Uncertainty Shocks and Monetary Policies
(Preliminary Draft- Not Circulate)

Valentina Colombo* Alessia Paccagnini†

Abstract

We investigate the interaction between uncertainty shocks and conventional and unconventional U.S. monetary policies. Uncertainty is captured by appealing to some indicators recently developed by Jurado, Ludvigson, and Ng (2015). Relying on a non-linear VAR, we isolate the effects of uncertainty shocks in recessions versus expansions. Uncertainty shocks trigger negative macroeconomic fluctuations across the business cycle. To offset such fluctuations, the Federal Reserve reacts relying on conventional monetary policy tools. However, when shocks to uncertainty occur during deep recessions, the Federal Reserve reacts switching from the conventional to the unconventional monetary tools.

JEL classification: C50, E32, E52

Keywords: Uncertainty, Smooth Transition VAR, Nonlinearities, Monetary Policy

*Department of Economics, University of Verona. Email: valentina.colombo@univr.it.
†School of Economics, University College Dublin. Email: alessia.paccagnini@ucd.ie.
1 Introduction

Due to the recent financial crisis and the subsequent recession period in the developed economies, the macroeconometrics literature has increased the interest in the impact of uncertainty shocks as main driver of economic fluctuations, focusing on the connection between the real economy and the financial markets. A number of studies proposes an empirical contribution on estimating the changes in real business cycle due to an uncertainty shock using econometric models to build proxies for uncertainty. Bloom (2009) has pioneered the use of the VIX, the implied stock market volatility based on S&P index, and Baker, Bloom, and Davis (2013) propose an Economic Policy Uncertainty index based on news article counts. Jurado, Ludvigson, and Ng (2015) develop a macroeconomic uncertainty index based on the common variation in forecast error of a large number of economic indicators. Rossi and Sekhposyan (2015) rely on the Survey Professional Forecasters to construct a forecasting index.

Several studies show that uncertainty shocks trigger negative effects on real activity and monetary policies (i.e., Baker, Bloom, and Davis, 2013; Colombo, 2013). A variety of empirical papers have further highlighted the role of non-linearities in the transition of uncertainty shocks on macroeconomic activities across the business cycle or at the zero lower bound (i.e., Enders and Jones, 2013; Bijsterbosch and Guérin, 2013; Caggiano, Castelnovo, and Groshenny, 2014; Caggiano, Castelnovo, and Nodari, 2015; Alessandri and Muntaz, 2014; Caggiano, Castelnovo, and Pellegrino, 2015; Popp and Zhang, 2015).

Moreover, according to the theoretical literature, uncertainty may exert negative effects on the macroeconomic activity through different channels: the real option effects (Bernanke, 1983); the financing constraint (Gilchrist, Sim, and Zakrajsek, 2010); the precautionary saving (i.e., Bloom, 2009; Leduc and Liu, 2013; Fernández-Villaverde, Pablo Guerron-Quintana, and Uribe, 2011).
From a monetary policy standpoint, Central Banks may offset the negative macroeconomic effects of uncertainty shocks lowering the interest rate. However, with monetary policy rates close to the zero lower bound (ZLB), as in the Great Recession, when further stimulus is needed, an uncertainty shock may push the Central Banks to rely on non-standard policy measures.

*How do uncertainty shocks affect the conventional and unconventional monetary policies conducted by the Federal Reserves?*

We answer this question by investigating the non-linear effects of uncertainty shocks on the U.S. macroeconomic activity allowing the Fed to react to such shocks via conventional and unconventional monetary policies.

To empirically scrutinize the potential asymmetric effects of macroeconomic uncertainty shocks, we model a set of macroeconomic indicators with a Smooth Transition Vector Auto Regression (STVAR). This approach allows us to estimate the effects of uncertainty shocks conditional on the state of economy (i.e., expansions versus recessions). To model the endogeneity of the transition from a state to another after an uncertainty shock occurs, we compute the Generalized Impulse Response Functions (GIRFs) proposed by Koop, Pesaran, and Potter (1996). Since the GIRFs depend on the initial condition, we study the evolution of the GIRFs over histories (i.e., recessions and expansions). This allows us to compare the IRFs in good times versus bad times. We estimate a vector of endogenous variables very close to the one proposed by Christiano, Eichenbaum, and Evans (2005) and by Jurado, Ludvigson, and Ng (2015). The STVAR includes real variables (industrial production, employment, consumption and new orders), prices (CPI), monetary, financial (stock price), and uncertainty measures. Following Gambacorta, Hofmann, and Peersman (2014), we proxy the unconventional monetary policy with the total asset of Fed's balance sheet. Since such measure is downloadable from the Federal Reserve of St. Louis only
from 2002, we collect monthly data of the total asset of Fed’s balance sheet for the remaining period (1985-2001). This proxy allows us to capture the unconventional monetary policy effectiveness in the Zero Lower Bound period. As proxy for macroeconomic uncertainty, we rely on the measure proposed by Juriado, Ludvigson, and Ng (2015). As far as we know, our paper is the first that quantifies the asymmetric effects of uncertainty shocks discriminating between conventional and unconventional monetary policies (via the Fed’s balance sheet).

Our results show that one-standard deviation uncertainty shock triggers asymmetric effects on macroeconomic aggregates across the business cycle. Uncertainty shocks have contractionary effects both in recessions than in expansions, but such effects are more pronounced in the former than in latter. To offset the macroeconomic fluctuation, the Federal Reserve reacts via both the conventional (decreasing the Federal Fund rate) and the unconventional monetary policies (increasing the assets of the Fed’s balance sheet by 40%). The reaction of FFR is found to be smaller in recessions than in expansions. Conversely, the reaction of the Federal Reserve to financial and macroeconomic shocks via the unconventional monetary policy is long-lasting. Overall the monetary policy easing associated with a contraction of economic activity is consistent with an inflation-targeting strategy pursued by the monetary policymakers. Excluding the proxy of unconventional monetary policy from our specification, the macroeconomic effects of such shocks are found to be negatively larger on all the macroeconomic aggregates.

Our findings provide new evidence on the role played by uncertainty shocks on unconventional monetary policies. A battery of robustness checks confirms our main findings. From a policy standpoint, our results help the policymaker to use tailored monetary policy instruments across the business cycle and in particular when ZLB is binding.
The rest of the paper is organized as follows. Section 2 introduces the data and the Smooth Transition VAR. Section 3 documents our empirical results. Section 4 discusses a number of robustness checks, whereas section 5 provides some statistical tests. Section 6 includes some extensions. Section 7 concludes.

2 Data and Methodology: A Smooth Transition VAR

We study the macroeconomic effects of an uncertainty shock relying on a Smooth-Transition VAR model (STVAR). Our STVAR is defined as follows:

\[ X_t = F(z_t)\Pi_R(L)X_t + (1 - F(z_t))\Pi_E(L)X_t + \varepsilon_t, \quad (1) \]
\[ \varepsilon_t \sim N(0, \Omega_t), \quad (2) \]
\[ \Omega_t = F(z_t)\Omega_R + (1 - F(z_t))\Omega_E, \quad (3) \]
\[ F(z_t) = \exp(-\gamma z_t)/(1 + \exp(-\gamma z_t)), \gamma > 0, z_t \sim N(0, 1). \quad (4) \]

where \( X_t \) is a set of endogenous variables, \( \Pi(L)_R \) and \( \Pi(L)_E \) are the polynomial matrices in the lag operator \( L \) capturing the dynamics of the system during recessions and expansions, respectively. The vector of reduced-form residuals \( (\varepsilon_t) \) has zero-mean and heteroskedastic, state-contingent variance-covariance matrix \( \Omega_t \), where \( \Omega_R \) and \( \Omega_E \) refer to the covariance structure of the residuals in recessions and expansions, respectively. \( F(z_t) \) is a logistic and continuous function bounded between zero and one which depends on the state variable \( z_t \). The slope parameter \( \gamma \) dictates how smooth is the transition from one regime to another, i.e. from recessions to expansions and vice versa. If \( \gamma \rightarrow \infty \) in (4), then the transition from one state of economy to the other one is abrupt. Conversely,
small value of $\gamma$ implies that such transition is smooth.

The vector of endogenous variables relies on $X_t = [X_{1t} X_{2t} X_{3t} X_{4t}]'$, where $X_{1t}$ includes the industrial production, the employment, the consumption, the CPI, the new orders. The $X_{2t}$ incorporates proxies for the conventional and unconventional monetary policy measure, the federal fund rate and the total assets of the Fed’s balance sheet, respectively. Following Gambacorta, Hofmann, and Peersman (2014), we proxy the unconventional monetary policies via the total assets of Fed’s balance sheet.\footnote{The Federal Reserve faced the Great Recession by adopting an extraordinarily expansionary monetary policy stance, lowering policy rates close to zero to stimulate the economy. However, with monetary policy rates close to the zero lower bound (ZLB), when further stimulus was needed, Central Banks turned to non-interest rate, or non-standard, policy measures. The measures adopted by Central Banks to counteract deflationary pressures and to foster economic growth included increased liquidity provision, extending the term of lending, modifying the collateral framework, forward guidance, and asset-purchase programs (i.e., quantitative easing, QE). The aims of these programs have been to reduce long-term interest rates and thereby stimulate the economy. Such stimulus has substantial effects on the size of central banks’ balance sheets (Colombo, 2015). Meaning and Zhu (2011) use the Federal Reserve balance sheet information to proxy the unconventional monetary policy tools. Peersman (2011) studies the (linear) macroeconomic effects of unconventional monetary policy in the Euro Area relying on the size of ECB’s balance sheet. Also, Gambacorta, Hofmann, and Peersman (2014) focus on the total assets of Central Banks’ balance sheet to proxy unconventional monetary policies.} The vector $X_{3t}$ includes the S&P500 index, whereas $X_{4t}$ is our proxy of uncertainty. We rely on recent measures of macroeconomic uncertainty proposed by Jurado, Ludvigson, and Ng (2015) based on the common variation in the h-steps-ahead forecast errors of a large number of economic indicators, $u(h)$. We use the uncertainty measure with forecast horizon at 1-month ($u_{01}$), 3-months ($u_{03}$), 12-months ($u_{12}$). Figure 1 plots the uncertainty measures versus the business cycle turning points (shades area). The correlation among the uncertainty measures $u(h)$ is very high (around 0.99) and the spikes occur during recessionary periods.

The uncertainty shocks is identified via the Cholesky-decomposition, with the sample assumption provided in Christiano, Eichenbaum, and Evans (2005) and widely adopted in the monetary policy VARs of the literature. In other words, the slow moving variables (industrial production, employment, consumption, in-
vestment, CPI) are ordered first, whereas the fast moving variables (monetary policy proxies) are ordered last. This ordering implies that monetary policies depend on the real activities. In setting the monetary policy proxies in vector $X_2$, we place the Fed total asset after the FFR. This reflects the idea that Fed relies on unconventional monetary policies by expanding its balance sheets after the FFR approaches to zero. The S&P index is placed after the monetary policy block and before our uncertainty proxy. The reason for this ordering of the variable is twofold. First, this ordering allows the Fed to influence directly the financial market sentiment, (i.e., Gambacorta, Hofmann, and Peersman, 2014; Bjørnland and Leitemo, 2009). Secondly, since a correlation between the S&P index and uncertainty measure exists (0.26 in our sample), this ordering derives the dynamics of uncertainty taking into account it (i.e., Bloom, 2009; Jurado, Ludvigson, and Ng, 2015).2 The uncertainty measure is set last in vector $X_t$. It means that we "purge" our uncertainty indicator from the contemporaneous movements of our macroeconomic variables, therefore sharpening the identification of uncertainty shocks. This identification implies that macroeconomic variables react to uncertainty shocks with a lag.3 This assumption is plausible for monthly estimations and is in line with Jurado, Ludvigson, and Ng (2015). However, our identification scheme differs from that of Jurado, Ludvigson, and Ng (2015) since we take into account the Fed policy implementation during the Great Recessions.

All the variables in $X_t$ enter in levels and in real terms (except the interest rate).

The transition variable $z_t$ and the calibration of the smoothing parameter $\gamma$ are justified as follows. Following Auerbach and Gorodnichenko (2012) and Caggiano, Castelnuovo, and Groshenny (2014), we employ a standardized

2 The main results are not affected when the uncertainty index is set first in vector $X_t$. The results are available upon request.
backward-looking of twelve-month moving average of industrial production growth.\(^4\) We calibrate the smoothness parameter \(\gamma\) to match the probability of being in recessions as identified by the NBER business cycle dates (15% in our sample). The recessionary phase is defined as a period in which \(\Pr(F(z_t) \geq 0.85) \approx 15\%\). It means that the economy spends about 15% of time in recessions and 85% in expansions. This implies setting \(\gamma = 1.8\). The choice is consistent with the threshold value \(z = -0.9\%\) discriminating recessions and expansions. In other words, if the realizations of the standardized transition variable \(z_t\) is lower (higher) than the threshold value \(z\), it will be associated to recessions (expansions). Figure 2 plots the transition function \(F(z_t)\) versus the NBER turning points and shows that high values of \(F(z_t)\) tend to be associated with NBER recessions.

Given the high nonlinearity of the model, we estimate the STVAR in (1) relying on Markov-Chain Monte Carlo simulation (Chernozhukov and Hong, 2014), see section B of the Appendix for details. To model the endogeneity of the transition from one state to another after an uncertainty shock occurs, we compute the Generalized Impulse Response Functions (GIRFs) proposed by Koop, Pesaran, and Potter (1996). Since the GIRFs depend on the initial condition, we study the evolution of the GIRFs over histories (i.e., recessions and expansions). This allows us to compare IRFs in normal times versus uncertainty times. Our data are monthly and spans from 1985M1 through 2011M12. We estimate a nonlinear VAR including five lags, as suggested by the Akaike information criterion. Our model includes a constant. The data are seasonally adjusted and retrieved from the Federal Reserve Bank of St. Louis.

Before estimating the STVAR in (1), we perform a linearity test. Linearity is tested replacing the transition variable \((z_t)\) by the third order Taylor series

\(^4\)The transition variable \(z_t\) has been standardized to be comparable to those employed in the literature.
approximation around $\gamma = 0$, as suggested by Teräsvirta and Yang (2014). We perform an LM test which suggests a strong rejection of the linearity for the system as a whole in favor of a STVAR.

3 Results

Figure 3 plots the Generalised IRFs (GIRFs) to a one-standard deviation uncertainty shock identified via the Jurado, Ludvigson, and Ng (2015) measure with forecast horizon equal to 1-month ($u01$). The dotted-blue lines denote the GIRFs in expansions, whereas the red lines the ones in recessions. The shaded bands and the blue lines refer to the 68% confidence intervals. The impulse responses are interpreted as deviations from the steady-state and expressed in percent change.

Uncertainty shocks trigger negative macroeconomic fluctuations both in expansions and in recessions. However, in expansions the reactions of macroeconomic variables to uncertainty shocks are quantitatively smaller than in recessions.

In expansions, the industrial production decreases with a trough effect of $-1.8\%$, twenty-four months after the shock occurs to gradually return to the steady-state. The reaction functions of the other macroeconomic variables is qualitatively similar to the industrial production one and their troughs coincide with that of industrial production. The Federal Reserve reacts to such shocks via the conventional monetary policy, following an inflation targeting strategy path.

In recessions, an uncertainty shock decreases the industrial production by $-1\%$ which hits a trough of $-4.5\%$, 9 months after the shock occurs. This reaction is statistically significant. Afterwards, it returns rather slowly to its steady-state. The reaction of our proxy for investment, the new orders, is sta-
tistically significant for the year after the shock. It decreases on impact by a small amount (−0.4%) but hits the trough (−10%) in the 8th month. Uncertainty shocks affect the consumption in the short-run, albeit such effects are small. Moreover, the shock has deflationary effect. Indeed, the inflation reaches a trough of −1.8% (the 8th month), then gradually goes back to the steady-state. The shock decreases employment by −1.4% twelve-months after the shock occurs. Interestingly, the GIRFs predict a strong reaction of the Federal Reserve via unconventional monetary policies which determine an increase in the Fed total assets of 40% with respect to the pre-shock levels. Conversely, the reaction of the Central Bank via conventional monetary policy tools (decreasing the FFR) is smaller in recessions (as the Great Recession) than in expansions. This results may be driven by the fact that our sample size includes the period in which the FFR approaches zero.

Our results corroborate those reported in previous contributions on the "demand" type of effects triggered by uncertainty shocks in the U.S. economy (i.e., Bloom, 2009; Baker, Bloom, and Davis, 2013; Caggiano, Castelnuovo, and Groshenny, 2014; Leduc and Liu, 2013; Colombo, 2013; Alessandri and Muntaz, 2014). Our findings are supported by the theoretical studies (i.e., Basu and Bundick, 2015; Basu and Bundick, 2015) which document the fall of nominal and real variables after an uncertainty shock occurs, and by the empirical analysis in which uncertainty shocks is found to trigger asymmetric effects across the business cycle (i.e., Caggiano, Castelnuovo, and Pellegrino, 2015; Caggiano, Castelnuovo, and Groshenny, 2014). Moreover, our evidences are in line with the previous studies which highlight that when the investment irreversibility, the level of uncertainty affects the value of investment opportunities (i.e., Bernanke, 1983; Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2014).
4 Robustness checks

Results highlight that the effects of uncertainty shock are state-dependent. Moreover, we highlight that uncertainty shocks trigger a reaction of the Fed via conventional and unconventional monetary policy tools. In this section, we check the robustness of our main findings to several changes of the baseline STVAR. In the vector (1), we implement the Jurado, Ludvigson, and Ng (2015) measure with forecast horizon equal to 1-month (u01) as uncertainty proxy. As first robustness check, we estimate the STVAR using the uncertainty proxy relied on forecasting horizon equal to 3-months (u03) and to 12-months (u12). Figure 4 and 5, respectively, show that qualitatively our baseline results are not affected by the horizon change. However, the forecast horizon of uncertainty measures affects quantitatively the macroeconomic effects of such shocks. Those results are in line with Jurado, Ludvigson, and Ng (2015). Indeed, they point out that when the forecast horizons of their measures increase, the macroeconomic effects of uncertainty increase as well. Because of that, the Fed reacts via a stronger unconventional reaction that is higher as the forecasting horizons of increases.

We repeat our exercise replacing the Jurado, Ludvigson, and Ng (2015) measures with an alternative indicator of uncertainty shock, the VXO.\textsuperscript{5} Figure 6 reveals the results. The reaction of macroeconomic variables is short-lived and smaller than the ones found relying on the Jurado, Ludvigson, and Ng (2015) proxies. Jurado, Ludvigson, and Ng (2015) point out that effects of uncertainty shocks might depends on the source of the shocks and on its duration. They found that the estimated duration of a shock to the VXO is around 4 months, whereas the one of macroeconomic uncertainty is much more persistent than the VXO. Our results are in line with the Jurado, Ludvigson, and Ng (2015)

\textsuperscript{5}The VXO is employed instead of the VIX, since the VIX is available from 1990. The VXO is from 1985M1 to 1985M12 the standard deviation of stock market returns as in Bloom (2009). From 1986M1 the VXO is from the Chicago Board of Options Exchange (CBOE).
prediction. Interestingly, the Federal Reserve reacts to a VXO shocks through unconventional monetary policies as shown by the behavior of the balance sheet.

To investigate whether the inclusion of the balance sheet in our baseline specification matters, we estimate our model excluding from vector $X_t$ our proxy for the unconventional monetary policy. In other words, we allow the Fed to react to uncertainty shocks only via conventional monetary tools (lowering the interest rate). Figure 7 reports the GIRFs for the above exercise. At the first glance, we note how the reaction of macroeconomic variables worsened with respect to the baseline specification. Furthermore, the effects of uncertainty shocks are more persistent. After 60 months, the macroeconomic variables are still below their pre-shock levels. Overall, when we include in our sample size the Zero Lower Bound (ZLB) period and we do not take into account the unconventional monetary policy tools, the macroeconomic effects of uncertainty become in absolute value larger than the ones derived from our baseline. In a theoretical contribution based of New Keynesian general equilibrium model, Fernández-Villaverde, Pablo Guerron-Quintana, and Uribe (2011) show that when the ZLB is at work, uncertainty shocks have larger and persistent negative effects on the economic activity.

As fourth robustness check, we estimate the baseline STVAR model focusing on a sample size spanning from 1985M1 to 2008M9, and excluding our proxy of unconventional monetary policy. Figure 8 depicts the results. In particular, the red lines refers to the median generalised IRFs (GIRFs) in recessions when uncertainty proxied by the Jurado, Ludvingson and Ng (2015) measure (u01). The blue and green lines plotted the GIRFs when uncertainty proxied by the Jurado, Ludvingson and Ng (2015) measures with forecast horizons equal to 3 and 12 months (u03 and u12, respectively). The magenta lines refers to the GIRFs

---

6 When we exclude the total assets Fed’s balance sheet from our specification the confidence interval bounds are wider due to a possible misspecification error such as an omitted relevant variable. Results available upon request.
when uncertainty proxied by the VXO. The uncertainty shocks trigger macroeconomic fluctuation even excluding the ZLB period. Of course, the reaction of the macroeconomic aggregates is weaker, whereas the ones of the FFR is stronger than our baseline specification. This results is in line with Evans, Fisher, Gourio, and Krane (2015). They find that uncertainty is important to study the FFR pattern in the pre-ZLB period. Comparing Figure 8 and 7 an interesting picture emerges. The presence of the ZLB may magnify the effects of uncertainty shocks (Basu and Bundick, 2015). Relying on unconventional monetary policy when the ZLB binds, we find that the Fed offsets the negative macroeconomic fluctuations.

Overall our robustness checks confirm the non-linearity of uncertainty shock effects and their impact on the conventional and unconventional monetary policy decision of the Federal Reserve.\(^7\)

### 5 Asymmetric reactions across regimes and specifications

Uncertainty shocks are recessionary both in expansions and in recessions. However, our results speak in favor of larger (in absolute value) negative effects in recessions than in expansions. *Are the reactions of macroeconomic variables to uncertainty shocks statistically significant different across regimes?* We answer this question running statistical test based on the empirical density of the difference between the reaction of macroeconomic variables across regimes. The empirical density is based on 500 realizations of such differences for each horizon \(h\). We run this test for all our variables of interest. Figure 9 reports the results when the Jurado, Ludvigson, and Ng (2015) measure with forecast horizon equal

---

\(^7\)Our results are also robust to: different ordering; lag specifications; different values of parameters that govern the transition from one regime to another. Moreover, our findings are qualitatively robust to the alternative proxy of uncertainty, such as the quarterly Rossi and Sekhposyan (2015) macroeconomic measure.
to 1-month (u01) is our uncertainty proxy. If the zero line is not included in the confidence bands, then there will be evidence of state-dependent reactions.

According to figure 9, we find statistically significant differences in the reactions of all variables included in our baseline specification across regimes.

We repeat the above exercise replacing the uncertainty shock u01 with alternative uncertainty proxies. Figures 10 and 11 plot the results from the test when we proxy uncertainty via the Jurado, Ludvigson, and Ng (2015) measure with forecast horizon equal to 3-months (u03) and 12-months (u12), whereas figure 12 displays the results when a VXO shocks is at work.

Overall, whether we jointly read figure 9-12, there are statistically evidences that the macroeconomic reactions to uncertainty shocks are state-dependent.

Does the unconventional monetary policy proxy matter in our specification?

We answer this question considering two specifications: 1) the one that includes the total asset’ balance sheet, as in our baseline framework (with-BS, hereafter); 2) and the one in which the proxy for unconventional monetary policy is excluded (without-BS, hereafter). We perform statistical tests based on the empirical density of the difference between the reaction of macroeconomic variables in the with-BS and without-BS specifications in recessionary phase. Also in this case, the empirical density is based on 500 realizations of such differences for each horizon $h$ across specifications. We run this test for all our variables of interest. Figure 13 depicts the results from above exercise when the Jurado, Ludvigson, and Ng (2015) measure with forecast horizon equal to 1-months (u01) is our uncertainty proxy in both specifications. The results show that the reactions of macroeconomic variables are statistically significant different across specifications. In other words, the inclusion among variables of our proxy for unconventional monetary policy matter. Figures 14, 15 and 16 confirm such result even when we proxy uncertainty via the u03, u12 and VXO measures, respectively.
6 Extension

Did the Fed’s balance sheet policies have a material impact on the US economy when uncertainty shocks occur? A counterfactual exercise in which we ’kill off’ the coefficients of the balance sheet equation in our VAR show that . . . .

TBC

7 Conclusion

We estimate a Smooth Transition VAR (STVAR) including standard macroeconomic variables and uncertainty proxy for the U.S. economy. We investigate the impact of the uncertainty shock on the monetary policies. For this reason, we introduce both the conventional (short term interest rate) and unconventional (balance sheet) tools implemented by the Federal Reserve. The non-linearities induced by the STVAR allow us to understand the behavior of the macroeconomic variables in the two regimes, in recessions and expansions. Uncertainty shocks is found to trigger negative macroeconomic fluctuations across the business cycle. To offset macroeconomic fluctuation, the Federal Reserve reacts lowering the FFR. However, when the FFR is close to zero uncertainty shocks push the Fed to react via non-standard monetary policy tools.

References


Figures

Figure 1: Uncertainty measures vs Business cycle

Notes: The shaded area indicate the U.S. recessionary phases (1985:1-2011:12), whereas the red, blue and green line refers to the uncertainty measure at 1, 3, 12 month(s) proposed by Jurado, Ludvigson and Ng (2014).

Figure 2: Transition function vs Business cycle

Notes: The shaded area indicate the U.S. recessionary phases (1985:1-2011:12), whereas the red line refers to the backward looking 12-month moving average of IP growth.
Notes: The red lines refer to the generalised IRFs (median) in recessions, whereas the blue lines to the ones in expansions. Uncertainty proxied by the Jurado, Ludvingson and Ng (2015) measure (u01). Solid and gray areas refers to the 68% confidence bands. The variables are expressed in percent deviations with respect to their steady state. The horizontal axis identifies months.
Figure 4: Effects of uncertainty shocks

Notes: The red lines refers to the generalised IRFs (median) in recessions, whereas the blue lines to the ones in expansions. Uncertainty proxied by the Jurado, Ludvingson and Ng (2015) measure (u03). Solid and gray areas refers to the 68% confidence bands. The variables are expressed in percent deviations with respect to their steady state. The horizontal axis identifies months.
Figure 5: Effects of uncertainty shocks

Notes: The red lines refers to the generalised IRFs (median) in recessions, whereas the blue lines to the ones in expansions. Uncertainty proxied by the Jurado, Ludvingson and Ng (2015) measure (u12). Solid and gray areas refers to the 68% confidence bands. The variables are expressed in percent deviations with respect to their steady state. The horizontal axis identifies months.
Figure 6: Effects of uncertainty shocks

Notes: The red lines refer to the generalised IRFs (median) in recessions, whereas the blue lines to the ones in expansions. Uncertainty proxied by VXO. Solid and gray areas refers to the 68% confidence bands. The variables are expressed in percent deviations with respect to their steady state. The horizontal axis identifies months.
Figure 7: Differences in Generalized Impulse Responses between with/without balance sheet specifications (u01)

Notes: The red lines refers to the generalised IRFs (median) in recessions including the balance sheet in our specification, whereas the red dotted lines to the ones in which the total asset Fed balance sheet is excluded. Uncertainty proxied by the Jurado, Ludvingson and Ng (2015) measure (u01). The variables are expressed in percent deviations with respect to their steady state. The horizontal axis identifies months.
Notes: The red lines refers to the median generalised IRFs (GIRFs) in recessions when uncertainty proxied by the Jurado, Ludvingson and Ng (2015) measure (u01). The blue and green lines plotted the GIRFs when uncertainty proxied by the Jurado, Ludvingson and Ng (2015) measures u03 and u12, respectively. The magenta lines refers to the GIRFs when uncertainty proxied by the VXO. The size spans from 1985M1 to 2008M9. The vector $X_t$ includes only the proxy for the conventional monetary policy excluding the unconventional one. The variables are expressed in percent deviations with respect to their steady state. The horizontal axis identifies months.
Figure 9: Differences in Generalized Impulse Responses between recessions and expansions (u01)

Notes: Differences in Generalized Impulse Responses between the recessions and expansions. Uncertainty proxied by the Jurado, Ludwigson and Ng (2015) measure (u01). Dotted lines refer to the the 68% confidence bands. Horizontal axis denotes monthly horizon.
Figure 10: Differences in Generalized Impulse Responses between recessions and expansions (u03)

Notes: Differences in Generalized Impulse Responses between the recessions and expansions. Uncertainty proxied by the Jurado, Ludvigson and Ng (2015) measure (u03). Dotted lines refer to the 68% confidence bands. Horizontal axis denotes monthly horizon.
Figure 11: Differences in Generalized Impulse Responses between recessions and expansions (u12)

Notes: Differences in Generalized Impulse Responses between the recessions and expansions. Uncertainty proxied by the Jurado, Ludvigson and Ng (2015) measure (u12). Dotted lines refer to the 68% confidence bands. Horizontal axis denotes monthly horizon.
Figure 12: Differences in Generalized Impulse Responses between recessions and expansions (VXO)

Notes: Differences in Generalized Impulse Responses between the recessions and expansions. Uncertainty proxied by the Jurado, Ludvigson and Ng (2015) measure (VXO). Dotted lines refer to the 68% confidence bands. Horizontal axis denotes monthly horizon.
Figure 13: Differences in Generalized Impulse Responses between with-BS and without-BS specifications (u01)

Notes: Differences in Generalized Impulse Responses between the baseline and the restricted specification in recessions. Uncertainty proxied by the Jurado, Ludvigson and Ng (2015) measure (u01). Dotted lines refer to the the 68% confidence bands. Horizontal axis denotes monthly horizon.
Notes: Differences in Generalized Impulse Responses between the baseline and the restricted specification in recessions. Uncertainty proxied by the Jurado, Ludvingson and Ng (2015) measure (u03). Dotted lines refer to the 68% confidence bands. Horizontal axis denotes monthly horizon.
Figure 15: Differences in Generalized Impulse Responses between with-BS and without-BS specifications (u12)

Notes: Differences in Generalized Impulse Responses between the baseline and the restricted specification in recessions. Uncertainty proxied by the Jurado, Ludvigson and Ng (2015) measure (u12). Dotted lines refer to the 68% confidence bands. Horizontal axis denotes monthly horizon.
Figure 16: Differences in Generalized Impulse Responses between with-BS and without-BS specifications (VXO)

Notes: Differences in Generalized Impulse Responses between the baseline and the restricted specification in recessions. Uncertainty proxied by VXO. Dotted lines refer to the the 68% confidence bands. Horizontal axis denotes monthly horizon.
Technical Appendix

This Technical Appendix reports the estimation of the non-linear VARs, the statistical evidence in favor of a nonlinear relationship between the endogenous variables included in the STVAR, and the computation of the Generalised Impulse Responses. All these Sections are partially drawn on Caggiano, Castelnuovo, Colombo, and Nodari (2015) Appendix.

A Linearity Test

We test linearity versus non-linearity applying the Teräsvirta and Yang (2014) test for Smooth Transition Vector AutoRegression (STVAR) with a single transition variable as in our framework. According to this test, we assume linearity under null hypothesis versus a nonlinear model with a logistic smooth transition component under alternative hypothesis. Let us assume a p-dimensional 2-regime approximate logistic STVAR model:

\[ X_t = \Theta_0'Y_t + \sum_{i=1}^{n} \Theta_i'Y_tz_i^t + \varepsilon_t, \]  

(5)

where \( X_t \) is the \((p \times 1)\) vector of endogenous variables, \( Y_t = [X_{t-1} | \ldots | X_{t-k}] \) is the \((k \times p+q)\) vector of exogenous variables which includes lagged variables \((k)\) and a vector of constants. The transition variable is \( z_t \), while \( \Theta_0 \) and \( \Theta_i \) are matrices of parameters. In our empirical assessment, we have \( p=9 \) as number of endogenous variables, \( q=1 \) as number of exogenous variables, and \( k=5 \) as number of lags. Under the null hypothesis of linearity, we assume \( H_0 : \Theta_i = 0 \ \forall i \). The Teräsvirta and Yang (2014) test features the following four steps:

1) We estimate the restricted model \( (H_0 : \Theta_i = 0 \ \forall i) \) by regressing \( X_t \) on \( Y_t \). We collect the residual \( \tilde{E} \) calculating the matrix for the residual sum of squares \( RSS_0 = \tilde{E}'\tilde{E} \).
2) We run an auxiliary regression of $\tilde{E}$ on $(Y_t, Z_n)$ where the subscript $n$ indicates the $n$-order Taylor expansion of the transition function. We save the residuals $\tilde{\Xi}$ computing the matrix for the residual sum of squares $RSS_1 = \tilde{\Xi}'\tilde{\Xi}$.

3) We compute the test-statistic:

$$LM = Ttr[RSS_0^{-1}(RSS_0 - RSS_1)] = T[p - tr(RSS_0^{-1}RSS_1)].$$

(6)

Under the null hypothesis, the test statistic is distributed as a $\chi^2$ with a number of degrees of freedom equals the number of restrictions, $p(kp + q)$. We compute two LM-type linearity tests fixing the value of the $n$-order of the Taylor expansion equal to $n = 1$ and $n = 3$ (as proposed by Luukkonen, Saikkonen, and Teräsvirta, 1988). In our estimation, $LM = 791$ and $LM = 1738$ when $n = 1$ and $n = 3$, respectively. The corresponding p-value in both tests are zero. In other words, our model is present non-linear dynamics.

**B Estimation of the Non-linear VARs**

Our STVAR model (1)-(4) is estimated via maximum likelihood. The log-likelihood function is as follows:

$$logL = const - \frac{1}{2} \sum_{t=1}^{T} \log|\Omega_t| - \frac{1}{2} \sum_{t=1}^{T} \varepsilon_t' \Omega^{-1} \varepsilon_t,$$

(7)

where the vector of residuals $\varepsilon_t = X_t - (1 - F(z_t))\Pi_{E}X_{t-1} - F(z_t)\Pi_{R}X_{t-1}$.

Our purpose is to estimate the parameters $\Psi = \{\Omega_R, \Omega_E, \Pi_{R}(L), \Pi_{E}(L)\}$, where $\Pi_{j}(L) = [\Pi_{j,1}, ..., \Pi_{j,p}]$, $j \in \{R, E\}$.

Due to the high non-linearity of the model its estimation is problematic using standard optimisation procedures. Hence, as in Auberbach and Gorodnichenko (2012), we employ the procedure as described as follows.
Conditional on $\gamma$, $\Omega_R$, $\Omega_E$, where $\gamma$ is the slope parameter calibrated as described in section 2, the model is linear in $\Pi_R$, $\Pi_E$. Hence, for a given guess on $\gamma$, $\Omega_R$, $\Omega_E$, the coefficients $\Pi_R$, $\Pi_E$ can be estimated by minimizing $\frac{1}{2} \sum_{t=1}^{T} \varepsilon_t' \Omega^{-1}_t \varepsilon_t$. Hence, we can re-write the regressors as below.

Let $W_t = [F(z_t)X_{t-1}(1-F(z_t))X_{t-1}...F(z_t)X_{t-p}(1-F(z_t))X_{t-p}]$ be the extended vector of regressors, and $\Pi = [\Pi_R(L)\Pi_E(L)]$. Consequently, we can write $\varepsilon_t = X_t - \Pi W'_t$. In this case, the objective function becomes:

$$\frac{1}{2} \sum_{t=1}^{T} (X_t - \Pi W'_t)' \Omega^{-1}_t (X_t - \Pi W'_t).$$ (8)

We can show that the first order condition with respect to $\Pi$ is given by:

$$vec\Pi' = (\sum_{t=1}^{T} [\Omega^{-1}_t \otimes W'_t W_t])^{-1} vec(\sum_{t=1}^{T} W'_t X_t \Omega^{-1}_t).$$ (9)

We iterate this procedure over different sets of values for $\{\Omega_R, \Omega_E\}$ (conditional on a given value for $\gamma$). For each set of values, $\Pi$ is obtained and the logL (7) is calculated.

Due to the high non-linearity of the model in its parameters, we might get several local optima. Then, it is recommended to try different starting values of $\gamma$. To guarantee positive definiteness of the matrices $\Omega_R$ and $\Omega_E$, we focus on the alternative vector of parameters $\Psi = \{chol(\Omega_R), chol(\Omega_E), \Pi_R(L), \Pi_E(L)\}$, where $chol$ means the Cholesky decomposition.

We compute the confidence intervals using a Markov Chain Monte Carlo (MCMC) algorithm developed by Chernozhukov and Hong (2003) (CH hereafter). This methodology gives us both a global optimum and densities for the parameter estimates.

We implement the CH estimation via a Metropolis-Hastings algorithm. Given a starting value $\Psi^0$, the procedure constructs chains of length $N$ of the parameters.
of the estimated model following two steps:

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

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

The starting value \( \Theta^{(0)} \) is calculated using the second-order Taylor approximation of the model described from (1) to (4) in the section 2, hence the model can be written as regressing \( X_t, X_tz_t, \) and \( X_tz_t^2 \). We employ the residuals from this regression to fit the expression for the reduced-form time-varying variance-covariance matrix of the VAR (as explained in the main text) using maximum likelihood to estimate \( \Omega_R \) and \( \Omega_E \).

We can construct \( \Omega_t \), conditional on these estimates and given the calibration for \( \gamma \). Conditional on \( \Omega_t \), we can compute the starting values for \( \Pi_R(L) \) and \( \Pi_E(L) \) using equation (9).

Given the calibration for the initial (diagonal matrix) \( \Omega_\Psi \), a scale factor is adjusted to generate an acceptance rate close to 0.3, the typical value for this computational methods as pointed out by Canova (2007). The estimation accounts for \( N = 50,000 \) draws and we use the last 20% for inference.

As described by CH, \( \Psi^* = \frac{1}{N} \sum_{t=1}^{T} \Psi^{(n)} \) is consistent estimate of \( \Psi \) under standard regularity assumptions on maximum likelihood estimators. The covariance matrix of \( \Psi \) is given by \( V = \frac{1}{N} \sum_{t=1}^{T} (\Psi^{(n)} - \Psi^*)^2 = \text{var}(\Psi^{(n)}) \), which is the variance of the estimates in the generated chain.
C Generalized Impulse Response Functions

The Impulse Response Functions for the STVAR model are computed following the approach introduced by Koop, Pesaran, and Potter (1996) which propose an algorithm to calculate the Generalized Impulse Response Functions (GIRFs). The implementation of their procedure is composed of the following steps.

1) We construct the set of all possible histories $\Lambda$ of length $p = 12 : \{\lambda_1 \in \Lambda\}$, where $\Lambda$ contain $T - p + 1$ histories $\lambda_i$ and $T$ is the sample size ($T=312$).

2) We separate the set of all recessionary histories from that of all expansionary histories. We calculate the transition variable $z_{\lambda_i}$ for each $\lambda_i$. If $z_{\lambda_i} \leq z^* = -0.9\%$, then $\lambda_i \in \Lambda^R$, where $\Lambda^R$ refers to all recessionary histories; if $z_{\lambda_i} > z^* = -0.9\%$, then $\lambda_i \in \Lambda^E$, where $\Lambda^E$ refers to all expansionary histories.

3) We select at random one history $\lambda_i$ from the set $\Lambda^R$, taking $\hat{\Omega}_{\lambda_i}$ obtained as follows:

$$\hat{\Omega}_{\lambda_i} = F(z_{\lambda_i})\hat{\Omega}_R + (1 - F(z_{\lambda_i}))\hat{\Omega}_E,$$  \hspace{1cm} (10)

where $z_{\lambda_i}$ is the transition variable computed for the selected history $\lambda_i$. $\hat{\Omega}_R$ and $\hat{\Omega}_E$ are calculated from the generated MCMC chain of the parameter values during the estimation step. As in Koop et al. (1996), we consider the distribution of parameters rather than their mean values to allow for parameter uncertainty.

4) We estimate the variance-covariance matrix $\hat{\Omega}_{\lambda_i}$ using the Cholesky-decomposition:

$$\hat{\Omega}_{\lambda_i} = \hat{C}_{\lambda_i}\hat{C}_{\lambda_i}^t,$$  \hspace{1cm} (11)

we orthogonalize the estimated residuals to get the structural shocks as:

$$e^{(j)}_{\lambda_i} = \hat{C}_{\lambda_i}^{-1}\hat{\varepsilon}.$$  \hspace{1cm} (12)
5) From $e_{\lambda_i}$ draw with replacement $h$ nine-dimensional shocks and get the vector of bootstrapped shocks

$$e^{(j)*}_{\lambda_i} = \{e^*_{\lambda_i,t}, e^*_{\lambda_i,t+1}, ..., e^*_{\lambda_i,t+h}\}, \quad (13)$$

where $h$ is the number of horizons for the IRFs we compute.

6) We form another set of bootstrapped shocks which are equal to (13) except for the $k_{th}$ shock in $e^{(j)*}_{\lambda_i}$ which is the shock we perturb by a $\delta$ amount. We call the vector of bootstrapped perturbed shocks as $e^{(j)\delta}_{\lambda_i}$.

7) We transform back $e^{(j)*}_{\lambda_i}$ and $e^{(j)\delta}_{\lambda_i}$ as follows:

$$\hat{\varepsilon}^{(j)*}_{\lambda_i} = \hat{C}_{\lambda_i} e^{(j)*}_{\lambda_i}, \quad (14)$$

and

$$\hat{\varepsilon}^{(j)\delta}_{\lambda_i} = \hat{C}_{\lambda_i} e^{(j)\delta}_{\lambda_i}. \quad (15)$$

8) We use (14) and (15) to simulate the evolution of $X^{(j)*}_{\lambda_i}$ and $X^{(j)\delta}_{\lambda_i}$ and we construct the $GIRF^{(j)}(h, \delta, \lambda_i)$ as $X^{(j)*}_{\lambda_i} - X^{(j)\delta}_{\lambda_i}$.

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

10) We calculate the GIRF conditional on history $\lambda_i$ as:

$$\hat{GIRF}^{(i)}(h, \delta, \lambda_i) = B^{-1} \sum_{j=1}^{B} GIRF^{(i,j)}(h, \delta, \lambda_i). \quad (16)$$

11) We repeat all previous steps for $i=1,...,500$ histories belonging to the set of recessionary histories, $\lambda_i \in \Lambda^R$, and we get $GIRF^{(1,R)}(h, \delta, \lambda_{1,R}), GIRF^{(2,R)}(h, \delta, \lambda_{2,R}), ..., GIRF^{(500,R)}(h, \delta, \lambda_{500,R})$ where the subscript $R$ means that we are condition-
ing upon recessionary histories.

12) We take the average and we get $\hat{\text{GIRF}}^{(R)}(h, \delta, \Lambda_R)$, which is the average GIRF under recessions.

13) We repeat all the previous steps from 3 to 12 for 500 histories belonging to the set of all expansions and we get $\hat{\text{GIRF}}^{(E)}(h, \delta, \Lambda_E)$.

14) We compute the 68% confidence bands for the IR by picking up for each horizon of each state, the 16th and 84th percentile of the densities $\hat{\text{GIRF}}^{(1:500), R}$ and $\hat{\text{GIRF}}^{(1:500), E}$.