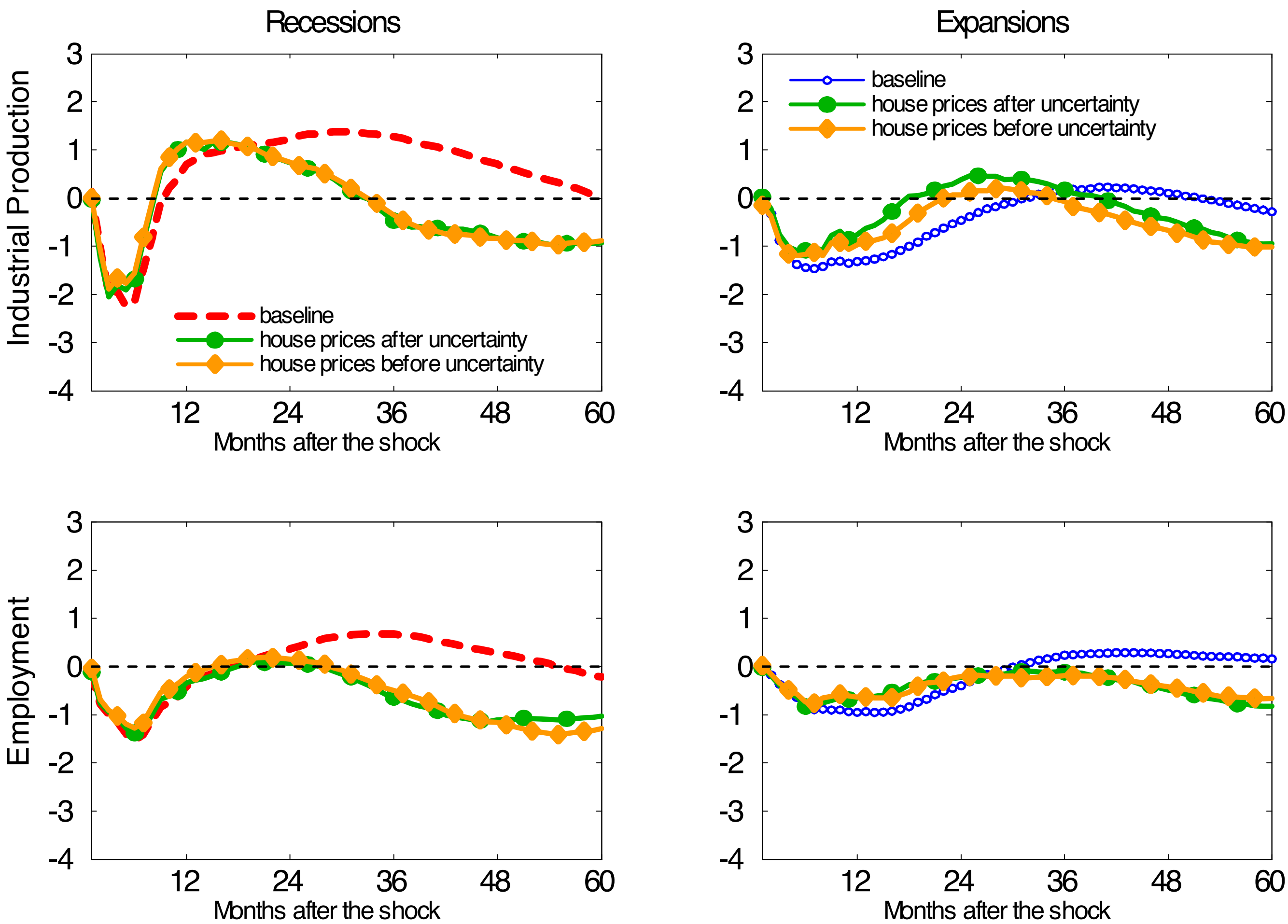

Figure 9: **Real Effects of Uncertainty Shocks: Role of House Prices.** Median impulse responses to a one-standard deviation uncertainty in scenarios without/with real house price index. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Responses of the models estimated with the real house price index in green (when the index spread is ordered after uncertainty) and orange (when the index is ordered before uncertainty). Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws. Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.

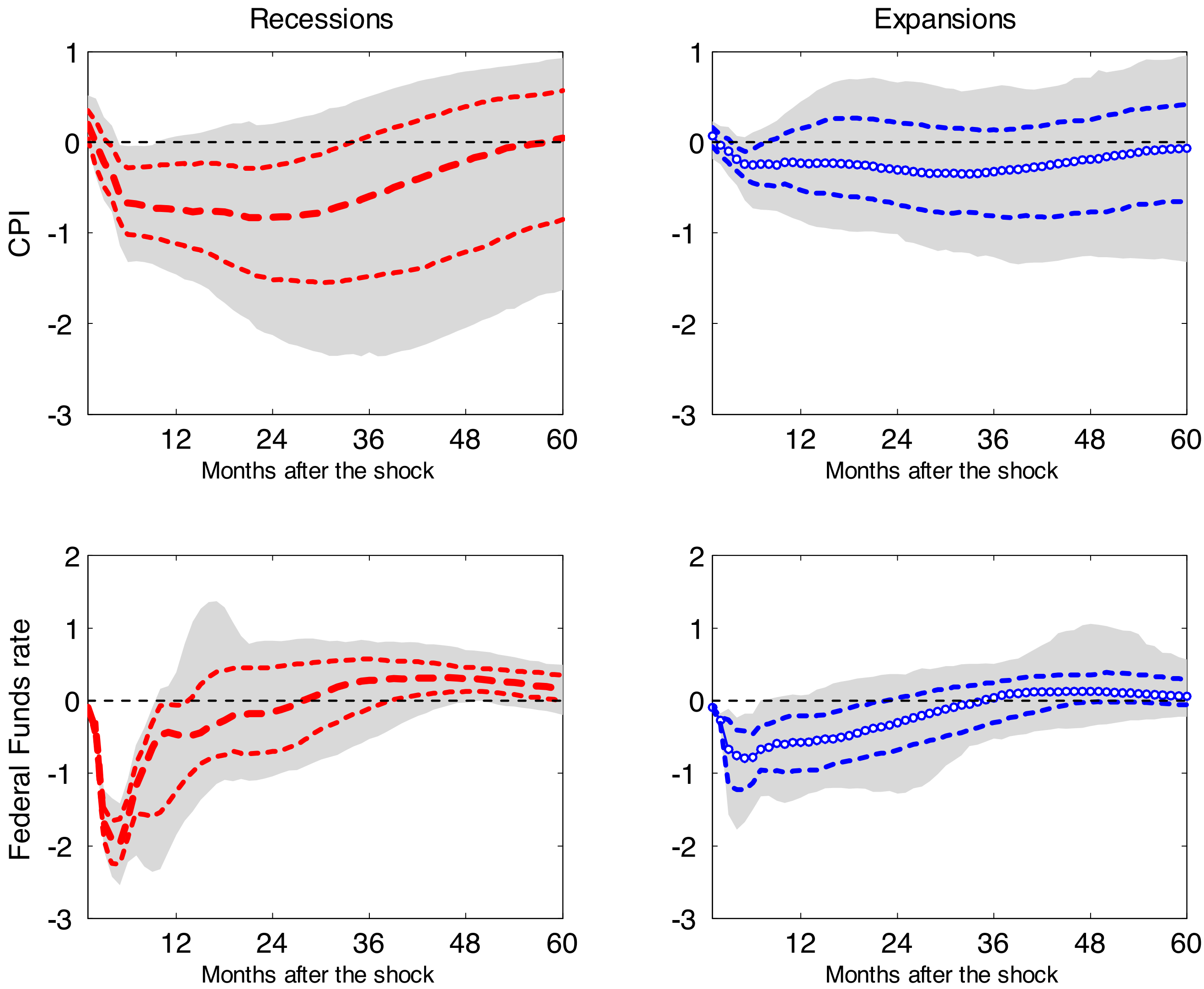

Figure 10: **Effects of Uncertainty Shocks on Prices and Policy Rate: Role of Nonlinearities.** Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands. Gray areas: 95% confidence bands. Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.

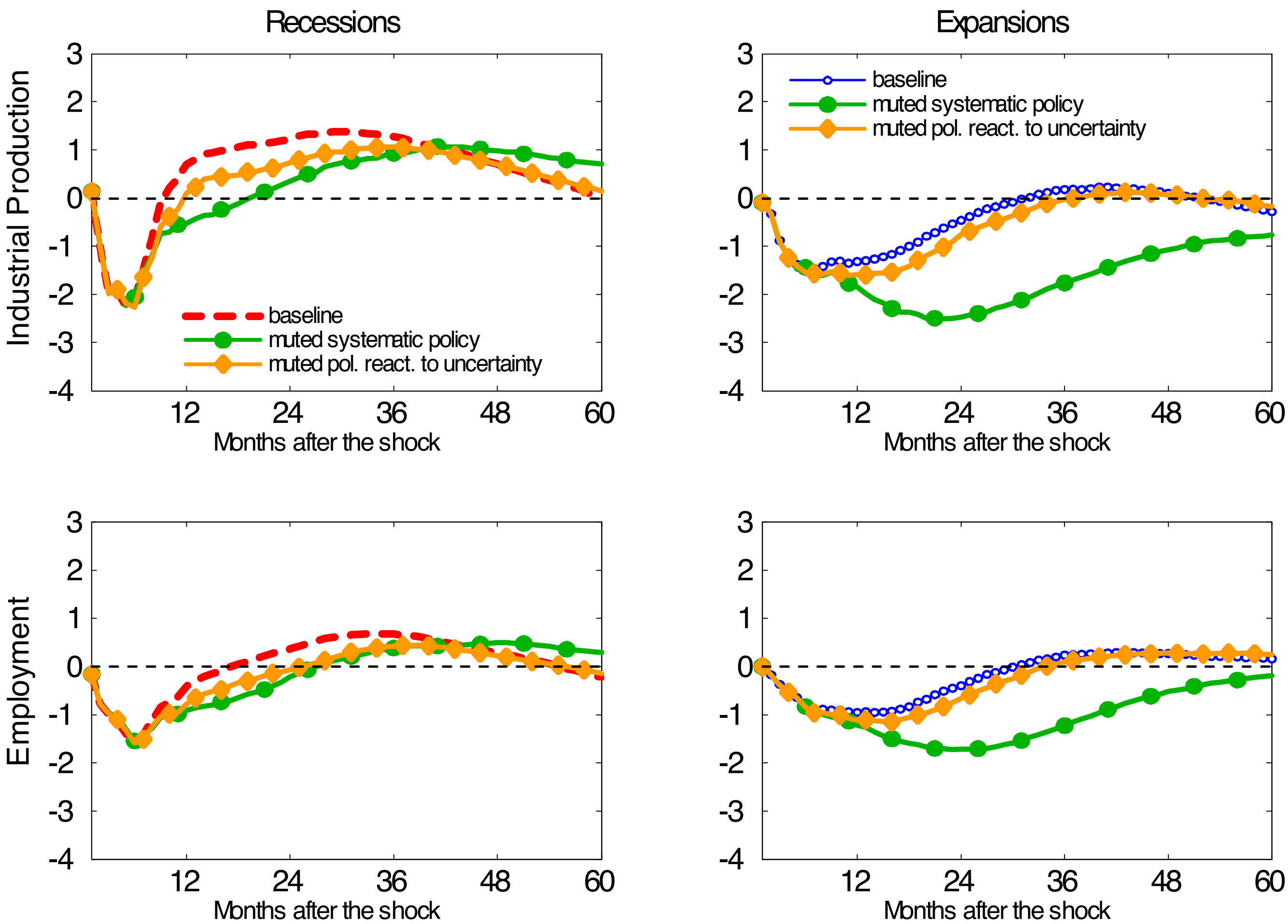

Figure 11: **Real Effects of Uncertainty Shocks: Role of Systematic Monetary Policy.** Median impulse responses to a one-standard deviation uncertainty in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Counterfactual responses computed conditional on a muted systematic policy (fixed federal funds rate) in green-circled lines. Counterfactual responses computed conditional on a systematic policy not responding to the uncertainty indicator in orange-diamonded lines. Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.

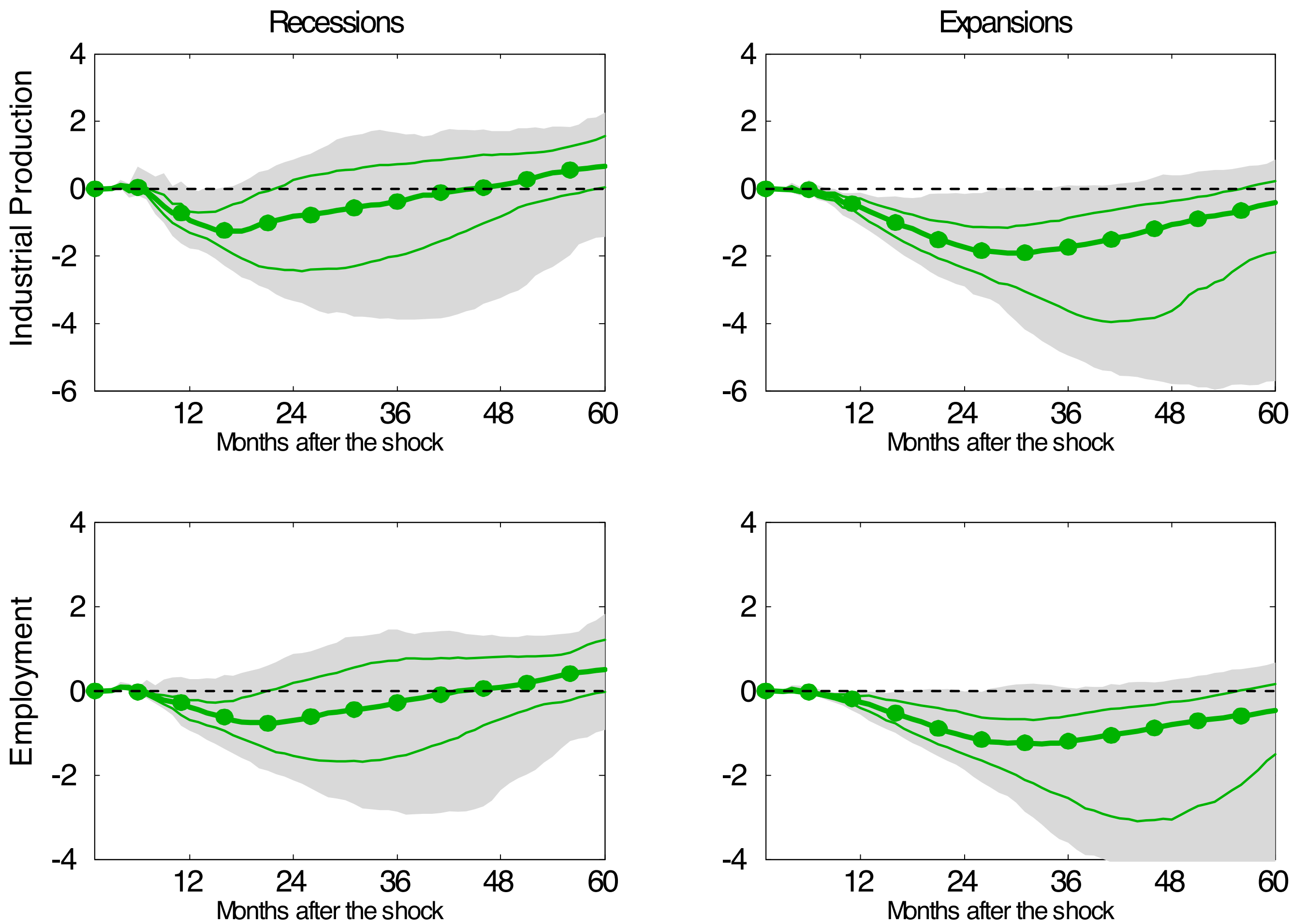

Figure 12: **Role of Monetary Policy: Statistical Difference.** Difference between "baseline" minus "muted monetary policy" impulse responses to a one-standard deviation uncertainty shock identified as described in the paper. Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Green lines: Median of the distribution of the differences. Solid green lines: 68% bands of the distribution of the differences. Gray areas: 95% bands of the distribution of the differences. Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.

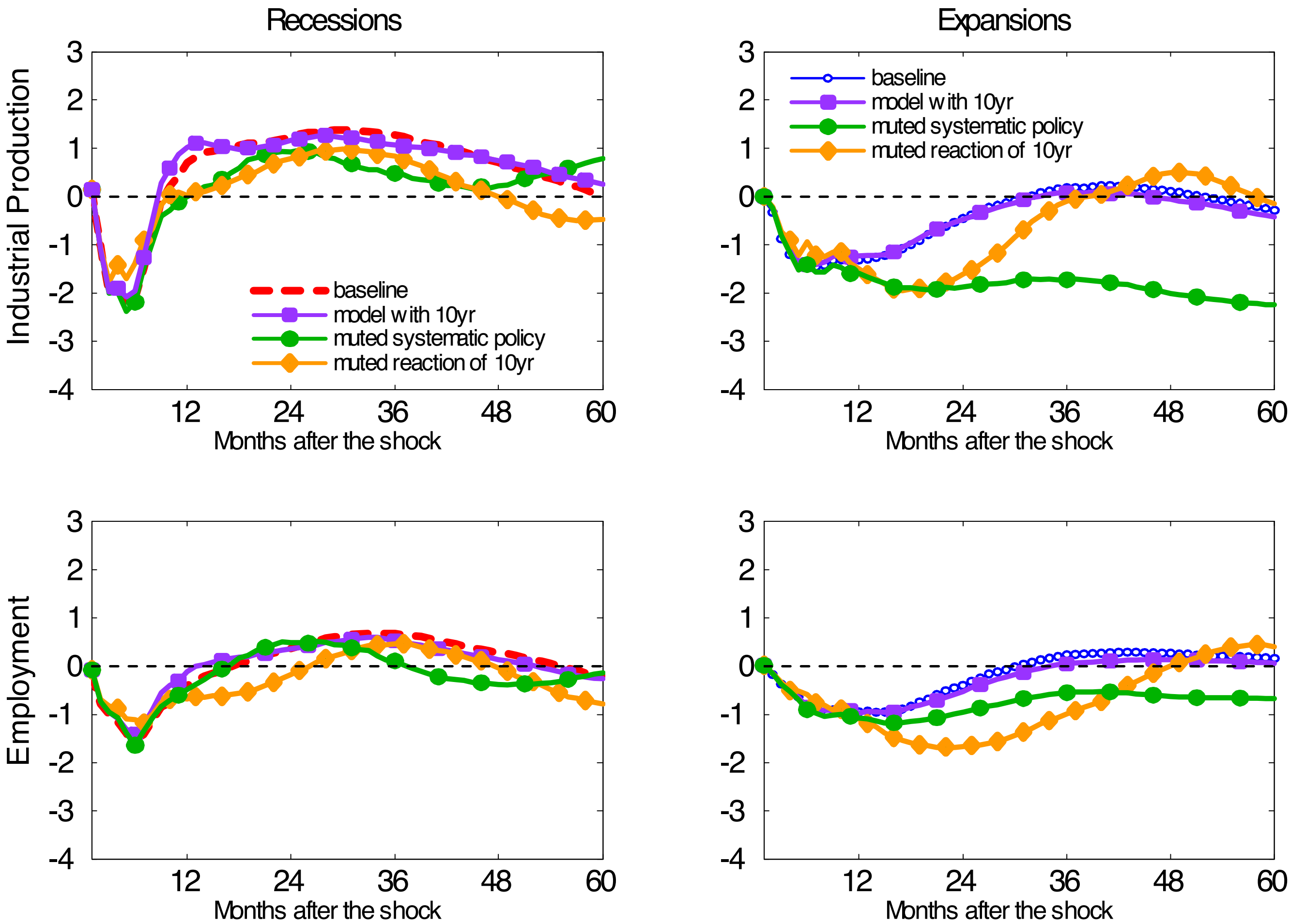

Figure 13: **Real Effects of Uncertainty Shocks: Role of Federal Funds Rate and Forward Guidance.** Median impulse responses to a one-standard deviation uncertainty in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed with the baseline Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Violet squared-lines: Responses computed with the estimated nine-variate STVAR with the 10 year Treasury yield (unrestricted model). Counterfactual responses computed conditional on a muted systematic policy (fixed federal funds rate) in green-circled lines. Counterfactual responses computed conditional on a muted response of the 10 year Treasury yield in orange-diamonded lines. Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.