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Uncertainty and Monetary Policy in Good and Bad Times

Abstract

We investigate the role played by systematic monetary policy in tackling the real effects of uncertainty shocks in U.S. recessions and expansions. We model key indicators of the business cycle with a nonlinear VAR that allows for different dynamics in busts and booms. Uncertainty shocks are identified by focusing on historical events that are associated to jumps in financial volatility. Uncertainty shocks hitting in recessions are found to trigger a more abrupt drop and a faster recovery in real activity than in expansions. Counterfactual simulations suggest that the effectiveness of systematic monetary policy in stabilizing real activity is greater in expansions. Finally, we provide empirical and narrative evidence pointing to a risk management approach by the Federal Reserve.

JEL-Codes: C320, E320.

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

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1 Introduction

Uncertainty shocks have recently been identified as one of the drivers of the U.S. business cycle (Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014), Leduc and Liu (2016), Jurado, Ludvigson, and Ng (2015), Basu and Bundick (2016)). This paper investigates the relationship between uncertainty shocks and monetary policy. It does so by addressing three different but related questions: Are the effects of uncertainty shocks different in good and bad times? Is the stabilizing power of systematic monetary policy in response to uncertainty shocks state-contingent? Do monetary policymakers respond to movements in uncertainty *per se*? We answer these questions 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 potential 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 which occur in expansions could 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 a "volatility effect" (Bloom (2009)).[1]

Our focus on nonlinearities is justified by two important stylized facts. First, most macroeconomic aggregates display asymmetric behavior over the business cycle (see, among others, Sichel (1993), Koop and Potter (1999), van Dijk, Teräsvirta, and Franses (2002), Caggiano and Castelnuovo (2011), Morley and Piger (2012), Abadir, Caggiano, and Talmain (2013), and Morley, Piger, and Tien (2013)). Second, uncertainty features different dynamics in good and bad 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). Moreover, different indicators of realized volatility, often taken as a proxy for expected volatility in empirical analysis, are

[1] In Bloom's (2009) model, the "volatility effect" is due to the fact that an uncertainty shock translates into an increase in the realized volatility of business conditions in the medium-term. The latter leads high productive firms to invest and hire, and low productive ones to disinvest and fire. Given that the majority of firms is clustered around the hiring and investing thresholds due to labor attrition and capital depreciation, this reallocation of resources causes a temporary increase in aggregate production and employment.

documented to be higher and more volatile in recessions (Bloom, 2014, 2017).[2] In light of this evidence, one might expect uncertainty shocks to exert different macroeconomic effects over the business cycle. A recent theoretical paper by Cacciatore and Ravenna (2015) offers support to this intuition. Working with a model featuring matching frictions in the labor market, Cacciatore and Ravenna (2015) find that deviations from the efficient wage-setting due to such frictions, combined with downward wage rigidities, imply a state-dependent amplification of the real effects of uncertainty shocks and contribute to make uncertainty countercyclical. Empirical support to this conjecture is provided by Caggiano, Castelnuovo, and Groshenny (2014), Nodari (2014), Ferrara and Guérin (2015), Casarin, Foroni, Marcellino, and Ravazzolo (2016), and Caggiano, Castelnuovo, and Figueres (2017). Our investigation complements these ones by unveiling the interactions between uncertainty shocks and systematic monetary policy in different phases of the business cycle.

Following Bloom (2009), the identification of uncertainty shocks pursued in this paper relies on "extreme events", i.e., events which are associated to large jumps in the VXO. These events are likely to be informative as regards unexpected movements in uncertainty which are not associated to the business cycle. We offer an interpretation to each of these jumps in uncertainty based on historical events. Moreover, we document the concerns expressed by members of the Federal Open Market Committee (FOMC) in discussions about monetary policy setting in the aftermath of these events. Hence, we see these events as valid instruments to overcome the endogeneity problem one faces when searching for exogenous variations in uncertainty. We anticipate here that our results are robust to the employment of the VXO *per se* as an indicator of uncertainty in our STVAR as well as to the construction of an alternative event dummy based on the financial uncertainty proxy recently constructed by Ludvigson, Ma, and Ng (2016).

Our focus on financial proxies of uncertainty is justified both theoretically and empirically. From a theoretical standpoint, Basu and Bundick (2016) show that movements in a measure of financial uncertainty which is conceptually in line with the VIX can be an important driver of the business cycle in a microfounded macroeconomic model of the business cycle. Empirically, recent findings by Ludvigson, Ma, and Ng (2016) and Casarin, Foroni, Marcellino, and Ravazzolo (2016) point to movements in financial uncertainty as possibly exogenous to the business cycle and able to explain a larger share

[2] 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 than those occurring in good times.

of real activity's forecast error variance than movements in real activity indicators of uncertainty.[3]

Are the effects of uncertainty shocks different in good and bad times? We find compelling evidence in favor of a positive answer. Real activity, measured by industrial production and employment, falls much more quickly and sharply when uncertainty shocks hit the economy during recessions. Moving to the reaction of nominal variables, uncertainty shocks are found to be deflationary, especially in recessions. The response of the policy rate is substantially more marked during economic downturns. Importantly, the difference in the estimated responses in the two states - recessions, expansions - is found to be statistically significant as regards real activity, prices, and the policy rate.

We next investigate whether the effectiveness of systematic monetary policy in stabilizing the business cycle after an uncertainty shock is state-dependent. To shed light on this issue, we run a counterfactual exercise in which systematic monetary policy is assumed not to react to macroeconomic fluctuations due to uncertainty shocks. We find the effectiveness of systematic monetary policy in tackling uncertainty shocks to be different in recessions and expansions. In bad times, the short-run response of real activity turns out to be virtually unaffected, while the medium-run response of real activity is only mildly influenced by changes in the nominal interest rate. Differently, our simulations suggest that a muted (i.e., non expansionary) monetary policy would induce a much deeper and longer-lasting downturn after an uncertainty shock occurring in expansions.

Finally, we dig deeper on the systematic relationship between uncertainty and monetary policy by running counterfactual simulations in which the policy rate is assumed not to respond to movements in uncertainty in our VAR. This is done to understand to what extent the Federal Reserve acted, borrowing the terminology proposed by Greenspan (2004), as a "risk manager", i.e., it set the nominal interest rate lower than what it would have done in absence of uncertainty. The counterfactual policy rate obtained by shutting down the reaction of the federal funds rate to uncertainty in our model is found to be systematically higher than the historical one in the aftermath of abrupt increases

[3] Carriero, Clark, and Marcellino (2016) model a large dataset of macroeconomic and financial variables and jointly compute the impact of macroeconomic and financial uncertainty shocks on such variables. They find that macroeconomic uncertainty has a large and significant effect on real activity, but has a limited impact on financial variables. Differently, financial uncertainty has an impact on both financial and macroeconomic indicators. Given the presence of variables such as the S&P500 index, the federal funds rate, and - in a robustness check - a long-term interest rate, our focus on the effects of financial uncertainty shocks is also intended to maximize the likelihood of capturing the real effects of financial uncertainty shocks via movements in financial markets.

in uncertainty. The gap between the historical federal funds rate and the counterfactual one, which we term "risk management-driven policy rate gap", confirms that elements of risk management importantly characterized monetary policy decisions in the 1962-2008 sample we analyze. This empirical evidence squares well with the narrative evidence we provide based on our reading of the FOMC minutes. Importantly, and in line with our previous findings, the risk management-driven policy rate gap is found to be larger in recessions. Our VAR also suggests that, absent the risk-management policy element, we would have observed a lower level of industrial production and a higher price level in the post-WWII U.S. period.

Our evidence on the risk management approach followed by the Federal Reserve is consistent with the results recently put forth by Evans, Fisher, Gourio, and Krane (2015). They estimate several Taylor rules and find evidence in favor of a systematic response of the federal funds rate to a number of different uncertainty indicators. Then, they corroborate their empirical findings with excerpts of the FOMC minutes that point to uncertainty as one of the elements systematically considered by the U.S. policymakers for determining the U.S. monetary policy. Our paper reaches a similar result via counterfactual simulations conducted with a multivariate VAR framework which accounts for second round effects involving the policy rate, uncertainty, and several measures of real economic activity, as well as through the reading of the FOMC minutes covering the period 1962-2008.

From a modeling standpoint, our results support the development and use of microfounded nonlinear frameworks able to replicate both the contractionary effects and the different transmission mechanism of uncertainty shocks over the business cycle. Policy wise, our findings offer support to research investigating how to efficiently tackle the state-dependent effects of such shocks.

The paper develops as follows. Section 2 discusses connections with the existing literature. Section 3 presents our nonlinear framework and the data employed in the empirical analysis. Section 4 documents the nonlinear effects of uncertainty shocks and discusses a number of robustness checks. Section 5 analyzes the role of systematic monetary policy in recessions and expansions, quantifies to which extent uncertainty systematically affects the policy rate setting, and offers narrative evidence in favor of risk management by the Federal Reserve. Section 6 concludes.

2 Connections with existing literature

A recent strand of the literature has dealt with the measurement of uncertainty. Bachmann, Elstner, and Sims (2013) use survey data to compute measures of forecast disagreement which proxy time-varying business level uncertainty for Germany and the United States. Rossi and Sekhposyan (2015, 2016) propose uncertainty indices based on the location of the real GDP forecast errors with respect to the sample distribution of the forecast errors of the same variable. Jurado, Ludvigson, and Ng (2015), Ludvigson, Ma, and Ng (2016), and Carriero, Clark, and Marcellino (2016) build up measures of uncertainty based on the (un)predictability of several macroeconomic and financial indicators. Baker, Bloom, and Davis (2016) develop an index of economic policy uncertainty which reflects the frequency of keywords related to economic concepts, uncertainty, and policy decisions in a set of leading newspapers. Scotti (2016) constructs a proxy for uncertainty based on Bloomberg forecasts which aims at capturing agents' uncertainty surrounding current realizations of real economic activity. Our papers focuses on events that are instrumental for the identification of exogenous variations in a financial uncertainty indicator.

Our contribution relates to other papers on the relationship between uncertainty and monetary policy. Caggiano, Castelnuovo, and Pellegrino (2016) study the effects of uncertainty shocks in normal times and during the zero lower bound period. They find that uncertainty shocks affect more strongly real activity when the bound is binding. With respect to them, we focus on a period during which monetary policy was conventional and investigate the business-cycle dependence of the effects of uncertainty shocks on real activity as well as nominal indicators. Hence, our paper is complementary to Caggiano, Castelnuovo, and Pellegrino (2016). A related paper is Alessandri and Mumtaz (2014), who investigate the effects of uncertainty shocks in presence of high/low financial stress. Differently, our conditioning variables are indicators of the business cycle. Moreover, our paper has a focus on the effectiveness of systematic monetary policy along the business cycle. A different strand of the literature analyzes the effects of monetary policy shocks in recessions/expansions - see, e.g., Weise (1999), Mumtaz and Surico (2015), and Tenreyro and Thwaites (2016) - or in presence of high/low uncertainty, as Aastveit, Natvik, and Sola (2013), Eickmeier, Metiu, and Prieto (2016), and Pellegrino (2017a,b). Our paper deals with a set of different questions, i.e., the impact of uncertainty shocks conditional on a given stance of the business cycle and a given systematic monetary policy conduct. Gnabo and Moccero (2015) find that risks in the inflation outlook and in financial markets are a more powerful driver of monetary policy regime changes in the U.S. than the level of inflation and the output gap. Our paper complements their study by investigating the ability of systematic monetary policy to stabilize the U.S. macroeconomic environment after an uncertainty shock.

Our findings on the weaker effectiveness of systematic monetary policy can also be interpreted via 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 changes in factor prices when uncertainty is high because of the dominant relevance of "wait-and-see" effects. Vavra (2014) and Baley and Blanco (2015) show that higher uncertainty generates higher aggregate price flexibility, which in turn 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. This dampens the response of aggregate durable consumption to aggregate shocks, including policy changes. Our findings are also in line with the empirical result put forth by Mumtaz and Surico (2015), who estimate the interest rate semi-elasticity in a state-dependent IS curve for the United States to be lower during recessions.

From a policy standpoint, our results offer support to the discussion on how to face uncertainty shocks. Blanchard (2009) proposes to design policies aimed at removing 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 (2016) find that policies that are unclear, hyperactive, or both, may raise uncertainty. In presence of zero nominal rates, Basu and Bundick (2015) find that uncertainty about future shocks may endogenously arise if state-dependent policies, and in particular forward guidance, are not engineered to exit the zero lower bound, while Evans et al. (2015) and Seneca (2016) show that, in presence of uncertainty on future economic conditions, it is optimal to delay the liftoff of the policy rate. Our evidence on the asymmetric effects of uncertainty shocks and on the effectiveness of systematic monetary policy adds to this literature by suggesting that policymakers should evaluate the possibility of implementing state-dependent policy responses, possibly close to first-moment policies in expansions, but clearly different from them in recessions.

3 Modeling nonlinear effects of uncertainty shocks

We estimate the impact of uncertainty shocks on real economic outcomes via a nonlinear VAR framework modeling eight U.S. macroeconomic indicators. The vector of 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.[4] All variables are in logs, except the uncertainty dummy, 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 over 1.65 standard deviations above the mean, and 0 otherwise. This indicator function is employed to ensure that identification comes from large, and likely to be exogenous, jumps in financial uncertainty which are unlikely to represent systematic reactions to business cycle movements. Given that we base our identification strategy on these well-known uncertainty-inducing events, the effects documented in this paper should be seen as responses to extreme jumps in uncertainty more than a characterization of the general effects of uncertainty in the economy.[6]

We use monthly data covering the period July 1962-June 2008. We cut the sample in June 2008 to avoid modeling the period that started with Lehman Brothers' bankruptcy and the acceleration of the 2007-09 financial crisis in September 2008. Such acceleration led the Fed to quickly drop the federal funds rate to zero (December 2008), and maintain such rate at that level until December 2015. We interpret this period as a third regime, the modeling of which would render the estimation of our nonlinear framework problematic.

[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 investigations that disentangle the effects of risk and uncertainty, see Bekaert, Hoerova, and Lo Duca (2013) and Rossi, Sekhposyan, and Soupre (2016).

[5]Unlike Bloom (2009), we do not Hodrick-Prescott (HP) filter these variables (other than the VXO). As shown by Cogley and Nason (1995), HP-filtering may induce spurious cyclical fluctuations, which may bias our results. However, exercises conducted with HP-filtered variables as in Bloom (2009) 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]Working with linear VARs, Furlanetto, Ravazzolo, and Sarferaz (2014) identify uncertainty shocks using sign restrictions, while Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016) adopt a penalty approach. We leave the investigation of the properties of these approaches in a nonlinear STVAR context to future research.

Figure 1 reports the VXO series used to construct the dummy variable 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, an evidence in line with the one summarized by Bloom (2014).

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

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

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

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

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

In this model, $F(z_{t-1})$ is a logistic transition function which captures the probability of being in a recession, γ is the smoothness parameter, z_t is a transition indicator, $\boldsymbol{\Pi}_R$ and $\boldsymbol{\Pi}_E$ are the VAR coefficients capturing the dynamics 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 $\boldsymbol{\Omega}_t$, where $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$ 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) and Caggiano, Castelnuovo, and Figueres (2017), 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 describing the economy in bad times and the other one in good times. 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, i.e., large (small) values of γ imply abrupt (smooth) switches from a regime to another.[7] The linear model à la Bloom (2009) is a special case of the STVAR, obtained

[7] A simpler, alternative approach would be that of adding an interaction term involving uncertainty

when $\gamma = 0$, which implies $\mathbf{\Pi}_R = \mathbf{\Pi}_E = \mathbf{\Pi}$ and $\mathbf{\Omega}_R = \mathbf{\Omega}_E = \mathbf{\Omega}$. We make sure that the residuals of the uncertainty dummy equation are orthogonal to the other residuals of the estimated VAR 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. This ordering assumes that shocks inducing movements in variables which are ordered after the uncertainty dummy do not contemporaneously affect such dummy, an assumption which is consistent with that of exogeneity of the spikes of the VXO identified with the strategy described at the beginning of this Section. More in general, this assumption is also consistent with the recent theoretical analysis by Basu and Bundick (2016) on the very mild effect exerted by first moment shocks as regards financial volatility. The inclusion of the SP500 index right before our uncertainty indicator is meant to control for the impact of stock market levels on financial volatility.

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) use a standardized moving-average of the quarterly real GDP growth rate as transition indicator. Our paper deals with monthly data. Similarly to Caggiano, Castelnuovo, and Figueres (2017), we employ a standardized backward-looking moving average involving twelve realizations of the month-to-month growth rate of industrial production.[8] Another important choice is the calibration of the smoothness parameter γ, whose estimation is affected by well-known identification issues (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 to match the frequency 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 $\Pr(F(z_t) \geqslant 0.86) \approx 0.14$.[9] This metric implies $\gamma = 1.8$.

and an indicator of the business cycle to the otherwise linear model à la Bloom (2009). The resulting Interacted-VAR would have the potential to discriminate between responses to uncertainty in recessions/expansions. We prefer to model a Smooth-Transition VAR for two reasons. First, it does not require us to take a stand on the features of the interaction term (e.g., number of lags, timing of the cross-products). Second, it is much less prone to instabilities, a problem often affecting Interacted-VARs when involving interaction terms of order two or higher (for a discussion, see Mittnik, 1990).

[8] Section 4.3 discusses the robustness of our results to the employment of the unemployment rate as transition indicator.

[9] 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

Figure 2 plots the transition function $F(z)$ for the U.S. post-WWII sample and superimposes the NBER recessions dating. It is important to notice two facts about our transition probability. First, it peaks with a slight delay relative to the NBER recessions. This is due to the choice of using a backward-looking transition indicator. This choice enables us to compute the transition probability by using observed values of industrial production, rather than predicted ones as a centered moving average would require. 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 the regime switches occurring in the two subsamples 1962-1983 and 1984-2008. The calibration of our slope parameter for the two periods reads, 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. All in all, our transition probability tracks well the downturns of the U.S. economy.

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

We estimate both the linear VAR model and the nonlinear STVAR framework with six lags, a choice supported by standard information criteria as regards the linear version of the VAR model, for which an extensive literature on optimal lag selection in VARs is available. Given the high nonlinearity of the model, we estimate it by employing the Markov-Chain Monte Carlo simulation method proposed by Chernozhukov and Hong

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

(2003).[10] The estimated model is then employed to compute GIRFs to an uncertainty shock.[11]

4 Results

Uncertainty shocks: Response of real activity. 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 in recessions and expansions along with 68% confidence bands.[12] These variables react negatively and significantly no matter what the phase of the business cycle one considers is. However, such responses are clearly asymmetric along the business cycle. In recessions, the peak short-run response of industrial production is about -2.5%, while that of employment is about -1.5%. The same values in expansions read, respectively, -1.5% and -0.9%. As shown below, these differences are statistically significant. Hence, we find evidence in favor of an asymmetric response of real activity to uncertainty shocks along the business cycle.

Our results are in line with recent contributions by Caggiano, Castelnuovo, and Groshenny (2014), Nodari (2014), Ferrara and Guérin (2015), Casarin, Foroni, Marcellino, and Ravazzolo (2016), and Caggiano, Castelnuovo, and Figueres (2017), who also find that uncertainty shocks have a larger effect on real activity when they hit during recessionary periods. Moreover, this evidence is robust to a variety of robustness checks, including: i) a different identification of uncertainty shocks alternatively based

[10] In principle, one could estimate the STVAR model we deal with via maximum likelihood. However, since the model is highly nonlinear 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 industrial production 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.

[12] The size of the shock in all scenarios is normalized to induce an on-impact response of uncertainty equal to one as in Bloom (2009). Nonlinear VAR impulse responses may depend on the size of the shock (as well as its sign and initial conditions). Simulations conducted to investigate the role of the size of the shock in shaping our impulse responses suggest that such role is negligible in our analysis.

on a dummy which focuses on events associated with terror, war, or oil events; the use of the VXO per se; the use of an alternative dummy which identifies extreme events conditional on the one-month ahead financial uncertainty indicator recently developed by Ludvigson, Ma, and Ng (2016); ii) different calibrations of the slope parameters of our logistic function; iii) the use of unemployment as transition indicator; iv) the use of control variables such as credit spreads, house prices, and a long-term interest rate. In all cases, we find that the evidence of 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. For the sake of brevity, a detailed documentation and discussion of these robustness exercises is provided in our Appendix.

Uncertainty shocks: Systematic monetary policy response. We now turn to studying the response of systematic monetary policy to an uncertainty shock. The asymmetric reaction of real activity documented above could lead to an asymmetric policy response and, therefore, a stronger reaction of the federal funds rate in recessions. However, a stronger reaction of the policy rate in recessions could also be justified by an asymmetric price response. We then study the response of prices on top of that of the federal funds rate to shed light of the relevant sources of the potential asymmetric response of the policy rate.

Figure 4 shows the effects of an uncertainty shock on the federal funds rate and the price level. An uncertainty shock triggers a negative reaction of prices which is statistically significant in recessions only. Prices go down and then gradually return to their pre-shock level. The interest rate goes down significantly, both in recessions and expansions. However, in terms of dynamics and quantitative response, the difference in the two states is remarkable. When an uncertainty shock hits the economy in good times, the interest rate goes down of about 0.8 percentage points at its peak, and the reaction is short-lived. When an uncertainty shock hits in a recession, the policy rate goes down to about two percentage points, and remains statistically significant for a prolonged period of time. The impulse responses associated to recessions offer clear support to the view put forward by Basu and Bundick (2016) and Leduc and Liu (2016) that uncertainty shocks act as demand shocks.

Statistical significance of the differences documented above. The evidence proposed so far points to differences in the response of real and nominal indicators to an uncertainty shocks when quantified in recessions vs. expansions. How relevant is this result from a statistical standpoint? Figure 5 contrasts the responses of industrial production, employment, prices, and the federal funds rate in recessions vs. expansions using 68% confidence intervals surrounding the response of the difference for each variable. Bottom line: Industrial production, employment, and the federal funds rate react significantly more in recessions to uncertainty shocks. Differently, we do not find significant evidence in favor of an asymmetric reaction of prices to an uncertainty shock. Hence, from a statistical standpoint, the more aggressive systematic policy reaction estimated in recessions must be driven by the response of real activity. In the rest of the paper we will then focus on the responses of industrial production and employment with the aim of understanding if the Federal Reserve's systematic policy was more effective - in terms of business cycle stabilization - in recessions or expansions.

5 Uncertainty and monetary policy

5.1 Systematic monetary policy effectiveness

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 uncertainty shocks? Would the recessionary effects of such shocks have been magnified? Answering these questions is key to understand the role that conventional monetary policy can play in tackling the negative effects triggered by sudden jumps in uncertainty. We then employ our STVAR and run a counterfactual simulation designed to answer these questions. Our counterfactual exercise 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.[13]

Figure 6 contrasts the dynamic reactions of real activity conditional on a muted systematic policy response with the baseline ones. Remarkably, the effectiveness of this counterfactual policy response is much lower in recessions. In other words, the recession is estimated to be almost as severe as the one which occurs when policymakers are allowed to lower the policy rate. Notably, the difference between the baseline and the

[13] We do so by zeroing the coefficients of the federal funds rate equation in our VAR. For a paper running counterfactual simulations by implementing perturbations of the coefficients of the policy rule in a VAR model, see Sims and Zha (2006). 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".

counterfactual scenarios mainly regards the speed with which real activity recovers and overshoots before going back to the steady state. Possibly, this is due to the lags via which monetary policy affects the real economy. A different picture emerges when our counterfactual monetary policy is implemented in good times. As Figure 6 shows, when the policy rate is kept fixed, industrial production goes down markedly (about -3% at its peak) and persistently, remaining statistically below zero for a prolonged period of time (for all 20 quarters according to 68% confidence bands).[14] 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.

5.2 Interpreting policy (in)effectiveness in recessions

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, the "wait-and-see" behavior becomes optimal for a larger number of firms, compared to normal times. If the real option value of waiting is high, firms become 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, 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, 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 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.

Very differently, a muted (non counter-cyclical) monetary policy is found to exert a

[14] The baseline and counterfactual scenarios produce similar responses for the first few months after the shock. This is due to the relevance of initial conditions, which is dominant during the first periods. In fact, initial conditions heavily influence the evolution of the transition indicator and, therefore, the probability of being in a recession. Different systematic policies take time before importantly affecting the economic system and, consequently, the value of the logistic function in our STVAR. However, as periods go by, different policies clearly exert a different impact on the evolution of the economic system, above all in expansions.

big influence (above all in the short run) to the downturn triggered by uncertainty shocks in expansions. If the option value of waiting due to uncertainty is lower in expansions, firms are more reactive to changes in factor prices. Hence, if the nominal interest rate remains unchanged, firms' investment is likely to be lower. Consequently, uncertainty shocks trigger stronger recessionary effects in absence of systematic monetary policy interventions.

These findings line up with those in 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 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). Our results complement Vavra's (2014) and Baley and Blanco's (2015), because we show that the systematic component of monetary policy is less effective in recessions, when uncertainty is higher.

Berger and Vavra (2015) 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, macroeconomic 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 Weise (1999), Aastveit, Natvik, and Sola (2013), Mumtaz and Surico (2015), Tenreyro and Thwaites (2016), Eickmeier, Metiu, and Prieto (2016), and Pellegrino (2017a,b), who also find monetary policy to be less powerful in periods of high uncertainty or, more generally, during recessions. In particular, Mumtaz and Surico (2015) show 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. Given the tight link between the IS schedule (which refers to the consumption/saving decisions by households) and 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.

5.3 Risk management by the Federal Reserve

The evidence provided so far shows that uncertainty shocks trigger a response by monetary policy makers, and that such response is particularly strong during recessions. But what role did uncertainty *per se* play as far as the U.S. monetary policy setting is concerned? In analyzing the conduct of monetary policy under his regime, Greenspan (2004, pp. 36-37) states that

> *"[...] The Federal Reserve's experiences over the past two decades make it clear that uncertainty is not just a pervasive feature of the monetary policy landscape; it is the defining characteristic of that landscape. [...] the conduct of monetary policy in the United States has come to involve, at its core, crucial elements of risk management."*

While being consistent with Greenspan's statement, the impulse response analysis documented in Section 4.1 does not necessarily point to a *systematic* monetary policy reaction to uncertainty *per se*. Second round effects, working via the impact that uncertainty shocks exerted on real activity and prices in our sample, represent an alternative, not mutually exclusive, potential explanation for the response of the policy rate to uncertainty shocks. It is then of interest to shed further light on whether the Federal Reserve reacted to movements in uncertainty *per se*, therefore acting as a "risk manager", or rather it simply reacted to movements in real activity and prices induced by uncertainty shocks. To isolate the systematic response of the Federal Reserve to variations in uncertainty, we proceed in two steps. First, we run a counterfactual simulation to produce what we label "risk management-driven policy rate gap". This gap is constructed by computing the difference between the observed federal funds rate and the counterfactual policy rate that, according to our nonlinear VAR, we would have observed if the Federal Reserve had not systematically reacted to uncertainty in our sample. Evidence of a negative gap would point to a higher interest rate in absence of systematic policy response to uncertainty. Hence, it would be consistent with the claim that the Federal Reserve acted as a "risk manager". As a second step, we refer to the minutes of the FOMC meetings to see whether there is narrative evidence in favor of risk management.

Risk management: Empirical evidence. Figure 7 plots the difference between the historical and the counterfactual federal funds rate. The counterfactual policy rate is computed by muting the response of the federal funds rate to contemporaneous and lagged realizations of uncertainty in our VAR. Given that we consider all shocks hitting the economic system, the factual scenario (the one which does allow for the estimated systematic response of the federal funds rate to contemporaneous and past realizations of uncertainty) just replicates the historical realizations of the federal funds rate. Two observations are in order. First, after the realization of an uncertainty shock, the contemporaneous difference between the historical rate and the counterfactual one turns out to be negative. This suggests that, in absence of systematic monetary policy response to uncertainty, the federal funds rate would have been higher in the aftermath of spikes in uncertainty. Second, the gap between the historical and the counterfactual policy rates, which has an average value of about -16 basis points, is found to be much wider in recessions, with an average value of about -48 basis points and peaks often larger than 100 basis points (in absolute value). By contrast, the average realization conditional on expansions is found to be -11 basis points. Consistently, the correlation between the "risk management-driven policy rate gap" and the NBER recession dummy is clearly negative, and reads -0.31. Finally, our counterfactual exercise also points to a non-negligible quantitative effect of this risk-management approach on industrial production and prices. As documented in Table 1, the deviations of the historical realizations with respect to the "no risk-management" ones point to a higher level of industrial production - on average, 0.66%, and a lower price level - on average, about 0.3%. Differently, not much change would have emerged as regards employment.[15] Focusing on recessions, industrial production is estimated to be 0.50% higher on average, while the price level is 0.41% lower. In expansions, these numbers read 0.69% and 0.28%, respectively. This analysis is conditional on all shocks hitting the economic system, which is something conceptually different from an impulse-response analysis. However, the indication of a lower push for industrial production by systematic monetary policy in recessions is in line with our previous impulse-response-related findings on a systematic monetary policy which is largely ineffective during economic downturns.

[15] The counterfactual paths of these variables modeled with our VAR, not shown here for the sake of brevity, are documented in our Appendix available upon request.

Our empirical analysis assigns a role to uncertainty as a driver of the U.S. monetary policy decisions. We now link this empirical evidence to the narrative evidence which emerges from the reading of the FOMC minutes.

Risk management: Narrative evidence. The reading of the FOMC minutes confirms that uncertainty was an element carefully considered by the members of the FOMC when deciding over the federal funds rate setting. Table 1 collects excerpts from the FOMC minutes with references to uncertainty, risk, and risk management undertaken by the U.S. monetary policymakers in correspondence of each of the jumps in uncertainty we analyze. The selected excerpts provide ample and convincing evidence pointing to uncertainty as one of the ingredients explicitly considered by FOMC members when setting monetary policy. To ease the reading of the information collected in Table 1, we highlight some of the most informative examples below.

Uncertainties related to external events like the first oil crisis and the Arab-Israeli suggested to implement a cautious behavior at the end of 1973:

> *"[...] in light of current uncertainties regarding the economic outlook and the sensitive state of financial market psychology, current money market conditions be maintained for the time being."*

The Black Monday is a textbook example of an uncertainty-inducing event. In October 1987, the minutes report that

> *"[...] The Committee recognizes that still sensitive conditions in financial markets and uncertainties in the economic outlook may continue to call for a special degree of flexibility in open market operations".*

The risk management approach by the Federal Reserve appears evident also in the case of the Asian crisis, as the reading of the December 1997 minutes suggests:

> *"[...] While developments in Southeast Asia were not expected to have much effect on the U.S. economy, global financial markets had not yet settled down and further adverse developments could have greater-than-anticipated spillover effects on the ongoing expansion. In this environment, with markets still skittish, a tightening of U.S. monetary policy risked an oversized reaction. [...] At the conclusion of the Committee's discussion, all but one member supported a directive that called for maintaining conditions in reserve markets that were consistent with an unchanged federal funds rate of*

about 5-1/2 percent and that retained a bias toward the possible firming of reserve conditions and a higher federal funds rate during the intermeeting period."

Finally, the Gulf War event in 2003 again suggested to the Committee to carefully consider the related degree of uncertainty surrounding the future domestic economic outcomes, as suggested by the March minutes:

"[...] members commented that an unusually high degree of uncertainty had made it very difficult to assess the factors underlying the performance of the economy. [...] In light of these considerable uncertainties, the members agreed that heightened surveillance of evolving economic trends would be especially useful in the weeks ahead. [...] the Committee in the immediate future seeks conditions in reserve markets consistent with maintaining the federal funds rate at an average of around 1-1/4 percent."

Wrapping up, both our econometric results and the narrative evidence based on the FOMC minutes point to a risk management approach by the Federal Reserve. In periods of expectations of sustained future growth and inflationary pressures surrounded by high uncertainty, this risk management practice translated into a "wait-and-see" behavior, i.e., the liftoff of the policy rate to tackle nascent inflation was postponed to collect more information about the state of the economy (e.g., the response to the 1997 uncertainty shock related to the Asian crisis). Differently, expectations of a gloomy economic scenario in a high uncertainty environment led the FOMC to implement larger decreases of the policy rate than those that the Federal Reserve would have been implemented in absence of uncertainty (e.g., the decisions taken after the 1990 first Gulf War shock and after the 9/11 attack).[16]

The attention paid by the FOMC to uncertainty and the consequent risk-management approach in setting the policy rate have also been documented in a recent paper by Evans, Fisher, Gourio, and Krane (2015). They also identify and discuss excerpts

[16] Interestingly, our evidence is also in line with the following recent statement by Janet Yellen (Chairman of the Federal Reserve): *"The recovery from the Great Recession has advanced sufficiently far, and domestic spending appears sufficiently robust, that an argument can be made for a rise in interest rates at this time. We discussed this possibility at our meeting. However, in light of the heightened uncertainties abroad and a slightly softer expected path for inflation, the Committee judged it appropriate to wait for more evidence, including some further improvement in the labor market, to bolster its confidence that inflation will rise to 2 percent in the medium term."* (FOMC Press Conference Opening Statement, September 17, 2015).

of the FOMC minutes which reveal the attention paid by the Committee members on uncertainty triggered by national and international factors. Then, they assess the statistical and economic relevance of risk management by the U.S. monetary policy makers by constructing judgemental and automatic (keyword-based) indicators using the minutes of the FOMC meetings as database. Finally, they use these indicators, along with a number of other proxies for uncertainty, to estimate augmented Taylor rules, in which all these measures of uncertainty are included one at a time on top of inflation and output. Evans et al. (2015) find evidence pointing to a significant and negative contemporaneous response of the Federal Reserve to uncertainty in the period 1987-2008. Hence, their evidence suggests that the Federal Reserve adopted a looser policy in presence of uncertainty. Our VAR dynamic analysis and our narrative-based investigation point exactly to the same qualitative conclusion.[17]

6 Conclusions

This paper quantifies the effects of uncertainty shocks in good and bad times and investigates the role that monetary policy plays in tackling such shocks. Using a nonlinear VAR model, we show that the contractionary effects of uncertainty shocks are much stronger when they hit the economy during recessions, compared to non recessionary times. Counterfactual simulations conducted to assess the role of systematic monetary policy in our framework point 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. Our empirical findings lend support to theoretical models like those developed by Vavra (2014), Berger and Vavra (2015), and Baley and Blanco (2015), which predict a reduced ability by monetary policymakers to influence output in presence of high uncertainty. Finally, we provide empirical and narrative evidence in favor of a risk management-type of behavior by the Federal Reserve. Uncertainty about future economic outcomes affected the decisions taken by the Fed-

[17] To understand how quantitatively close our results are to Evans et al.'s (2015), we conduct the following exercise. We estimate their Taylor rule over the sample 1987Q1-2008Q2 by allowing for a nonlinear response of the policy rate in NBER recessions/expansions to uncertainty, which is proxied by the VXO. Then, we produce the "Taylor rule-consistent risk-management policy rate gap" by taking the difference between the historical policy rate and the one produced by sticking to historical values of core inflation, the output gap, and (lagged realizations of) the policy rate, in a version of the Taylor rule conditional on a zero response to uncertainty. The resulting Taylor rule-policy rate gap: i) displays large realizations (in absolute terms) in recessions, and ii) points to a value as large as 114 basis points in 2001Q4. Details on the derivation of the Taylor rate gap are documented in our Appendix.

eral Open Market Committee, which acted as a risk manager hedging against downside risks. This induced the U.S. policymakers to keep the federal funds rate lower than what suggested by inflation and output when spikes in uncertainty occurred to insure against adverse outcomes. Our evidence, which is based on counterfactual simulations conducted with our multivariate nonlinear VAR model, lines up with the one proposed in a recent paper by Evans, Fisher, Gourio, and Krane (2015) and Seneca (2016), who work with augmented Taylor rules. This empirical evidence is corroborated by narrative evidence coming from the minutes of the FOMC meetings.

Overall, our findings support a research agenda aiming at identifying state-dependent frictions able to induce different dynamic responses to structural shocks in recessions and expansions. In terms of stabilization policies, high uncertainty is found to reduce the sensitivity of output to stimulus interventions, above all in recessions. 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, Bloom, and Davis (2016) point to the role of clear policy communication and steady policy implementation. Basu and Bundick (2015) find that in economies characterized by a binding zero lower bound the inability of the central bank to tackle adverse shocks may contribute to increase uncertainty about future shocks and lead to severe contractions. They advocate the use of state-dependent policies, and in particular forward guidance, to exit the zero lower bound. Evans et al. (2015) and Seneca (2016) show that it is optimal to delay the liftoff of the policy rate when expectations of improving future economic conditions are surrounded by uncertainty. Our results suggest that policy prescriptions like those proposed by these authors should be carefully assessed in order to exit phases characterized by severe economic conditions in presence of high uncertainty.

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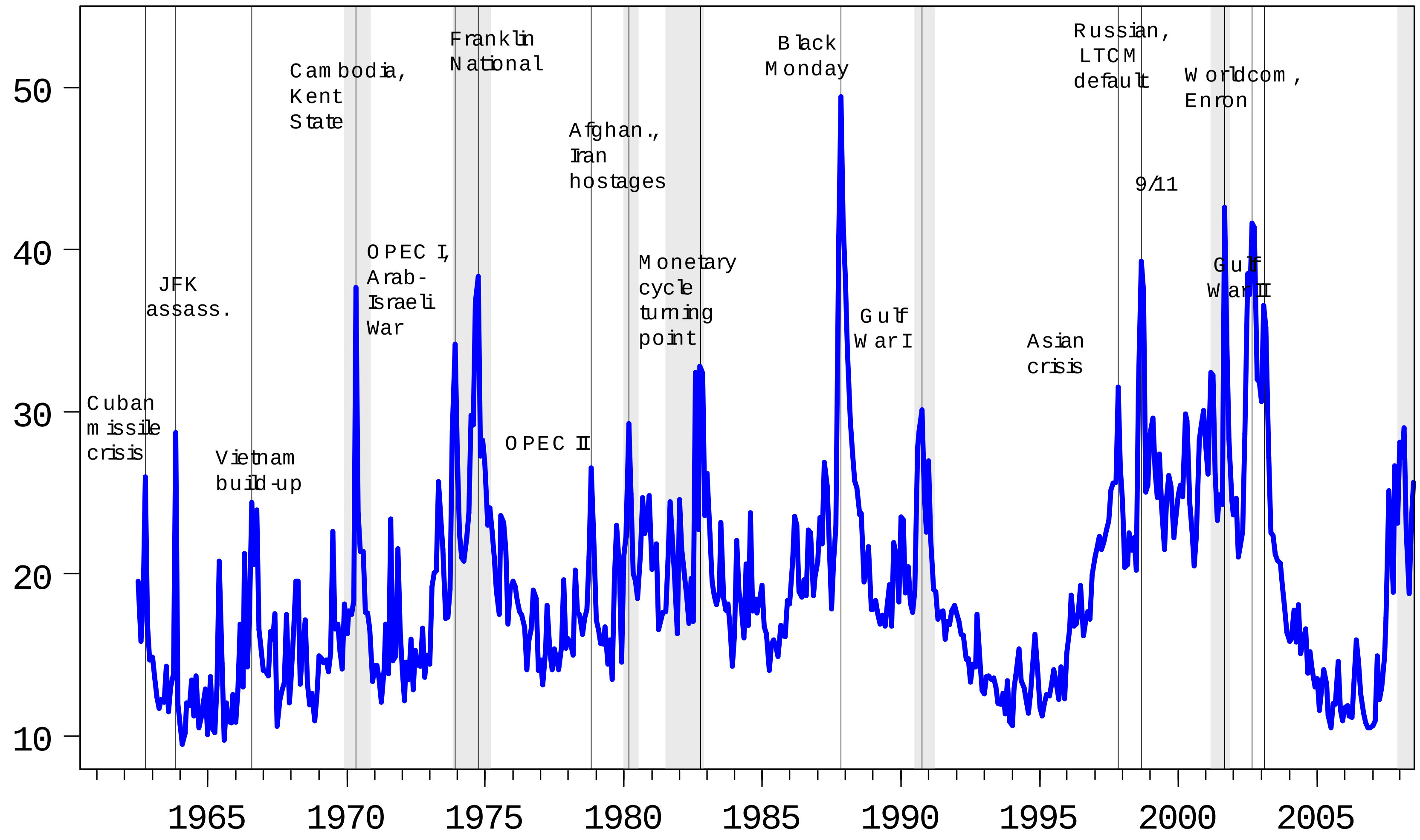

Figure 1: **Uncertainty shocks and the business cycle.** Sample: 1962M7-2008M6. Blue line: U.S. stock market volatility. Shaded areas: NBER recessions. U.S. stock market volatility: Chicago Board of Options Exchange VXO index of implied volatility (on a hypothetical at the money Standard and Poor's 100 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).

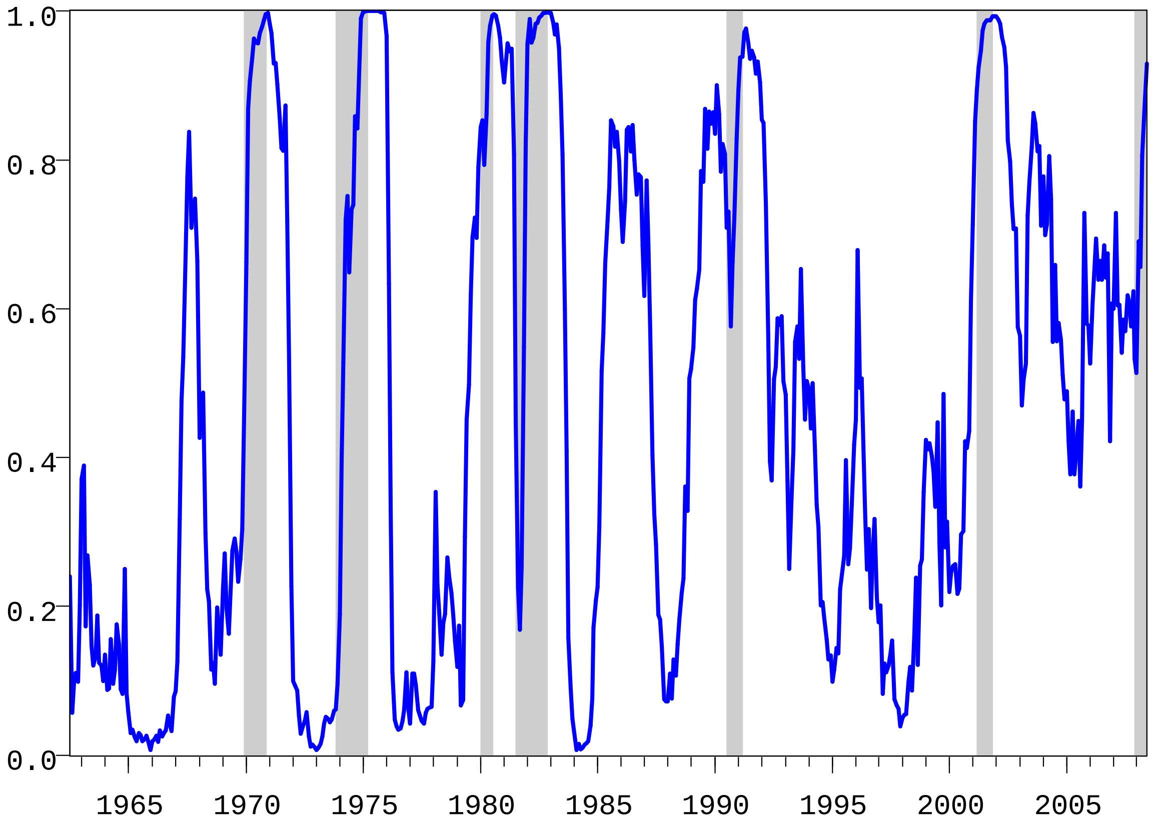

Figure 2: **Probability of being in a recessionary phase.** Blue line: Transition function F(z). Shaded columns: NBER recessions. Transition function computed by employing the standardized moving average (12 terms) of the month-on-month growth rate of industrial production.

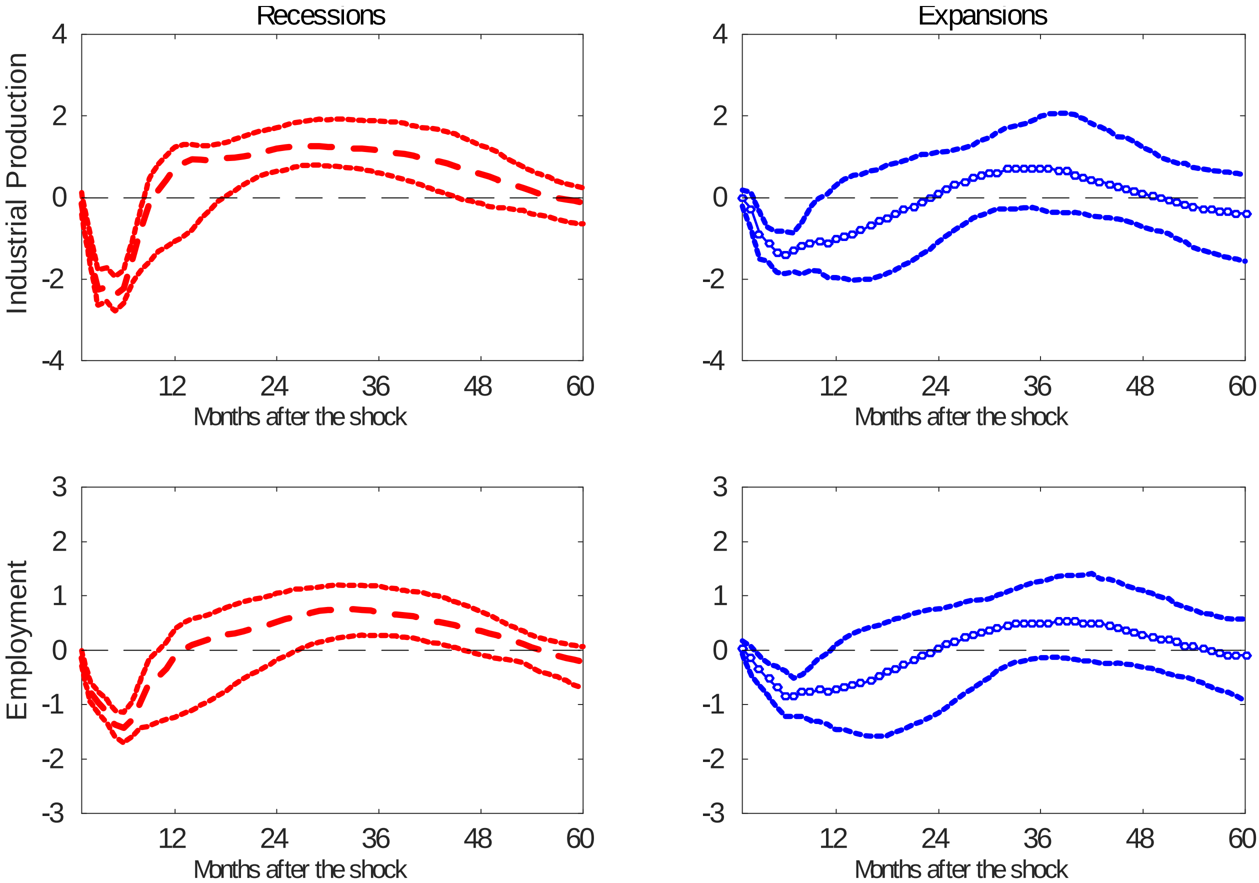

Figure 3: **Real Effects of Uncertainty Shocks: Good and Bad Times.** Impulse responses (median values) to an uncertainty shock inducing an on-impact reaction of uncertainty equal to one as in Bloom (2009). Uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands. Markov-Chain Monte Carlo simulations to estimate the VAR coefficients based on 50,000 draws.

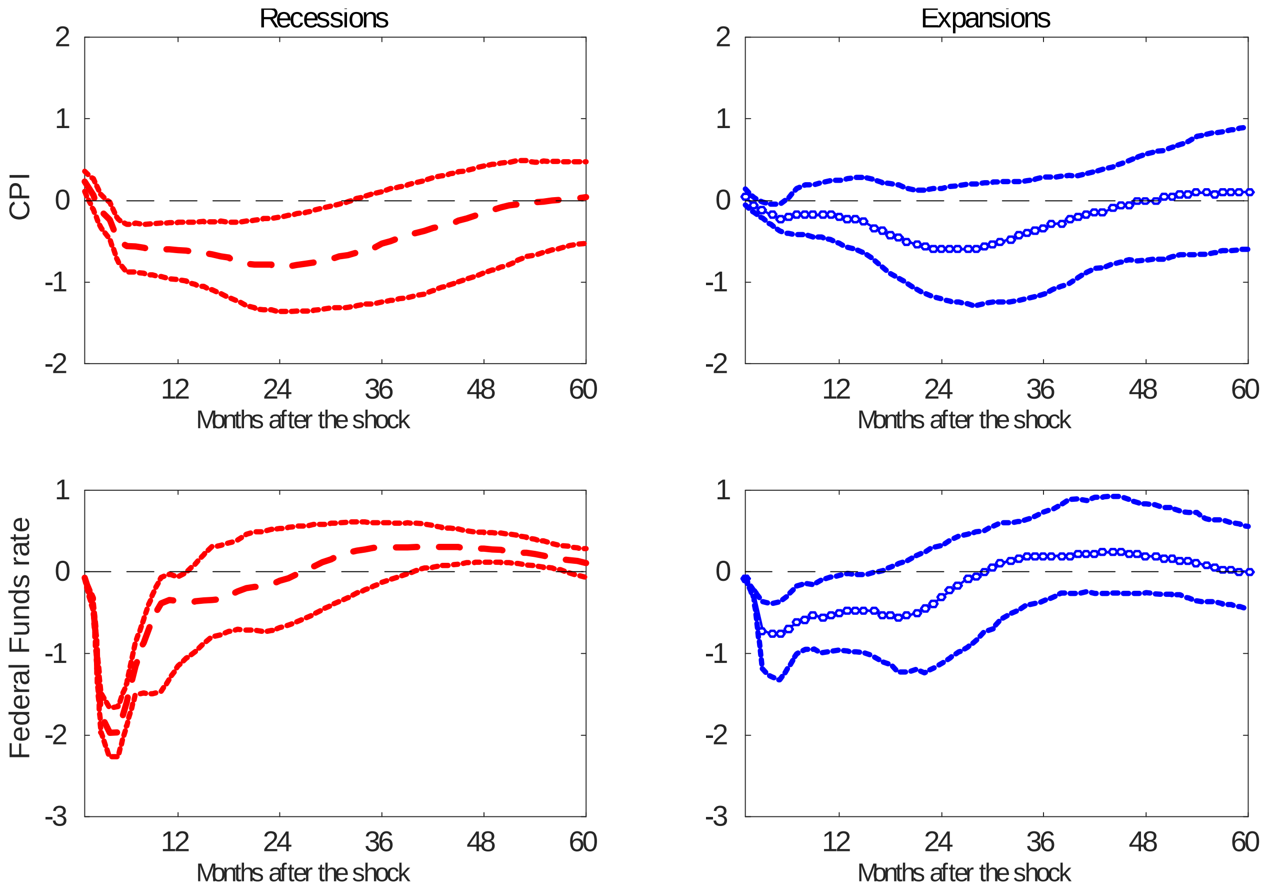

Figure 4: **Effects of Uncertainty Shocks on Prices and Policy Rate: Role of Nonlinearities.** Impulse responses (median values) to an uncertainty shock inducing an on-impact reaction of uncertainty equal to one as in Bloom (2009). Uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands. Markov-Chain Monte Carlo simulations to estimate the VAR coefficients based on 50,000 draws.

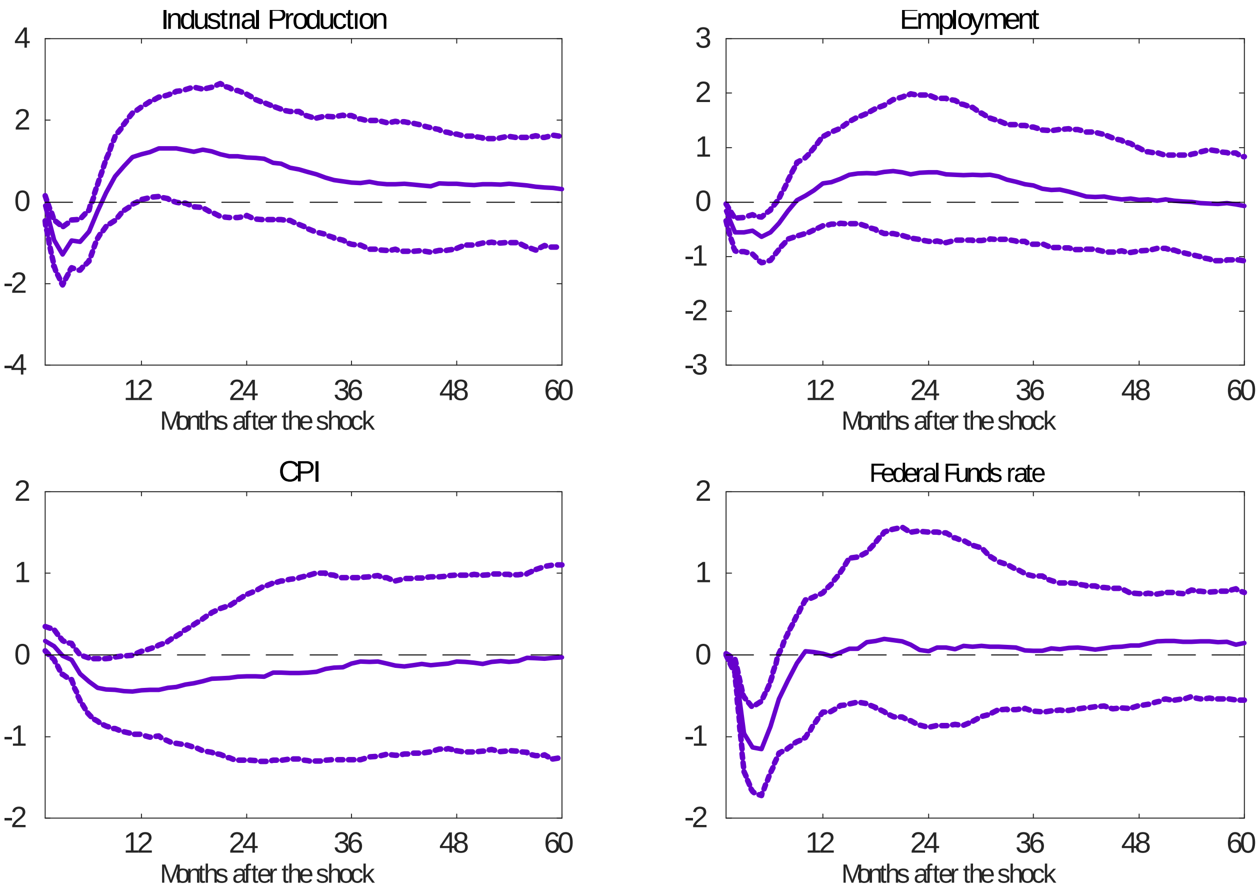

Figure 5: **Effects of Uncertainty Shocks: Differences between Recessions and Expansions.** Differences between generalized median impulse responses in busts and booms to an uncertainty shock inducing an on-impact reaction of uncertainty equal to one as in Bloom (2009). Solid line: Median realizations. 68% confidence intervals identified via dotted lines. Uncertainty shock identified as described in the paper. Markov-Chain Monte Carlo simulations to estimate the VAR coefficients based on 50,000 draws.

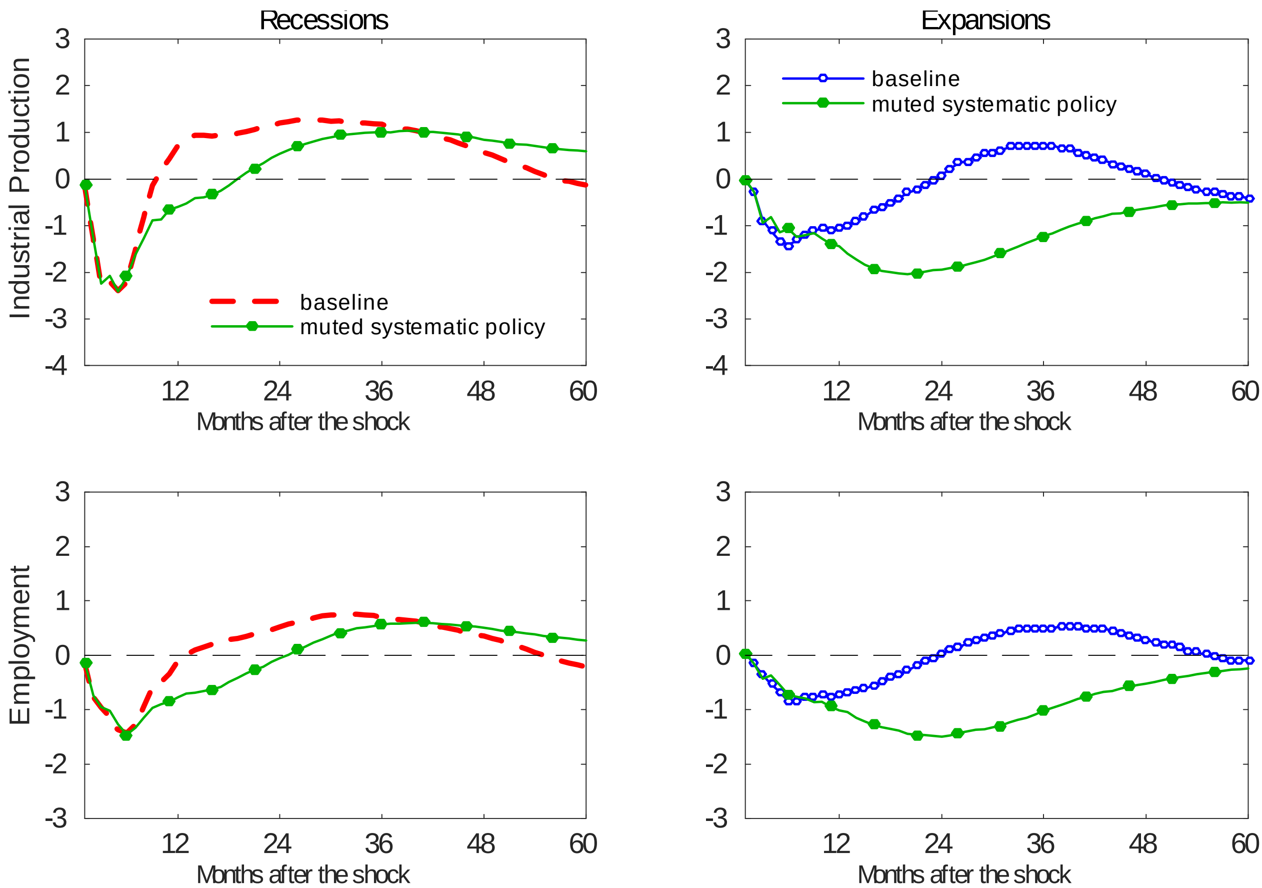

Figure 6: **Real Effects of Uncertainty Shocks: Role of Systematic Monetary Policy.** Median impulse responses to a one-standard deviation uncertainty in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR 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 coefficients based on 50,000 draws.

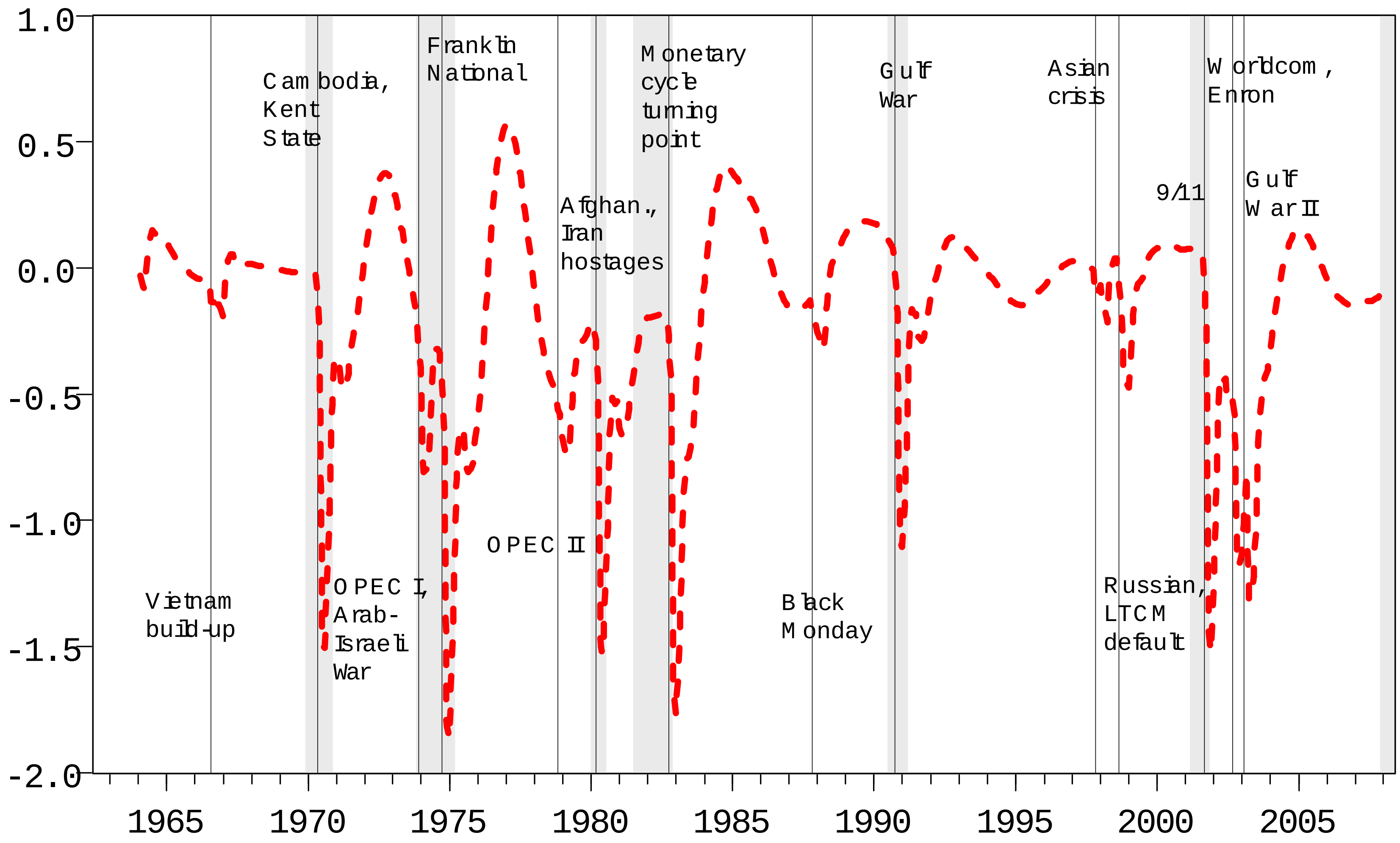

Figure 7: **Risk management-driven policy rate gap.** Sample: 1962M7-2008M6. Difference between the historical federal funds rate and the counterfactual federal funds rate computed by muting the systematic reponse of the policy rate to current and past realizations of uncertainty. Shaded areas: NBER recessions. Realizations of the counterfactual rate start in 1964M2 because of initial conditions (lags of the VAR, transition indicator of the logistic function).

Gap	*Full*	*Recess.*	*Expans.*
Federal funds rate	$-16bp$	$-47bp$	$-11bp$
Prices	-0.30%	-0.41%	-0.28%
Industrial Production	0.66%	0.50%	0.69%
Employment	-0.02%	-0.17%	-0.07%

Table 1: **Risk-managent by the Federal Reserve: Macroeconomic gaps.** Sample: 1964M2-2008M6. Gaps constructed by taking the difference between the historical realizations of each variable and their counterfactual values obtained by muting the systematic response of the policy rate to current and past realizations of uncertainty in our VAR. Federal funds rate: Difference expressed in basis points. Other variables: Percentage differences computed as log-deviations of the historical realizations with respect to the counterfactual, "no risk-management" values. Realizations of the counterfactual rate start in 1964M2 because of initial conditions (lags of the VAR, transition indicator of the logistic function).

Unc. shock	Reference	Statements
Cuban missile crisis	FOMC HM 10/23/'62	*"[...] With regard to policy, Mr. Swan [President of the Federal Reserve Bank of San Francisco] expressed the view that the uncertainties presented by the international situation, and in particular the Cuban crisis, ruled out doing anything at the moment except to maintain as even a keel as possible."*
Assassination of JFK	FOMC HM 12/03/'63	*"[...] there was little immediate effect that could be discerned, but that uncertainty had been introduced into the current economic and financial scene. [...] System open market operations shall be conducted with a view to cushioning any unsettlement that might arise in money markets stemming from the death of President Kennedy and to maintaining about the same conditions in the money market as have prevailed in recent weeks, while accommodating moderate expansion in aggregate bank reserves."*
Vietnam buildup	FOMC HM 08/23/'66	*"[...] in view of those developments, the substantially increased rate structure, and the market uncertainties that existed, it seemed to him [Mr. Swan, President of the Federal Reserve Bank of San Francisco] the Committee should not take further action to tighten irrespective of market forces."*
Cambodia, Kent State	FOMC MA 05/26/'70	*"[...] Attitudes in financial markets generally are being affected by the widespread uncertainties arising from recent international and domestic events [...] in view of current market uncertainties and liquidity strains, open market operations until the next meeting of the Committee shall be conducted with a view to moderating pressures on financial markets."*
OPEC I, Arab-Israeli War	FOMC RPA 12/17-18/'73	*"[...] On November 30, however, the available members of the Committee concurred in a recommendation by the Chairman that, in light of current uncertainties regarding the economic outlook and the sensitive state of financial market psychology, current money market conditions be maintained for the time being."*

Table 2: **References to uncertainty in FOMC meetings.** Source: Federal Open Market Committee: Transcripts and Other Historical Material (where not otherwise specified). Labels: FOMC HM: FOMC Historical Minutes, FOMC MA: FOMC Minutes of Actions, FOMC RPA: FOMC Record of Policy Actions, TIME: http://time.com/3479314/franklin-national-bank/ , FOMC CCT: FOMC Conference Call Transcript, FOMC M: FOMC Minutes.

Unc. shock	Source	Statements
Franklin National	TIME 08/10/'14	In 1974, as Franklin began to collapse, the Federal Reserve's strategy was to lend it money in order to buy time for a bigger strategy [...] *"The entire financial world,"* Arthur Burns, the chairman of the Federal Reserve Board, told TIME shortly after, *"can breathe more easily, not only in this country but abroad."*
OPEC II	FOMC RPA 12/19/'78	*"[...] The uncertainties in the current situation also provided the grounds for the proposal to base the Committee's objective for money market conditions altogether on the incoming evidence on the behavior of the monetary aggregates: It was suggested that whether fundamental economic conditions were strong or weak would inevitably become evident in renewal of rapid monetary expansion or in continuation of sluggish expansion, leading in either case to appropriate objectives for money market conditions."*
Afghanistan, Iran hostages	FOMC CCT 04/29/'80	*"[...] I [Mr. Forrestal, Vice President, Federal Reserve Bank of Atlanta] think the greater risk at this point, both domestically and internationally, would be to run the risk of underkill on inflation. Without any reduction of the inflation rate we'd be making a serious mistake if we didn't [show] some resistance at this point to a precipitous decline in interest rates. I think they've fallen enough already and I would like to see the Committee opt for resisting [further declines] at the 14 to 14-1/2 percent level, wait a week to see what happens, and consult again.."*
Monet. cycle turning point	FOMC RPA 08/24/'82	*"[...] The Committee decided that somewhat more rapid growth in the monetary aggregates would be acceptable depending upon evidence that economic and financial uncertainties were fostering unusual liquidity demands for monetary assets and were contributing to substantial volatility in interest rates."*

Table 1 (cont'd): **References to uncertainty in FOMC meetings.** Source: Federal Open Market Committee: Transcripts and Other Historical Material (where not otherwise specified). Labels: FOMC HM: FOMC Historical Minutes, FOMC MA: FOMC Minutes of Actions, FOMC RPA: FOMC Record of Policy Actions, TIME: http://time.com/3479314/franklin-national-bank/ , FOMC CCT: FOMC Conference Call Transcript, FOMC M: FOMC Minutes.

Unc. shock	Source	Statements
Black Monday	FOMC RPA 10/15-16/'87	*"[...]The Committee recognizes that still sensitive conditions in financial markets and uncertainties in the economic outlook may continue to call for a special degree of flexibility in open market operations."*
Gulf War I	FOMC RPA 12/18/'90	*"[...] Even under the assumption that the Persian Gulf situation would be more settled and oil prices lower, restoration of the degree of confidence needed to induce a substantial upturn in spending was not assured. [...] At the conclusion of the Committee's discussion, all of the members indicated that they could support a directive that called for some slight further easing in the degree of pressure on reserve positions [...]."*
Asian Crisis	FOMC M 12/11/'97	*"[...] The current momentum of the expansion, together with broadly supportive financial conditions and favorable business and consumer sentiment, suggested that economic growth was likely to be well maintained [...]. As a consequence, the members agreed that there remained a clear risk of additional pressures on already tight resources and ultimately on prices that could well need to be curbed by tighter monetary policy. But the members also focused on two important influences that were injecting new uncertainties into this outlook. Turmoil in Asian financial markets and economies would tend to damp output and prices in the United States. [...] The second influence was the apparently sharp increase in productivity in the second and third quarters. [...] At the conclusion of the Committee's discussion, all but one member supported a directive that called for maintaining conditions in reserve markets that were consistent with an unchanged federal funds rate of about 5-1/2 percent [...]."*

Table 1 (cont'd): **References to uncertainty in FOMC meetings.** Source: Federal Open Market Committee: Transcripts and Other Historical Material (where not otherwise specified). Labels: FOMC HM: FOMC Historical Minutes, FOMC MA: FOMC Minutes of Actions, FOMC RPA: FOMC Record of Policy Actions, TIME: http://time.com/3479314/franklin-national-bank/ , FOMC CCT: FOMC Conference Call Transcript, FOMC M: FOMC Minutes.

Unc. shock	Source	Statements
Russian, LTCM default	FOMC M 09/29/'98	*"[...] In a telephone conference held on October 15, 1998, the Committee members discussed recent economic and financial developments and their implications for monetary policy. Risk aversion in financial markets had increased further since the Committee's meeting in September, raising volatility and risk spreads even more, eroding market liquidity, and constraining borrowing and lending in a number of sectors of the financial markets. Although indications of any softening in the pace of the economic expansion across the country remained sparse, the widespread signs of deteriorating business confidence and evidence of less accommodative domestic financial conditions suggested that the downside risks to the expansion had continued to mount. [...] Against this background, a consensus emerged in favor of a 1/4 percentage point reduction in the federal funds rate [...]."*
9/11	FOMC M 11/06/'01	*"[...] The staff forecast prepared for this meeting emphasized the continuing wide range of uncertainty surrounding the outlook in the wake of the September attacks. The mild downturn in economic activity in the third quarter was seen as likely to deepen over the remainder of the year and to continue for a time next year. However, the cumulative easing that had occurred in the stance of monetary policy, coupled with the fiscal stimulus already in place and prospective additional measures, would provide support for economic activity. [...] However, the strength and timing of the eventual recovery remained subject to question especially in light of the marked degree of uncertainty that surrounded the prospects for further fiscal policy legislation, developments in the war against terrorism, and weakness in foreign economies. [...] In the Committee's discussion of policy for the intermeeting period ahead, all the members indicated that they could support a proposal calling for further easing in reserve conditions consistent with a 50 basis point reduction in the federal funds rate to a level of 2 percent."*
Worldcom, Enron	FOMC M 11/06/'02	*"[...] Business investment expenditures continued to be constrained by a high degree of uncertainty and related caution. [...] All the members indicated that, in light of the contemplated 50 basis point easing action, they could support a shift in the Committee's assessment of the risks to the economy from tilted toward economic weakness to balanced for the foreseeable future [...]."*

Table 1 (cont'd): **References to uncertainty in FOMC meetings.** Source: Federal Open Market Committee: Transcripts and Other Historical Material (where not otherwise specified). Labels: FOMC HM: FOMC Historical Minutes, FOMC MA: FOMC Minutes of Actions, FOMC RPA: FOMC Record of Policy Actions, TIME: http://time.com/3479314/franklin-national-bank/ , FOMC CCT: FOMC Conference Call Transcript, FOMC M: FOMC Minutes.

Unc. shock	Minutes	Statements
Gulf War II	FOMC M 03/18/'03	*"[...] The staff forecast prepared for this meeting continued to suggest that economic expansion would be muted for a time. Faced with the likely onset of war in the very near term and the large uncertainties relating to its aftermath, businesses and consumers were likely to hold down their spending. [...] In the Committee's discussion of current and prospective economic developments, members commented that an unusually high degree of uncertainty had made it very difficult to assess the factors underlying the performance of the economy. [...] In light of these considerable uncertainties, the members agreed that heightened surveillance of evolving economic trends would be especially useful in the weeks ahead. [...] the Committee in the immediate future seeks conditions in reserve markets consistent with maintaining the federal funds rate at an average of around 1-1/4 percent."*

Table 1 (cont'd): **References to uncertainty in FOMC meetings.** Source: Federal Open Market Committee: Transcripts and Other Historical Material (where not otherwise specified). Labels: FOMC HM: FOMC Historical Minutes, FOMC MA: FOMC Minutes of Actions, FOMC RPA: FOMC Record of Policy Actions, TIME: http://time.com/3479314/franklin-national-bank/ , FOMC CCT: FOMC Conference Call Transcript, FOMC M: FOMC Minutes.

Appendix of "Uncertainty and Monetary Policy in Good and Bad Times" by Giovanni Caggiano, Efrem Castelnuovo, Gabriela Nodari [not for publication]

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 and on our robustness checks. Finally, it presents some extra-results on the risk-management part of our paper.

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 Smooth Transition Vector AutoRegression with a single transition variable.

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

$$\mathbf{X}_t = \mathbf{\Theta}_0'\mathbf{Y}_t + \sum_{i=1}^{n} \mathbf{\Theta}_i'\mathbf{Y}_t z_t^i + \boldsymbol{\varepsilon}_t \tag{A1}$$

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:

$$\log L = const - \frac{1}{2}\sum_{t=1}^{T} \log|\boldsymbol{\Omega}_t| - \frac{1}{2}\sum_{t=1}^{T} \boldsymbol{\varepsilon}_t'\boldsymbol{\Omega}_t^{-1}\boldsymbol{\varepsilon}_t \qquad \text{(A2)}$$

where $\boldsymbol{\varepsilon}_t = \boldsymbol{X}_t - (1-F(z_{t-1})\boldsymbol{\Pi}_E\boldsymbol{X}_{t-1} - F(z_{t-1})\boldsymbol{\Pi}_R\boldsymbol{X}_{t-1}$ is the vector of residuals. Our goal is to estimate the parameters $\boldsymbol{\Psi} = \{\boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E, \boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$, where $\boldsymbol{\Pi}_j(L) = \left[\begin{array}{ccc} \boldsymbol{\Pi}_{j,1} & \ldots & \boldsymbol{\Pi}_{j,p} \end{array}\right]$, $j \in \{R, E\}$. We do so by conditioning on a given value for the slope parameter γ, which is calibrated as described in the text. The high nonlinearity 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.

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

Conditional on $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$, the model is linear in $\{\boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$. Then, for a given guess on $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$, the coefficients $\{\boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$ can be estimated by minimizing $\frac{1}{2}\sum_{t=1}^{T} \boldsymbol{\varepsilon}_t' \boldsymbol{\Omega}_t^{-1} \boldsymbol{\varepsilon}_t$. 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 $\boldsymbol{\varepsilon}_t = \boldsymbol{X}_t - \boldsymbol{\Pi} \boldsymbol{W}_t'$. 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

$$vec\boldsymbol{\Pi}' = \left(\sum_{t=1}^{T} \left[\boldsymbol{\Omega}_t^{-1} \otimes \boldsymbol{W}_t' \boldsymbol{W}_t\right]\right)^{-1} vec\left(\sum_{t=1}^{T} \boldsymbol{W}_t' \boldsymbol{X}_t \boldsymbol{\Omega}_t^{-1}\right). \tag{A3}$$

This procedure iterates over different sets of values for $\{\boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$ (conditional on a given value for γ). For each set of values, $\boldsymbol{\Pi}$ is obtained and the $logL$ (A2) 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 $\{\boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$ and then explore the robustness of the estimates to different values of γ. To ensure positive definiteness of the matrices $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$, we focus on the alternative vector of parameters $\boldsymbol{\Psi} = \{chol(\boldsymbol{\Omega}_R), chol(\boldsymbol{\Omega}_E), \boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$, 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 $\mathbf{\Theta}^{(0)}$ is computed by working with a second-order Taylor approximation of the model (1)-(4) (see the main text), 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 (A3).

Given a calibration for the initial (diagonal matrix) $\mathbf{\Omega}_\Psi$, a scale factor is adjusted 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. Checks performed with $N = 200,000$ draws delivered very similar results.

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 $p = 12$:[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:
$$\widehat{\mathbf{\Omega}}_{\lambda_i} = F\left(z_{\lambda i}\right)\widehat{\mathbf{\Omega}}_R + \left(1 - F\left(z_{\lambda_i}\right)\right)\widehat{\mathbf{\Omega}}_E, \tag{A4}$$

[2] The choice $p = 12$ is due to the number of moving average terms (twelve) of our transition variable z_t.

where $\widehat{\boldsymbol{\Omega}}_R$ and $\widehat{\boldsymbol{\Omega}}_E$ are obtained from the generated MCMC chain of parameter values during the estimation phase.[3] z_{λ_i} is the transition variable calculated for the selected history $\boldsymbol{\lambda}_i$.

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

$$\widehat{\boldsymbol{\Omega}}_{\lambda_i} = \widehat{\mathbf{C}}_{\lambda_i}\widehat{\mathbf{C}}'_{\lambda_i} \tag{A5}$$

and orthogonalize the estimated residuals to get the structural shocks:

$$\mathbf{e}^{(j)}_{\lambda_i} = \widehat{\mathbf{C}}^{-1}_{\lambda_i}\widehat{\boldsymbol{\varepsilon}}. \tag{A6}$$

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

$$\mathbf{e}^{(j)*}_{\lambda_i} = \left\{\mathbf{e}^{*}_{\lambda_i,t}, \mathbf{e}^{*}_{\lambda_i,t+1}, \ldots, \mathbf{e}^{*}_{\lambda_i,t+h}\right\}, \tag{A7}$$

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

6. Form another set of bootstrapped shocks which will be equal to $(A7)$ except for the k_{th} shock in $\mathbf{e}^{(j)*}_{\lambda_i,t}$ which is the shock we want to perturb by an amount equal to δ. Denote the vector of bootstrapped perturbed 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:

$$\widehat{\boldsymbol{\varepsilon}}^{(j)*}_{\lambda_i} = \widehat{\mathbf{C}}_{\lambda_i}\mathbf{e}^{(j)*}_{\lambda_i} \tag{A8}$$

and

$$\widehat{\boldsymbol{\varepsilon}}^{(j)\delta}_{\lambda_i} = \widehat{\mathbf{C}}_{\lambda_i}\mathbf{e}^{(j)\delta}_{\lambda_i}. \tag{A9}$$

8. Use $(A8)$ and $(A9)$ to simulate the evolution of $\mathbf{X}^{(j)*}_{\lambda_i}$ and $\mathbf{X}^{(j)\delta}_{\lambda_i}$ and construct the $GIRF^{(j)}(h, \delta, \lambda_i)$ 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 $GIRF^{(1)}(h, \delta, \lambda_i), GIRF^{(2)}(h, \delta, \lambda_i), \ldots, GIRF^{(B)}(h, \delta, \lambda_i)$. Set $B = 500$.

[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).

10. Calculate the GIRF conditional on history λ_i as

$$\widehat{GIRF}^{(i)}(h,\delta,\lambda_i) = B^{-1}\sum_{j=1}^{B} GIRF^{(i,j)}(h,\delta,\lambda_i). \tag{A10}$$

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 68% confidence bands for our impulse responses is undertaken by picking up, per each horizon of each state, the 16th and 84th percentile of the densities $\widehat{GIRF}^{([1:500],R)}$ and $\widehat{GIRF}^{([1:500],E)}$.

Robustness analysis

Identification of the financial uncertainty shock. Our baseline exercise is based on uncertainty shocks identified via events associated to large jumps in the VXO, which is our proxy of financial uncertainty. We verify the solidity of results to three departures with respect to this baseline scenario. First, we employ a different 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.[4] This is done in order to maximize the probability of handling a dummy associated to exogenous movements in financial uncertainty. Second, we consider the VXO *per se* in our VAR, and identify a financial uncertainty shock as an unpredictable movement of the VXO identified via a Cholesky decomposition of the variance-covariance matrix of the estimated VAR residuals. In this exercise, the VXO replaces the uncertainty dummy in the vector of variables we model. Hence, we assume that financial uncertainty shocks can affect

[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.

the economy contemporaneously, while shocks hitting the economic system (apart from the VXO and the S&P500 index) can hit the VXO only with a lag. As discussed before, this assumption is theoretically supported by the recent analysis conducted by Basu and Bundick (2016). Moreover, the assumption of exogeneity of the VXO is corroborated by a Granger-causality analysis conducted with two different bivariate VARs. In particular, we model the vectors $[indpro, VXO]'$ and $[empl, VXO]'$, where VXO, $indpro$, and $empl$ stand for (respectively), the log of industrial production, the log of employment, and the VXO index. At any conventional level, these bivariate VARs point to i) strong evidence against the null hypothesis that the VXO does not Granger-cause real activity, and ii) no evidence against the null hypothesis that real activity Granger-cause the VXO. Third, we compute an "extreme event dummy" by following the same identification strategy presented in Section 2 but considering the one-month ahead financial uncertainty indicator recently developed by Ludvigson, Ma, and Ng (2016). Figure A1 plots the impulse responses of industrial production and employment conditional on these alternative indicators of uncertainty, and contrasts such responses with the baseline ones. The baseline results turn out to be robust.

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 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 re-estimate 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 check the robustness of our baseline results to the employment of the unemployment rate in place of the growth rate of industrial production as transition indicator. Following the modeling choice in Ramey and Zubairy (2016), we classify periods in which the unemployment rate is over (under) 6.5% as recessionary (expansionary). In doing this exercise, we calibrate the slope parameter $\gamma = 1.7$ to match the 14% frequency of recessions in the sample as classified by the NBER. 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 Zakrajšek (2016) provide empirical evidence in favor of larger real effects of uncertainty shocks in periods of high financial stress. A way to control for the presence of time-varying financial risk is to include a measure of credit spread in our VAR. Gilchrist and Zakrajšek (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. The original version of the GZ spread is available from 1973. Our baseline analysis starts in 1962. Then, we regress the GZ spread against the difference between i) the AAA corporate bonds and the 10-year Treasury yield; ii) the BAA corporate bonds and the 10-year Treasury yield; iii) the 6-month T-Bill rate and the 3-month T-Bill rate; iv) the 1-year Treasury yield and the 3-month T-Bill rate; v) the 10-year Treasury yield and the 3-month T-Bill rate. We do this for the sample 1973-2008, and then we use the fitted values of the regression to backcast the GZ spread and match our baseline sample. All data are taken from the Federal Reserve Bank of St. Louis' database. We then add this measure of credit 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 Lo 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. (2016), 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, especially 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.[5] As before, two alternative orderings are considered, one in which the house price index is ordered just before uncertainty, and the other one in which such index is ordered after uncertainty. Figure 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,

[5] 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.

and an indicator of real house prices.

Short- vs. long-term interest rates. The differences documented in Figures 6 in the paper 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. Gürkaynak, 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.[6] Kulish (2007) shows that long-term rates may effectively help stabilizing inflation in the context of a new-Keynesian framework featuring a term-structure of interest rates. 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 A6 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

[6] 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 (2015) and Bacchiocchi, Castelnuovo, and Fanelli (2016) 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 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. Gürkaynak, 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.

impulse responses, which are very similar to those obtained with our baseline STVAR (shown in Figure 3 in the paper). 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 in the paper, 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 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.[7]

[7] 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

Risk management-driven policy decisions: Further results

Quantity and price-gaps. Our paper documents the risk management-driven policy rate gap, i.e., the difference between the historical federal funds rate and the policy rate that, according to our VAR, would have been in place in absence of a systematic policy response to movements in uncertainty. In addition, we show here the risk management-driven gaps for other key variables of our analysis, i.e., industrial production, employment, and prices. These gaps are shown in Figure A7.

Risk management-driven policy rate gap: Comparison with Evans et al. (2015). The "risk management-driven policy rate gap" documented in Section 4.4 points to a state-dependent policymakers' response to uncertainty. It is of interest to contrast our VAR-based results with those one can produce by working with a Taylor rule à la Evans, Fisher, Gourio, and Krane (2015). The interest arises because our multivariate model and their uni-equational framework obviously have different characteristics. While our VAR model enables us to keep track of feedbacks going from the rest of the economy to the policy rule (and, therefore, policy rate) and back when simulating the counterfactual scenario in which the Federal Reserve does not react to uncertainty, the Taylor rule estimated by Evans et al. (2015) does not. At the same time, the latter model focuses on the information possessed by the FOMC in real time, while our VAR framework employes revised data. Hence, if the Evans et al. (2015) model produced a risk management-driven policy rate gap in line with ours, we would be reassured about the credibility of our policy rate gap.

We then turn to Evans et al.'s (2015) model, which is the following:

$$
\begin{aligned}
R_t^* &= R^* + \beta(E_t[\pi_{t,k}] - \pi^*) + \gamma E_t[x_{t,q}] + \mu s_t \\
R_t &= (1 - A(L))R^* + A(L)R_{t-1} + v_t
\end{aligned}
$$

where $\pi_{t,k}$ stands for the average annualized inflation rate from t to $t+k$, π^* models the inflation target, $x_{t,q}$ is the average output gap from t to $t+q$, s_t is a risk management proxy, and E_t denotes expectations conditional on information available to the FOMC at time t. The coefficients β, γ, and μ are fixed over time, while R^* is the Taylor rate conditional on an inflation rate equal to the target, a zero output gap, and a consideration of uncertainty by the policymakers μ set to zero. In this case, the natural real rate of interest $r^* = R^* + \pi^*$.

research agenda.

Given that the FOMC has a preference for implementing variations in the policy rate in a smooth manner, and that it does not have full control of interest rates, the polynomial $A(L) = \Sigma_{j=0}^{N-1} a_{j+1} L^j$ and the zero-mean, constant variance error term v_t are also modeled. As regards the former, L is the lag operator, while N denotes the number of federal funds rate lags.

Combining the equations above yields to the following estimation equation:

$$R_t = b_0 + b_1 E_t[\pi_{t,k}] + b_2 E_t[x_{t,q}] + b_3 s_t + \rho_1 R_{t-1} + \rho_2 R_{t-2} + v_t$$

where $b_i, i = 0, 1, 2, 3$ are nonlinear functions of the structural parameters β, γ, μ, R^*, and π^*.

The estimation of the above equation confirms that we are able to replicate the results documented in Evans et al. (2015).[8] In particular, we obtain a significant coefficient for the long-run response of the policy rate to the (standardized) VXO, whose size is -0.43.[9] To get closer to our nonlinear VAR analysis, we then estimate the following state-dependent version of the Taylor rule:

$$R_t = b_0 + b_1 E_t[\pi_{t,k}] + b_2 E_t[x_{t,q}] + b_3 D_t s_t + b_4 (1 - D_t) s_t + \rho_1 R_{t-1} + \rho_2 R_{t-2} + v_t$$

where D_t is a zero/one dummy taking a value equal to one in correspondence of quarters classified as "recessions" by the NBER and zero otherwise, and s_t is now the non-standardized VXO, which is the proxy for uncertainty exploited in Bloom (2009) to identify the uncertainty shock-dummy. This equation has the potential of capturing nonlinearities in the relationship between the policy rate and uncertainty. We estimate

[8] The replication files containing their datasets are available at https://www.chicagofed.org/publications/working-papers/2015/wp2015-03 . We focus on the thirty-day forward average of the target rate following each FOMC meeting as policy rate, and on the Greenbook measures of CPI inflation and output gap expectations for modeling the response to inflation and real activity. A detailed description of the data is provided in Evans et al.'s (2015) Appendix, which is available here: https://www.chicagofed.org/~/media/publications/working-papers/2015/wp2015-03-main-appendix-pdf.pdf?la=en . Given our choice of proxying uncertainty with the VXO, we focus on the case in which the measure of uncertainty is the VXO. Following Evans et al. (2015), we first standardize the VXO in order to interpret the long-run response of the policy rate as the reaction to a one-standard deviation increase in uncertainty. We then estimate the last equation reported above via least squares by focusing on the sample 1987Q1-2008Q4, which is the very same sample they focus on, and we account for heteroskedasticity by modeling the White-correction of the VCV matrix, as they do.

[9] See Table 9 p. 50 in their working paper version, i.e., https://www.chicagofed.org/publications/working-papers/2015/wp2015-03 .

this equation over the sample 1987Q1-2008Q2 to align the end-of-sample of this empirical analysis to the one we conduct with our VAR. Interestingly, we get a more aggressive long-run response of the policy rate to uncertainty in recessions, and we verify that the restriction $b_3 = b_4$ is rejected at a 1% level. We use this version of the Taylor rule to compute the "risk management-driven policy rate gap" consistent with this nonlinear Taylor rule as $R_t^{TRgap} = \widehat{b_3} D_t s_t + \widehat{b_4}(1 - D_t)s_t$.

Figure A8 plots the Taylor rule policy rate gap obtained as explained above. Evidently, the values of the policy rate gaps in recessions are much larger, with peaks (in absolute values) of 114 (2001Q4), 109 (2008Q1), and 101 (1990Q4) basis points. If one considers that the lack of a feedback mechanism accounting for different paths of the policy rate, their effects on the economic system, and the feedback on the regressors of the Taylor rule in the Taylor rule model is likely to downplay the dynamics effects induced by role played by risk management in monetary policy setting, this result can be seen as reasonably close to the one documented in our paper.

Comparison with linear VAR

Figure A9 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. Clearly, a linear model provides a distorted picture of the real effects of uncertainty shocks in terms of the magnitude of the impact over the business cycle with respect to a nonlinear model (which is supported by the formal tests documented in the first Section of this Appendix).

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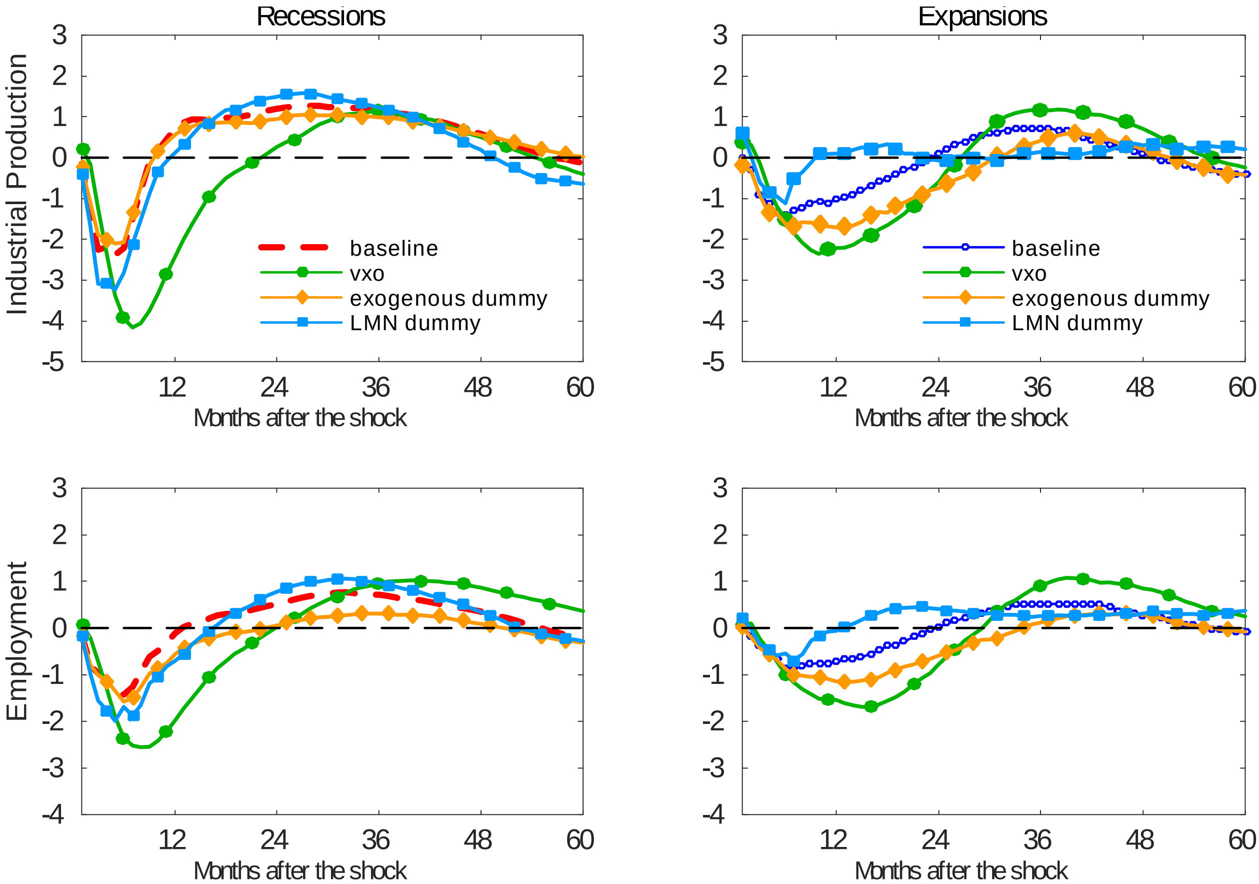

Figure A1. **Real Effects of Uncertainty Shocks: Alternative uncertainty indicators.** Baseline: Uncertainty dummy as described in the paper. VXO: Uncertainty shock identified as the orthogonalized residual of the of the VXO in the VAR. Exogenous dummy: Uncertainty dummy constructed by considering extreme realizations of the VXO index related to terror, war, and oil events only. LMN dummy: Uncertainty dummy constructed by considering extreme events as defined in the paper and associated to the financial uncertainty indicator à la Ludvigson, Mah, and Ng (2016). Impulse responses (median values) to an uncertainty shock for the dummy-related cases identified as described in the paper. Markov-Chain Monte Carlo simulations to estimate the VAR coefficients based on 50,000 draws.

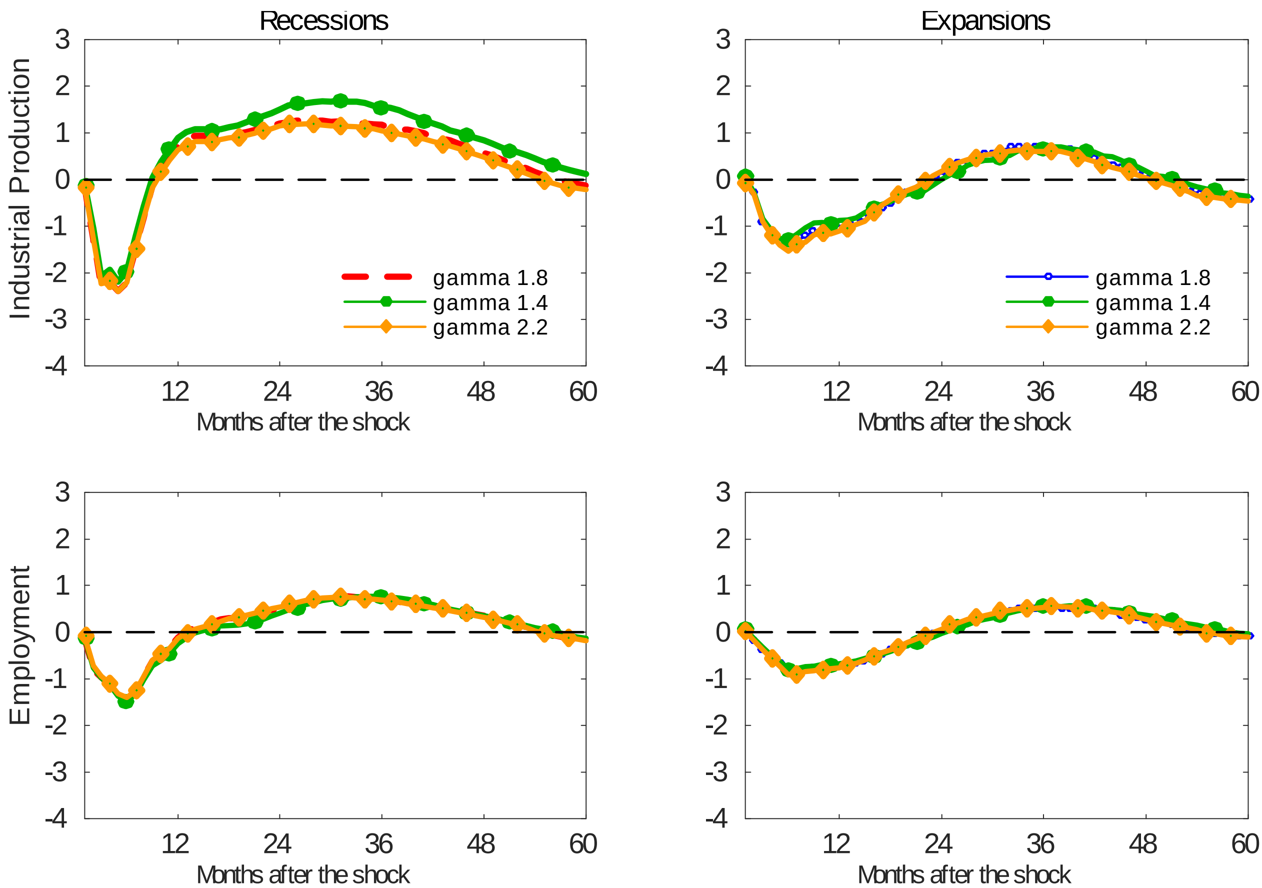

Figure A2. **Real Effects of Uncertainty Shocks: Different Calibrations of the Slope Parameter.** Impulse responses (median values) to an uncertainty shock identified as described in the paper. Red dashed/blue dashed-circled lines: GIRFs conditional on $\gamma = 1.8$. Green lines: GIRFs conditional on $\gamma = 1.4$. Orange lines: GIRFs conditional on $\gamma = 2.2$. Markov-Chain Monte Carlo simulations to estimate the VAR coefficients based on 50,000 draws.

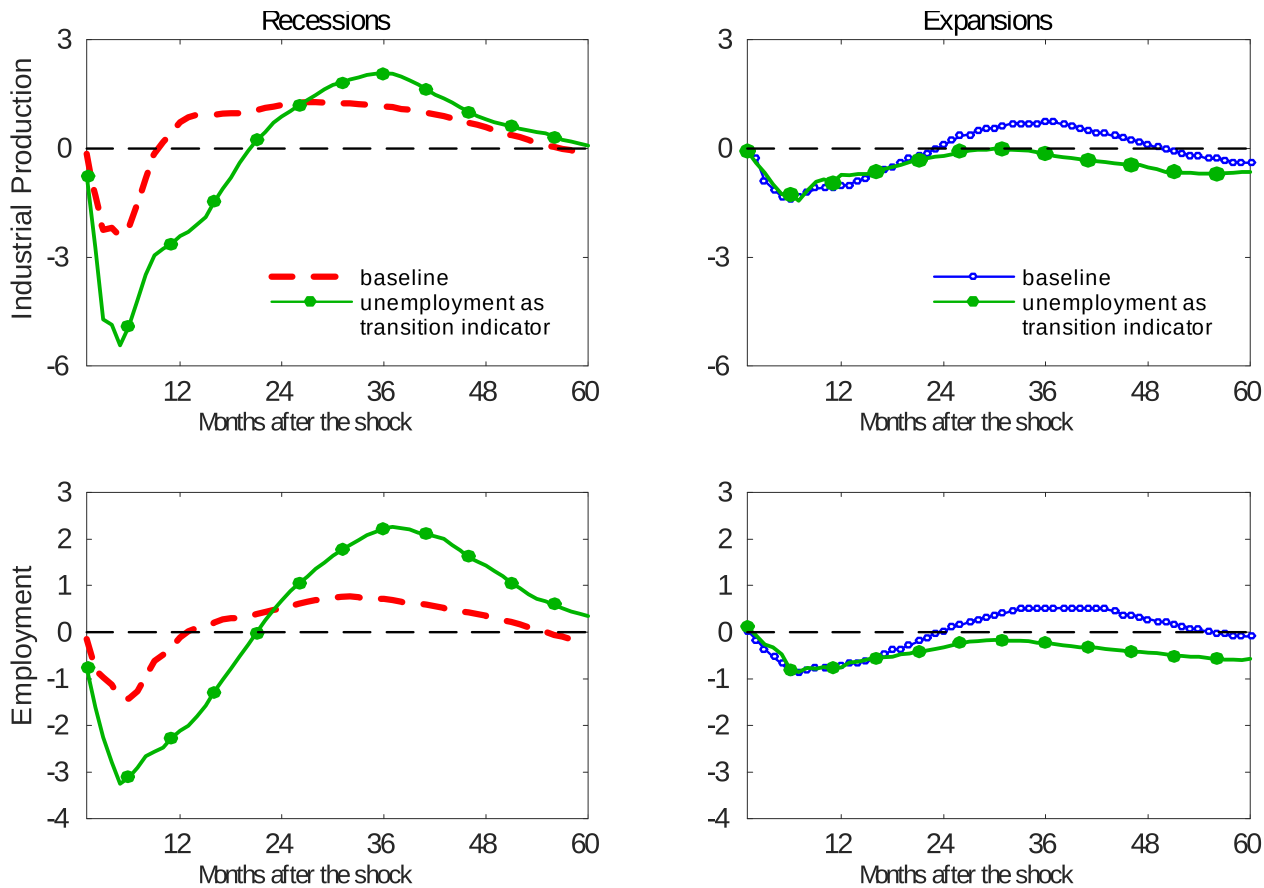

Figure A3. **Real Effects of Uncertainty Shocks: Unemployment as transition indicator.** Unemployment added to our baseline model and employed as transition indicator. Realizations of unemployment above (below) 6.5% are associated to recessions (expansions). Impulse responses (median values and confidence bands) to an 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 coefficients based on 50,000 draws.

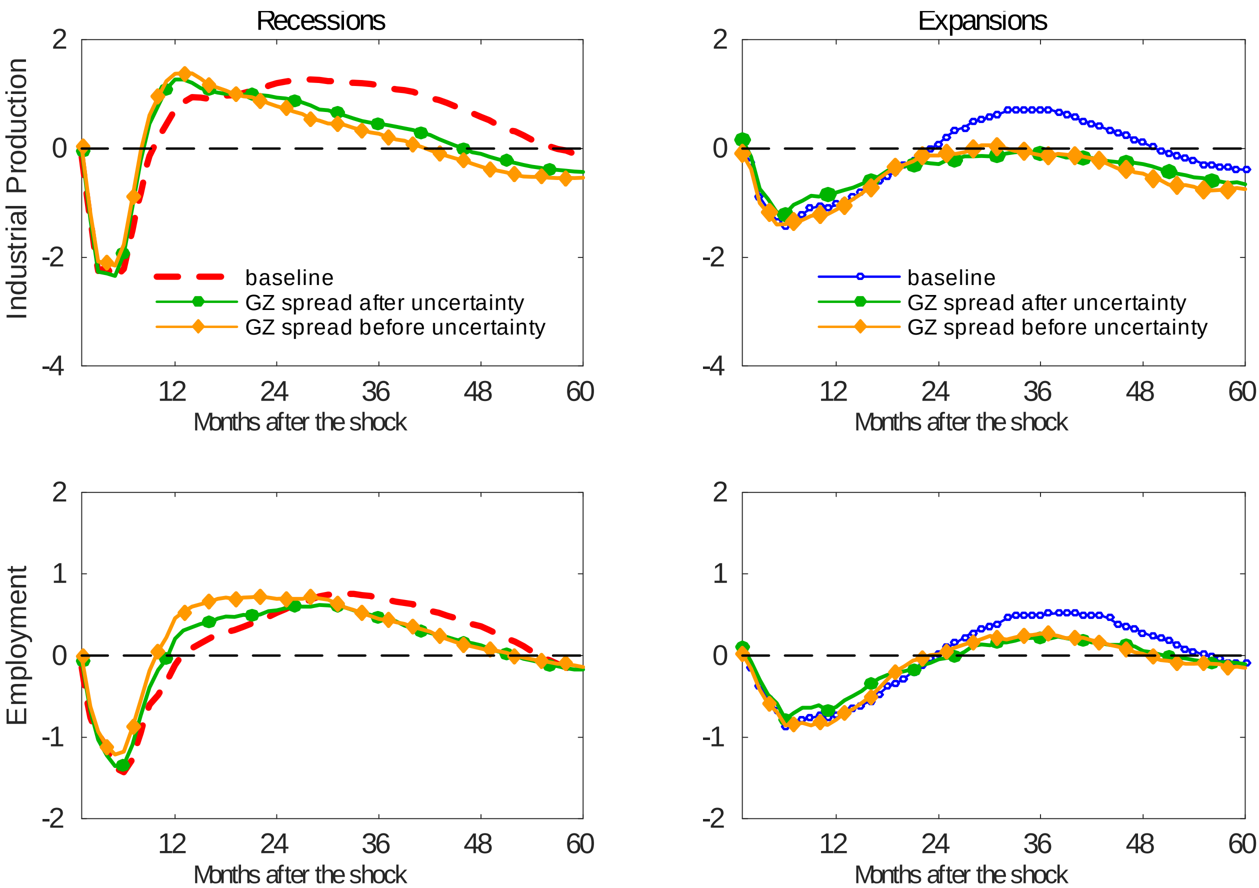

Figure A4. **Real Effects of Uncertainty Shocks: Role of Credit Spreads.** Median impulse responses to an uncertainty in scenarios without/with credit spreads. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). 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 coefficients based on 50,000 draws.

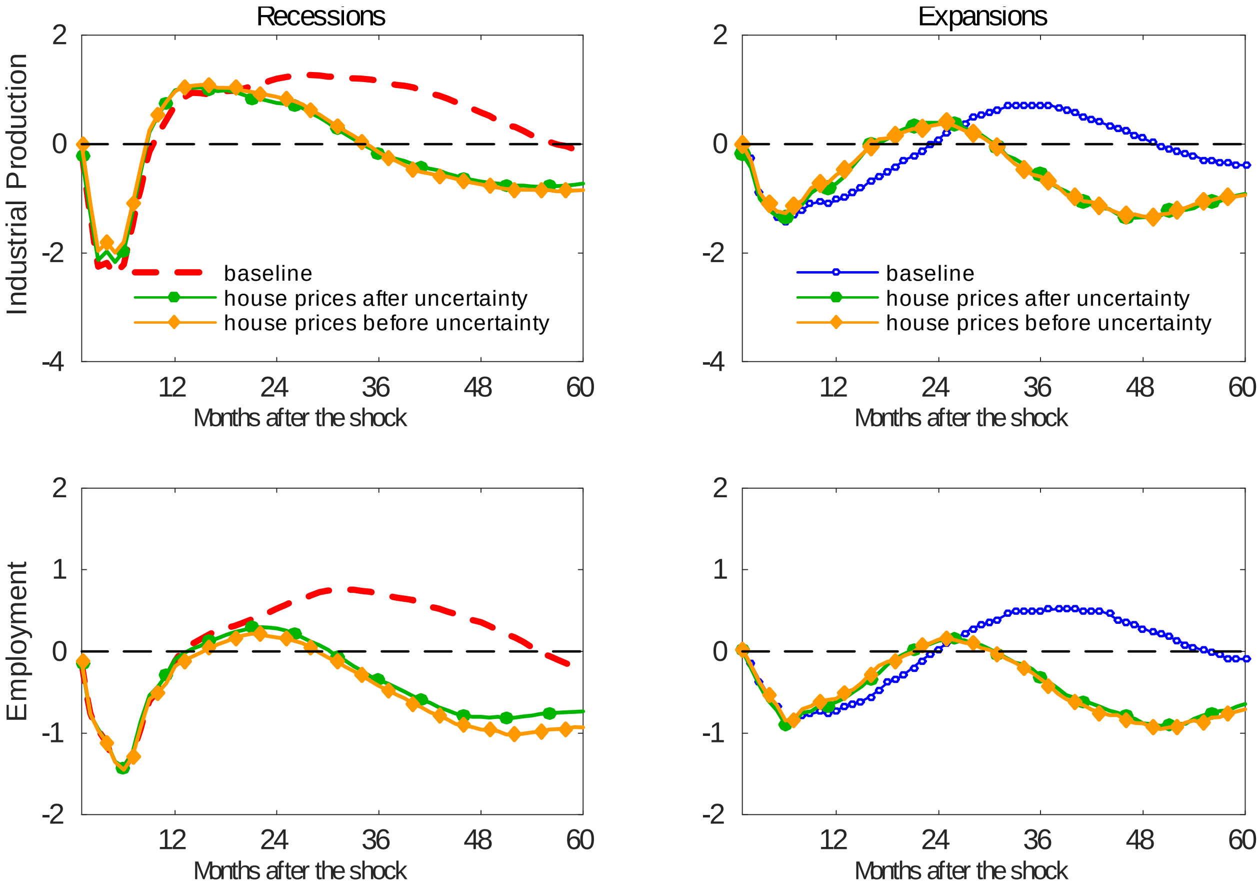

Figure A5. **Real Effects of Uncertainty Shocks: Role of House Prices.** Median impulse responses to an uncertainty shock identified as described in the text in scenarios without/with real house price index. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and 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 coefficients based on 50,000 draws.

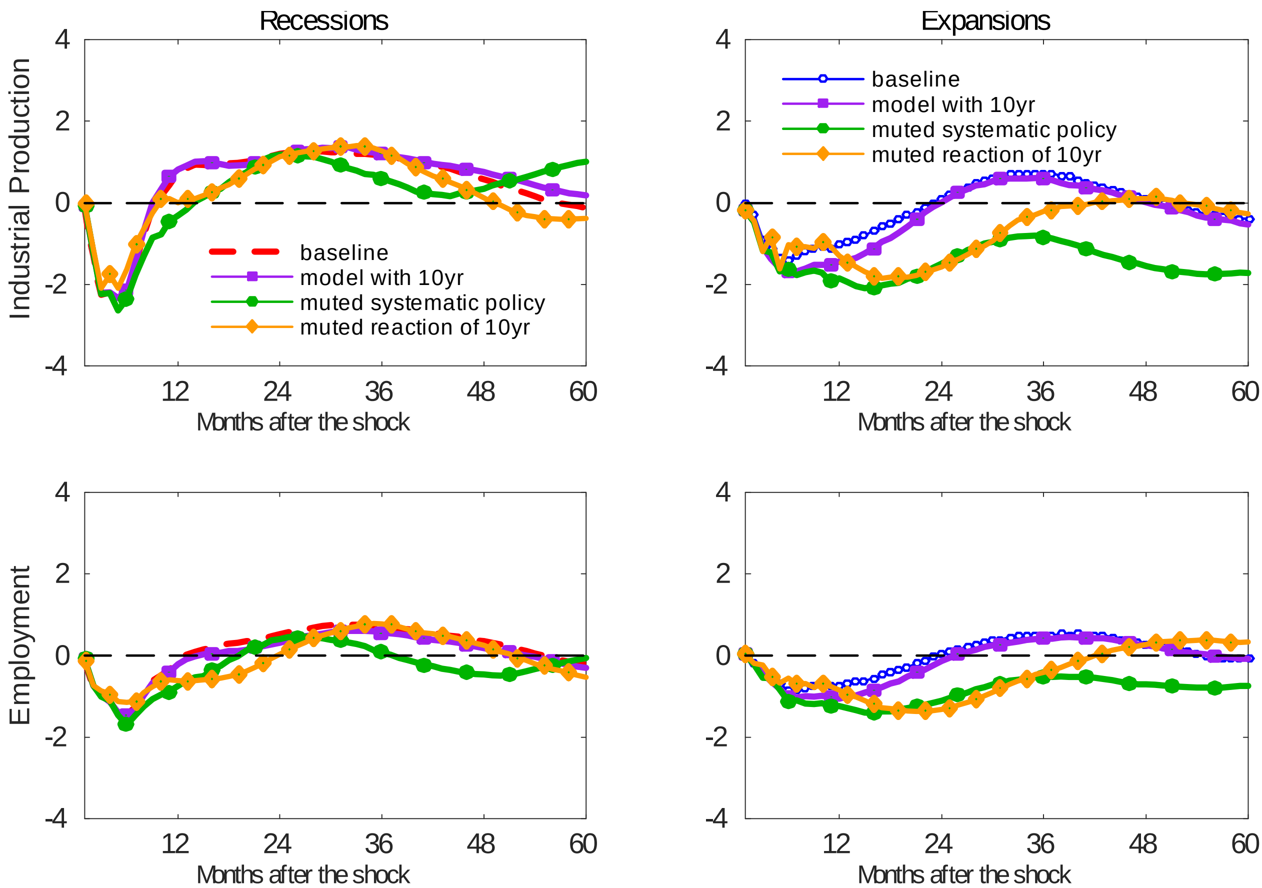

Figure A6. **Real Effects of Uncertainty Shocks: Role of Short- and Long-term Interest Rates.** Median impulse responses to an uncertainty shock identified as described in the text in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed with 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 coefficients based on 50,000 draws.

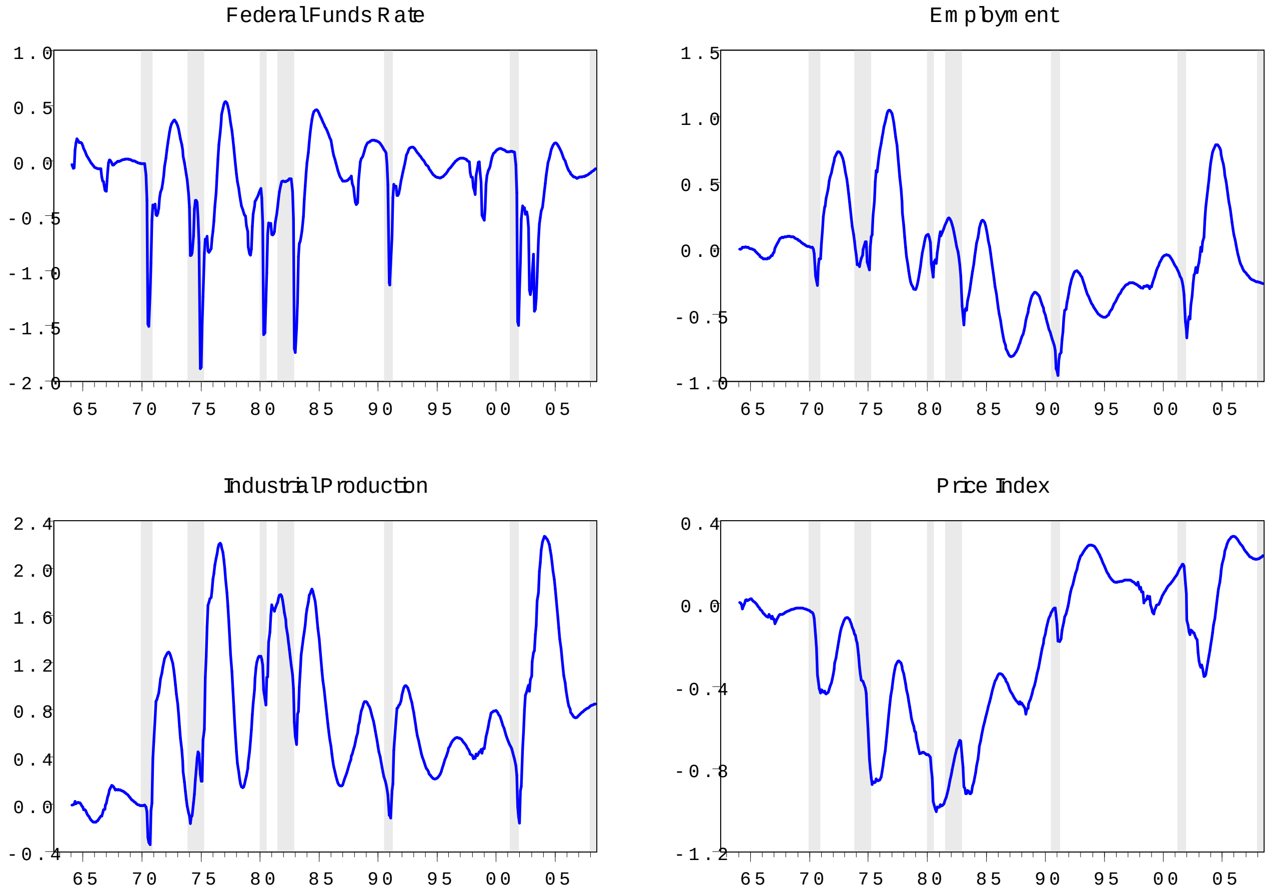

Figure A7. **Macroeconomic gaps**. Sample: 1962M7-2008M6. Gaps constructed by taking the difference between the historical realizations of each variable and their counterfactual values obtained by muting the systematic response of the policy rate to current and past realizations of uncertainty in our VAR. Shaded areas: NBER recessions. Realizations of the counterfactual rate start in 1964M2 because of initial conditions (lags of the VAR, transition indicator of the logistic function).

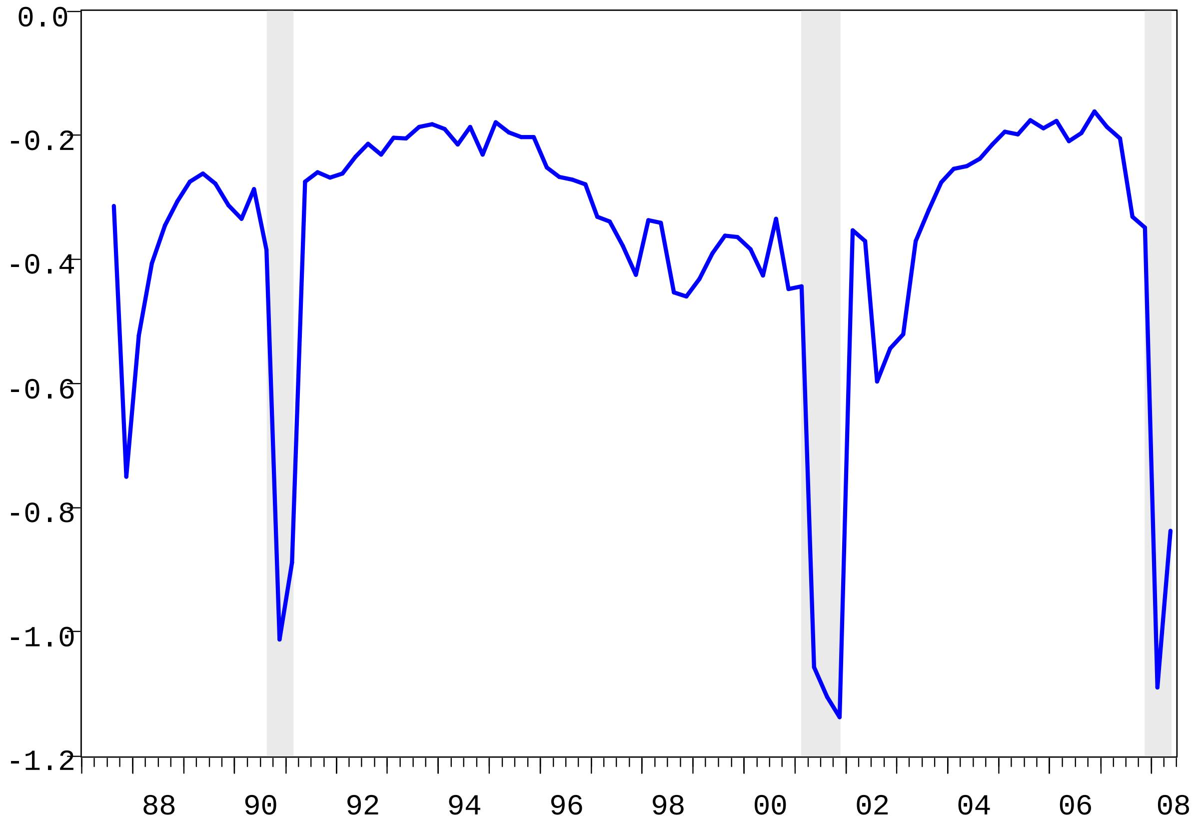

Figure A8. **Taylor Rule Risk Management-driven Policy Rate Gap.** Taylor rule policy rate gap constructed on the basis of an estimated nonlinear Taylor rule as explained in this Appendix.

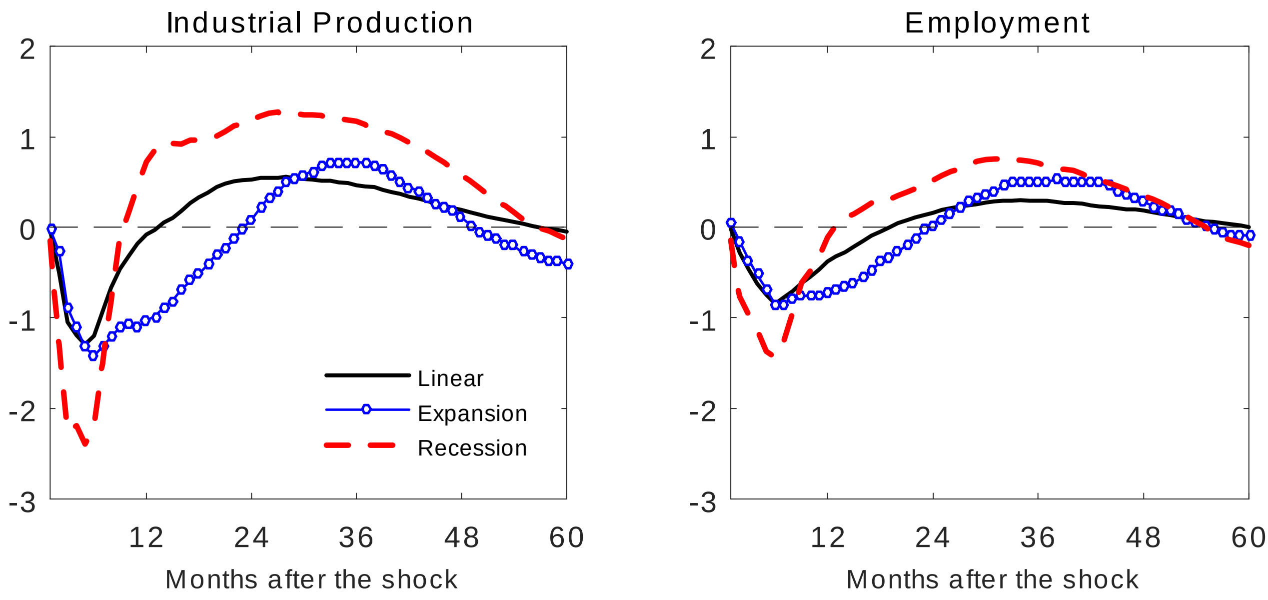

Figure A9. **Real Effects of Uncertainty Shocks: Linear vs. Nonlinear Frameworks.** Impulse responses (median values) to an uncertainty shock inducing an on-impact reaction of uncertainty equal to one as in Bloom (2009). Uncertainty shock identified as described in the paper. Solid black lines: Responses computed with the linear VAR. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions).