Uncertainty and Monetary Policy in Good and Bad Times*

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Abstract

Are the effects of uncertainty shocks different in recessions and expansions? Is the stabilizing power of systematic monetary policy state-contingent? We answer these questions by estimating a nonlinear VAR for post-WWII U.S. data. We find uncertainty shocks hitting in recessions to trigger a more abrupt drop and a faster recovery than in expansions. A temporary medium-term real activity overshoot is found to be present only when uncertainty shocks realize in bad times. Uncertainty shocks hitting in expansions are shown to trigger hump-shaped, persistent reactions of real activity indicators. Counterfactual simulations suggest that the effectiveness of systematic monetary policy in stabilizing real activity is greater in expansions.

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

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 and empirical models have further examined the role of uncertainty in affecting agents' decisions and triggering macroeconomic dynamics.[1]

This paper asks two questions: Are the effects of uncertainty shocks different in good and bad times? Is the stabilizing power of systematic monetary policy state-contingent? We answer them by modeling a standard set of post-WWII U.S. macroeconomic variables with a Smooth Transition Vector AutoRegression (STVAR) model. This nonlinear framework allows us to capture the possibly different macroeconomic responses to an uncertainty shock occurring in different phases of the business cycle. We endogenously account for possible regime-switches due to an uncertainty shock by computing Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran, and Potter (1996). This is important to correctly address the above mentioned questions 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 to the "volatility effect" as in Bloom (2009).[2]

Our focus on nonlinearities stems from two important but often neglected stylized facts. First, there is growing evidence that most macroeconomic aggregates display

[1] A non-exhaustive list includes the theoretical models by Basu and Bundick (2014), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014), Leduc and Liu (2013), Johannsen (2013), Christiano, Motto, and Rostagno (2014) and the empirical studies by Alexopoulos and Cohen (2009), Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011), Baker, Bloom, and Davis (2013), Gilchrist, Sim, and Zakrajsek (2013), Mumtaz and Theodoridis (2012), Stock and Watson (2012), Aastveit, Natvik, and Sola (2013), Mumtaz and Surico (2013), Mumtaz and Zanetti (2013), Colombo (2013), Nodari (2014), Pellegrino (2014), Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2014), Furlanetto, Ravazzolo, and Sarferaz (2014), and Jurado, Ludvigson, and Ng (2015).

[2] In Bloom's (2009) model, the "volatility effect" is due to the fact that an uncertainty shock translates in an increase in the realized volatility of business conditions. The latter leads high productive firms to investing and hiring, and low productive ones to disinvesting and firing. Given that the majority of firms is clustered around the hiring and investing thresholds, 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.

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 much sharply in bad than in good times. Micro- and macro-evidence of countercyclical uncertainty with abrupt increases in recessions is documented by Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014), Orlik and Veldkamp (2014), and Jurado, Ludvigson, and Ng (2015).[3] 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)). In light of this evidence, it may very well be that uncertainty shocks have different macroeconomic effects over the business cycle.

Are the effects of uncertainty shocks different in good and bad times? We find clear-cut evidence of asymmetric effects of uncertainty shocks. First, industrial production and employment fall much more quickly and sharply when uncertainty shocks hit the economy during recessions: we show that a linear VAR framework would lead to substantial, statistically significant underestimation of these contractionary effects. Second, real activity follows a drop, rebound, and overshoot dynamic path only when uncertainty rises during recessions. In expansions, the response of real activity to uncertainty shocks follows a milder drop, a prolonged recovery, and no overshoot. Moving to the reaction of nominal variables, uncertainty shocks are found to be deflationary, especially in recessions. This result, combined with that on real activity, suggests that uncertainty shocks can be classified as negative "demand" shocks as in Leduc and Liu (2013), Johannsen (2013), and Basu and Bundick (2014). The response of the policy rate is found to be substantially more marked during economic downturns, with a drop, rebound, and overshoot pattern in recessions only. To our knowledge, the empirical facts established in this paper, i.e., the statistically relevant qualitative and quantitative difference in the response of real activity and prices over the business cycle to an uncertainty shock, are novel in this literature.

Is the stabilizing power of systematic monetary policy state-contingent? To answer this question, we run counterfactual exercises in which systematic monetary policy remains still after an uncertainty shock. We find that the effectiveness of systematic monetary policy in tackling uncertainty shocks is clearly state-dependent. In bad times, the short-run response of real activity is found to be virtually unchanged, and the medium-

[3] Spikes in uncertainty indicators 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.

run response of real activity is only partly affected when monetary authorities do not react. In good times, our simulations suggest that a muted (i.e., non expansionary) monetary policy would induce a much deeper and longer-lasting recession following an uncertainty shock. This remains true also after including long-term rates to account for expectations about future monetary policy stance (see Bernanke (2013) and the literature cited therein). This result is consistent with recent empirical findings by Mumtaz and Surico (2014), who estimate the interest rate semi-elasticity in a state-dependent IS curve for the United States to be lower during recessions, and can be interpreted by appealing to the theory of "real-options". Heightened uncertainty increases the real option value of waiting for firms. Given that uncertainty is typically higher in recessions (Bloom (2014)), optimizing firms will be less responsive to variations in the nominal interest rate during bad times because the value of waiting is very high.

Our results complement the current theoretical literature on the real effects of uncertainty shocks. The drop-rebound-overshoot dynamics followed by real activity during recessions supports the predictions coming from the theoretical model put forth by Bloom (2009), where firms face non-convex adjustment costs in labor and capital, which in turn imply Ss-type optimal behavior, so that a sudden increase in the level of uncertainty would make a "wait-and-see" behavior optimal for a larger number of firms. Differently, our impulse responses document hump-shaped responses of real activity indicators in expansions. A way of reading this result is the following. The general equilibrium model by Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014) predicts, in general, no overshoot in real activity. This because such overshoot would be inconsistent with consumption smoothing. As a result, the response of output predicted by Bloom et al.'s (2014) model is, at least qualitatively, in line with our evidence conditional on expansions. Importantly, Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014) show that, if consumption smoothing is shut down, the drop-rebound-overshoot dynamics predicted by Bloom's (2009) partial equilibrium model arise again. In fact, consumption smoothing in recessions may be impeded by harsh financial conditions (Canzoneri, Collard, Dellas, and Diba (2015)), something that could restore the partial equilibrium-type of response of real activity documented by Bloom (2009).

Our empirical results on the weaker effectiveness of systematic monetary policy can also be read via the lens of a number of theoretical models. In presence of labor and capital non-convex adjustment costs, Bloom (2009) and Bloom et al. (2014) predict a weak impact of monetary policy when uncertainty is high because of the magnified importance of "wait-and-see" effects. Vavra (2014) and Baley and Blanco (2015) show that higher uncertainty generates higher aggregate price flexibility, which in turns harms the central bank's ability to influence aggregate demand. Berger and Vavra (2015) build up a model featuring microeconomic frictions which lead to a decline in the frequency of households' durable adjustment during recessions, which in turn implies a procyclical impulse response of aggregate durable spending to macroeconomic shocks. Our empirical findings lend support to these theoretical contributions.

There are important implications for the conduct of monetary policy in presence of heightened uncertainty. 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 add to this literature by suggesting that policymakers should evaluate the possibility of implementing 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 both the contractionary effects and the different transmission mechanism of uncertainty shocks over the business cycle (for a recent example, see Cacciatore and Ravenna (2014)).

The paper develops as follows. Section 2 presents our nonlinear 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 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).[4] The vector of

[4] 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 VXO-related dummy as a proxy for uncertainty, though we acknowledge it is a mixture of both risk and uncertainty. For an

endogenous variables $\boldsymbol{X}_t$ includes (from the top to the bottom): the S&P500 stock market index, an uncertainty dummy based on the VXO, the federal funds rate, a measure of average hourly earnings, the consumer price index, hours, employment, and industrial production. All variables are in logs, except the volatility indicator, the policy rate, and hours.[5] As in Bloom (2009), the uncertainty dummy 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, uncertainty 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.[6]

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

analysis that disentangles the effects of risk and uncertainty, see Bekaert, Hoerova, and Duca (2013).

[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. 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.

[6] Jurado, Ludvigson, and Ng (2015) construct a measure of macroeconomic uncertainty by estimating the time-varying common volatility in the unforecastable component of a large number of economic indicators. While documenting a correlation of about 0.5 with the VXO index, they find that their indicator points to high realizations of uncertainty mainly in three big recessions (1973-74, 1981-82, 2007-09). It is worth noticing, however, that this result is not robust to the employment of alternative datasets/ways of constructing uncertainty indices based on macroeconomic forecast errors. Rossi and Sekhposyan (2015) employ data from the Survey of Professional Forecasters to construct an uncertainty index which relies on the unconditional likelihood of realized real GDP forecast errors. Their index features spikes both in recessions and in expansions. Moreover, they document a correlation between their index and the VXO of about 0.3, i.e., the highest among the uncertainty measures they consider. Other proxies of uncertainty proposed in the literature that document uncertainty spikes in non-recessionary periods are Bachmann, Elstner, and Sims (2013), Leduc and Liu (2013) and Scotti (2013) These considerations, along with comparability reasons with Bloom's (2009) work, explain the employment of Bloom's proxy of uncertainty in our analysis.

$$\begin{aligned}
\mathbf{X}_t &= F(z_{t-1})\mathbf{\Pi}_R(L)\mathbf{X}_t + (1 - F(z_{t-1}))\mathbf{\Pi}_E(L)\mathbf{X}_t + \boldsymbol{\varepsilon}_t, \quad (1)\\
\boldsymbol{\varepsilon}_t &\sim N(0, \mathbf{\Omega}_t), \quad (2)\\
\mathbf{\Omega}_t &= F(z_{t-1})\mathbf{\Omega}_R + (1 - F(z_{t-1}))\mathbf{\Omega}_E, \quad (3)\\
F(z_t) &= \exp(-\gamma z_t)/(1 + \exp(-\gamma z_t)), \gamma > 0, z_t \sim N(0,1). \quad (4)
\end{aligned}$$

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, $\mathbf{\Pi}_R$ and $\mathbf{\Pi}_E$ are the VAR coefficients capturing the dynamics of the system in recessions and expansions respectively, $\boldsymbol{\varepsilon}_t$ is the vector of reduced-form residuals with zero-mean and time-varying, state-contingent variance-covariance matrix $\mathbf{\Omega}_t$, where $\mathbf{\Omega}_R$ and $\mathbf{\Omega}_E$ are covariance matrices of the reduced-form residuals estimated during recessions and expansions, respectively. Recent applications of the STVAR model 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 (2015), 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 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, obtained when $\gamma = 0$, which implies $\mathbf{\Pi}_R = \mathbf{\Pi}_E = \mathbf{\Pi}$ and $\mathbf{\Omega}_R = \mathbf{\Omega}_E = \mathbf{\Omega}$. Following Bloom (2009), we orthogonalize the residuals of the dummy variable with those of the rest of the system by imposing a Cholesky-decomposition of the covariance matrix of the residuals. Hence, the ordering of the variables admits an immediate response of industrial production and employment, as well as prices and the federal funds rate, to an uncertainty shock. The inclusion of the SP500 index right before our uncertainty indicator is meant to control for the impact of stock market levels on volatility. Our STVAR model can then be interpreted as a generalization of Bloom's (2009) linear approach, which is included as a special case.

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 (2015) 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.[7] Another important feature of the STVAR model is the choice of the smoothness parameter γ. Given that well-known identification issues affect its estimation (see the discussion in Teräsvirta, Tjøstheim, and Granger (2010)), we exploit the dating of recessionary phases produced by the National Bureau of Economic Research (NBER) and calibrate γ so 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 $\Pr(F(z_t) \geqslant 0.86) \approx 0.14$.[8] This metric implies $\gamma = 1.8$. Figure 2 plots the transition function for the U.S. post-WWII sample and superimposes the NBER recessions dating. As the Figure shows, our transition probability tracks well the downturns of the U.S. economy.[9]

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

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

[8] 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 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., $\overline{z}^{nonstd} = (\overline{z}^{std}\sigma_z + \overline{z}) = (-1.01 \times 0.27 + 0.40) \approx 0.13\%$.

[9] It is important to notice two facts about our $F(z)$. First, our transition probability peaks in occurrence of a recession with a slight delay relative to the NBER dating. This is due to the choice of using a backward-looking transition indicator. Such a choice enables us to compute the probability $F(z)$ by using observed values of industrial production, rather than predicted ones as a centred moving average would have required. Second, the volatility of $F(z)$ 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.

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).[10] The estimated model is then employed to compute GIRFs to an uncertainty shock.[11]

We interpret our impulse responses as the reaction of economic variables to an uncertainty shock. There are, however, theoretical and empirical results which might point to potential endogeneity of uncertainty shocks. Bachmann and Bayer (2013) show that fluctuations in uncertainty may be caused by first-moment shocks like, e.g., aggregate TFP shocks, and are therefore endogenous to the economic system. Bachmann and Moscarini (2012) work with a framework in which strategic price experimentation during recessions (due to first moment shocks) implies a higher dispersion of firms' profits. 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. At any conventional level, all these bivariate VARs point to i) strong evidence against the null hypothesis that the VXO does not Granger-cause the other variables, and ii) no evidence 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,

[10] 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.

[11] Following Koop, Pesaran, and Potter (1996), our GIRFs are computed as follows. First, we draw an initial condition, i.e., starting values for the lags of our VARs as well as the transition indicator z, which - given the logistic function (4) - provides us with the starting value for $F(z)$. Then, we simulate two scenarios, one with all the shocks identified with the Cholesky decomposition of the VCV matrix (3), and another one with the same shocks plus a $\delta > 0$ corresponding to the first realization of the uncertainty shock. The difference between these two scenarios (each of which accounts for the evolution of $F(z)$ by keeping track of the evolution of output and, therefore, z) gives us the GIRFs to an uncertainty shock of size δ. Per each given initial condition z, we compute 500 different stochastic realizations of our GIRFs, then store the median realization. We repeat these steps until 500 initial conditions (drawn by allowing for repetitions) associated to recessions (expansions) are considered. Then, we construct the distribution of our GIRFs by considering these 500 median realizations. Our Appendix provides details on the algorithm we employed to compute the GIRFs.

Jaimovich, Saporta-Eksten, and Terry (2014), who work with industry-level data and find no significant impact of first-moments shocks on measures of TFP dispersions. They are also consistent with those in Baker and Bloom (2013), who exploit natural disasters and a panel approach to show that exogenous variations in uncertainty are indeed important drivers of the business cycle.

3 Results

3.1 Nonlinear effects of uncertainty shocks

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 estimated by our STVAR model.[12] 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. Notably, 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 about -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.[13]

How relevant is this result from a statistical standpoint? Figure 4 contrasts the responses of industrial production and employment obtained in recessions and expansions using 68% (areas identified with dashed and dotted lines) and 95% (grey areas) con-

[12] For comparability reasons, the size of the shock is normalized to one in all scenarios. Nonlinear VAR impulse responses may depend on the size of the shock (as well as its sign and initial conditions). We conducted a large set of simulations, and we found the role played by the size of the shock *per se* in shaping our impulse responses to be negligible.

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

fidence intervals. The abrupt drop-and-rebound reaction of industrial production in recessions, followed by a persistent overshoot, turns out to be clearly significant even at a 5% 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 in recessions looking at the 68% confidence intervals. Again, expansions suggest a different conditional path for employment characterized by a much slower return to its trend level and no overshoot.

3.2 Asymmetric effects of uncertainty shocks: Possible interpretations

Our GIRFs suggest a drop-rebound-overshoot type of response of industrial production and employment only in recessions. Differently, uncertainty shocks occurring in good times induce a hump-shaped response of these variables, and no medium term overshoot. How to interpret such different dynamic paths? We propose a possible interpretations based on the extant literature. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014) provide an extension of Bloom's (2009) partial equilibrium model which embeds consumption decisions in the framework. They show that, when consumers' optimization is taken into account, the "wait-and-see" optimal behavior adopted by firms after an uncertainty shock leads to a drop and rebound in real activity, but no overshoot. This is because, given the amount of resources available in the economic system, big variations in investment would imply implausibly large changes in consumption, which would be just not consistent with consumption smoothing. From a qualitative standpoint, this prediction is supported by our impulse responses when an uncertainty shock hits in good times. Consumption smoothing is intuitively possible when agents have access to financial markets. However, access to credit may be cyclical, and less easy in recessions. Binding credit constraints in recessions could then prevent (at least to some extent) consumption smoothing, therefore leading to a quick drop and rebound followed by a temporary overshoot in real activity, as predicted by Bloom (2009) (or a version of Bloom et al. (2014) in which consumption smoothing is impeded by some frictions). Interestingly, at least from a qualitative standpoint, this is exactly what our impulse responses predict.[14]

[14]In a different but related context, Canzoneri, Collard, Dellas, and Diba (2015) show the importance of countercyclical financial frictions in a DSGE model to explain the nonlinear dynamics of real activity indicators after fiscal policy shocks.

3.3 Robustness checks

Our main results may be driven by some form of misspecification of the baseline STVAR model. Here we propose a number of robustness checks, all motivated by relevant contributions in the related literature about uncertainty and the use of nonlinear VAR models. These checks include: i) the employment of an alternative uncertainty dummy, which is constructed by considering just 10 out of 16 extreme realizations of uncertainty, i.e., those which are associated to terror, war, or oil events as in Bloom (2009);[15] ii) different calibrations for the slope parameter γ ranging between 1.4 and 2.2, which imply a frequency of recessionary periods in the sample equal to 10% and 25%, respectively; iii) the use of unemployment as transition indicator z. In particular, 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] iv) the inclusion in the vector of a measure of credit spread. 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. To control for the presence of time-varying financial risk, we include in our VAR as a measure of credit spread in our VAR the difference between the Baa corporate bonds and the 10-year Treasury yield, which highly correlate with the measure of excess bond premium proposed by Gilchrist and Zakrajsek (2012);[17] v) house prices. The housing market is particularly important for us in 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

[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.

[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."*

[17] 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. The correlation between the Baa-10-year Treasury yield spread and the Gilchrist and Zakrajsek's excess bond premium reads 0.63.

price index computed by Robert Shiller to our baseline vector.[18]

In all cases, we find that the 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 documented with our baseline STVAR is confirmed. A detailed discussion of the above mentioned robustness exercises is provided in our Appendix.

4 Uncertainty shocks and monetary policy

4.1 Baseline responses

We now turn to studying the dynamics of prices and the federal funds rate to an uncertainty shock. Figure 5 focuses on the differences between recessions and expansions, and plots 68% and 95% confidence bands around the estimated generalized impulse responses. An uncertainty shock triggers a negative reaction of prices which is clearly statistically significant in recessions only. Prices go down and then gradually returns to their pre-shock level. As both quantities and prices fall after an uncertainty shock, though 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 in good times, 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 a recession, 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 (2014) and Leduc and Liu (2013) that uncertainty shocks act as 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

[18] 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.

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, October 20 from over 7.5 percent on Monday, October 19 (Carlson (2007)).

4.2 Counterfactual scenarios

The previous 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.[19] 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 6 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"). Remarkably, 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 occurs 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 after about one year. Notably, 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 run in good times. As Figure 6 shows, when the policy rate is kept fixed,

[19] 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".

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.[20]

Are the impulse responses reported in Figure 6 statistically different? Figure 7 plots the distribution of the difference between the GIRFs obtained with our "muted systematic policy" scenario and the baseline case. In line with the previous discussion, such a 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 only a few periods, while in expansions such effect is present and significant for a much prolonged period of time (more than four years after the shock). These results are robust to the inclusion of long term rates, which aim at capturing, though imperfectly, the role played by expectations about future monetary policy stance. The results are shown and discussed at length in our Appendix.

4.3 Interpreting policy (in)effectiveness

How can one interpret the state-dependence of monetary policy effectiveness? As suggested by Bloom (2009) and Bloom et al. (2014), these findings might find a rationale in the real option value theory. When uncertainty is high, firms' inaction region expands (Bloom, 2009). Since the real option value of waiting increases, "wait-and-see" behavior becomes the optimal strategy for a larger number of firms, compared to normal times. When the real option value of waiting is very high, firms become quite insensitive to changes in the interest rate, which explains why the peak recessionary effect is virtually identical regardless of the reaction of monetary policy. When uncertainty starts to drop down, the inaction region shrinks, firms become more willing to invest and face their pent-up demand. In turn, the elasticity of investment with respect to the interest rate starts increasing. If monetary policy does not react, as in our counterfactual scenario,

[20] When only the systematic component related to uncertainty in the federal funds rate equation is switched off, uncertainty shocks are found to trigger a response in real activity very similar to the baseline one (result documented in the Appendix). Hence, uncertainty shocks trigger significant monetary policy responses mainly via the effects they exert on the macroeconomic indicators embedded in our vector. This findings point to a Taylor rule not featuring uncertainty among the variables policymakers directly respond to as a possible interpretative model of the U.S. monetary policy.

the higher (relative to the baseline) cost of borrowing starts playing a role. Hence, firms 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 the medium run, once uncertainty has vanished, firms would invest less with respect to the baseline case, and the overshoot is substantially milder, if any. A similar reasoning can be done 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 policy stimulus. Hence, if the nominal interest rate remains unchanged, firms' investment and labor demand is likely to be lower. Consequently, uncertainty shocks would trigger stronger recessionary effects in absence of systematic monetary policy interventions.[21]

These findings line up with Vavra (2014), who shows that monetary policy shocks are less effective during periods of high volatility. In his model, despite the presence of an inaction region due to price adjustment costs, second moment shocks push firms, in equilibrium, to adjust their prices more often. This increased price dispersion translates into higher aggregate price flexibility, which dampens the real effects of monetary policy shocks. Given the countercyclicality of price volatility, monetary policy shocks turn out to be less powerful in recessions. A similar mechanism is present in Baley and Blanco (2015). To the extent that uncertainty is higher in recessions (as discussed in our Introduction), our results complement Vavra's (2014) and Baley and Blanco's (2015), since we show that the systematic component of monetary policy is less effective in recessions, when uncertainty is higher.

A different channel is presented by Berger and Vavra (2015). They build up partial- and general-equilibrium models which focus on the response of aggregate durable expenditures to a variety of macroeconomic shocks. In particular, their model features microeconomic frictions which lead to a decline in the frequency of households' durable adjustment during recessions. This decline in the probability of adjusting during recessions, joint with the variation over time in the distribution of households' durable holdings, implies a procyclical impulse response of aggregate durable spending to macroeconomic shocks, a result also documented in Berger and Vavra (2014). Hence, macro-

[21] Given that uncertainty is countercyclical, our STVAR coefficients are conditional on two different average levels of uncertainty in recessions and expansions. The average value of the VXO in our sample is 24.69 in NBER recessions, and 18.28 in NBER expansions. Then, our impulse responses can be interpreted as responses to shocks occurring in presence of two different levels of uncertainty.

economic policies are less effective in stabilizing the business cycle (at least, durable spending) in recessions, consistently with our counterfactual impulse responses.

Our empirical findings, which highlight the role of the systematic component of monetary policy, are also 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: they find that, 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.

5 Conclusions

After the 2007 financial turmoil and the subsequent deep recession, policymakers have often looked at heightened uncertainty as a major culprit of the slow recovery. This paper shows that one crucial element in understanding the transmission mechanism of uncertainty shocks to the real economy is the state of the business cycle. Using a nonlinear VAR model, we show that after an uncertainty shock the drop in real activity is much larger during recessions, compared to what a linear model would put forward. Given that uncertainty shocks hit the economy more often during recessions, our findings imply that they may be substantially more costly than what linear frameworks suggest. We also find that the dynamic path followed by real activity variables is different. In bad times, uncertainty shocks trigger a sharp drop, a quick rebound and a medium-term overshoot in real activity. Differently, the reaction of real activity in expansions is much more gradual and displays no overshoot. Counterfactual simulations conducted to assess the role of systematic monetary policy in our framework points to policy ineffectiveness in the short run, especially when uncertainty shocks hit in bad times. Policy effectiveness is found to increase in the medium run, especially in good times. This message holds true also when a long-term interest rate is included to control for expectations.

Our results are informative from a modeling standpoint. 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., 2014). 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 perspective, high uncertainty is found to reduce the sensitivity of output to stimulus policies, above all in recessions. Theoretical models like those developed by Vavra (2014), Berger and Vavra (2015), and Baley and Blanco (2015), 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 systematic monetary policy interventions. 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. Blanchard (2009) and Bloom (2014) call for larger policy stimuli in bad times, as well as "second moment policies" like stabilization packages designed to reduce systemic risk. Baker et al.'s (2013) point to the role of clear policy communication and steady policy implementation. Our results confirm that these policy suggestions may be particularly suited to exit phases characterized by particularly severe economics conditions in presence of high uncertainty.

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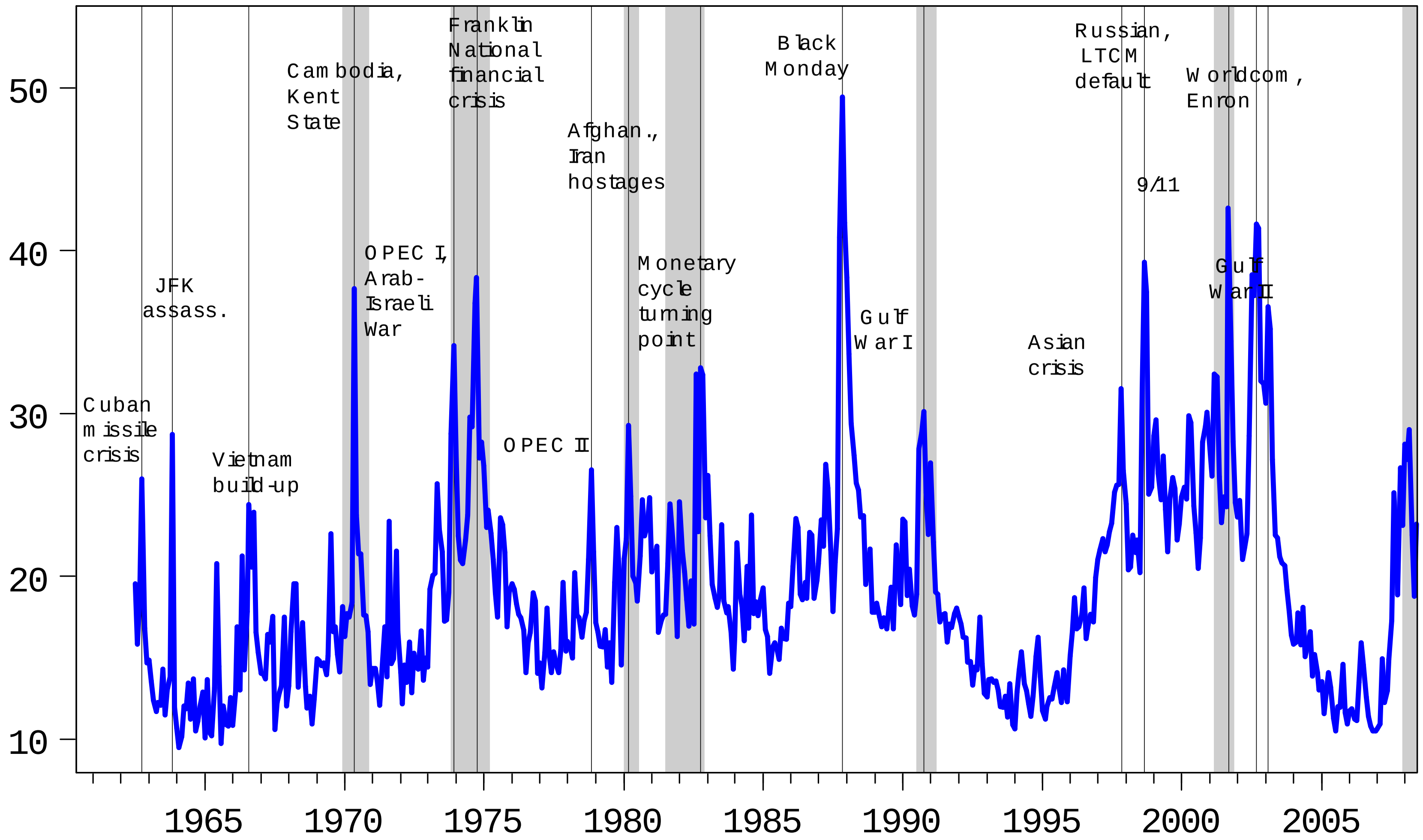

Figure 1: **Uncertainty shocks and the business cycle.** Sample: 1962M7-2008M6. Blue line: U.S. stock market volatility. Shaded areas: NBER recessions. U.S. stock market volatility: Chicago Board of Options Exchange VXO index of percentage implied volatility (on a hypothetical at the money Standard and 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).

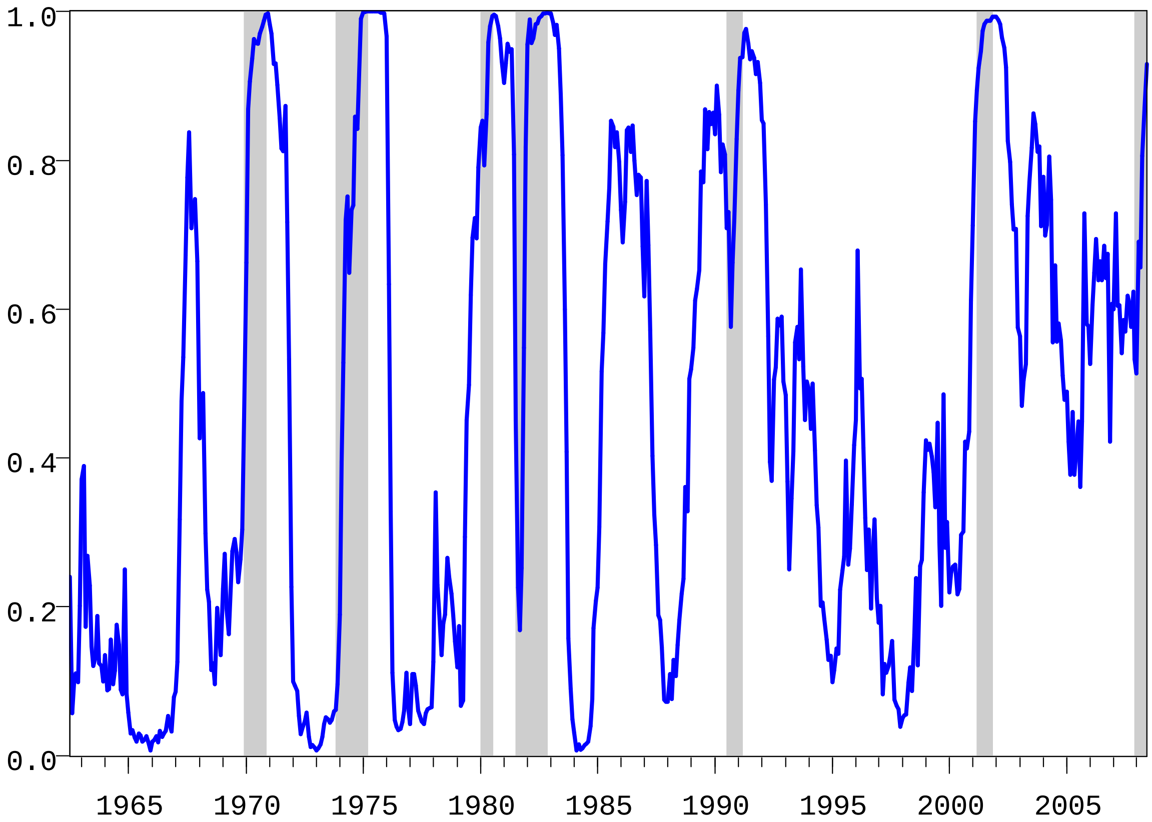

Figure 2: **Probability of being in a recessionary phase.** Blue line: Transition function F(z). Shaded columns: NBER recessions. Transition function computed by employing the standardized moving average (12 terms) of the month-on-month growth rate of industrial production.

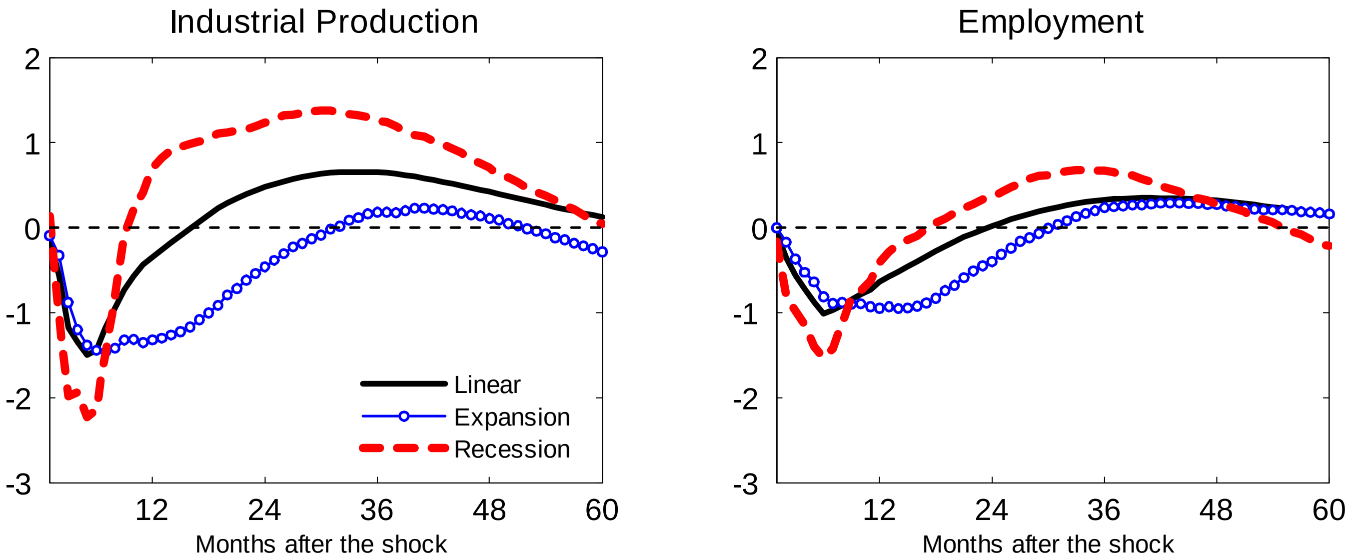

Figure 3: **Real Effects of Uncertainty Shocks: Linear vs. Nonlinear Frameworks.** Impulse responses (median values) to a one-standard deviation uncertainty shock identified as described in the paper. Solid black lines: Responses computed with the linear VAR. Red dashed (blue dashed-circled) lines: Responses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

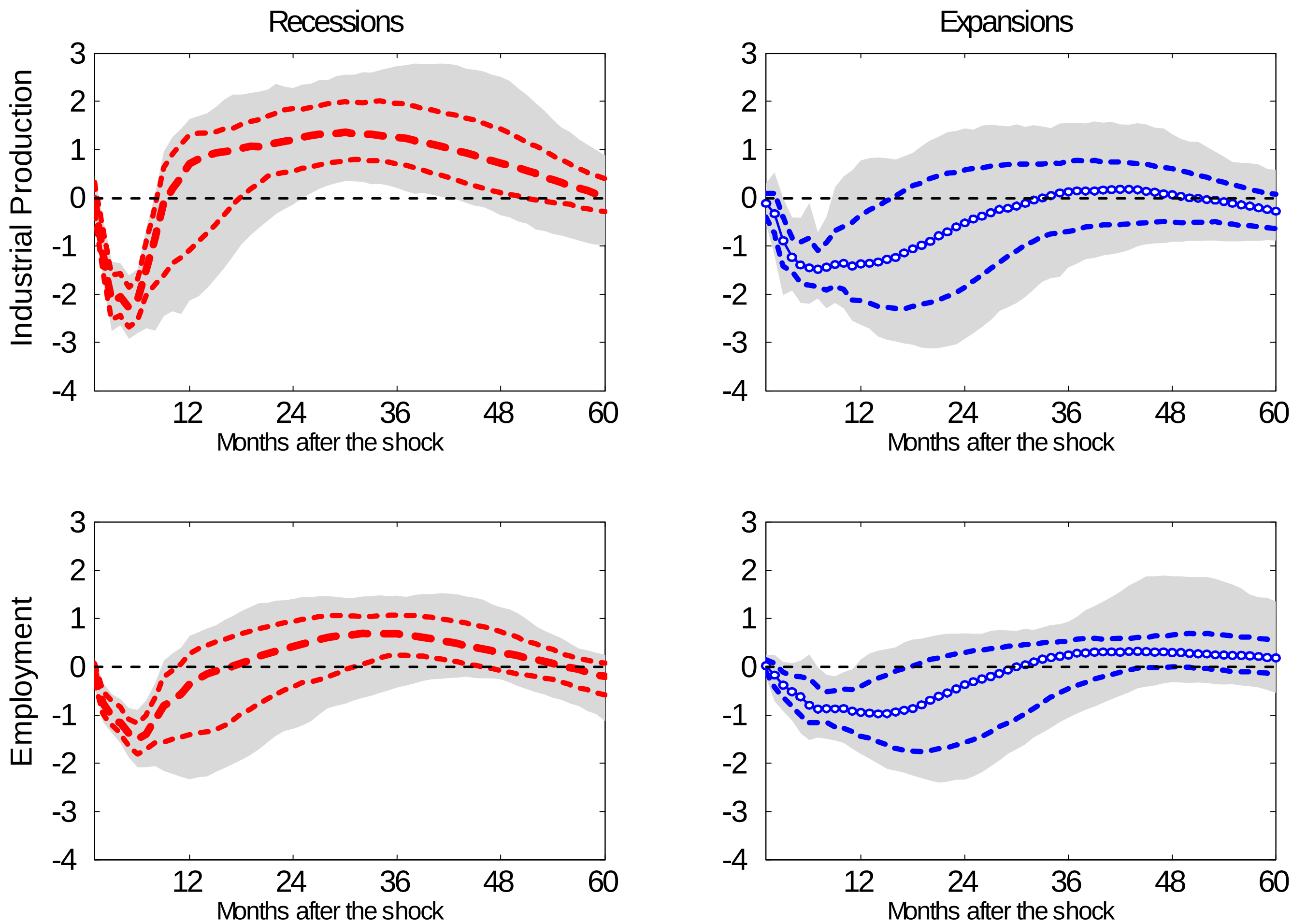

Figure 4: **Real Effects of Uncertainty Shocks: Good and Bad Times.** Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and 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.

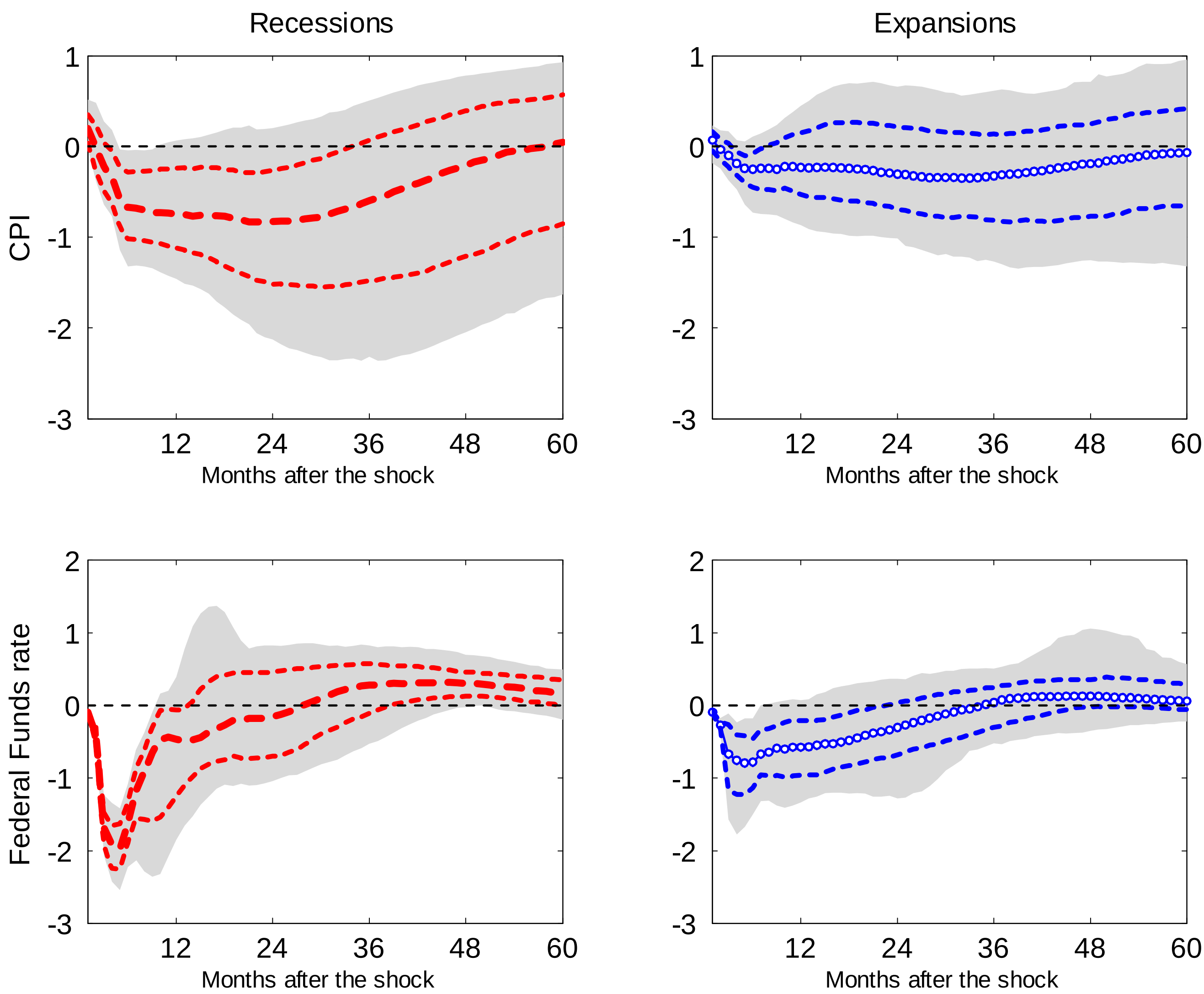

Figure 5: **Effects of Uncertainty Shocks on Prices and Policy Rate: Role of Nonlinearities.** Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled) lines: Responses computed with the 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.

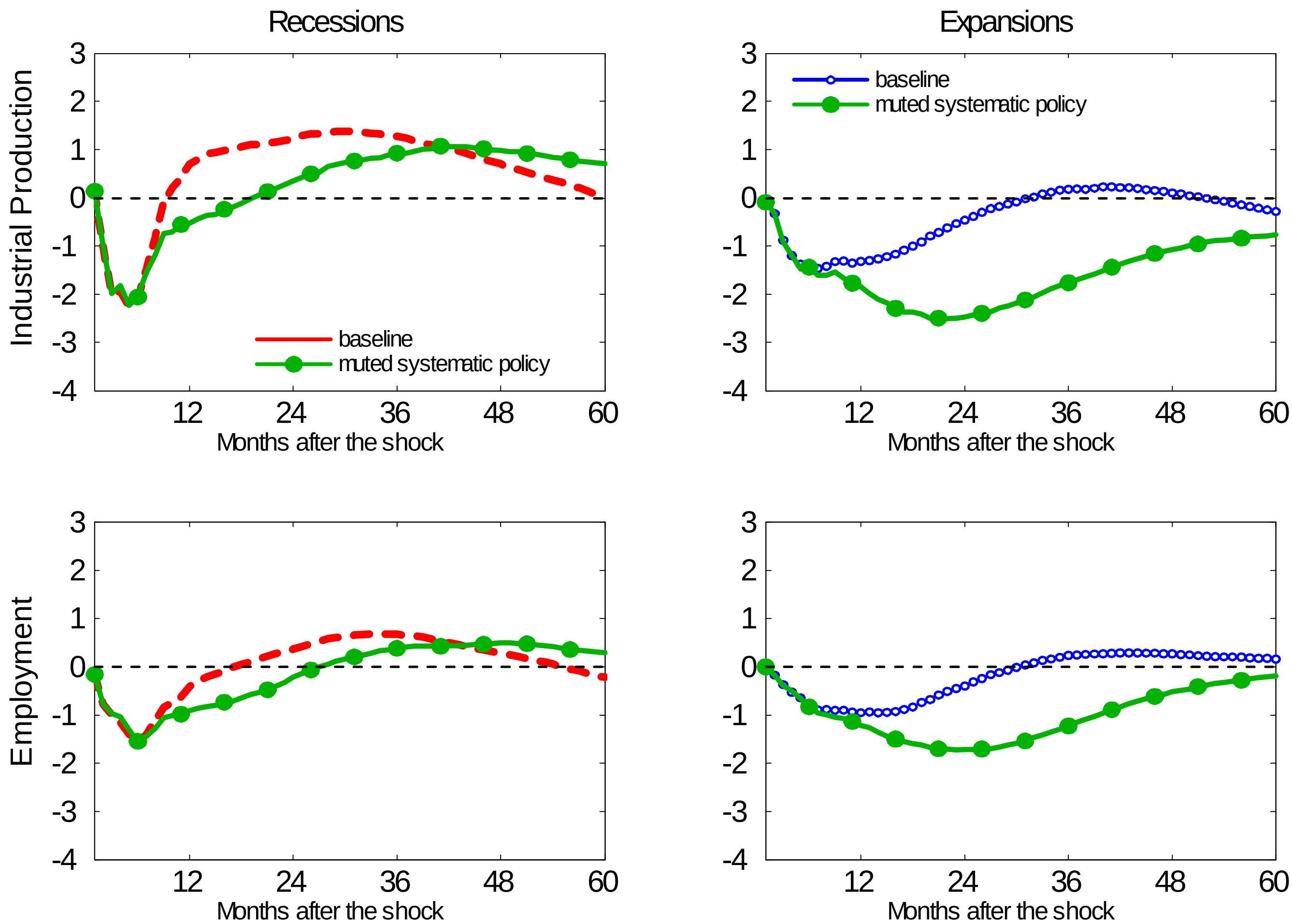

Figure 6: **Real Effects of Uncertainty Shocks: Role of Systematic Monetary Policy.** Median impulse responses to a one-standard deviation uncertainty in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Counterfactual responses computed conditional on a muted systematic policy (fixed federal funds rate) in green-circled lines. Markov-Chain Monte Carlo simulations to estimate the VAR coefficient based on 10,000 draws.

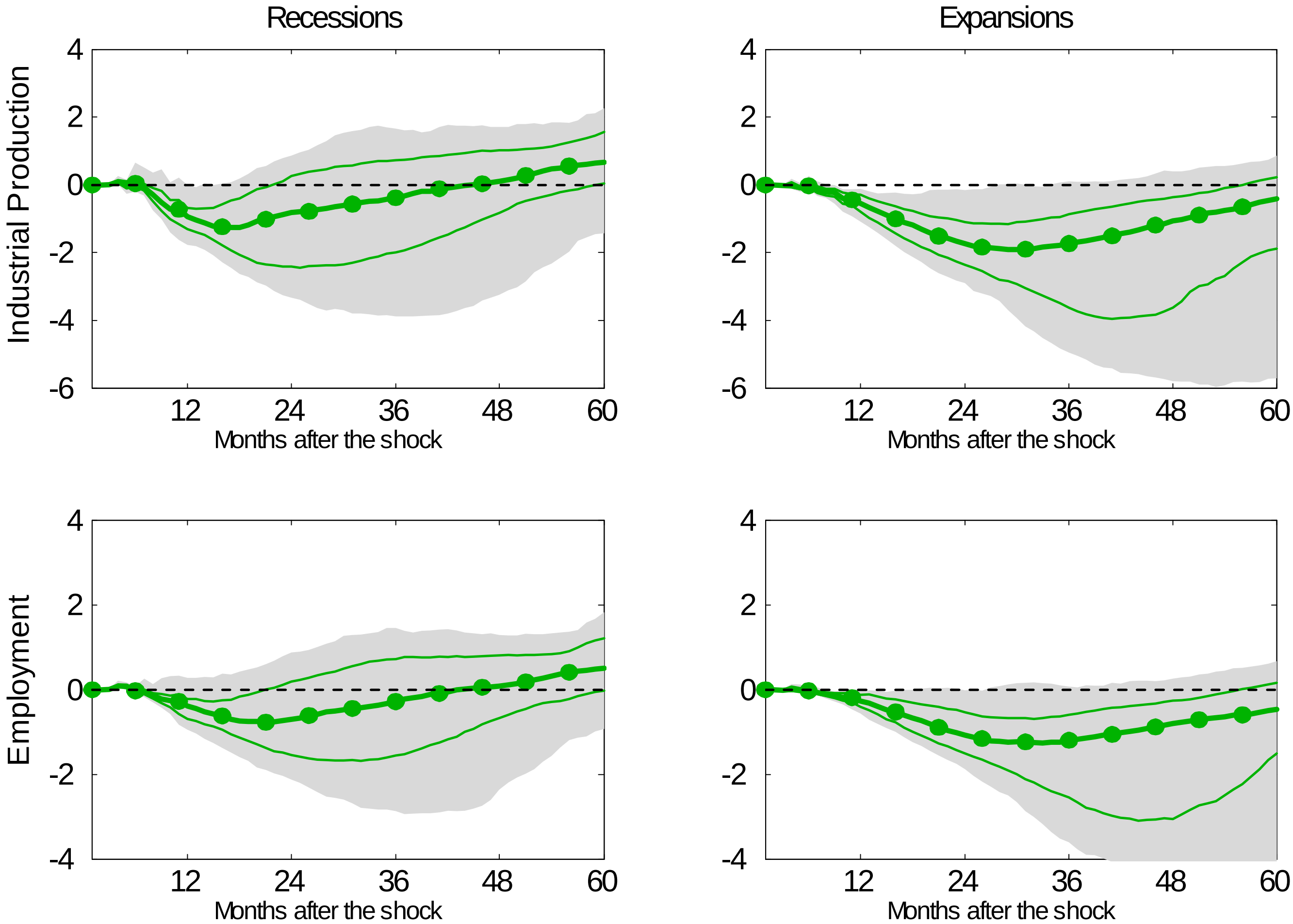

Figure 7: **Role of Monetary Policy: Statistical Difference.** Difference between "baseline" minus "muted monetary policy" impulse responses to a one-standard deviation uncertainty shock identified as described in the paper. Responses computed with the Smooth-Transition VAR and conditional on recessions (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.

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

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. It then reports details on the computation of the GIRFs. Finally, it documents our robustness checks.

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:

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

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.[1] 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 $\mathbf{\Pi}_j(L) = \left[\begin{array}{ccc} \mathbf{\Pi}_{j,1} & \ldots & \mathbf{\Pi}_{j,p} \end{array}\right]$, $j \in \{R, E\}$. 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

[1] 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 $p = 13$:[2] $\{\boldsymbol{\lambda}_i \in \mathbf{\Lambda}\}$. $\mathbf{\Lambda}$ 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:
$$\widehat{\mathbf{\Omega}}_{\lambda_i} = F\left(z_{\lambda i}\right)\widehat{\mathbf{\Omega}}_R + \left(1 - F\left(z_{\lambda_i}\right)\right)\widehat{\mathbf{\Omega}}_E, \tag{2}$$
where $\widehat{\mathbf{\Omega}}_R$ and $\widehat{\mathbf{\Omega}}_E$ are obtained from the generated MCMC chain of parameter values during the estimation phase.[3] z_{λ_i} is the transition variable calculated for

[2] 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.

[3] 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 $\widehat{\boldsymbol{\Omega}}_{\lambda_i}$:

$$\widehat{\boldsymbol{\Omega}}_{\lambda_i} = \widehat{\mathbf{C}}_{\lambda_i} \widehat{\mathbf{C}}'_{\lambda_i} \tag{3}$$

   and orthogonalize the estimated residuals to get the structural shocks:

$$\mathbf{e}^{(j)}_{\lambda_i} = \widehat{\mathbf{C}}^{-1}_{\lambda_i} \widehat{\boldsymbol{\varepsilon}}. \tag{4}$$

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

$$\mathbf{e}^{(j)*}_{\lambda_i} = \left\{ \mathbf{e}^*_{\lambda_i,t}, \mathbf{e}^*_{\lambda_i,t+1}, \ldots, \mathbf{e}^*_{\lambda_i,t+h} \right\}, \tag{5}$$

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

6. Form another set of bootstrapped shocks which will be equal to (5) except for the k_{th} shock in $\mathbf{e}^{(j)*}_{\lambda_i,t}$ which is the shock we want to perturbate by an amount equal to δ. Denote the vector of bootstrapped perturbated shocks by $\mathbf{e}^{(j)\delta}_{\lambda_i}$.

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

$$\widehat{\boldsymbol{\varepsilon}}^{(j)*}_{\lambda_i} = \widehat{\mathbf{C}}_{\lambda_i} \mathbf{e}^{(j)*}_{\lambda_i} \tag{6}$$

   and

$$\widehat{\boldsymbol{\varepsilon}}^{(j)\delta}_{\lambda_i} = \widehat{\mathbf{C}}_{\lambda_i} \mathbf{e}^{(j)\delta}_{\lambda_i}. \tag{7}$$

8. Use (6) and (7) to simulate the evolution of $\mathbf{X}^{(j)*}_{\lambda_i}$ and $\mathbf{X}^{(j)\delta}_{\lambda_i}$ and construct the $GIRF^{(j)}\left(h, \delta, \lambda_i\right)$ as $\mathbf{X}^{(j)*}_{\lambda_i} - \mathbf{X}^{(j)\delta}_{\lambda_i}$.

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

10. Calculate the GIRF conditional on history λ_i as

$$\widehat{GIRF}^{(i)}\left(h, \delta, \lambda_i\right) = B^{-1} \sum_{j=1}^{B} GIRF^{(i,j)}\left(h, \delta, \lambda_i\right). \tag{8}$$

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 $\widehat{GIRF}^{([1:500],E)}$.

Robustness analysis

Exogenous uncertainty shocks. Following Bloom (2009), our baseline analysis is conducted by working with 16 extreme realizations of uncertainty, identified as all the spikes which are 1.65 standard deviations above the mean of the HP-detrended VXO. 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 as in Bloom (2009).[4] Figure A1 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 empirical exercise is that the slope parameter γ of the logistic function of our STVAR, which drives the smoothness with which the economy switches from one regime to

[4] 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.

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 A2, which plots our baseline GIRFs along with the GIRFs obtained with alternative calibrated 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-term 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).[5] Figure A3 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.

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

[5]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."*

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 A4 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),, there has been a revamped attention toward the relationship between housing market dynamics and the business cycle, attention which has intensified after the 2007-09 financial and real crisis. The housing market is particularly important for us in 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.[6] As before, two alternative orderings are

[6] The index is available here: http://www.econ.yale.edu/~shiller/data/Fig2-1.xls. This index is

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 A5 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. The next Section turns to the analysis of monetary policy effectiveness after uncertainty shocks.

Systematic response to uncertainty. To complement those presented in the paper, Figure A6 shows that a muted systematic policy response (engineered via movements in the federal funds rate) to our uncertainty dummy *per se* would have a negligible impact on our baseline results obtained by allowing for an unconstrained response of the federal funds rate to an uncertainty shock.

Short- vs. long-term interest rates. The differences documented in Figures 6 are attributed to different policies as captured by different paths of the federal funds rate. As recalled by Bernanke (2013), however, monetary policy is likely to work mainly through the term structure, and in particular via long-term interest rates. Gurkaynak, Sack, and Swanson (2005) argue that the Federal Reserve has increasingly relied on communication to affect agents's expectations over future policy moves to eventually influence long-term rates.[7] Kulish (2007) shows that long-rates may effectively help

quarterly. We moved to monthly frequencies via a cubic interpolation of the quarterly series. Our VAR models the log of such interpolated index.

[7] Such rates are a function of future expected monetary policy and term premia. An overview of the analysis of the term structure of interest rates is provided by Gürkaynak and Wright (2012). It would be of interest to pin down the role played by expectations over future policy moves *per se*. Gertler and Karadi (2014) employ federal funds rate futures as measure of expectations (as in Kuttner (2001)) to investigate the empirical relevance of forward guidance by the Federal Reserve. Unfortunately, federal

stabilizing inflation in the context of a new-Keynesian framework featuring a term-structure of interest rate. Following Bagliano and Favero (1998), we then enrich our VAR with the 10-year Treasury constant maturity rate (ordered after the uncertainty dummy), and re-run our estimates. We use this nine-variate VAR model to compute impulse responses to an uncertainty shock in the unconstrained case, as well as in two counterfactual scenarios. The first counterfactual focuses on the response of real activity conditional on a fixed path of the federal funds rate. The aim of this counterfactual is to assess the role of systematic monetary policy when expectations about future rates, as captured by the 10-year rate, are allowed to change. In the second counterfactual, we estimate the responses to an uncertainty shock conditional on a fixed path of the long-term interest rate, i.e. under the assumption that expectations about the future stance of monetary policy remain unchanged. This exercise is intended to capture the role that the 10-year rate plays in transmitting the effects of uncertainty shocks. Clearly, the 10-year rate is a combination of expectations over future monetary policy moves and the risk-premium, and as such should be considered only as an imperfect proxy of expectations.

Figure A7 plots the impulse responses. Three results stand out. First, the presence of the long-term interest rate *per se* does not exert any appreciable impact on the impulse responses, which are very similar to those obtained with our baseline STVAR (shown in Figure 2). This holds true regardless of whether the economy is in a recession or in an expansion. Second, a counterfactually still monetary policy is confirmed to deliver a deeper recession than that predicted by our baseline exercise even when controlling for the role of expectations about future monetary policy. However, relative to the baseline case reported in Figure 6, the counterfactual recession in this case is milder. In particular, after an uncertainty shock hitting the economy in bad times, real activity goes back much more quickly to the pre-shock level relative to the baseline case (about 12 versus 18 months for industrial production, and 15 versus 24 for employment). This happens because of the role played by the long-term interest rate in this system (possibly, via changes in expectations over future monetary policy moves), which substitutes in part the federal funds rate in influencing the response of real activity. Finally, the

funds rate futures are available from 1989 only, which would imply a substantial loss in degrees of freedom if we used them in our econometric analysis. 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. Attempts to model short-term interest rates led us to experience multicollinearity-related problems due to their very high correlation with the federal funds rate.

third message of this exercise is that shutting down the long-rate channel implies that uncertainty shocks hitting in recessions trigger a slower and less marked medium-run recovery (relative to the baseline model augmented with the long-term interest rate). The effect is even more pronounced when uncertainty shocks hit in good times.

Our results suggest that the long-end of the term structure represents an important bit to understand the effects of an unexpected increase in volatility when the economy experiences booms. Interestingly, the two channels through which monetary policy may dampen the recessionary effects of uncertainty shocks seem to play a similar role, especially during recessions. Shutting down the short-term interest rate, which captures systematic monetary policy, or the long-term interest rate, which captures expectations about future monetary policy stance as well as the risk-premium, appears to produce quite similar dynamic responses during the first eighteen months when we look at industrial production in recessions. Some differences, however, arise when we look at the response of industrial production to uncertainty shocks in good times. In such a case, the role of the long-term interest rate seems to be less important, while the federal funds rate matters much more. 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.[8]

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[8]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.

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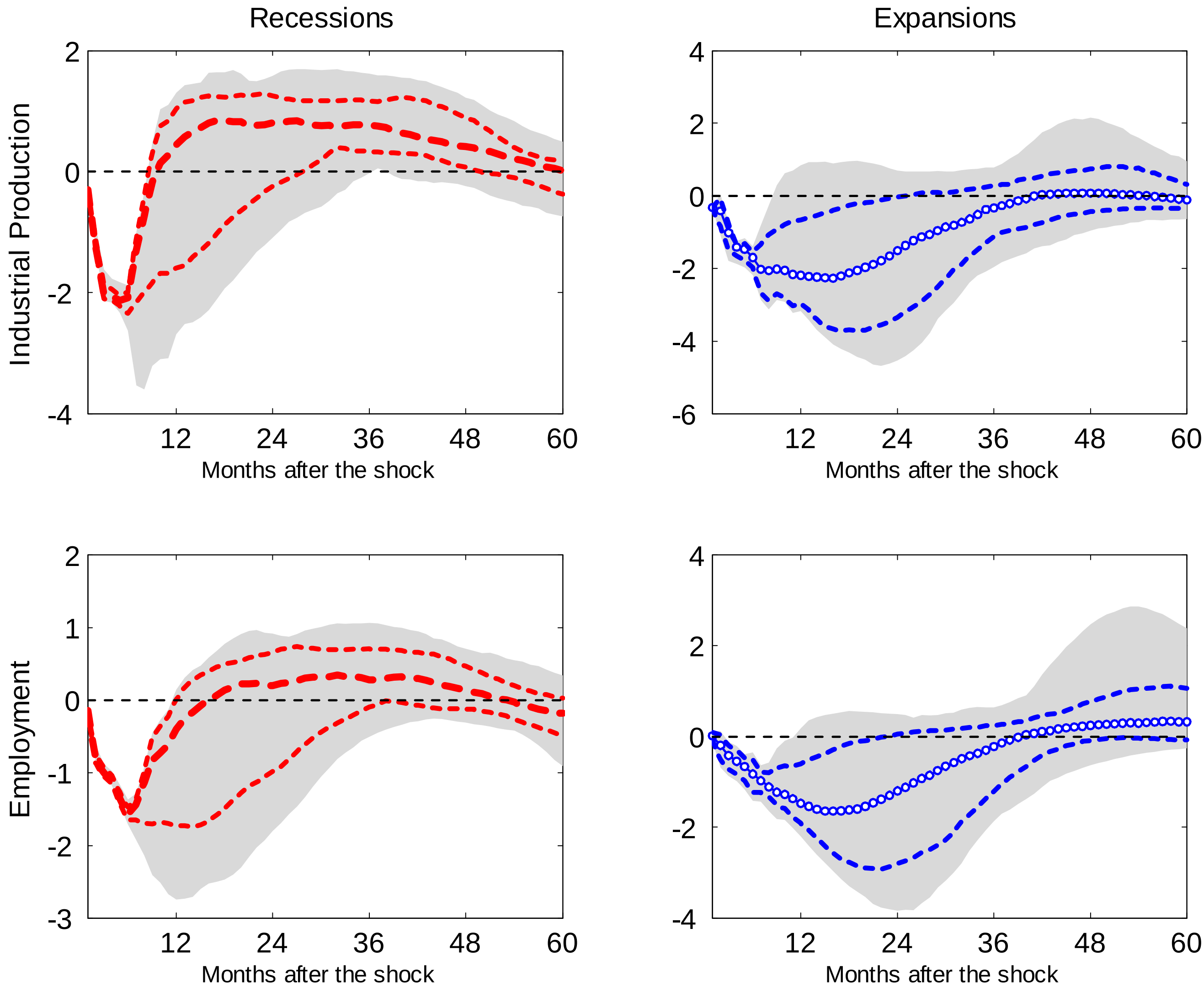

Figure A1. **Real Effects of Uncertainty Shocks: Exogenous dummy.** Uncertainty dummy constructed by considering extreme realizations of the VXO index related to terror, war, and oil events only. Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified 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.

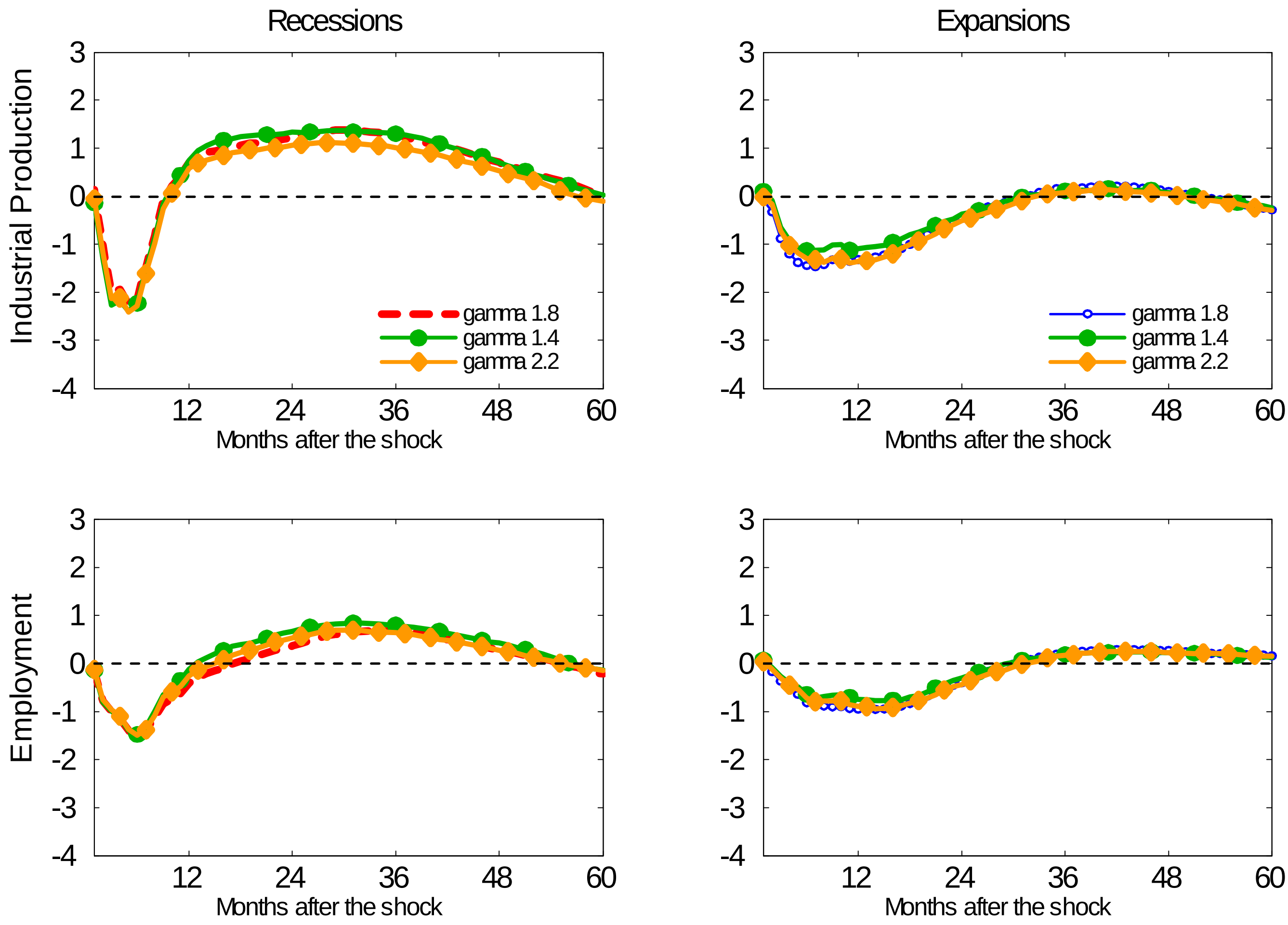

Figure A2. **Real Effects of Uncertainty Shocks: Different Calibrations of the Slope Parameters.** Impulse responses (median values) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed/blue dashed-circled lines: GIRFs conditional on $\gamma = 1.8$. Green lines: 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.

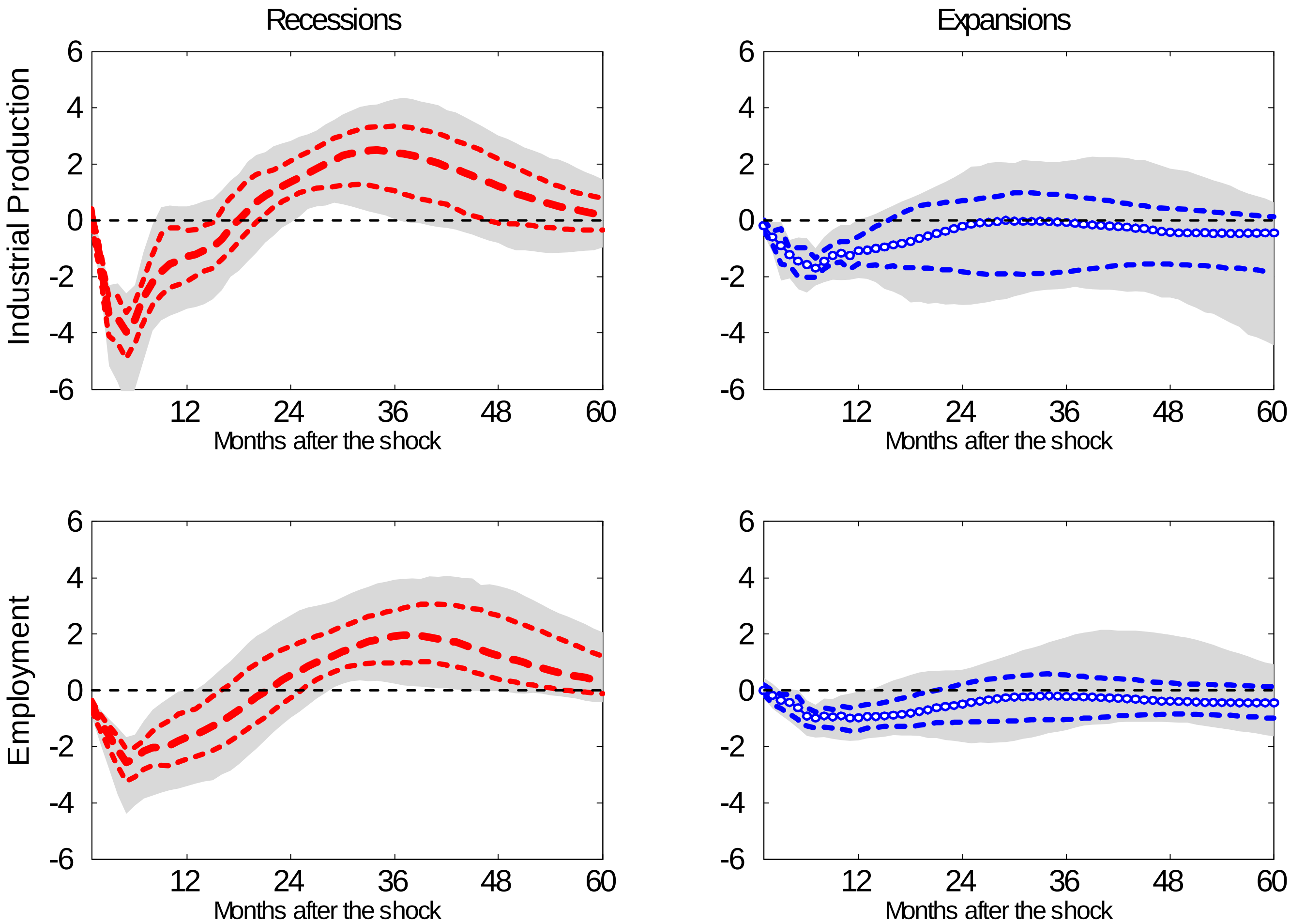

Figure A3. **Real Effects of Uncertainty Shocks: Unemployment as transition indicator.** Unemployment added to our baseline model and employed and transition indicator. Realizations of unemployment above (below) 6.5% are associated to recessions (expansions). Impulse responses (median values and confidence 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.

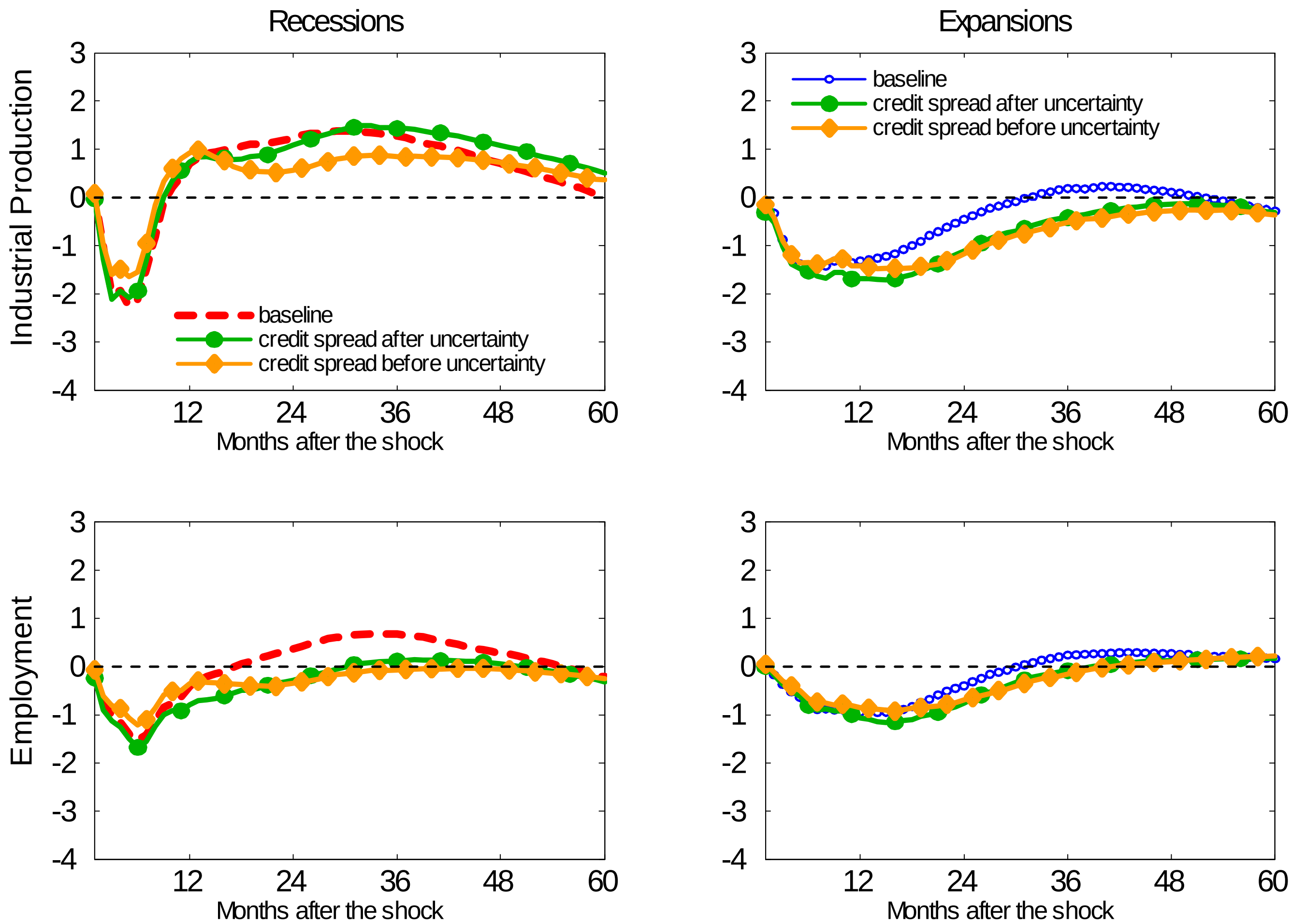

Figure A4. **Real Effects of Uncertainty Shocks: Role of Credit Spreads.** Median impulse responses to a one-standard deviation uncertainty in scenarios without/with credit spreads. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (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.

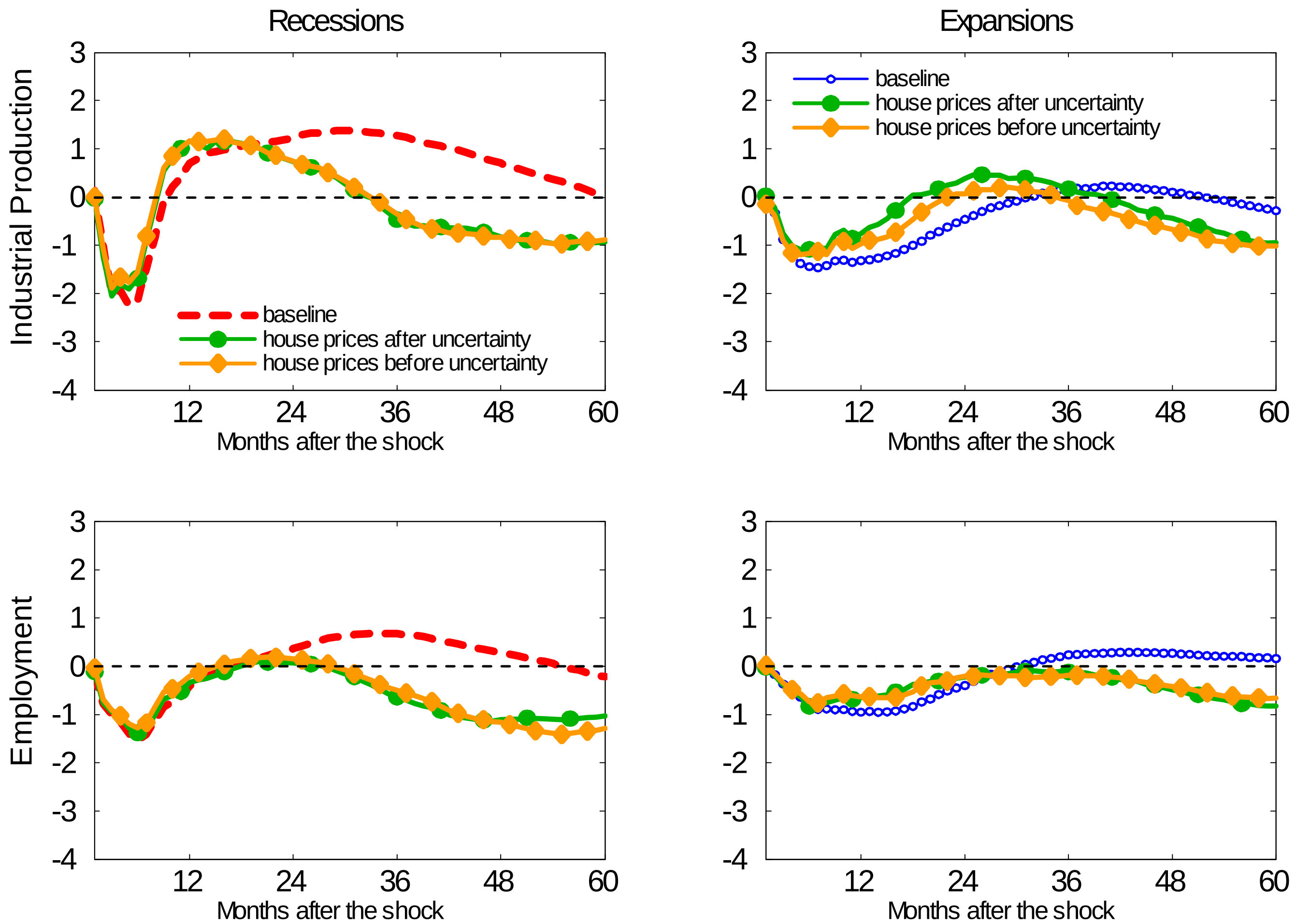

Figure A5. **Real Effects of Uncertainty Shocks: Role of House Prices.** Median impulse responses to a one-standard deviation uncertainty in scenarios without/with real house price index. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (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.

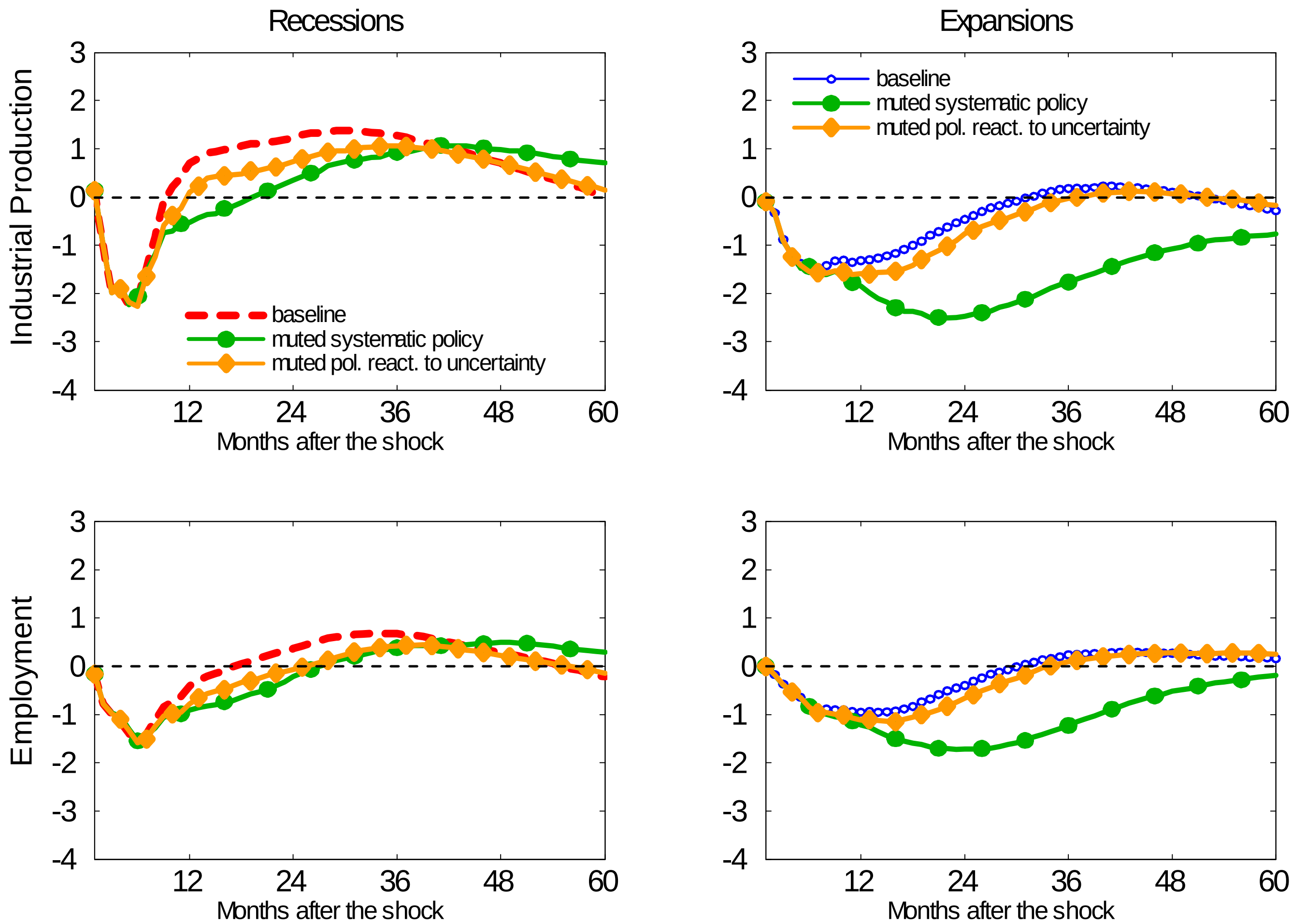

Figure A6. **Real Effects of Uncertainty Shocks: Role of Systematic Monetary Policy.** Median impulse responses to a one-standard deviation uncertainty in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR 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.

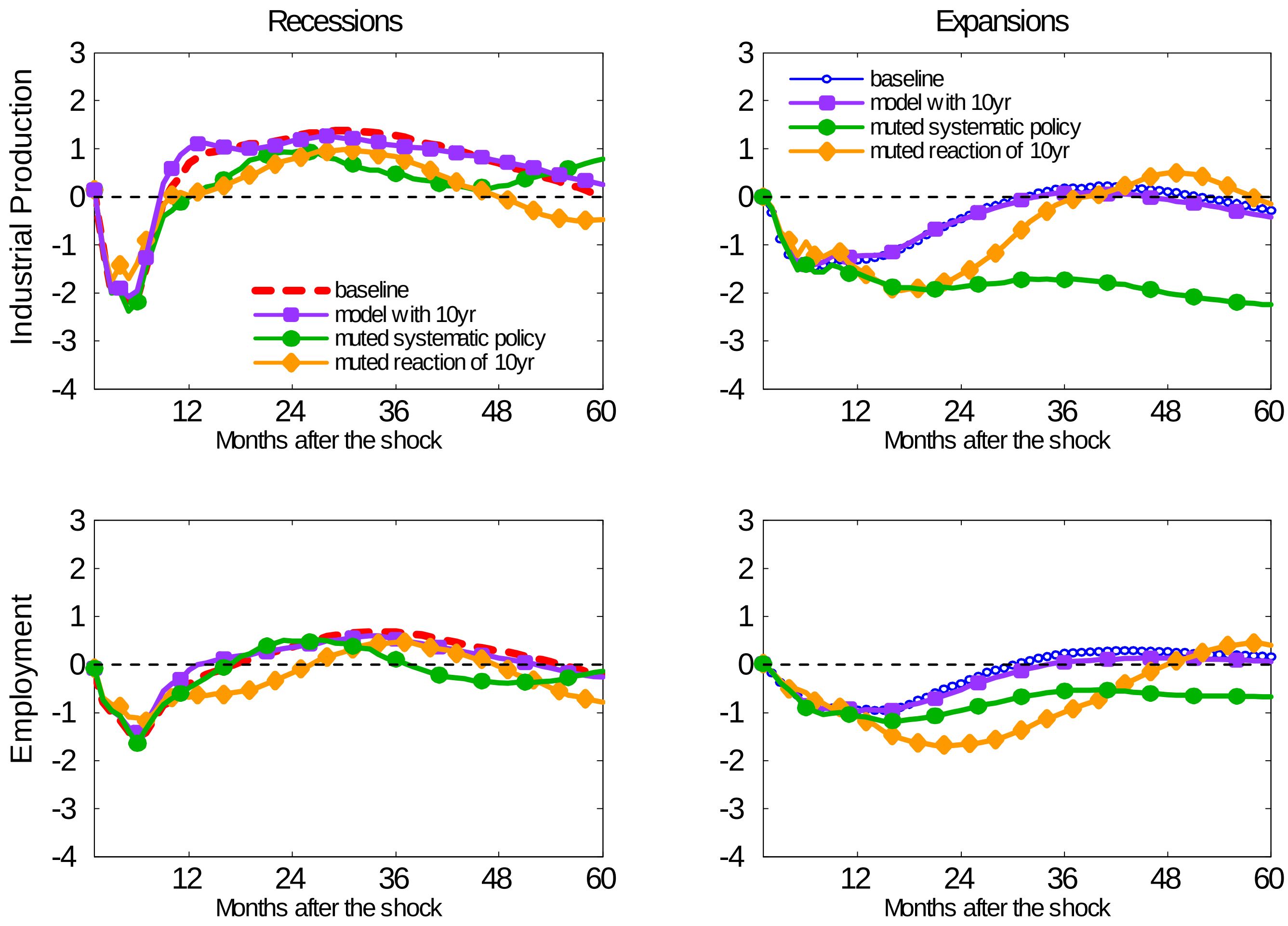

Figure A7. **Real Effects of Uncertainty Shocks: Role of Short- and Long-term Interest Rates.** Median impulse responses to a one-standard deviation uncertainty in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed with the baseline Smooth-Transition 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.