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Uncertainty and monetary policy in good and bad times



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Uncertainty and Monetary Policy in Good and Bad Times*

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Abstract

We 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. Counterfactual simulations point to a greater effectiveness of systematic monetary policy in stabilizing real activity in expansions. Differently, the ability of monetary policy to tackle the macroeconomic effects of first moment financial shocks is found to be similar between states.

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

JEL codes: C32, E32.

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1 Introduction

Uncertainty shocks have recently been identified as one of the drivers of the U.S. business cycle (Bloom (2014)). This paper investigates the ability of the Federal Reserve to minimize the macroeconomic impact of financial uncertainty shocks in booms and busts. It does so by modeling a standard set of macroeconomic variables with a smooth-transition VAR (STVAR) framework. This framework, estimated with post-WWII US data, is then employed to run counterfactual simulations to pin down the role played by systematic monetary policy (i.e., the monetary policy response to macroeconomic fluctuations) in tackling the macroeconomic effects of jumps in uncertainty. In particular, we perform a thought experiment by counterfactually assuming, within each state of the economy modeled by our nonlinear framework, a muted response of monetary policy to macroeconomic fluctuations. The comparison between the baseline (factual) dynamics obtained with the estimated policy response and those computed under the counterfactual policy scenario is informative as regards the role played by the US systematic monetary policy in reducing the deviations of real activity and inflation from their long run trends.¹

We find the effectiveness of monetary policy to reduce deviations of real activity and inflation from their trends after an uncertainty shock to be greater during expansions. In bad times, the depth of the economic downturn following an uncertainty shock remains virtually unchanged when moving from the estimated policy response to the counterfactual one, while its persistence is only mildly influenced. Differently, in expansions the counterfactual monetary policy implies a much deeper and longer lasting downturn after an uncertainty shock. Thus, monetary policy plays an important role in reducing the probability of entering a recession if an uncertainty shock hits in good times, while it is not as effective if the economy is already in a recessionary state. Interestingly, in the case of a first moment financial shock, we find that this asymmetry disappears, i.e., monetary policy is effective in both states of the economy. This finding points to the ability of our VAR to discriminate between the different types of dynamics triggered by second vs. first-moment financial shocks, and the different ways such dynamics are influenced by monetary policy.

¹Previous examples of counterfactual simulations conducted with VARs can be found in academic papers (see, e.g., Bernanke, Gertler, and Watson (1997) and Sims and Zha (2006)) as well as in analysis conducted by policy institutions such as, for instance, the Federal Reserve Bank of New York (Boivin and Giannoni (2002)). Section 5 offers a discussion on counterfactual exercises conducted with VAR frameworks.

The use of a nonlinear framework is motivated by existing research showing that uncertainty shocks have regime-dependent effects. Cacciatore and Ravenna (2018) work with a model featuring matching frictions in the labor market, and 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 prediction is provided by Caggiano, Castelnuovo, and Groshenny (2014), ?, Caggiano, Castelnuovo, and Figueres (2017a,b), Casarin, Forni, Marcellino, and Ravazzolo (2018), ?, and Ferrara and Guérin (2018). Moreover, 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)).

We account for endogenous 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 our research 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" caused by a reallocation of resources from low to high-productive firms (Bloom (2009)).

Our focus on financial uncertainty is justified both theoretically and empirically. From a theoretical standpoint, Basu and Bundick (2017) show that financial uncertainty is an important driver of the business cycle in a microfounded macroeconomic framework which replicates stylized facts of the US economy. Empirically, ?, Carriero, Clark, and Marcellino (2018), Casarin, Forni, Marcellino, and Ravazzolo (2018), and Ludvigson, Ma, and Ng (2019) point to movements in financial uncertainty as possibly exogenous to the business cycle and able to explain a larger share of real activity's forecast error variance than macroeconomic uncertainty. Bekaert, Hoerova, and Lo Duca (2013) decompose the VIX into uncertainty and risk aversion. They show that uncertainty exerts a much stronger effect on the business cycle than risk. Bekaert and Hoerova (2016) propose a similar decomposition as in Bekaert, Hoerova, and Lo Duca (2013) and document a significant and positive correlation between their uncertainty measure and existing proxies for uncertainty, among which stock market uncertainty.²

²A recent paper by Bekaert, Engstrom, and Xu (2019) proposes a measure of financial uncertainty with a sophisticated latent factor structure estimated with a large number of observables. They show

Following Bloom (2009), we identify uncertainty shocks based on "extreme events", i.e., historical events which are associated with large jumps in the VXO. To the extent that these jumps are exogenous to the business cycle, they represent valid instruments to overcome the endogeneity problem one faces when attempting to identify the macroeconomic effects of uncertainty shocks. Interestingly, the proxy for financial uncertainty shocks we employ in this paper is the same exploited by Carriero, Mumtaz, Theodoridis, and Theophilopoulou (2015) in the proxy-SVAR approach with which they investigate the real effects of financial uncertainty shocks. With respect to them, who employ a linear framework, we use a nonlinear model and unveil significant differences regarding the ability of monetary policy to tackle uncertainty shocks along the business cycle. Our results are robust to the employment of the level of the VXO 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 (2019).

To our knowledge, our paper is the first one in the literature to investigate the role of systematic monetary policy in tackling the effects of financial uncertainty shocks.³ Our contribution relates to previous papers on the relationship between uncertainty and monetary policy. Caggiano, Castelnuovo, and Pellegrino (2017) 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 its effectiveness in tackling hikes in financial uncertainty in booms and busts. ? investigate the effects of uncertainty shocks in presence of high/low financial stress. Differently, we 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 Eickmeier, Metiu, and Prieto (2016), Aastveit, Natvik, and Sola (2017), Pellegrino

that such measure of financial uncertainty predicts future movements in the US business cycle even when controlling for the VIX. We see the employment of Bekaert et al.'s (2019) measure of financial uncertainty in a nonlinear framework like ours as material for future research.

³While revising this paper in February 2019, we found out a similar contribution by Jackson, Kliesen, and Owyang (2018). They estimate a nonlinear "max VAR" model (a threshold VAR model with a time-varying threshold) and study the effects of jumps in uncertainty in high vs. low uncertainty states. Our analysis focuses on the ability of systematic monetary policy to tackle the macroeconomic effects of uncertainty shocks in expansions and recessions. We see Jackson et al.'s (2018) paper as complementary to ours.

(2017,2018), and Castelnuovo and Pellegrino (2018). Our paper deals with a different question, i.e., the ability of the Federal Reserve to minimize the macroeconomic impact of uncertainty shocks in booms and busts. Gnabo and Moccerro (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 in recessionary periods are consistent with the predictions of a number of theoretical models. In presence of labor and capital non-convex adjustment costs, Bloom (2009) and Bloom et al. (2018) predict a weak impact of changes in factor prices when uncertainty is high because of the dominant relevance of "wait-and-see" effects. 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. Dibiasi (2018) works with a general equilibrium RBC model à la Bloom et al. (2018) in which the degree of irreversibility of investment is countercyclical. The responses of real activity to an uncertainty shock produced with his model replicate those proposed in our paper. 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.

The paper develops as follows. Section 2 presents our nonlinear framework and the data employed in the empirical analysis. Section 3 documents the nonlinear effects of uncertainty shocks and discusses a number of robustness checks. Section 4 analyzes the role of systematic monetary policy in recessions and expansions. Section 5 discusses counterfactual exercises in the context of VAR frameworks. Section 6 concludes.

2 Modeling nonlinear effects of uncertainty shocks

Modeled variables. We estimate the impact of uncertainty shocks on real economic outcomes using a STVAR model which features eight U.S. macroeconomic indicators. Following Bloom (2009), the vector of endogenous variables \mathbf{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 Variables are in logs, except the uncertainty dummy, the policy rate, and hours. Unlike Bloom (2009), we do not Hodrick-Prescott (HP) filter these variables (other than the VXO) to avoid inducing spurious cyclical fluctuations which could bias our results (Cogley and Nason (1995)).

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), maintain such rate at that level until December 2015, and implement unconventional policy moves. We interpret this period as a third regime, the modeling of which would render the estimation of our nonlinear framework much more complex (for recent evidence in this sense, see Caggiano, Castelnuovo, and Pellegrino (2017)). Hence, our baseline exercise excludes the acceleration of the financial crises and the subsequent recovery. However, our Appendix (Figure A1) documents the robustness of our results to updating the sample to June 2018.

Identification. 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.⁵ In this sense, our analysis is similar to the ones by Romer and Romer (1994), who identify seven large monetary policy shocks in the post-WWII sample to study their

⁴The realized volatility of the returns of the S&P500 index is used before 1986 due to the unavailability of the VXO. The proxy for financial uncertainty used in this study may very well be a composite of two different objects, i.e., uncertainty and risk aversion. Bekaert et al. (2013) work on this distinction by projecting monthly realized variances over a constant, the squared value of the VIX, and the past realization of the dependent variable. As shown in Bekaert, Hoerova, and Lo Duca (2010), the log of the fitted value of this regression (which is, the log of the estimated physical variance) is a measure of uncertainty, while risk aversion is obtained by computing the log of the difference between the squared value of the VIX and the fitted value of the above mentioned regression. Unfortunately, this regression is unfeasible in our sample because the VIX is not available before January 1990. ? propose a decomposition between risk and uncertainty which regards macroeconomic (and not financial) uncertainty.

⁵Working with linear VARs, ? 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.

effects on the US economy; Ramey and Shapiro (1998) and Burnside, Eichenbaum, and Fisher (2004), who exploit a dummy based on three events (Korean and Vietnam wars, Carter-Reagan military spending build-up) to analyze the effects of fiscal spending over the period 1947-1996; Bloom (2009), who identifies sixteen large jumps in financial uncertainty (those we exploit in this analysis) in the very same sample we analyze here; and Carriero, Mumtaz, Theodoridis, and Theophilopoulou (2015), who build a dummy based on jumps in financial uncertainty to implement a proxy-SVAR analysis. Figure 1 shows the VXO index used to construct the dummy variable along with the NBER recessions dates and the identified uncertainty shocks. The sixteen episodes which Bloom identifies as uncertainty shocks are equally split between recessions and expansions. Our Appendix shows that our results are robust to the employment of continuous variables such as the VXO and the measure of financial uncertainty recently developed by Ludvigson et al. (2019).

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

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

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

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

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

In this model, $F(z_{t-1})$ is a logistic transition function which captures the probability of being in a recession, γ is the smoothness parameter, z_t is a standardized transition indicator (whose generic distribution d is not necessarily Gaussian), $\mathbf{\Pi}_R$ and $\mathbf{\Pi}_E$ are the VAR coefficients capturing the dynamics of the system in recessions and expansions respectively, $\boldsymbol{\varepsilon}_t$ is the vector of reduced-form residuals with zero-mean and time-varying, state-contingent variance-covariance matrix $\boldsymbol{\Omega}_t$, and $\boldsymbol{\Omega}_R$ 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. Teräsvirta (2018) offers a survey of recent contributions in the macroeconomic context.

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. 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.⁶ 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. 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. This assumption 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 (2017) on the negligible effects 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 moving-average of the quarterly real GDP growth rate as transition indicator. Given that our investigation deals with monthly data, we employ the standardized backward-looking yearly growth rate of industrial production (for a similar choice, see Caggiano, Castelnuovo, and Figueres (2017)). Our Appendix (Figure A2) documents the robustness of our results to alternatively employing labor market indicators such as unemployment, non-farm payrolls, and manufacturing employment as transition indicator.

Another important choice is the calibration of the smoothness parameter γ , whose es-

⁶As pointed out by Teräsvirta, Tjøstheim, and Granger (2010) (page 37), this model collapses to a two-regime switching framework with an observable switching variable when the slope parameter $\gamma \rightarrow \infty$. The assumption behind the use of the smooth transition framework in this paper is that changes in economic regimes take more than one month to occur. Such assumption seems to be a plausible one given the persistence of the data we model in this paper. Finally, the linear model à la Bloom (2009) obtains as a special case of the STVAR when $\gamma = 0$, which implies $\mathbf{\Pi}_R = \mathbf{\Pi}_E = \mathbf{\Pi}$ and $\mathbf{\Omega}_R = \mathbf{\Omega}_E = \mathbf{\Omega}$.

timation 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 $F(z_t) \geq 0.86$, and calibrate γ to obtain $\Pr(F(z_t) \geq 0.86) \approx 0.14$.⁷ This calibration strategy, which closely follows the one first proposed by Auerbach and Gorodnichenko (2012), leads us to set $\gamma = 1.8$.

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 necessity (explained below) of using a backward-looking (i.e., not contemporaneous) transition indicator. Second, the volatility of $F(z)$ 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. When we do this, 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.

Generalized impulse responses and logistic function. We compute generalized impulse responses by taking into account the effects exerted by uncertainty shocks on industrial production. Hence, the determination of the economic regime the economy finds itself in after the shock is fully endogenous in our analysis. For this desirable feature to be implemented in our framework, we have to model the probability of being in a recession $F(z)$ as a function of the lagged value of the transition indicator z . We have to do so because z is a fully endogenous object in our framework. Our Appendix further elaborates on this point. Importantly, the use of the nonlinear model presented in this Section (conditional on the dataset at hand) is strongly supported by statistical

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

tests designed by Teräsvirta and Yang (2014) to contrast the fit of a linear VAR vs. the one of the framework we work with (results available in our Appendix).

The modeling choice described above implies a built-in delay via which monetary policy can influence industrial production and, therefore, the probability of being in a recession. Two things are worth noting here. First, this delay is consistent with the lagged impact of monetary policy shocks on real activity documented by e.g. Christiano, Eichenbaum, and Evans (1999) and Christiano, Eichenbaum, and Evans (2005). Second, such a delay is technically present in both states of the economy. Hence, differences in the effectiveness of monetary policy between states in our model cannot be attributed to this built-in delay.

Estimation of the model. We estimate the nonlinear STVAR model 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 (2003), which overcomes the difficulties often encountered when one tries to estimate this framework with maximum likelihood due to the high nonlinearity and the rich parameterization of our framework. 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. The estimated model is then employed to compute GIRFs to an uncertainty shock. Our Appendix provides details on the algorithm we employ to compute the GIRFs.

3 Results

Response of real activity. Are the real effects of uncertainty shocks state-dependent? Figure 3 (first and second rows) plots the estimated dynamic responses of employment and industrial production to an uncertainty shock in recessions and expansions along with 68% confidence bands.⁸ These variables react negatively and significantly no matter what phase of the business cycle the economy is in. 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% .

⁸The 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.

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.

The evidence provided here is in line with recent contributions by Caggiano, Castelnuovo, and Groshenny (2014), ?, Caggiano, Castelnuovo, and Figueres (2017a,b), Casarin, Foroni, Marcellino, and Ravazzolo (2018), ?, and Ferrara and Guérin (2018), which also find that uncertainty shocks have a larger effect on real activity when they hit during recessionary periods. Evidence on the negative effects of hikes in uncertainty on real activity is also provided by Bekaert, Hoerova, and Lo Duca (2013). Our results are robust to a variety of checks (available in our Appendix), which include: i) a different identification of uncertainty shocks alternatively based on a dummy which focuses on events associated with terror, war, or oil; 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 developed by Ludvigson, Ma, and Ng (2019); 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.

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 response of prices and the policy rate. The policy rate could also respond asymmetrically to real activity and/or to uncertainty *per se*. It is then of interest to investigate how the nominal side of the economy evolves after an uncertainty shock.

Figure 3 (third and fourth rows) 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 decrease in the short-run and then gradually return to their pre-shock level. The federal funds rate falls 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 fall in the interest rate is about 0.8 percentage points at its peak. Differently, when an uncertainty shock hits in a recession, the policy rate goes down by about two percentage points. The impulse responses associated with recessions offer clear support to the view put forward by Leduc and Liu (2016) and Basu and Bundick (2017) that uncertainty shocks act as demand shocks. The fact that periods of high uncertainty are followed by a looser

monetary policy is in line with the findings in Bekaert, Hoerova, and Lo Duca (2013), who also find that exogenous increases in the uncertainty component of the VIX are followed by a lax monetary policy.

Statistical significance of state-dependence. Our evidence 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 4 contrasts the responses of industrial production, employment, prices, and the federal funds rate in recessions vs. expansions using 68% confidence intervals surrounding the estimated median differences for each variable. Industrial production, employment, and the federal funds rate react significantly more in recessions to uncertainty shocks, while we find the evidence in favor of an asymmetric reaction of prices to be practically insignificant.

4 Uncertainty and monetary policy

4.1 Systematic monetary policy effectiveness

The previous evidence shows that the Federal Reserve reacts 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 larger? 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 by zeroing the coefficients of the federal funds rate equation in our VAR. We engineer this thought experiment with the aim of identifying the effectiveness of the estimated (factual) systematic monetary policy response by contrasting the factual and the counterfactual scenarios.

Figure 5 contrasts the responses of real activity and prices conditional on the absence of the systematic policy response with the baseline results. Focusing on real activity, the differences between the factual and counterfactual responses point to a dramatically lower monetary policy effectiveness in recessions. The recession is estimated to be almost as severe as the one which occurs when policymakers are allowed to lower the policy

rate (an evidence possibly due the lags via which monetary policy affects real activity).⁹ Notably, the difference between the baseline and the counterfactual scenarios mainly regards the speed with which real activity recovers and overshoots before going back to the steady state.

A different picture emerges when our counterfactual monetary policy is implemented in good times. As Figure 5 shows, when the policy rate is kept fixed, industrial production goes down markedly (about -2.5% at its peak) and persistently, remaining statistically below zero for a prolonged period of time. The same holds when looking at the response of employment, i.e., the gap between the baseline response and the one associated with our counterfactual exercise is quantitatively substantial. Interestingly, prices display a more persistent departure from their trend in both states.

One potential limitation of this exercise is that the ordering of the variables in our VAR does not allow for a contemporaneous response of the federal funds rate to movements in prices and quantities after an uncertainty shock. We then check if our results are robust to ordering the federal funds rate last in the vector. From an economic standpoint, this means that we are endowing the central bank with all information available at time t in the economic system. In other words, this robustness check enables the central bank to contemporaneously react to prices, real indicators of the business cycle such as average hourly earnings, industrial production, hours, and employment, and financial indicators such as the S&P500 index and financial uncertainty. This ordering admits (without requiring it) a systematic response of the policy rate to movements in stock prices (as in, e.g., Bjørnland and Leitemo (2009) and Castelnuovo and Nisticò (2010)) and to uncertainty per se, the latter being consistent with a risk-management approach by the Federal Reserve (Evans, Fisher, Gourio, and Krane (2015) and ?). Following Christiano, Eichenbaum, and Evans (1999), we keep the variables in log-levels to avoid information losses due to over-differentiation of the variables. As shown in our Appendix (Figure A8), our main finding - i.e., monetary policy being more effective in expansions as far as the response of real activity is concerned - is robust to ordering the federal funds rate last.

⁹The 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.

4.2 Quantifying policy effectiveness

The impulse responses plotted in Figure 5 document a different ability by the Federal Reserve to tackle the macroeconomic effects of uncertainty shocks in recession and expansions. We quantify this difference in policy effectiveness by appealing to two different metrics, i.e., the "distance from the baseline", which measures the extent to which the counterfactual policy implies deviations of real activity and prices from their paths in the factual scenario, and the "speed of recovery", which is the rapidity with which the economy goes back to trend after a shock.

Distance from the baseline. We formalize the concept of the distance from the baseline as follows:

$$DB_x = \sum_{h=1}^H \left[\frac{\partial x_h}{\partial \varepsilon_0^{unc}} \Big|_{fact.} - \frac{\partial x_h}{\partial \varepsilon_0^{unc}} \Big|_{count.} \right]^2 \quad (5)$$

where $x \in \{p, ip, empl\}$, p is the price index, ip is industrial production, $empl$ is employment (all expressed in logarithms), ε_0^{unc} is the uncertainty shock hitting at time zero, and the forecast horizon is truncated at $H = 60$. In words, the distance from the baseline (5) is the sum, over H horizons, of the squared deviations of the factual impulse response of a variable x from its counterfactual response at each horizon h . The idea of this metric is simple: when comparing factual and counterfactual scenarios in recessions vs. expansions, the DB tell us how "different" the path of a given variable x is when influenced by different systematic monetary policies. Hence, a comparison of the differences is informative as regards how effective monetary policy is in influencing the macroeconomic environment.¹⁰

Speed of recovery. An additional metric we consider is the speed of recovery. The speed of recovery is captured by the number of periods after the shock a variable x takes before going back to its pre-shock trend, i.e.,

$$SR_x = \min \left[h \left| \frac{\partial \tilde{x}_h}{\partial \varepsilon_0^{unc}} \geq 0, \frac{\partial \tilde{x}_{h+1}}{\partial \varepsilon_0^{unc}} \leq 0 \right. \right], h \in \{1, 2, \dots, H - 1\} \quad (6)$$

¹⁰This metric does not refer in any manner to the optimality of the historical policy. Assessing optimal policy would require us to employ a micro-founded loss function and, consequently, a micro-founded DSGE model in first place (Woodford (2003), Benigno and Woodford (2012)). Our VAR does not offer us relevant information on how to build up a micro-founded loss function to assess the costs of macroeconomic fluctuations in our factual and counterfactual scenarios. However, we show in our Appendix that our main finding (stronger impact of monetary policy in expansions) is robust to the employment of an ad-hoc loss function similar to the one recently used by Blanchard, Erceg, and Lindé (2017).

In words, eq. (6) searches for the minimum value of h which identifies a change in sign in the impulse response of a variable x after the shock, the change in sign confirming that the variable has got back to its trend. If $SR_x = \emptyset$ (because the length h of the recovery after the shock is larger than $H = 60$ in our empirical application), then we automatically set $SR_x = H$.

Table 1 collects the figures relative to the DB and SR metrics. The message arising from the former is clear: changes in systematic monetary policy in recessions have a much lower effectiveness (ability to influence macroeconomic conditions) than in expansions, with the latter being relatively more effective by factors as large as 4 (industrial production), 6 (employment), and 9 (prices). The speed of recovery confirms the main message of this paper, i.e., the real effects of uncertainty shocks are tackled much more effectively by systematic monetary policy in expansions. In this state, the speed of recovery is much faster under factual policies (about two years) than under the muted one (5 years, which is the binding upper bound naturally imposed on this exercise by the impulse response horizon we consider). Differently, in recessions, real activity goes back to its long run trend even in absence of an active systematic policy response, although the recovery is faster when the historical policies are in place. Qualitatively, this finding is confirmed by the behavior of prices, although the quantitative differences are much less spectacular.

4.3 Interpreting policy (in)effectiveness in recessions

How can one interpret the state-dependence of monetary policy effectiveness? As suggested by Bloom (2009), Bloom et al. (2018), and Dibiasi (2018), these results 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 - associated to the policy rate - 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.

Differently, the response of monetary policy has a larger countercyclical effect on 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.

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.

The literature has also proposed frameworks relating monetary policy effectiveness to price volatility. Vavra (2014) writes a model in which, 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 countercyclicity of price volatility, monetary policy shocks turn out to be less powerful in recessions. A similar mechanism is present in Baley and Blanco (2019). We refrain from relating our findings on the different responses of aggregate prices to uncertainty shocks under alternative forms of systematic monetary policy to Vavra's (2014) and Baley and Blanco's (2019) frameworks. As correctly pointed out by ?, such frameworks elaborate on the role of disaggregated prices and their response to monetary policy shocks, something which we do not deal with in this analysis.

4.4 First vs. second moment financial shocks

The discussion about the potential transmission channels of uncertainty behind our results offers a testable prediction. If the lower effectiveness of monetary policy in recessions is actually related to an optimal wait-and-see behavior by agents in presence of high uncertainty, different types of shocks - in particular, first moment shocks - should not lead to the same type of ineffectiveness. Given the emphasis on financial uncertainty shocks in this paper, we test this prediction by focusing on a first moment financial shocks, i.e., an unexpected drop in the S&P500 stock price index.¹¹

Figure 6 plots the responses of industrial production, employment, and prices under the two different monetary policy scenarios discussed above, i.e., the factual monetary policy and the muted counterfactual one. Interestingly, these responses tell a different story with respect to what we find in presence of a second moment shock. First, the factual responses of industrial production and employment do not display any sign of overshoot, which is instead a characteristic of the response to second moment shocks (Bloom (2009)). Differently, responses to first moment shocks like monetary policy, fiscal, and financial shocks typically display hump shaped paths with no overshoot (Ramey (2016)). Second, and more interestingly for the main result of our paper, monetary policy turns out to be effective in both scenarios, with a performance in recessions comparable to the one in expansions. This finding is consistent with the idea of real option mechanisms at work in presence of second moment shocks whose consequences for the effectiveness of monetary policy are not present when first moment disturbances hit the economic system. Finally, our VAR points to an inflationary response after a drop in stock prices. Hence, our financial shock is interpreted by the VAR as a supply shock moving quantities (industrial production and employment) and prices in opposite directions. This evidence is exactly the same as the one proposed in Abbate, Eickmeier, and Prieto (2016), who focus on financial shocks and inflation dynamics and find unexpected increases in stock prices to be deflationary. The interpretation relates to the existence of a cost channel which translates the higher cost of borrowing following a drop in stock prices into higher marginal costs and, therefore, higher inflation. Our results qualify Abbate, Eickmeier, and Prieto's (2016) by unveiling an interesting nonlinearity in the response of prices to a first moment financial shock, i.e., positive in recessions and nonsignificant in expansions.

¹¹Given that the aim of this exercise is to compare dynamics rather than magnitudes, we do not calibrate the shock to any particular value and consider the usual one standard deviation size.

5 Counterfactual exercises with VAR frameworks: A discussion

Our analysis uses a (nonlinear) VAR framework. One advantage of working with VARs over DSGE frameworks is the former's superior ability to fit the data (Del Negro, Schorfheide, Smets, and Wouters (2007)). On the other hand, one disadvantage, at least from a theoretical standpoint, is that counterfactuals conducted with VAR frameworks are subject to the Lucas critique. This is so because VAR frameworks do not allow for reduced-form coefficients to adjust to changes in policies which influence them, i.e., they do not acknowledge cross-equation restrictions. In a world with rational agents, changes in policies influence expectations and have agents adjust their optimal decisions. Hence, in theory, not only the VAR coefficients of the policy equation should change, but also the VAR coefficients of the non-policy equations should adjust to changes in policy.

Admittedly, our counterfactual exercise falls under this critique, very much like counterfactuals conducted with VARs by, among others, Bernanke, Gertler, and Watson (1997), Boivin and Giannoni (2002), and Sims and Zha (2006). Hence, how informative is the counterfactual exercise conducted here, given that it is theoretically subject to the Lucas critique? The answer to this question depends on how relevant the Lucas critique is from an empirical standpoint. While the answer to this question is clearly case-specific, it is of interest to note that not all papers in the literature point to a strong empirical evidence of such relevance. Rudebusch (2005) finds reduced-form VAR coefficients to be relatively insensitive to changes in the VAR monetary policy rule. Canova and Gambetti (2010) find the properties of different measures of inflation expectations in the US not to be influenced by breaks in monetary policy. Moreover, they find the VAR frameworks with and without expectations to display similar reduced-form characteristics. Chan and Eisenstat (2018) find that a VAR estimated over several US monetary policy regimes does not statistically support changes in the reduced-form coefficients once stochastic volatility (which our STVAR approximates with a state-dependent variance-covariance matrix of the estimated residuals) is modeled. We interpret this evidence as pointing to the possibility that a VAR analysis like ours could actually provide an indication, at least in first approximation, on the different ability by monetary policy to stabilize the macroeconomic environment in different phases of the business cycle.

Our counterfactuals imply a different response of real activity and inflation to the very same (counterfactual) monetary policy stance all else being equal, i.e., keeping

constant all the modeling choices behind our STVAR (e.g., definition of the transition indicator, calibration of the nuisance parameters of the logistic function, lags of the VAR, and so on). Hence, we believe our results point to a genuine finding coming from the data and not being mechanically generated by the way in which we set up our VAR simulations. We see the possibility of interpreting our results on the different monetary policy effectiveness in booms and busts with the theoretical models discussed in the previous Section as reassuring.

Finally, going back to the mapping between DSGE models and VARs, it is important to note the following. A fixed interest rate would induce indeterminacy under rational expectations in a standard linear(ized) DSGE model of the business cycle featuring fixed parameters. Differently, multiple equilibria do not necessarily arise when a DSGE framework endowed with rational expectations allows for switches in regimes. As shown by Davig and Leeper (2007), a generalized Taylor principle holds when regime switching frameworks are considered. Such a generalized principle is the outcome of the combination of the systematic monetary policies occurring in each given regime and the probabilities to switch from a regime to another. As stated by Davig and Leeper (2007, page 613), if the systematic response in the active monetary policy regime is sufficiently large, a unique equilibrium can occur even in presence of a pegged nominal interest rate (a response to macroeconomic conditions arbitrarily close to zero), so long as the regime in which the passive policy is realized is sufficiently short-lived. Moreover, Castelnuovo and Surico (2010) show that an informationally sufficient VAR (i.e., a VAR rich enough to capture the true dynamics in response to a given shock) estimated under passive monetary policy in the US is able to replicate the true impulse responses generated by a monetary policy DSGE model (which is the data generating process in their exercise). We test the informational sufficiency of our estimated VAR as regards the effects of a jump in uncertainty by running the Forni and Gambetti (2014) informational sufficiency test. Such test amounts to regressing our estimated uncertainty shocks series against lags of the principal components extracted from a large macroeconomic dataset. We use the McCracken and Ng (2016) monthly macroeconomic dataset to extract 7 principal components, as indicated by the Bai and Ng (2002) test. Our uncertainty shocks series is found to be orthogonal to information contained in the estimated principal components. Regressing our dummy over a constant and the seven factors lagged one period, we find that the F-test related to the null hypothesis of the factors not having predictive power has an associated p-value equal to 0.27. This evidence lends support to the hypothesis that our VAR is informational sufficient.

Before closing this Section, we would like to clarify that, ideally, a microfounded nonlinear DSGE framework approximated at a third-order around the steady state and allowing for an endogenous switch from a phase of the business cycle to another represents the ideal tool to conduct an investigation like ours. As far as we know, the extant literature has proposed no such tool so far. We see our reduced-form approach as potentially indicative of the findings one could obtain when working with such a framework.

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 an estimated nonlinear VAR model, we run counterfactual simulations by assuming that the systematic component of monetary policy does not respond to macroeconomic fluctuations triggered by financial uncertainty shocks, which we identify with large jumps in financial volatility. Our simulations point to a relatively higher policy effectiveness (i.e., ability to keep macroeconomic conditions in line with their trend) in expansionary phases.

Our findings lend support to theoretical models featuring a real-option effect like those developed by Bloom (2009), Berger and Vavra (2015), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), and Dibiasi (2018), which are consistent with a reduced ability by policymakers to influence output in presence of high uncertainty. More in general, our paper represents a first step toward a better understanding of the role that systematic monetary policy can play in tackling the effects of uncertainty shocks over the business cycle. The construction and estimation of microfounded nonlinear DSGE frameworks to analyze the role of monetary policy in tackling uncertainty shocks in booms and busts is the natural following step in this research agenda.

From a policy standpoint, the results of this study lend support to a more active role of central banks and policy makers in recessions, in particular deep recessions as the recent global crisis. Normatively, our findings call for a better understanding of the design of optimal state-dependent 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, Fisher, Gourio, and Krane (2015) and Seneca (2018) 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.

References

- AASTVEIT, K. A., G. J. NATVIK, AND S. SOLA (2017): “Economic Uncertainty and the Influence of Monetary Policy,” *Journal of International Money and Finance*, 76, 50–67.
- ABADIR, K., G. CAGGIANO, AND G. TALMAIN (2013): “Nelson-Plosser revisited: the ACF approach,” *Journal of Econometrics*, 175, 22–34.
- ABBATE, A., S. EICKMEIER, AND E. PRIETO (2016): “Financial Shocks and Inflation Dynamics,” CAMA Working Paper 53/2016.
- AUERBACH, A., AND Y. GORODNICHENKO (2012): “Measuring the Output Responses to Fiscal Policy,” *American Economic Journal: Economic Policy*, 4(2), 1–27.
- BACHMANN, R., AND E. SIMS (2012): “Confidence and the transmission of government spending shocks,” *Journal of Monetary Economics*, 59(3), 235–249.
- BAI, J., AND S. NG (2002): “Determining the Number of Factors in Approximate Factor Models,” *Econometrica*, 70(1), 191–221.
- BAKER, S., N. BLOOM, AND S. J. DAVIS (2016): “Measuring Economic Policy Uncertainty,” *Quarterly Journal of Economics*, 131(4), 1539–1636.
- BALEY, I., AND J. A. BLANCO (2019): “Firm Uncertainty Cycles and the Propagation of Nominal Shocks,” *American Economic Journal: Macroeconomics*, forthcoming.
- BASU, S., AND B. BUNDICK (2015): “Endogenous Volatility at the Zero Lower Bound: Implications for Stabilization Policy,” Federal Reserve Bank of Kansas City Research Working Paper No. 15-01.
- (2017): “Uncertainty Shocks in a Model of Effective Demand,” *Econometrica*, 85(3), 937–958.
- BEKAERT, G., E. ENGSTROM, AND N. R. XU (2019): “The Time Variation in Risk Appetite and Uncertainty,” Columbia Business School Research Paper No. 17-108.

- BEKAERT, G., AND M. HOEROVA (2016): “What do asset prices have to say about risk appetite and uncertainty?,” *Journal of Banking and Finance*, 67, 103–118.
- BEKAERT, G., M. HOEROVA, AND M. LO DUCA (2010): “Risk, Uncertainty and Monetary Policy,” NBER Working Paper No. 16397.
- (2013): “Risk, Uncertainty and Monetary Policy,” *Journal of Monetary Economics*, 60, 771–788.
- BENIGNO, P., AND M. WOODFORD (2012): “Linear-Quadratic Approximation of Optimal Policy Problems,” *Journal of Economic Theory*, 147(1), 1–42.
- BERGER, D., AND J. VAVRA (2014): “Measuring How Fiscal Shocks Affect Durable Spending in Recessions and Expansions,” *American Economic Review Papers and Proceedings*, 104(5), 112–115.
- (2015): “Consumption Dynamics During Recessions,” *Econometrica*, 83(1), 101–154.
- BERNANKE, B. S., M. GERTLER, AND M. W. WATSON (1997): “Systematic Monetary Policy and the Effects of Oil Price Shocks,” *Brookings Papers on Economic Activity*, 1, 91–142.
- BJØRNLAND, H. C., AND K. LEITEMO (2009): “Identifying the Interdependence Between U.S. Monetary Policy and the Stock Market,” *Journal of Monetary Economics*, 56, 275–282.
- BLANCHARD, O. (2009): “(Nearly) nothing to fear but fear itself,” *The Economist*, Economics focus (guest article), January 29.
- BLANCHARD, O., C. J. ERCEG, AND J. LINDE (2017): “Jump-Starting the Euro-Area Recovery: Would a Rise in Core Fiscal Spending Help the Periphery?,” NBER Macroeconomics Annual, University of Chicago Press, 31(1), 103–182.
- BLOOM, N. (2009): “The Impact of Uncertainty Shocks,” *Econometrica*, 77(3), 623–685.
- (2014): “Fluctuations in Uncertainty,” *Journal of Economic Perspectives*, 28(2), 153–176.
- BLOOM, N., M. FLOETOTTO, N. JAIMOVICH, I. SAPORTA-EKSTEN, AND S. J. TERRY (2018): “Really Uncertain Business Cycles,” *Econometrica*, 86(3), 1031–1065.
- BOIVIN, J., AND M. GIANNONI (2002): “Assessing Changes in the Monetary Transmission Mechanism: A VAR Approach,” *Federal Reserve Bank of New York Policy Review*, May, 97–111.
- BURNSIDE, C., M. EICHENBAUM, AND J. D. FISHER (2004): “Fiscal shocks and their consequences,” *Journal of Economic Theory*, 115(1), 89–117.
- CACCIATORE, M., AND F. RAVENNA (2018): “Uncertainty, Wages, and the Business Cycle,” HEC Montreal, mimeo.
- CAGGIANO, G., AND E. CASTELNUOVO (2011): “On the Dynamics of International Inflation,” *Economics Letters*, 112(2), 189–191.

- CAGGIANO, G., E. CASTELNUOVO, V. COLOMBO, AND G. NODARI (2015): “Estimating Fiscal Multipliers: News From a Nonlinear World,” *Economic Journal*, 125(584), 746–776.
- CAGGIANO, G., E. CASTELNUOVO, AND J. M. FIGUERES (2017): “Economic Policy Uncertainty and Unemployment in the United States: A Nonlinear Approach,” *Economics Letters*, 151, 31–34.
- CAGGIANO, G., E. CASTELNUOVO, AND N. GROSHENNY (2014): “Uncertainty Shocks and Unemployment Dynamics: An Analysis of Post-WWII U.S. Recessions,” *Journal of Monetary Economics*, 67, 78–92.
- CAGGIANO, G., E. CASTELNUOVO, AND G. PELLEGRINO (2017): “Estimating the Real Effects of Uncertainty Shocks at the Zero Lower Bound,” *European Economic Review*, 100, 257–272.
- CALDARA, D., C. FUENTES-ALBERO, S. GILCHRIST, AND E. ZAKRAJŠEK (2016): “The Macroeconomic Impact of Financial and Uncertainty Shocks,” *European Economic Review*, 88, 185–207.
- CANOVA, F., AND L. GAMBETTI (2010): “Do Expectations Matter? The Great Moderation Revisited,” *American Economic Journal: Macroeconomics*, 2(3), 183–205.
- CARRIERO, A., T. E. CLARK, AND M. MARCELLINO (2018): “Measuring Uncertainty and Its Impact on the Economy,” *Review of Economics and Statistics*, 100(5), 799–815.
- CARRIERO, A., H. MUMTAZ, K. THEODORIDIS, AND A. THEOPHILOPOULOU (2015): “The Impact of Uncertainty Shocks under Measurement Error: A Proxy SVAR Approach,” *Journal of Money, Credit and Banking*, 47(6), 1223–1238.
- CASARIN, R., C. FORONI, M. MARCELLINO, AND F. RAVAZZOLO (2018): “Uncertainty Through the Lenses of A Mixed-Frequency Bayesian Panel Markov Switching Model,” *Annals of Applied Statistics*, 12(4), 2559–2586.
- CASTELNUOVO, E., AND S. NISTICÒ (2010): “Stock Market Conditions and Monetary Policy in a DSGE Model for the U.S.,” *Journal of Economic Dynamics and Control*, 34(9), 1700–1731.
- CASTELNUOVO, E., AND G. PELLEGRINO (2018): “Uncertainty-dependent Effects of Monetary Policy Shocks: A New Keynesian Interpretation,” *Journal of Economic Dynamics and Control*, 93, 277–296.
- CASTELNUOVO, E., AND P. SURICO (2010): “Monetary Policy Shifts, Inflation Expectations and the Price Puzzle,” *Economic Journal*, 120(549), 1262–1283.
- CHAN, J. C. C., AND E. EISENSTAT (2018): “Bayesian model comparison for time-varying parameter VARs with stochastic volatility,” *Journal of Applied Econometrics*, forthcoming.
- CHERNOZHUKOV, V., AND H. HONG (2003): “An MCMC Approach to Classical Estimation,” *Journal of Econometrics*, 115(2), 293–346.

- CHRISTIANO, L., M. EICHENBAUM, AND C. EVANS (2005): “Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy,” *Journal of Political Economy*, 113(1), 1–45.
- CHRISTIANO, L. J., M. EICHENBAUM, AND C. EVANS (1999): “Monetary Policy Shocks: What Have We Learned and to What End?,” In: J.B. Taylor and M. Woodford (eds.): *Handbook of Macroeconomics*, Elsevier Science, 65–148.
- COGLEY, T., AND J. NASON (1995): “Effects of the Hodrick-Prescott Filter on Trend and Difference Stationary Time-Series: Implications for Business Cycle Research,” *Journal of Economic Dynamics and Control*, 19, 253–278.
- DAVIG, Y., AND E. LEEPER (2007): “Generalizing the Taylor Principle,” *American Economic Review*, 97(3), 607–635.
- DEL NEGRO, M., F. SCHORFHEIDE, F. SMETS, AND R. WOUTERS (2007): “On the Fit of New-Keynesian Models,” *Journal of Business and Economic Statistics*, 25(2), 124–162.
- DIBIASI, A. (2018): “Non-linear Effects of Uncertainty,” KOF ETH Zurich Swiss Economic Institute, mimeo.
- EICKMEIER, S., N. METIU, AND E. PRIETO (2016): “Time-Varying Volatility, Financial Intermediation and Monetary Policy,” CAMA Working Paper No. 32/2016.
- EVANS, C., J. D. M. FISHER, F. GOURIO, AND S. KRANE (2015): “Risk Management for Monetary Policy Near the Zero Lower Bound,” *Brookings Papers on Economic Activity*, Spring, 141–196.
- FERRARA, L., AND P. GUÉRIN (2018): “What Are The Macroeconomic Effects of High-Frequency Uncertainty Shocks?,” *Journal of Applied Econometrics*, 33(5), 662–679.
- FORNI, M., AND L. GAMBETTI (2014): “Sufficient information in structural VARs,” *Journal of Monetary Economics*, 66, 124–136.
- GNABO, J. Y., AND D. N. MOCCERO (2015): “Risk Management, Nonlinearity and Aggressiveness in Monetary Policy: The Case of the US Fed,” *Journal of Banking and Finance*, 55, 281–294.
- JACKSON, L. E., K. L. KLIESEN, AND M. T. OWYANG (2018): “The Nonlinear Effects of Uncertainty Shocks,” Federal Reserve Bank of St. Louis Working Paper No. 2018-035A.
- KOOP, G., M. PESARAN, AND S. POTTER (1996): “Impulse response analysis in nonlinear multivariate models,” *Journal of Econometrics*, 74(1), 119–147.
- KOOP, G., AND S. POTTER (1999): “Dynamic Asymmetries in U.S. Unemployment,” *Journal of Business and Economic Statistics*, 17(3), 298–312.
- LEDUC, S., AND Z. LIU (2016): “Uncertainty Shocks are Aggregate Demand Shocks,” *Journal of Monetary Economics*, 82, 20–35.
- LUDVIGSON, S. C., S. MA, AND S. NG (2019): “Shock Restricted Structural Vector-Autoregressions,” New York University, Federal Reserve Board, and Columbia University.

- MCCRACKEN, M. W., AND S. NG (2016): “FRED-MD: A Monthly Database for Macroeconomic Research,” *Journal of Business and Economic Statistics*, 34(4), 574–589.
- MORLEY, J., AND J. PIGER (2012): “The Asymmetric Business Cycle,” *Review of Economics and Statistics*, 94(1), 208–221.
- MORLEY, J., J. PIGER, AND P.-L. TIEN (2013): “Reproducing Business Cycle Features: Are Nonlinear Dynamics a Proxy for Multivariate Information?,” *Studies in Nonlinear Dynamics & Econometrics*, 17(5), 483–498.
- MUMTAZ, H., AND P. SURICO (2015): “The Transmission Mechanism in Good and Bad Times,” *International Economic Review*, 56, 1237–1260.
- PELLEGRINO, G. (2018): “Uncertainty and the Real Effects of Monetary Policy Shocks in the Euro Area,” *Economics Letters*, 162, 177–181.
- RAMEY, V. A. (2016): “Macroeconomic Shocks and Their Propagation,” in: J.B. Taylor and H. Uhlig (Eds.): *Handbook of Macroeconomics*, Volume 2, Elsevier Science, 71–162.
- RAMEY, V. A., AND M. D. SHAPIRO (1998): “Costly capital reallocation and the effects of government spending,” *Carnegie-Rochester Conference Series on Public Policy*, 48, 145–194.
- ROMER, C. D., AND D. H. ROMER (1994): “Monetary Policy Matters,” *Journal of Monetary Economics*, 34, 75–88.
- RUDEBUSCH, G. D. (2005): “Assessing the Lucas Critique in Monetary Policy Models,” *Journal of Money, Credit and Banking*, 37(2), 245–272.
- SENECA, M. (2018): “Risk Shocks and Monetary Policy in the New Normal,” Bank of England Staff Working Paper No. 606.
- SICHEL, D. E. (1993): “Business Cycle Asymmetry: A Deeper Look,” *Economic Inquiry*, 31(2), 224–236.
- SIMS, C., AND T. ZHA (2006): “Were There Regime Switches in U.S. Monetary Policy?,” *American Economic Review*, 96(1), 54–81.
- TENREYRO, S., AND G. THWAITES (2016): “Pushing on a string: US monetary policy is less powerful in recessions,” *American Economic Journal: Macroeconomics*, 8(4), 43–74.
- TERÄSVIRTA, T. (2018): “Nonlinear Models in Macroeconometrics,” *Oxford Research Encyclopedias in Economics and Finance*, Oxford: Oxford University Press.
- TERÄSVIRTA, T., D. TJØSTHEIM, AND C. W. GRANGER (2010): “Modeling Nonlinear Economic Time Series,” Oxford University Press, Oxford.
- TERÄSVIRTA, T., AND Y. YANG (2014): “Linearity and Misspecification Tests for Vector Smooth Transition Regression Models,” CREATES Research Papers 2014-04, School of Economics and Management, University of Aarhus.

- VAN DIJK, D., T. TERÄSVIRTA, AND P. H. FRANSES (2002): “Smooth Transition Autoregressive Models - A Survey of Recent Developments,” *Econometric Reviews*, 21(1), 1–47.
- VAVRA, J. (2014): “Inflation Dynamics and Time-Varying Volatility: New Evidence and an Ss Interpretation,” *Quarterly Journal of Economics*, 129(1), 215–258.
- WEISE, C. L. (1999): “The Asymmetric Effects of Monetary Policy: A Nonlinear Vector Autoregression Approach,” *Journal of Money, Credit and Banking*, 31(1), 85–108.
- WOODFORD, M. (2003): *Interest and Prices: Foundations of a Theory of Monetary Policy*. Princeton University Press. Princeton, New Jersey.

<i>Uncertainty shock</i>				
	Recessions		Expansions	
<i>DB</i>				
ind. prod.	24.75		107.36	
employment	10.90		64.57	
prices	1.40		13.17	
<i>SR</i>	factual	counterf.	factual	counterf.
ind. prod.	9	19	23	60
employment	12	24	23	60
prices	55	60	48	60

Table 1: **Monetary Policy (In)effectiveness in Recessions: Deviations from the Baseline and Speed of Recovery.** DB = Deviations from the Baseline; SR = Speed of Recovery. Values of the metrics computed as indicated in the text. Upper bound for the SR metric set to 60.

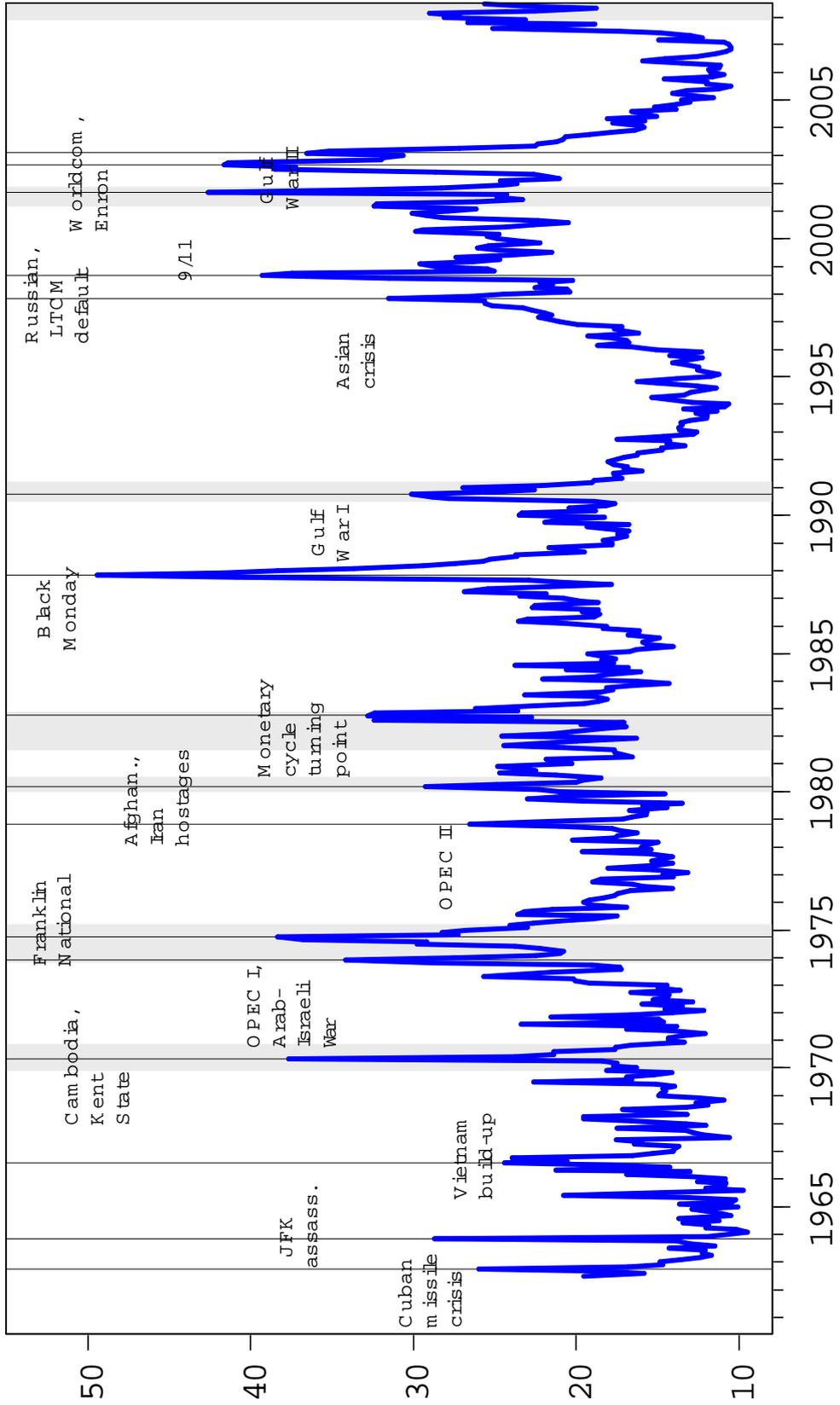


Figure 1: **Uncertainty shocks and the business cycle.** Sample: 1962M7-2008M6. Blue line: U.S. stock market volatility. Shaded areas: NBER recessions. U.S. stock market volatility: Chicago Board of Options Exchange VXO index of implied volatility (on a hypothetical at the money Standard and Poor's 100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

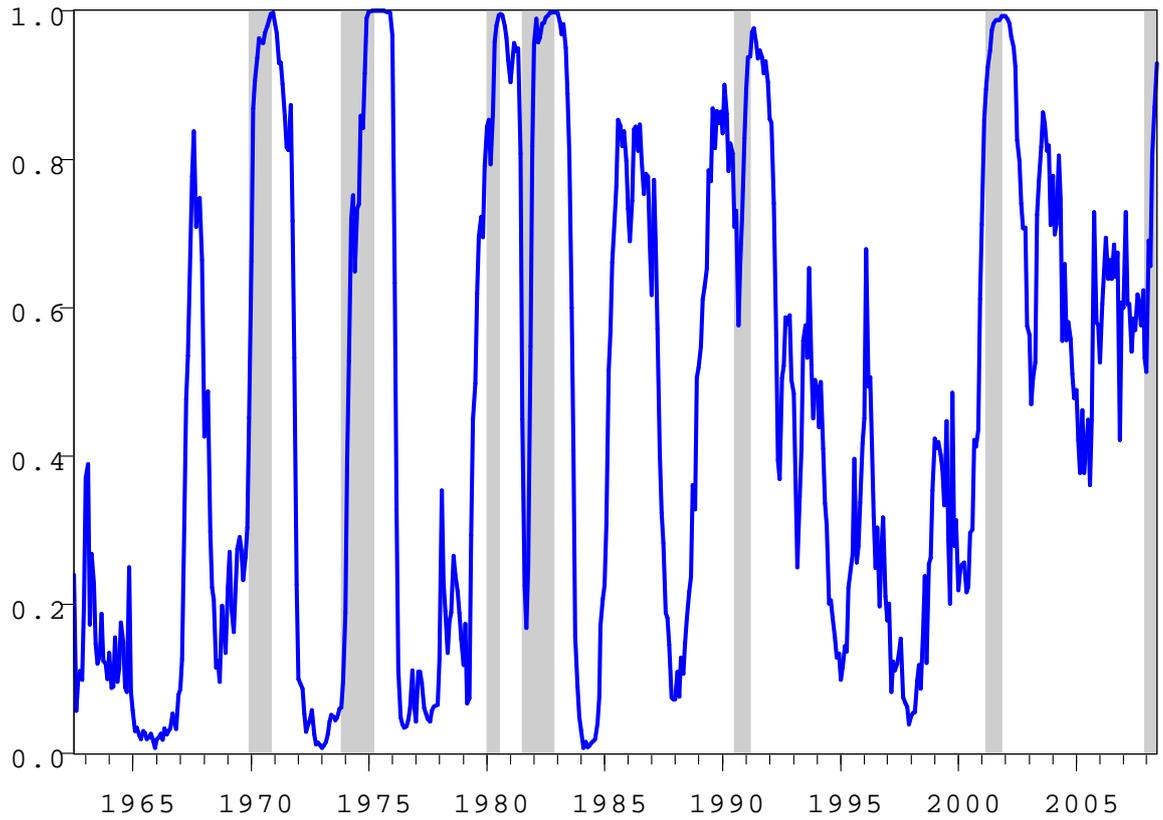


Figure 2: **Probability of being in a recessionary phase.** Blue line: Transition function $F(z)$. Shaded columns: NBER recessions. Transition function computed by employing the standardized moving average (12 terms) of the month-on-month growth rate of industrial production.

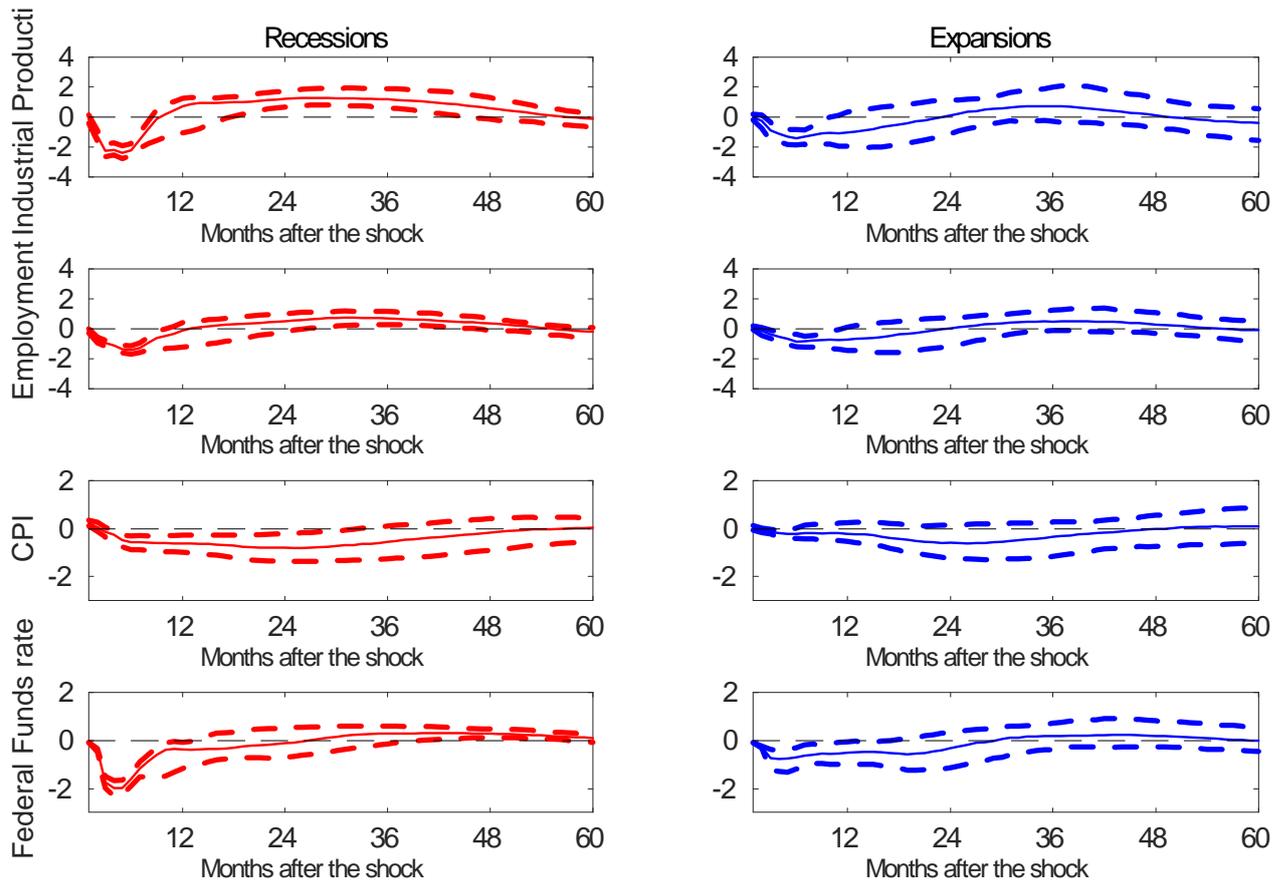


Figure 3: **Macroeconomic Effects of Uncertainty Shocks: Good and Bad Times.** Impulse responses (median values) to an uncertainty shock inducing an on-impact reaction of uncertainty equal to one as in Bloom (2009). Uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled)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

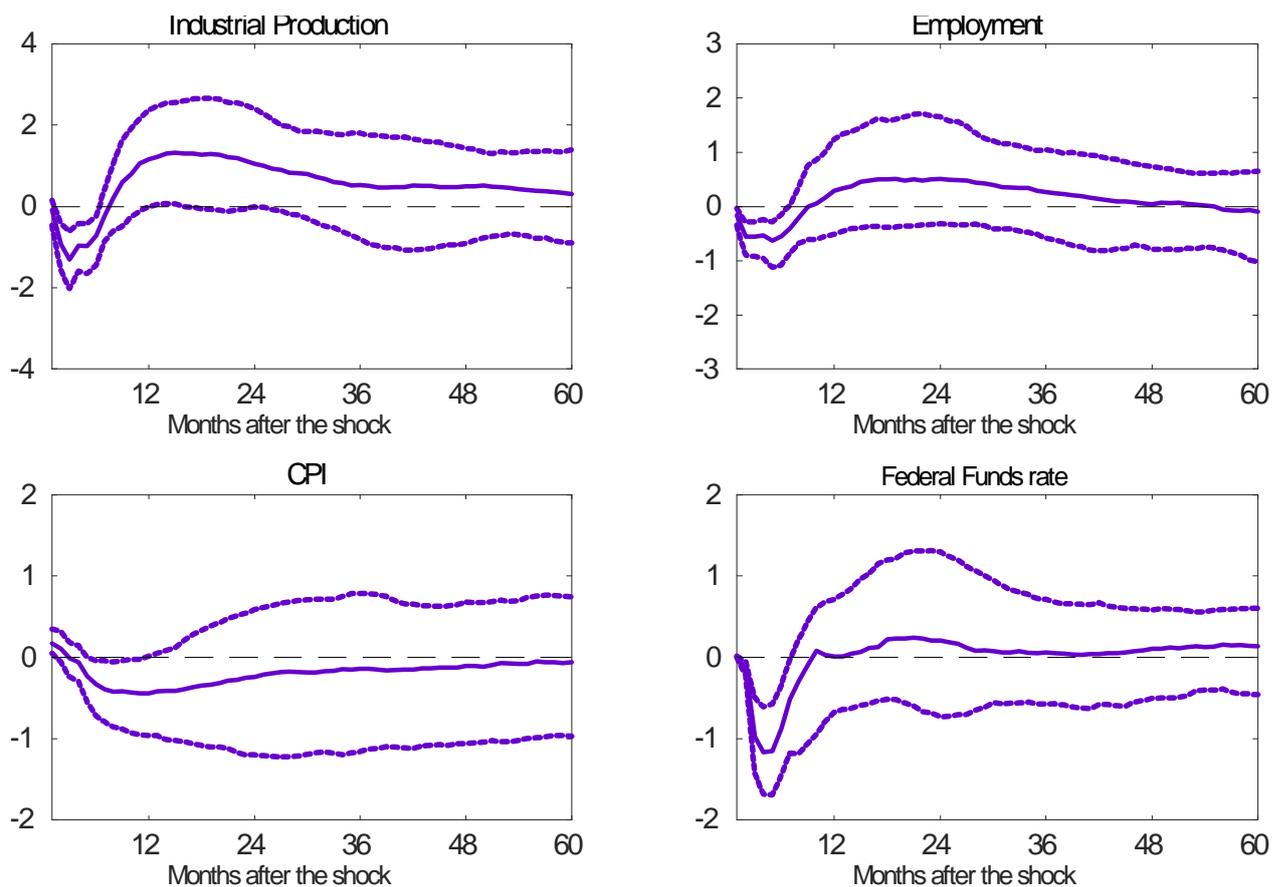


Figure 4: **Effects of Uncertainty Shocks: Differences between Recessions and Expansions.** Differences between generalized median impulse responses in busts and booms to an uncertainty shock inducing an on-impact reaction of uncertainty equal to one as in Bloom (2009). Solid line: Median realizations. 68% confidence intervals identified via dotted lines. Uncertainty shock identified as described in the paper.

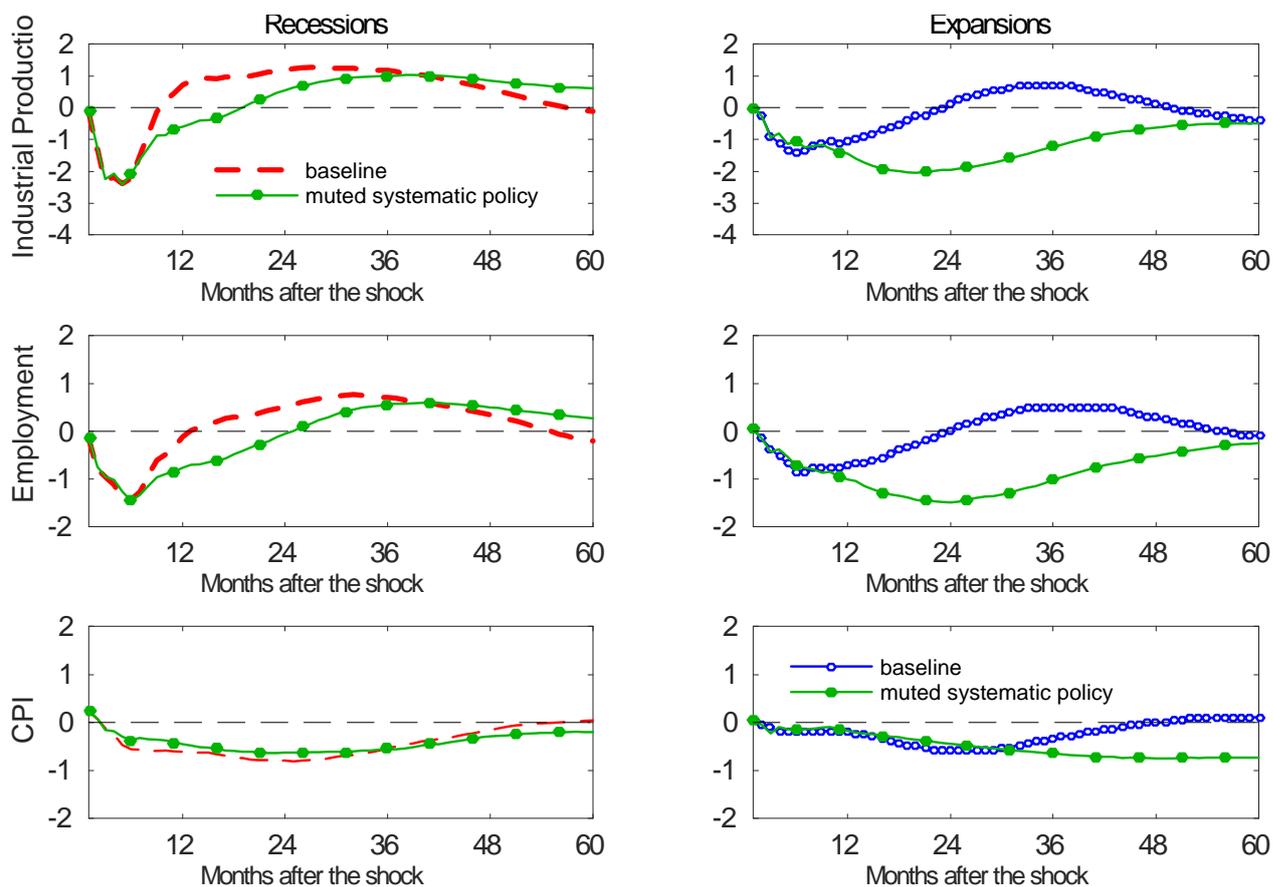


Figure 5: **Real Effects of Uncertainty Shocks: Role of Systematic Monetary Policy.** Median impulse responses to a one-standard deviation uncertainty in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Counterfactual responses computed conditional on a muted systematic policy (fixed federal funds rate) in green-circled lines.

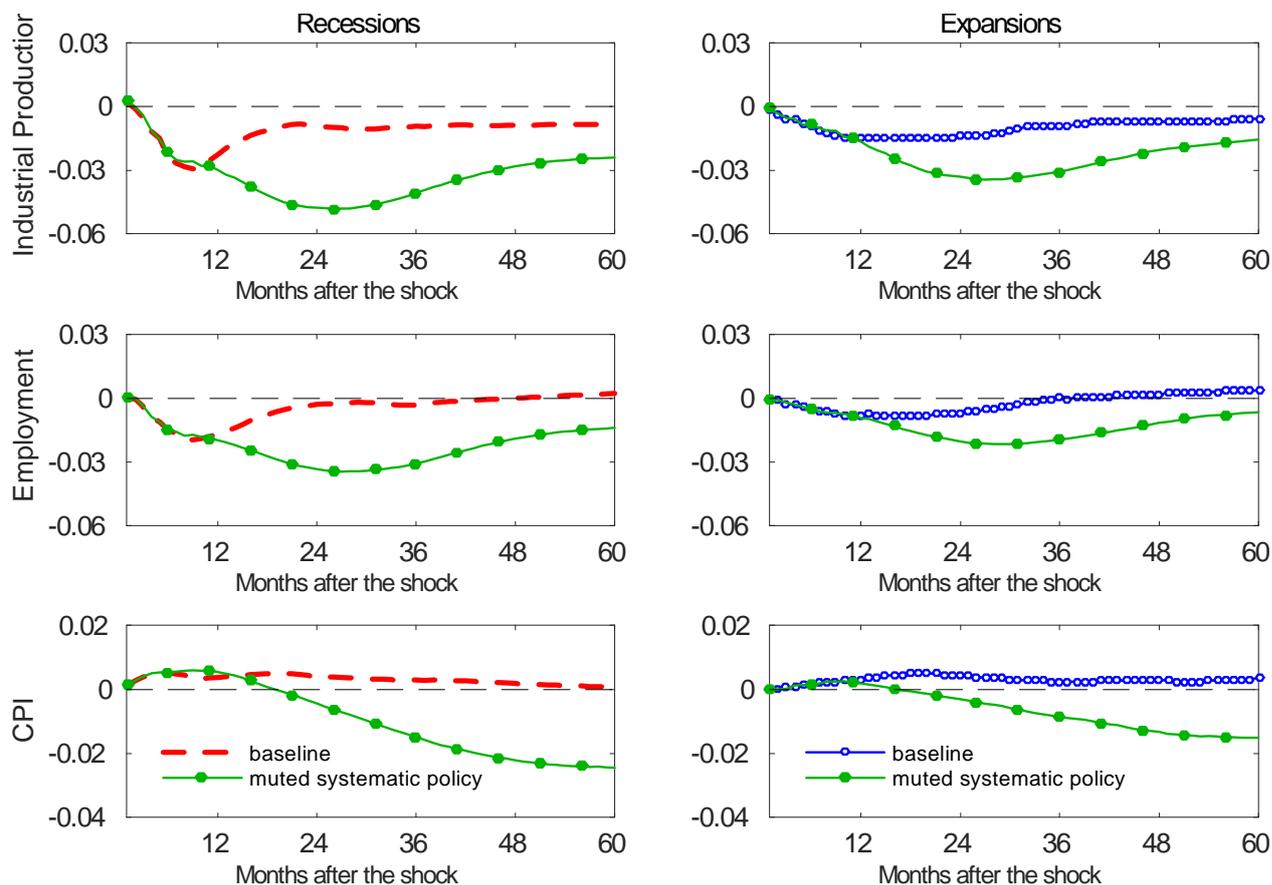


Figure 6: **Macroeconomic Effects of First Moment Financial Shocks: Role of Systematic Monetary Policy.** Median impulse responses to a one-standard deviation decrease in the S&P500 index in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed 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.

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.

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:

$$\mathbf{X}_t = \Theta'_0 \mathbf{Y}_t + \sum_{i=1}^n \Theta'_i \mathbf{Y}_t z_t^i + \varepsilon_t \quad (\text{A1})$$

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 Θ_0 and Θ_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, $\Theta_i = \mathbf{0} \forall i$.

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

1. Estimate the restricted model ($\Theta_i = \mathbf{0}, \forall i$) 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 $\tilde{\tilde{\mathbf{E}}}$ and compute the matrix residual sum of squares $\mathbf{RSS}_1 = \tilde{\tilde{\mathbf{E}}}' \tilde{\tilde{\mathbf{E}}}$.

3. Compute the test-statistic

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

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:

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

where $\boldsymbol{\varepsilon}_t = \mathbf{X}_t - (1 - F(z_{t-1}))\boldsymbol{\Pi}_E \mathbf{X}_{t-1} - F(z_{t-1})\boldsymbol{\Pi}_R \mathbf{X}_{t-1}$ 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 $\boldsymbol{\Pi}_j(L) = [\boldsymbol{\Pi}_{j,1} \ \dots \ \boldsymbol{\Pi}_{j,p}]$, $j \in \{R, E\}$. 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.

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

Conditional on $\{\gamma, \mathbf{\Omega}_R, \mathbf{\Omega}_E\}$, the model is linear in $\{\mathbf{\Pi}_R(L), \mathbf{\Pi}_E(L)\}$. Then, for a given guess on $\{\gamma, \mathbf{\Omega}_R, \mathbf{\Omega}_E\}$, the coefficients $\{\mathbf{\Pi}_R(L), \mathbf{\Pi}_E(L)\}$ can be estimated by minimizing $\frac{1}{2} \sum_{t=1}^T \boldsymbol{\varepsilon}_t' \mathbf{\Omega}_t^{-1} \boldsymbol{\varepsilon}_t$. This can be seen by re-writing the regressors as follows. Let $\mathbf{W}_t = [F(z_{t-1})\mathbf{X}_{t-1} \quad (1 - F(z_{t-1}))\mathbf{X}_{t-1} \quad \dots \quad F(z_{t-1})\mathbf{X}_{t-p} \quad 1 - F(z_{t-1})\mathbf{X}_{t-p}]$ be the extended vector of regressors, and $\mathbf{\Pi} = [\mathbf{\Pi}_R(L) \quad \mathbf{\Pi}_E(L)]$. Then, we can write $\boldsymbol{\varepsilon}_t = \mathbf{X}_t - \mathbf{\Pi}\mathbf{W}_t'$. Consequently, the objective function becomes

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

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

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

This procedure iterates over different sets of values for $\{\mathbf{\Omega}_R, \mathbf{\Omega}_E\}$ (conditional on a given value for γ). For each set of values, $\mathbf{\Pi}$ 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 $\{\mathbf{\Omega}_R, \mathbf{\Omega}_E\}$ and then explore the robustness of the estimates to different values of γ . To ensure positive definiteness of the matrices $\mathbf{\Omega}_R$ and $\mathbf{\Omega}_E$, we focus on the alternative vector of parameters $\boldsymbol{\Psi} = \{chol(\mathbf{\Omega}_R), chol(\mathbf{\Omega}_E), \mathbf{\Pi}_R(L), \mathbf{\Pi}_E(L)\}$, 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 $N(0, \mathbf{\Omega}_{\boldsymbol{\Psi}})$, and $\mathbf{\Omega}_{\boldsymbol{\Psi}}$ 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 $\Theta^{(0)}$ 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 \mathbf{X}_t on lags of \mathbf{X}_t , $\mathbf{X}_t z_t$, and $\mathbf{X}_t z_t^2$. 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 Ω_R and Ω_E . Conditional on these estimates and given a calibration for γ , we can construct Ω_t . Conditional on Ω_t , we can get starting values for $\Pi_R(L)$ and $\Pi_E(L)$ via equation (A3).

Given a calibration for the initial (diagonal matrix) Ω_Ψ , 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 $N = 10,000$ draws for our estimates, and retain the last 20% for inference. Checks performed with $N = 50,000$ draws delivered very similar results.

As shown by CH, $\bar{\Psi} = \frac{1}{N} \sum_{n=1}^N \Psi^{(n)}$ is a consistent estimate of Ψ under standard regularity assumptions on maximum likelihood estimators. Moreover, the covariance matrix of Ψ is given by $\mathbf{V} = \frac{1}{N} \sum_{n=1}^N (\Psi^{(n)} - \bar{\Psi})^2 = \text{var}(\Psi^{(n)})$, 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 $t = 1962M7, \dots, 2008M6$, with $T = 552$, and construct the set of all possible histories Λ of length $p = 12$:² $\{\lambda_i \in \Lambda\}$. Λ will contain $T - p + 1$ histories λ_i .
2. Separate the set of all recessionary histories from that of all expansionary histories. For each λ_i calculate the transition variable z_{λ_i} . If $z_{\lambda_i} \leq \bar{z} = -1.01\%$, then $\lambda_i \in \Lambda^R$, where Λ^R is the set of all recessionary histories; if $z_{\lambda_i} > \bar{z} = -1.01\%$, then $\lambda_i \in \Lambda^E$, where Λ^E is the set of all expansionary histories.
3. Select at random one history λ_i from the set Λ^R . For the selected history λ_i , take $\hat{\Omega}_{\lambda_i}$ obtained as:

$$\hat{\Omega}_{\lambda_i} = F(z_{\lambda_i}) \hat{\Omega}_R + (1 - F(z_{\lambda_i})) \hat{\Omega}_E, \quad (\text{A4})$$

²The 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 $\widehat{\boldsymbol{\Omega}}_{\lambda_i}$:

$$\widehat{\boldsymbol{\Omega}}_{\lambda_i} = \widehat{\mathbf{C}}_{\lambda_i} \widehat{\mathbf{C}}_{\lambda_i}' \quad (\text{A5})$$

and orthogonalize the estimated residuals to get the structural shocks:

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

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

$$\mathbf{e}_{\lambda_i}^{(j)*} = \{ \mathbf{e}_{\lambda_i, t}^*, \mathbf{e}_{\lambda_i, t+1}^*, \dots, \mathbf{e}_{\lambda_i, t+h}^* \}, \quad (\text{A7})$$

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 $\mathbf{e}_{\lambda_i, t}^{(j)*}$ which is the shock we want to perturb by an amount equal to δ . Denote the vector of bootstrapped perturbed shocks by $\mathbf{e}_{\lambda_i}^{(j)\delta}$.
7. Transform back $\mathbf{e}_{\lambda_i}^{(j)*}$ and $\mathbf{e}_{\lambda_i}^{(j)\delta}$ as follows:

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

and

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

8. Use (A8) and (A9) to simulate the evolution of $\mathbf{X}_{\lambda_i}^{(j)*}$ and $\mathbf{X}_{\lambda_i}^{(j)\delta}$ and construct the $GIRF^{(j)}(h, \delta, \lambda_i)$ as $\mathbf{X}_{\lambda_i}^{(j)*} - \mathbf{X}_{\lambda_i}^{(j)\delta}$.
9. Conditional on history λ_i , repeat for $j = 1, \dots, B$ vectors of bootstrapped residuals and get $GIRF^{(1)}(h, \delta, \lambda_i), GIRF^{(2)}(h, \delta, \lambda_i), \dots, GIRF^{(B)}(h, \delta, \lambda_i)$. Set $B = 500$.

³We 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

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

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

12. Take the average and get $\widehat{GIRF}^{(R)}(h, \delta, \Lambda^R)$, 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 $\widehat{GIRF}^{(E)}(h, \delta, \Lambda^E)$.

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

Conditional on the algorithm outlined above, the transition indicator z has to enter the equations explaining the dynamics of the endogenous variables with a lag. The reason is the following. Consider $z_t \equiv \frac{\log(ip_t/ip_{t-12}) - \overline{\log(ip_t/ip_{t-12})}}{\sigma[\log(ip_t/ip_{t-12})]}$, where ip_t = industrial production at time t , and $\overline{\log(ip_t/ip_{t-12})}$ and $\sigma[\log(ip_t/ip_{t-12})]$ respectively indicate the sample mean of the yearly growth rate of industrial production and its standard deviation, and where $\log(ip_t/ip_{t-12}) = \sum_{h=0}^{11} \log(ip_{t-h}/ip_{t-h-1})$. Given that ip_t belongs to the vector of endogenous variables X_t , we cannot dynamically simulate X_t by modeling the logistic function as $F(z_t(ip_t, \dots))$, because the presence of z_t on the right-hand side of eq. (1) in the text of the paper would imply that ip_t is contemporaneously present in both sides of such equation. This would break down the dynamic chain linking past variables on the right-hand side of eq. (1) to contemporaneous variables on its the left-hand side. This is the reason why, in computing the GIRFs, we condition on past values of z to endogenously determine X_t and z_t . The latter object is then used in the following period to determine the probability of recession $F(z_t)$ and, consequently, X_{t+1} .

Robustness analysis

We now analyze the robustness of our main finding - i.e., the asymmetric effects of systematic monetary policy on real activity - along a battery of variations of our baseline model.

Longer sample. Our baseline analysis investigates data until June 2008. There are two reasons for this choice. First, our baseline sample is the same as the one employed by Bloom (2009). This choice facilitates the comparison between his results and ours. Second, and more important, using data until the middle of 2008 avoids us to deal with the acceleration of the global financial crisis, which quickly led the Federal Reserve to slash the federal funds rate down to zero, i.e., to hit the zero lower bound (ZLB). Recent research (Caggiano, Castelnuovo, and Pellegrino (2017)) points to larger real effects of financial uncertainty shocks due to the ZLB, an empirical finding which the authors show to be present above and beyond the larger real effects of uncertainty shocks often associated to recessions *per se*. However, we check if our stylized facts are robust to modeling the global financial crisis and the subsequent recovery by updating the sample until June 2018. To do so, we update the series of the variables modeled by our VAR and identify further large spikes in the HP-detrended VXO whose values are above 1.65 standard deviation. As a measure of monetary policy stance, we use Leo Krippner's measure of the shadow rate, available here: <https://www.rbzn.govt.nz/research-and-publications/research-programme/additional-research/measures-of-the-stance-of-united-states-monetary-policy>. (The same website provides documents with details on the construction of such shadow rate). The re-calibrated slope parameter of the logistic function is $\gamma = 1.9$, which implies that recessions are about 14% of our sample. Figure A1 documents the GIRFs associated to this longer sample. Reassuringly, such GIRFs confirm our baseline findings.

Labor market variables as transition indicators. Our baseline exercise hinges up the employment of a MA(12) monthly growth rate of industrial production as transition indicator. Labor market indicators are often seen as informative for the stance of the business cycle. We then run three checks focusing on three different labor market indicators as transition indicators. First, we estimate a model by employing a MA(6) for the monthly growth rate of total non-farm payrolls. Second, we employ a MA(12) process for the monthly growth rate of manufacturing employment as an alternative endogenous transition indicator. Third, we use the level of the unemployment rate. In particular, we follow Ramey and Zubairy (2016) and classify periods in which the

unemployment rate is over (under) 6.5% as recessionary (expansionary). For all these exercises, we re-calibrate the slope parameter γ to match the 14% frequency of recessions in the sample as classified by the NBER. Figure A2 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.

Alternative financial uncertainty indicators. 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 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

⁴The 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.

one-month ahead financial uncertainty indicator recently developed by Ludvigson, Ma, and Ng (2019). Figure A3 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 A4, which plots our baseline GIRFs along with the GIRFs obtained with alternative calibrated values for γ . This robustness check clearly confirms our baseline results.

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 A5 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 (2017), 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 A6 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.

⁵The 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.

These results are consistent with those in with Furlanetto, Ravazzolo, and Sarferaz (2017), who show that part of the effects often attributed to uncertainty shocks may be an artifact due to the omission of house prices from VAR analysis. However, even when controlling for house prices, we find asymmetric responses of industrial production and employment (in terms of severity of the recession, speed of the recovery, and overall dynamics) over the business cycle.

Wrapping up, our findings are robust to the inclusion of a different uncertainty indicators, calibration of the slope parameter of the logistic function, business cycle indicators to detect the transition from a state to another, a measure of credit spread, and an indicator of real house prices.

Short- vs. long-term interest rates. The differences documented in Figure 5 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 sec-

⁶Such 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.

ond counterfactual, we estimate the responses to an uncertainty shock conditional on a fixed path of the long-term interest rate, i.e. under the assumption that expectations about the future stance of monetary policy remain unchanged. This exercise is intended to capture the role that the 10-year rate plays in transmitting the effects of uncertainty shocks. Clearly, the 10-year rate is a combination of expectations over future monetary policy moves and the risk-premium, and as such should be considered only as an imperfect proxy of expectations.

Figure A7 plots the impulse responses. Three results stand out. First, the presence of the long-term interest rate *per se* does not exert any appreciable impact on the impulse responses, which are very similar to those obtained with our baseline STVAR (shown in Figure 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 5 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

Federal funds rate ordered last. As discussed in the text, one could question the ordering of the variables in our baseline VAR because it does not allow for a contemporaneous response of the federal funds rate to movements in prices and quantities after an uncertainty shock. We then check if our results are robust to ordering the federal funds rate last in the vector. From an economic standpoint, this means that we are endowing the central bank with all information available at time t in the economic system. In other words, this robustness check enables the central bank to contemporaneously react to prices, real indicators of the business cycle such as average hourly earnings, industrial production, hours, and employment, and financial indicators such as the S&P500 index and financial uncertainty. This ordering admits (without requiring it) a systematic response of the policy rate to movements in stock prices (as in, e.g., Bjørnland and Leitemo (2009) and Castelnuovo and Nisticò (2010)) and to uncertainty *per se*, the latter being consistent with a risk-management approach by the Federal Reserve (Evans, Fisher, Gourio, and Krane (2015) and Caggiano, Castelnuovo, and Nodari (2018)). Following Christiano, Eichenbaum, and Evans (1999), we keep the variables in log-levels to avoid information losses due to over-differentiation of the variables. Figure A8 shows that our main finding - i.e., monetary policy being more effective in expansions as far as the response of real activity is concerned - is robust to ordering the federal funds rate last.

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 mag-

⁷Obviously, caution should be used in interpreting these results, which come from exercises that are subject to the Lucas critique. Ideally, one should build up a model which meaningfully features uncertainty shocks, financial frictions, short- and long-term interest rates, and mechanisms inducing a nonlinear response of real aggregates to uncertainty shocks. We see our results as supporting this research agenda.

nitude 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).

Ad-hoc loss function analysis

When working with a microfounded DSGE models, monetary policy efficiency is typically assessed by appealing to micro-founded, model-specific loss functions (Woodford (2003), Benigno and Woodford (2012)).⁸ Our VAR does not offer us relevant information on how to build up a micro-founded loss function. Hence, to assess monetary policy efficiency, we appeal to an ad-hoc loss function which has already been coupled with backward looking, VAR-type of models (Rudebusch and Svensson (2002)). Following Rudebusch and Svensson (2002), and adapting their approach to our case, we consider the following period loss function

$$L_t = \tilde{\pi}_t^2 + \lambda_{ip} \tilde{ip}_t^2 + \lambda_{empl} \widetilde{empl}_t^2 \quad (1)$$

where $\pi_t = p_t - p_{t-1}$, p is the price index, ip is industrial production, and $empl$ is employment (all expressed in logarithms). The variables in eq. (1) are wiggled to indicate that they are expressed in deviations with respect to their steady-state (inflation) or their trend (industrial production, employment). Hence, the loss function (1) associates a cost to fluctuations in inflation, industrial production, and employment with respect to their steady-state (inflation) and trends (real activity). The cost associated to the three arguments in the loss function (1) is weighted by the relative weights λ_{ip} and λ_{empl} .

A common assumption in modern macroeconomics is that central banks minimize intertemporal loss functions (Woodford (2003)). Following Rudebusch and Svensson (2002), and assuming a discount factor $\beta \in (0, 1)$, such a loss function at time t can be written as

$$E_t(1 - \beta) \sum_{h=0}^{\infty} L_{t+h} \quad (2)$$

⁸Deviations from this trend are present in the recent literature. For instance, Blanchard, Erceg, and Lindé (2017) study welfare implications of various macroeconomic policies both with the lens of a microfounded welfare function and via an ad hoc one. Commenting such exercise, Blanchard (2016, page 2) writes: "Having looked [...] at welfare implications of various policies through both an ad hoc welfare function reflecting deviations of output from potential and inflation from target and the welfare function implied by the model, I drew two conclusions. First, the exercise of deriving the internally consistent welfare function was useful in showing potential welfare effects I had not thought about but concluded ex post was probably relevant. Second, between the two, I still had more confidence in the conclusions of the ad hoc welfare function."

Rudebusch and Svensson (2002, Appendix) show that, when $\beta \rightarrow 1$ (a plausible assumption when working with monthly data), the loss function (1) and (2) approaches

$$E(L_t) = \sigma_{\tilde{\pi}}^2 + \lambda_{ip}\sigma_{\tilde{ip}}^2 + \lambda_{empl}\sigma_{\widetilde{empl}}^2 \quad (3)$$

Given that the variances $\sigma_{\tilde{x}}^2$, $\tilde{x} \in \{\tilde{\pi}, \tilde{ip}, \widetilde{empl}\}$ in (3) refer to variables in deviations with respect to their trends (or, in the case of inflation, its target), we can approximate the value of such variances conditional on an uncertainty shock by appealing to our impulse responses, i.e.,

$$\sigma_{\tilde{x}}^2 \simeq \sum_{h=0}^H \left(\frac{\partial \tilde{x}_h}{\partial \varepsilon_0^{unc}} \right)^2 \quad (4)$$

where ε_0^{unc} is the uncertainty shock hitting at time zero, and the forecast horizon is truncated at $H = 60$. In words, eq. (4) approximates the volatility of the welfare-relevant objects with the squared response of each given variable \tilde{x} to an uncertainty shock ε_0^{unc} per each given period h over an horizon H . Notice that our VAR model features prices in log levels. Hence, we compute the inflation rate by working with the first difference of the impulse responses of log prices. As regards the relative importance of the volatility of real activity with respect to that of inflation in the loss function (3), we follow Blanchard, Erceg, and Lindé (2017) and set the relative weights of real activity indicators $\lambda_{ip} = \lambda_{empl} = 1/3$.

Table A1 collects the values of the computed volatilities and the corresponding loss functions in the scenarios of interest. In line with the already documented stronger macroeconomic effect of uncertainty shocks in recessions, the factual scenario is associated to larger factual volatilities in that state. In terms of scale, the volatilities of real activity are much bigger than that of inflation, a fact in line with the mild effects of uncertainty shocks on the growth rate (as opposed to the level) of prices. Turning to our counterfactuals, the volatilities of employment in both states are larger (above all in expansions) than the ones conditional on the historical (factual) policy. The same can be said as regards the volatility of industrial production and inflation, but only in expansions. When computing the value of the loss function (3) and (4), we observe a mild change (actually, a slight reduction of about 10%) in recessions. Quite differently, the muted policy response in expansions turn out to be very costly, with a loss function in the counterfactual scenario whose value is 327%, i.e., four times as large as the one under the active monetary policy. This result confirms that different systematic monetary policies in recessions are pretty ineffective in influencing the paths of prices and

real activity in relative terms with respect to the same policies in good times.

References

- AUERBACH, A., AND Y. GORODNICHENKO (2012): “Measuring the Output Responses to Fiscal Policy,” *American Economic Journal: Economic Policy*, 4(2), 1–27.
- BACCHIOCCHI, E., E. CASTELNUOVO, AND L. FANELLI (2016): “Gimme a Break! Identification and Estimation of the Macroeconomic Effects of Monetary Policy Shocks in the U.S.,” *Macroeconomic Dynamics*, forthcoming.
- BAGLIANO, F. C., AND C. A. FAVERO (1998): “Measuring monetary policy with VAR models: An evaluation,” *European Economic Review*, 42, 1069–1112.
- BEKAERT, G., M. HOEROVA, AND M. LO DUCA (2013): “Risk, Uncertainty and Monetary Policy,” *Journal of Monetary Economics*, 60, 771–788.
- BENIGNO, P., AND M. WOODFORD (2012): “Linear-Quadratic Approximation of Optimal Policy Problems,” *Journal of Economic Theory*, 147(1), 1–42.
- BERNANKE, B. (2013): “Long-Term Interest Rates,” Speech held at the Annual Monetary/Macroeconomics Conference: The Past and Future of Monetary Policy, Federal Reserve Bank of San Francisco, San Francisco, California, March 1.
- BJØRNLAND, H. C., AND K. LEITEMO (2009): “Identifying the Interdependence Between U.S. Monetary Policy and the Stock Market,” *Journal of Monetary Economics*, 56, 275–282.
- BLANCHARD, O. (2016): “Do DSGE Models Have a Future?,” Peterson Institute for International Economics Policy Brief 16-11.
- BLANCHARD, O., C. J. ERCEG, AND J. LINDE (2017): “Jump-Starting the Euro-Area Recovery: Would a Rise in Core Fiscal Spending Help the Periphery?,” NBER Macroeconomics Annual, University of Chicago Press, 31(1), 103–182.
- CAGGIANO, G., E. CASTELNUOVO, AND G. NODARI (2018): “Risk Management-Driven Policy Rate Gap,” *Economics Letters*, 171, 235–238.
- CAGGIANO, G., E. CASTELNUOVO, AND G. PELLEGRINO (2017): “Estimating the Real Effects of Uncertainty Shocks at the Zero Lower Bound,” *European Economic Review*, 100, 257–272.
- CALDARA, D., C. FUENTES-ALBERO, S. GILCHRIST, AND E. ZAKRAJŠEK (2016): “The Macroeconomic Impact of Financial and Uncertainty Shocks,” *European Economic Review*, 88, 185–207.
- CANOVA, F. (2007): *Methods for Applied Macroeconomic Research*, Princeton University Press, Princeton, New Jersey.
- CASTELNUOVO, E., AND S. NISTICÒ (2010): “Stock Market Conditions and Monetary Policy in a DSGE Model for the U.S.,” *Journal of Economic Dynamics and Control*, 34(9), 1700–1731.

- CHERNOZHUKOV, V., AND H. HONG (2003): “An MCMC Approach to Classical Estimation,” *Journal of Econometrics*, 115(2), 293–346.
- CHRISTIANO, L. J., M. EICHENBAUM, AND C. EVANS (1999): “Monetary Policy Shocks: What Have We Learned and to What End?,” In: J.B. Taylor and M. Woodford (eds.): *Handbook of Macroeconomics*, Elsevier Science, 65–148.
- EVANS, C., J. D. M. FISHER, F. GOURIO, AND S. KRANE (2015): “Risk Management for Monetary Policy Near the Zero Lower Bound,” *Brookings Papers on Economic Activity*, Spring, 141–196.
- FURLANETTO, F., F. RAVAZZOLO, AND S. SARFERAZ (2017): “Identification of financial factors in economic fluctuations,” *Economic Journal*, forthcoming.
- GERTLER, M., AND P. KARADI (2015): “Monetary Policy Surprises, Credit Costs, and Economic Activity,” *American Economic Journal: Macroeconomics*, 7(1), 44–76.
- GILCHRIST, S., AND E. ZAKRAJŠEK (2012): “Credit Spreads and Business Cycle Fluctuations,” *American Economic Review*, 102(4), 1692–1720.
- GÜRKAYNAK, R. S., B. SACK, AND E. SWANSON (2005): “The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models,” *American Economic Review*, 95(1), 425–36.
- (2007): “Market-Based Measures of Monetary Policy Expectations,” *Journal of Business and Economic Statistics*, 25(2), 201–212.
- GÜRKAYNAK, R. S., AND J. H. WRIGHT (2012): “Macroeconomics and the Term Structure,” *Journal of Economic Literature*, 50(2), 331–367.
- HANSEN, B. E. (1999): “Testing for Linearity,” *Journal of Economic Surveys*, 13(5), 551–576.
- IACOVIELLO, M. (2005): “House Prices, Borrowing Constraints and Monetary Policy in the Business Cycle,” *American Economic Review*, 95(3), 739–764.
- KOOP, G., M. PESARAN, AND S. POTTER (1996): “Impulse response analysis in nonlinear multivariate models,” *Journal of Econometrics*, 74(1), 119–147.
- KULISH, M. (2007): “Should Monetary Policy Use Long-Term Rates?,” *B.E. Journal of Macroeconomics (Advances)*, 7(1), 1935–1690.
- KUTTNER, K. (2001): “Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market,” *Journal of Monetary Economics*, 47(3), 523–544.
- LUDVIGSON, S. C., S. MA, AND S. NG (2019): “Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?,” New York University and Columbia University, mimeo.
- LUUKKONEN, R., P. SAIKKONEN, AND T. TERÄSVIRTA (1988): “Testing linearity against smooth transition autoregressive models,” *Biometrika*, 75, 491–499.
- RAMEY, V. A., AND S. ZUBAIRY (2016): “Government Spending Multipliers in Good Times and in Bad: Evidence from U.S. Historical Data,” *Journal of Political Economy*, forthcoming.

- RUDEBUSCH, G. D., AND L. E. SVENSSON (2002): “Eurosystem monetary targeting: Lessons from U.S. data,” *European Economic Review*, 46(3), 417–442.
- STOCK, J. H., AND M. W. WATSON (2012): “Disentangling the Channels of the 2007-2009 Recession,” *Brookings Papers on Economic Activity*, Spring, 81–135.
- TERÄSVIRTA, T., AND Y. YANG (2014): “Linearity and Misspecification Tests for Vector Smooth Transition Regression Models,” CREATES Research Papers 2014-04, School of Economics and Management, University of Aarhus.
- WOODFORD, M. (2003): *Interest and Prices: Foundations of a Theory of Monetary Policy*. Princeton University Press. Princeton, New Jersey.

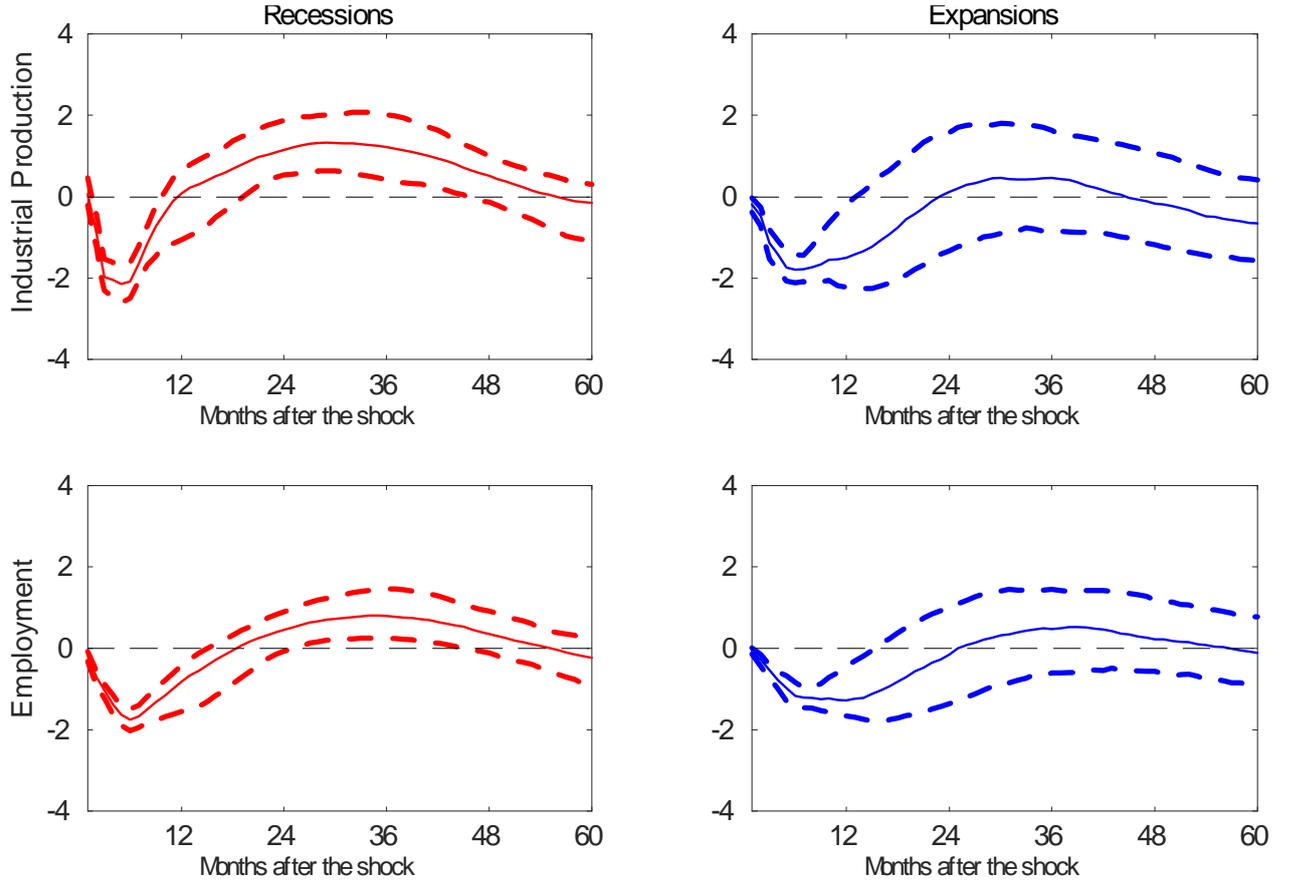


Figure A1: **Real Effects of Uncertainty Shocks: Longer Sample (July 1962 - June 2018)**. Impulse responses (median values) to an uncertainty shock identified as described in the paper. GIRFs conditional on $\gamma = 1.9$. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands.

	Recessions		Expansions	
σ_x^2	factual	count.	factual	count.
ind. prod.	67.22	56.12	25.10	102.50
employment	21.20	22.65	11.78	55.28
inflation	0.17	0.11	0.04	0.07
Loss	29.64	26.37	12.33	52.66

Table 1: **Monetary Policy (In)effectiveness in Recessions: Ad-hoc Loss Function Analysis**. State-dependent volatilities in recessions and expansions computed as explained in the text.

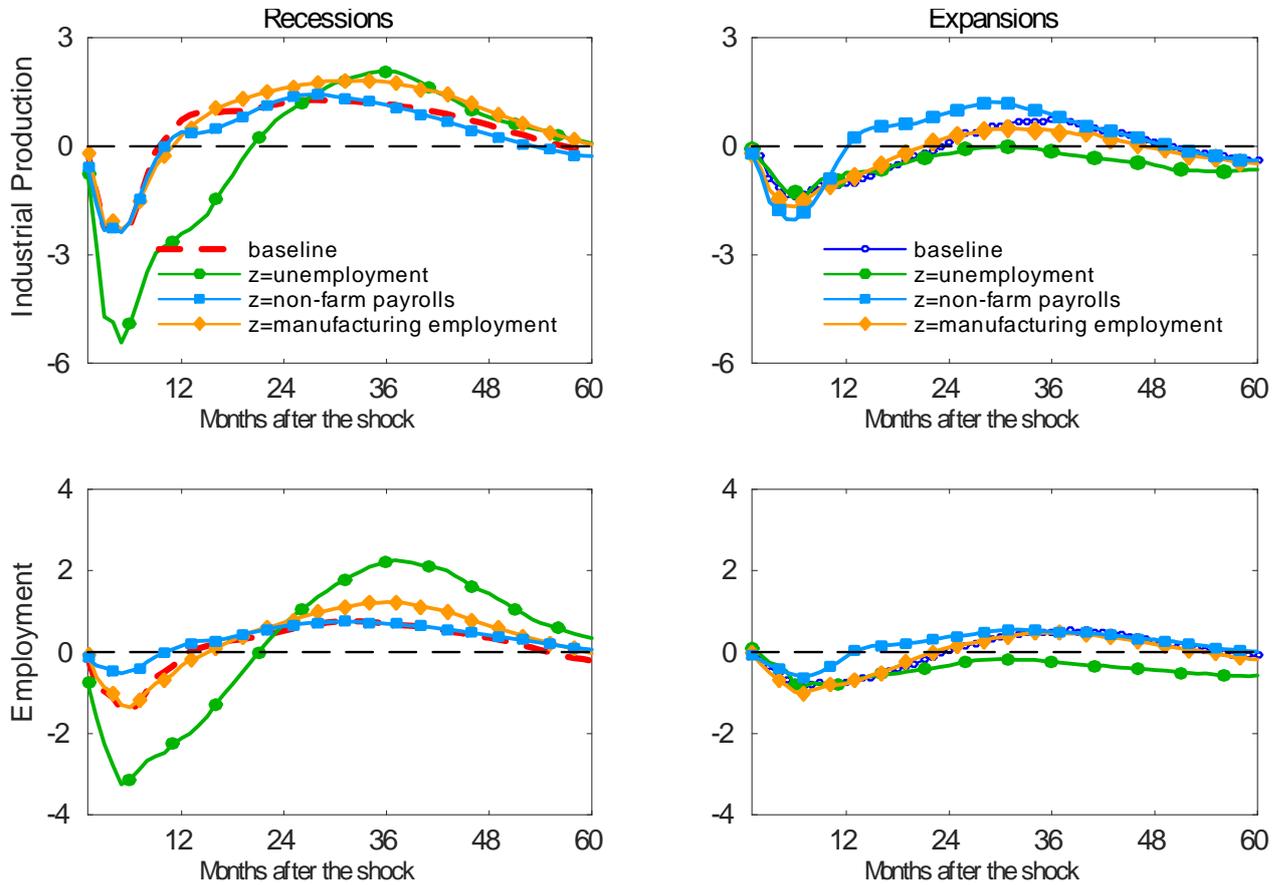


Figure A2: **Real Effects of Uncertainty Shocks: Alternative Labor-related Transition Indicators.** Impulse responses (median values) to an uncertainty shock identified as described in the paper. GIRFs conditional on $\gamma = 1.6$ and unemployment, $\gamma = 1.6$ and non-farm payrolls (MA(6)), $\gamma = 1.7$ and manufacturing employment (MA(12)) as (alternative) transition indicators. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands.

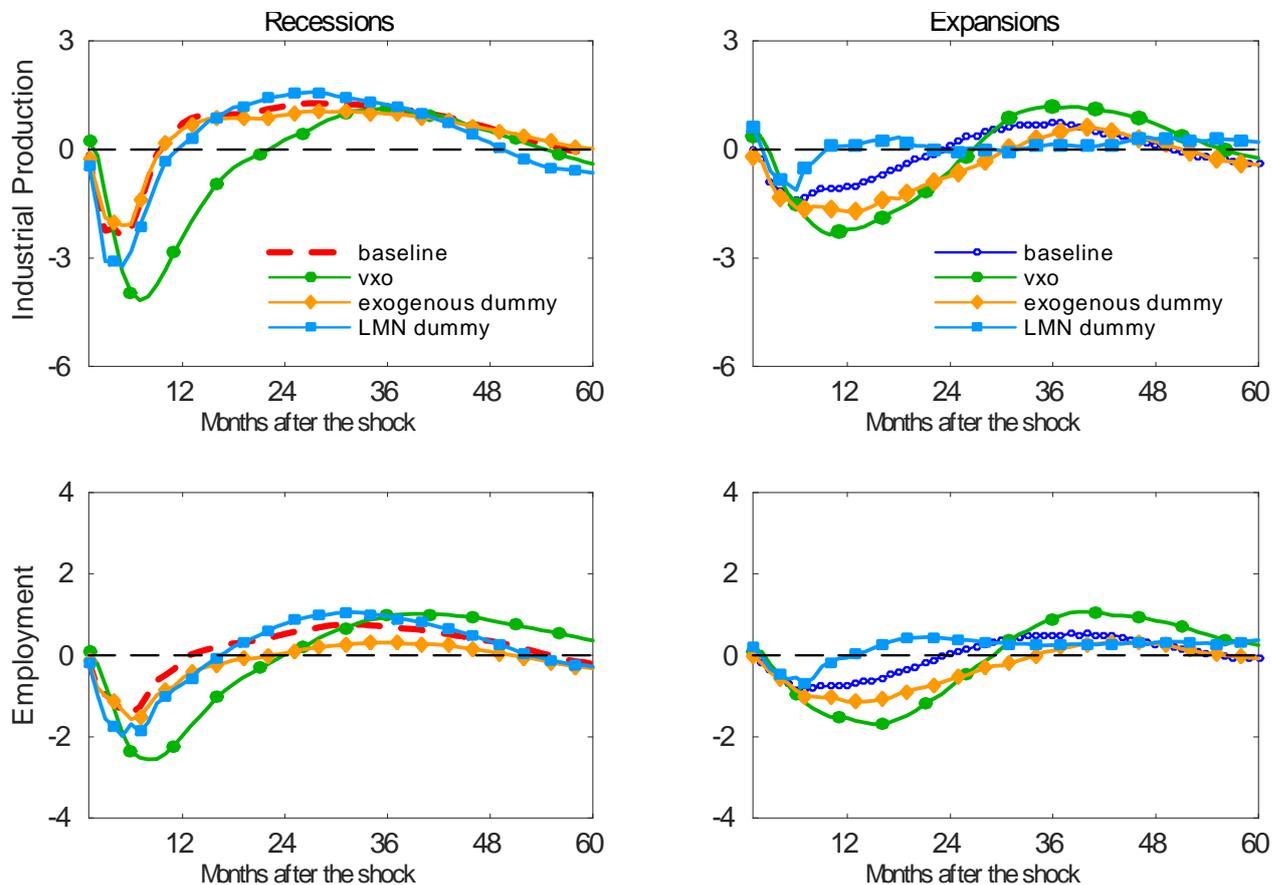


Figure A3: **Real Effects of Uncertainty Shocks: Alternative financial uncertainty indicators.** Baseline: Uncertainty dummy as described in the paper. VXO: Uncertainty shock identified as the orthogonalized residual of the of the VXO in the VAR. Exogenous dummy: Uncertainty dummy constructed by considering 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.

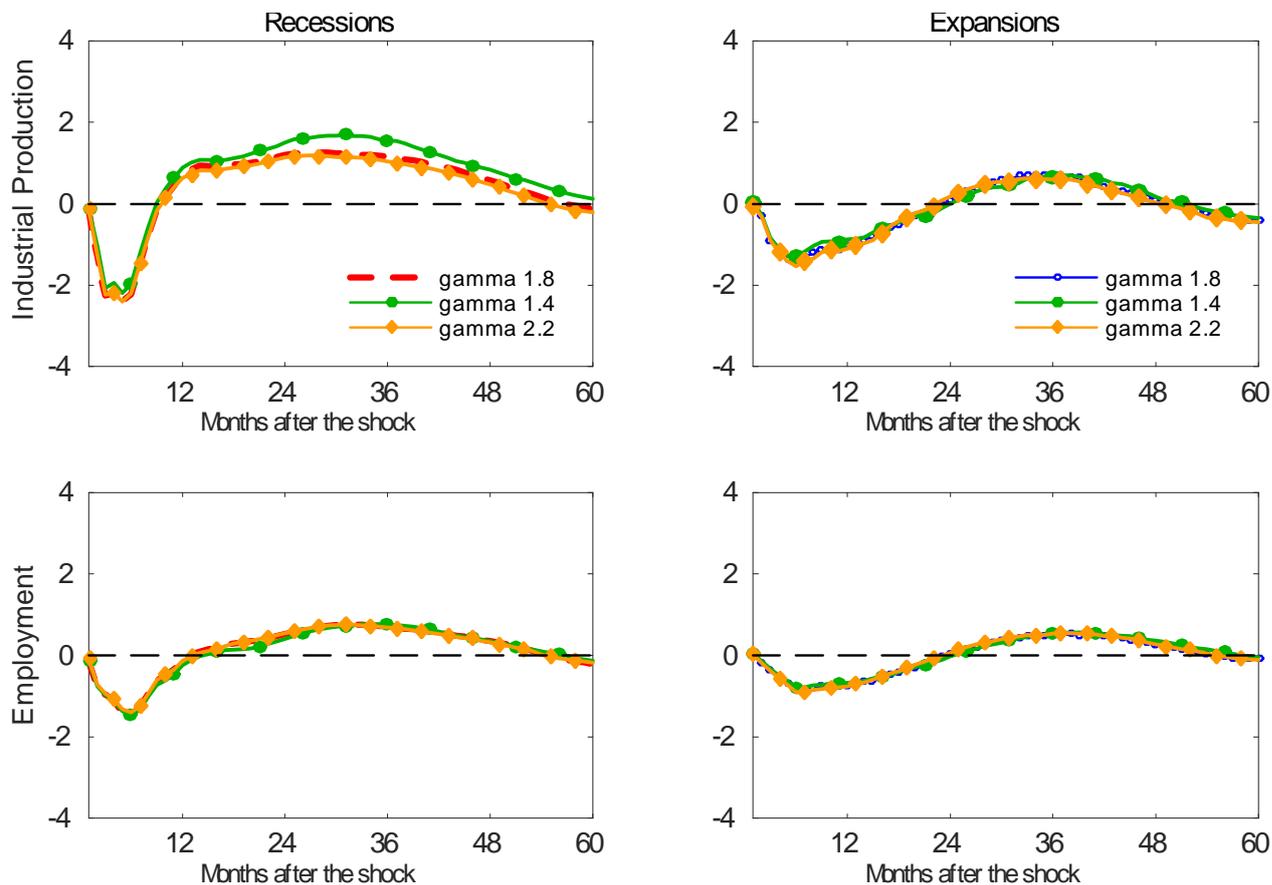


Figure A4: **Real Effects of Uncertainty Shocks: Different Calibrations of the Slope Parameter.** Impulse responses (median values) to an uncertainty shock identified as described in the paper. Red dashed/blue dashed-circled lines: GIRFs conditional on $\gamma = 1.8$. Green lines: GIRFs conditional on $\gamma = 1.4$. Orange lines: GIRFs conditional on $\gamma = 2.2$.

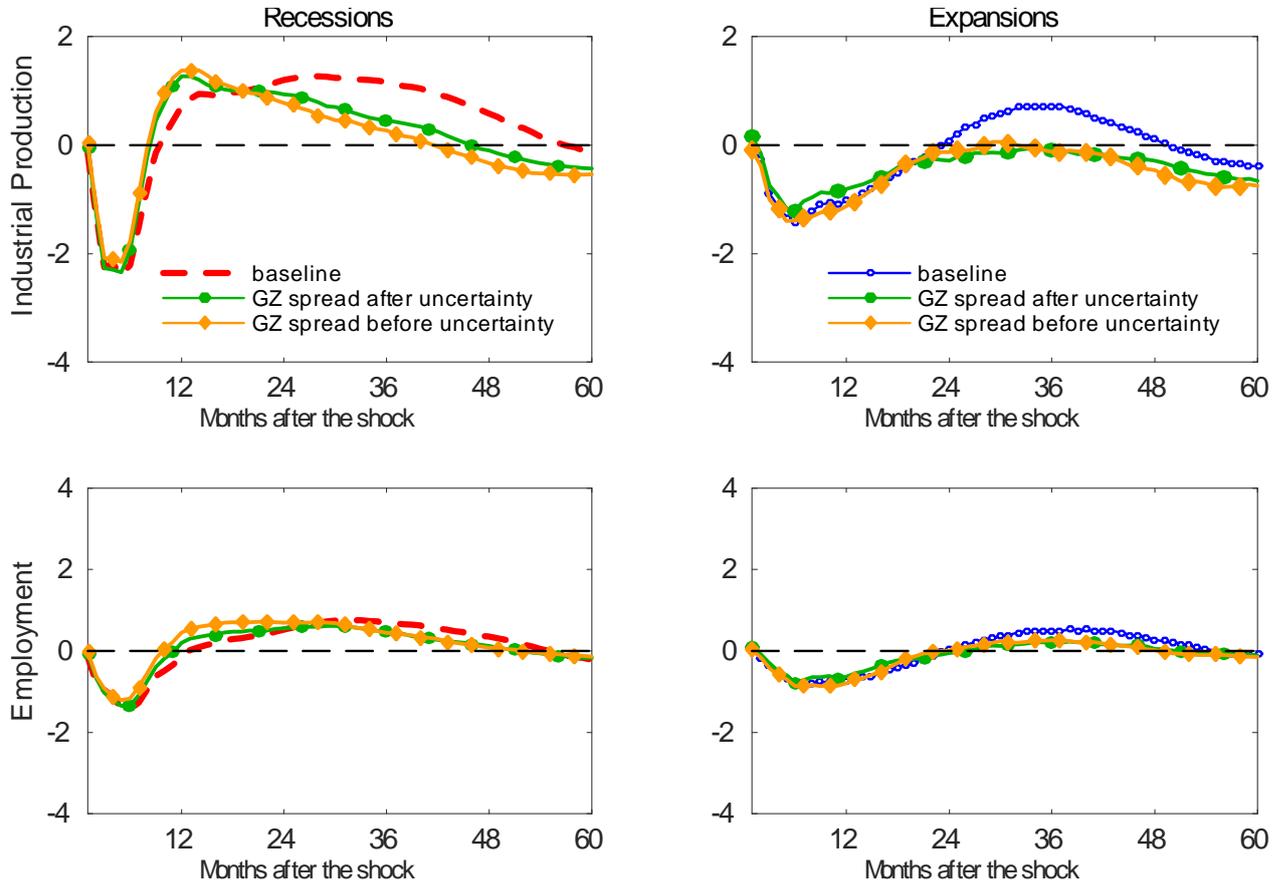


Figure A5: **Real Effects of Uncertainty Shocks: Role of Credit Spreads.** Median impulse responses to an uncertainty in scenarios without/with credit spreads. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). 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.

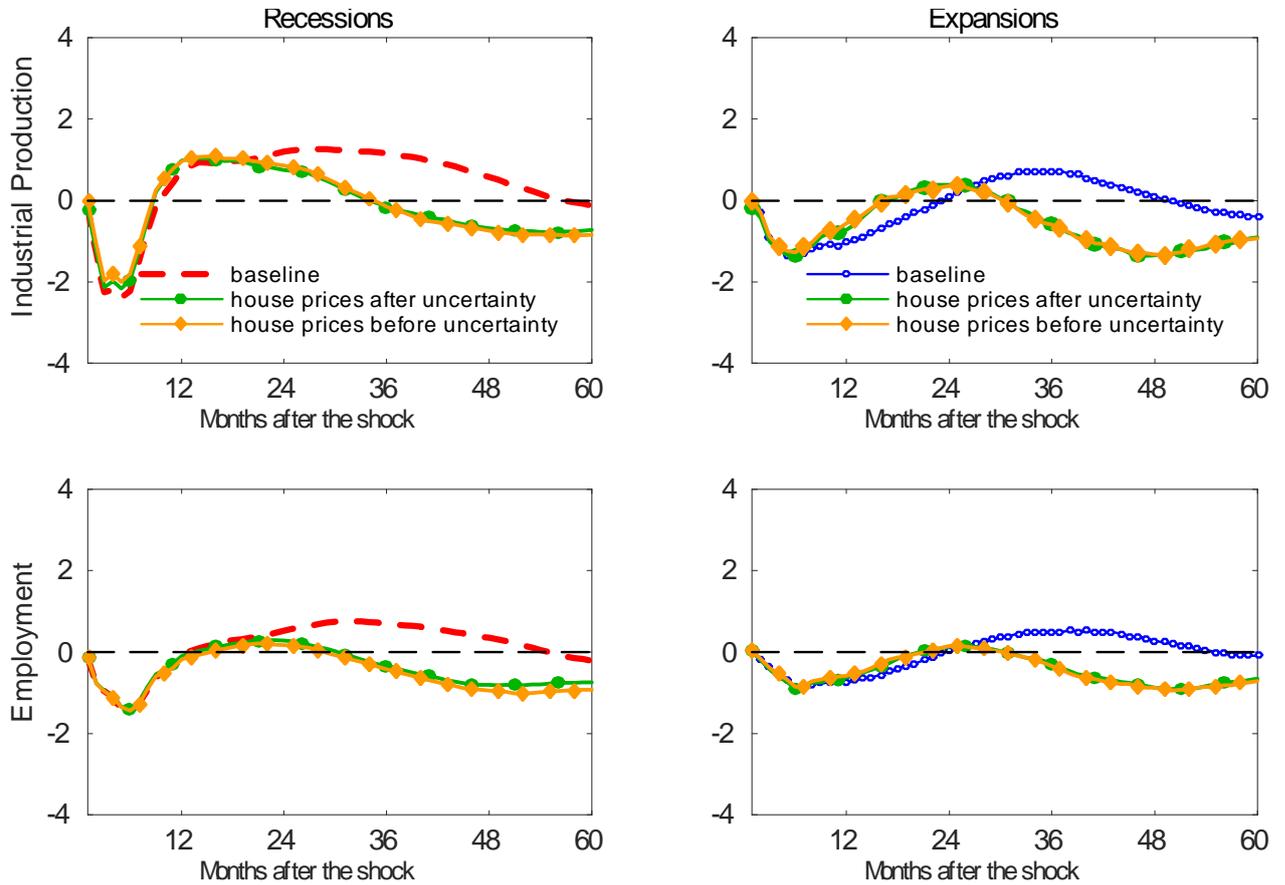


Figure A6: **Real Effects of Uncertainty Shocks: Role of House Prices.** Median impulse responses to an uncertainty shock identified as described in the text in scenarios without/with real house price index. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and 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).

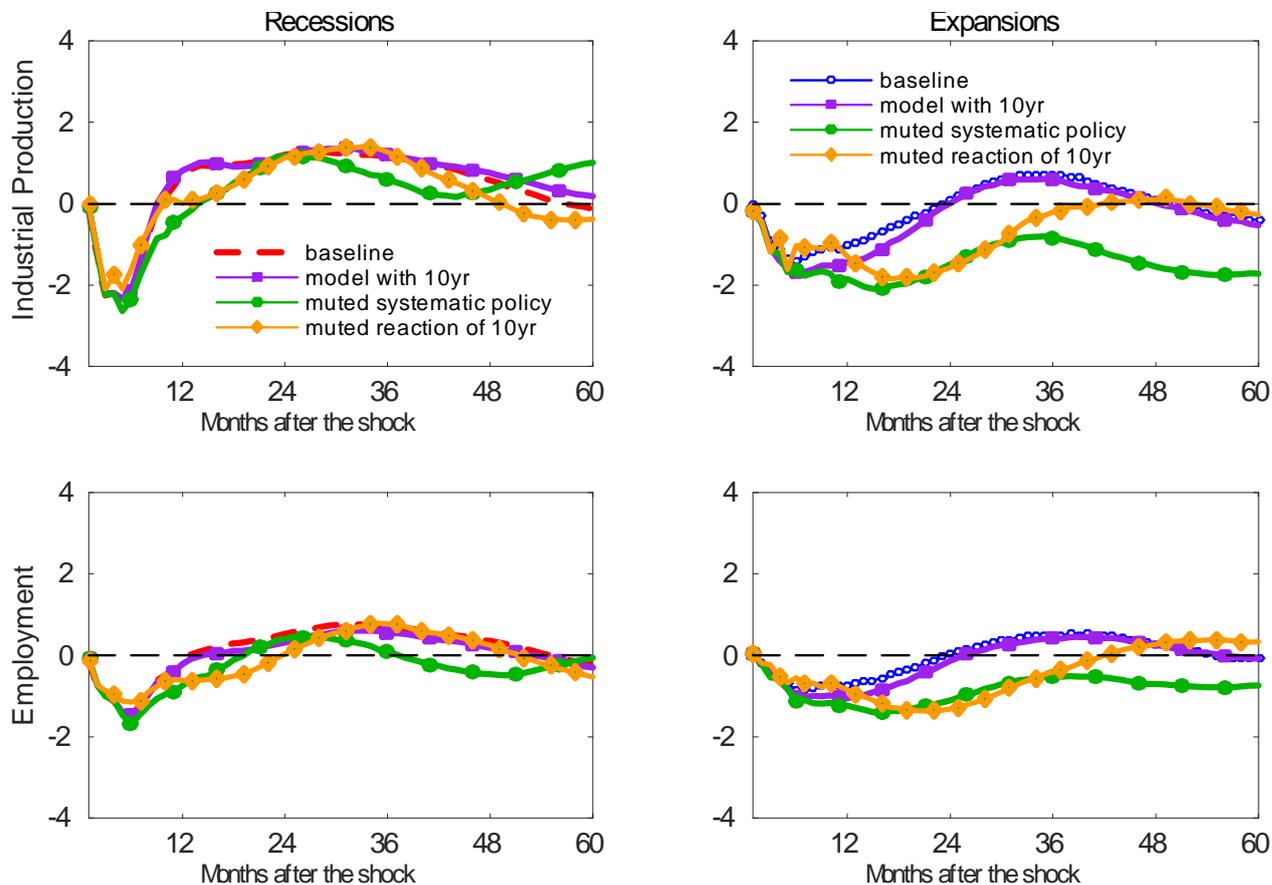


Figure A7: **Real Effects of Uncertainty Shocks: Role of Short- and Long-term Interest Rates.** Median impulse responses to an uncertainty shock identified as described in the text in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed with 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.

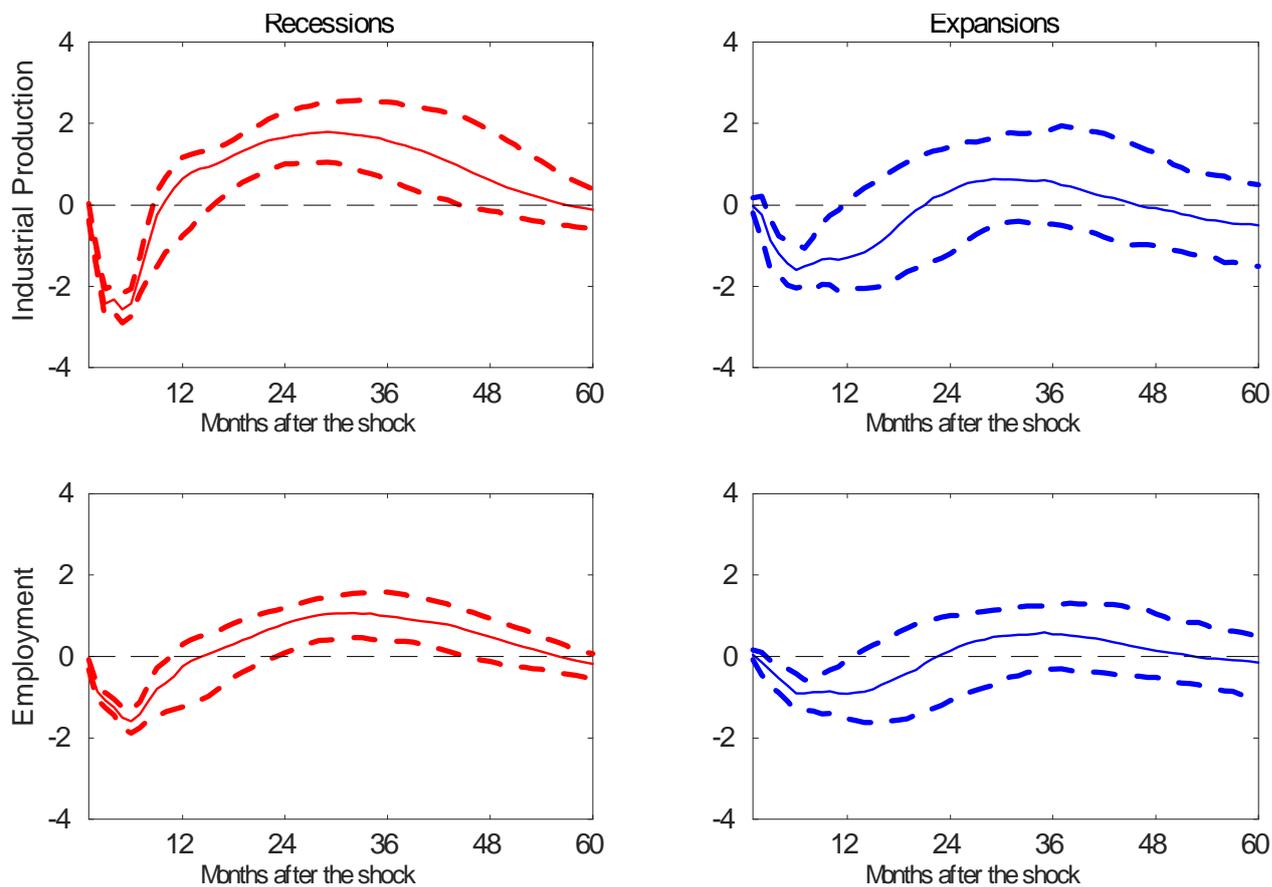


Figure A8: **Real Effects of Uncertainty Shocks: Federal Funds Rate Ordered Last.** Impulse responses (median values) to an uncertainty shock identified as described in the paper. GIRFs conditional on $\gamma = 1.6$. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands.

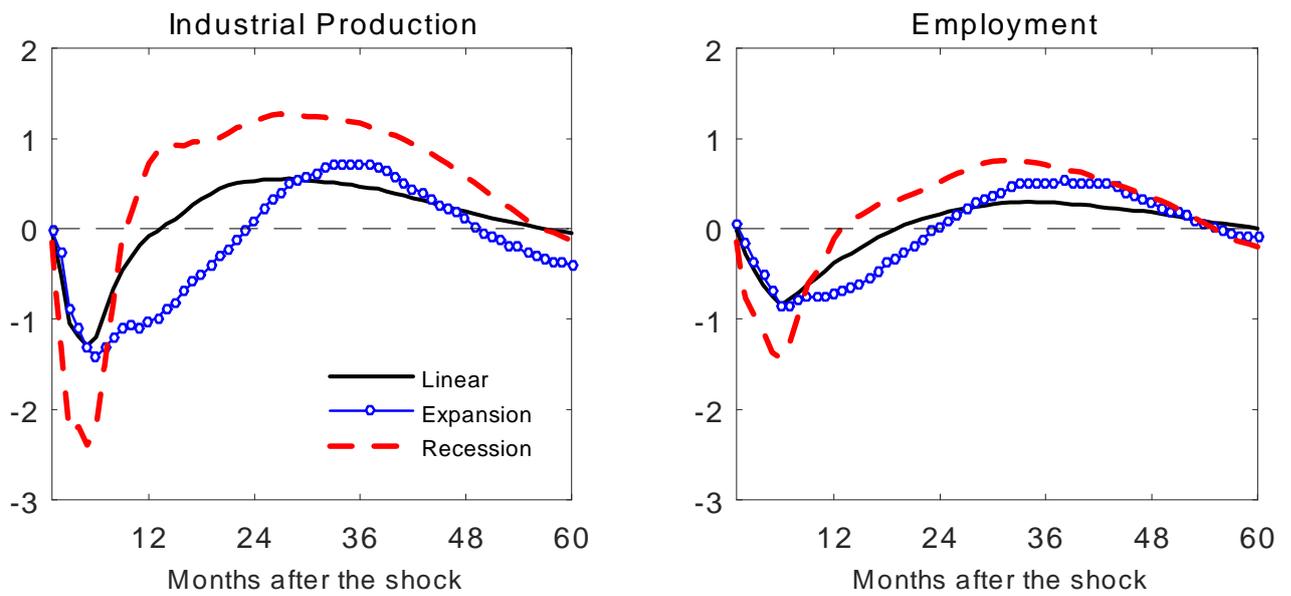


Figure A9: **Real Effects of Uncertainty Shocks: Linear vs. Nonlinear Frameworks.** Impulse responses (median values) to an uncertainty shock inducing an on-impact reaction of uncertainty equal to one as in Bloom (2009). Uncertainty shock identified as described in the paper. Solid black lines: Responses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

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