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Uncertainty, Fiscal, and Financial Shocks in a Nonlinear World

Empirical Investigations

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Summary

This thesis investigates the macroeconomic effects of uncertainty, fiscal and financial shocks, which are analyzed within a nonlinear time series framework. It consists of four self-contained chapters. In each chapter, empirical methods are used to extend the empirical literature, and evaluate the importance of different transmission channels of macroeconomic shocks suggested by theoretical models.

Chapter 1 investigates the effects of financial regulation policy uncertainty (FRPU) in the U.S. economy, using a Vector Autoregressive (VAR) model. It focuses on two important issues in the empirical context of uncertainty: the role of financial frictions as a transmission mechanism of uncertainty shocks, and the relevance of financial regulation policies as a source of uncertainty. Policy uncertainty is quantified with a news-based index developed by Baker, Bloom, and Davis (2013). To assess the relevance of financial frictions for the transmission of uncertainty shocks, I model credit spreads along with a number of key U.S. macro variables. I then compute impulse responses of these variables to a shock to the FRPU index. My results suggest that FRPU shocks trigger increases in spreads as well as a persistent negative impact on the real economy. Next, I study whether these effects differ if the shock hits during a recession rather than in a non-recessionary phase. To do so, I estimate a nonlinear Smooth-Transition VAR (STVAR) model and compute state-dependent impulse responses of the same variables to the same shock. My nonlinear estimates show that FRPU shocks have an asymmetric impact over the business cycle. Credit spreads and unemployment, for example, are estimated to increase three times more during bad times than in good ones. Importantly, forecast error variance decompositions indicate that FRPU shocks account for large shares of the variability of macro aggregates.

Chapter 2 is based on joint work with Giovanni Caggiano and Efrem Castelnuovo. It digs deeper on the nonlinearities of U.S. uncertainty shocks by investigating i) whether the effects of economic uncertainty are different in good and bad times, and ii) how systematic monetary policy interacts with

uncertainty in these two states of the economy. To answer these questions, we first model a standard set of macro variables with a STVAR model, and compute Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran, and Potter (1996). Our GIRFs provide clear-cut evidence of asymmetric effects of uncertainty shocks over the business cycle. In recessions, real activity follows a drop-rebound-overshoot pattern after the shock. Differently, in expansions the drop is milder and recovery takes place very slowly, with no overshoot in the medium term. The policy rate reacts to uncertainty shocks in both states, although its decrease is more marked during recessions. Turning to our second question, we then simulate some counterfactual exercises in which systematic monetary policy remains still in spite of an uncertainty shock. Our results point to policy ineffectiveness in bad times, i.e. the negative peak of real activity remains exactly the same. On the contrary, monetary policy plays an important role during expansions, i.e., in absence of an accommodative policy, the drop in output would have been almost twice the one observed in the unconstrained scenario. We provide a possible interpretation for our results, based on the theoretical work by Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), by emphasizing the role of time-varying financial frictions and/or labor and capital adjustment costs.

Chapter 3 is based on joint work with Giovanni Caggiano, Efrem Castelnuovo and Valentina Colombo. It estimates state-dependent fiscal multipliers for the U.S. economy by explicitly addressing the issue of fiscal foresight. Simple theoretical examples show that foresight produces equilibrium time series with a non-invertible moving average component, which misaligns the agents' and the econometrician's information sets in standard VARs (Leeper, Walker, and Yang, 2013). We deal with this issue by appealing to sums of revisions of expectations about future government spending. We then model these fiscal news shocks, along with a set of standard macro-fiscal variables, by using a nonlinear Smooth-Transition VAR framework. To compute fiscal multipliers in recessions and expansions, we use Generalized Impulse Response Functions (GIRFs), which allow us to endogenize the possibly stabilizing effects of fiscal policy, and most important, to distinguish between "extreme" and "moderate" business cycle phases. As a result, this Chapter establish some new stylized facts about government spending multipliers in the U.S., in particular, the fact that firm evidence of state dependent multipliers arises only when looking at extreme phases of the cycle, i.e., deep recessions and strong expansionary periods.

Chapter 4 looks at the real effects of credit supply shocks originating in U.S. corporate bond markets. It does so by distinguishing once again between phases of the business cycle. However, this Chapter differs substantially from the previous ones in terms of methodology. I estimate linear and nonlinear local projection models (Jordà, 2005), in which the credit supply shock is proxied by the *excess bond premium* (EBP) developed by Gilchrist and Zakrajšek (2012). In short, the EBP is a measure of marketwide corporate bond spreads net of expected default losses. I use the local projection estimates to compute two sets of impulse responses of real activity to an EBP shock: one conditional on a linear view of the world, and the other allowing the economy to react differently in recessions vs. normal times. The linear estimates provide evidence that the financial sector may very well be an originator, other than propagator of shocks. When economic activity is allowed to respond asymmetrically to the EBP shock, evidence of nonlinearities arise. Specifically, a drop-rebound-overshoot pattern is found when the credit shock hits the economy in recessions. Whereas a long-lasting, hump-shaped reaction is found in normal times. Given that these results echo recent findings in the business cycle literature as for uncertainty shocks, I ensure that my estimates are not driven by misspecification by undertaking a number of robustness checks. Finally, I provide an interpretation of my results based on Dow, Gorton, and Krishnamurthy (2005) and Philippon (2006), who develop theoretical models able to replicate amplification and persistence of otherwise i.i.d. shocks during upward phases of the business cycle.

Chapter 1

Financial Regulation Policy Uncertainty and Credit Spreads in the U.S.

1.1 Introduction

The U.S. financial regulation system has come under criticism in the aftermath of the financial crisis of 2007-08. Since then, policymakers have instituted various reforms, and have thereby substantially increased public uncertainty about the financial regulatory framework. Regulatory reforms play an important role in re-establishing trust in the financial system. The reforms underway in the U.S. are aimed at making markets and institutions more transparent, less complex, and less leveraged. These features are a precondition for restoring appropriate levels of credit growth to support economic recovery. However, the ongoing reforms may trigger undesirable effects on the economy due to the policymaking process concerning implementation being surrounded by uncertainty.

This Chapter quantifies the macroeconomic effects of financial regulation policy uncertainty shocks within a Vector Autoregressive (VAR) framework. Financial regulation policy uncertainty can be thought of as the increased volatility of the expected outcome resulting from changes in the regulatory framework, which is unforecastable from the perspective of economic agents.[1] The fact that there is no directly observed measure of uncertainty in the

[1] The definition of financial regulation policy uncertainty is adopted from Jurado, Ludvigson, and Ng's (2015) definition of economic uncertainty: "at a general level, uncertainty is

economy poses a significant problem for researchers, who have to resort to uncertainty proxies. The empirical counterpart of uncertainty employed in my analysis is the news-based financial regulation policy uncertainty index (henceforth, the FRPU index) developed by Baker et al. (2013). The FRPU index quantifies perceived macroeconomic uncertainty concerning U.S. financial regulation policies since 1985. My investigation aims to provide empirical evidence on the linear and nonlinear effects of FRPU shocks in presence of financial frictions. To do so, I focus on the role of FRPU shocks in driving corporate credit spreads and some key macroeconomic aggregates, namely industrial production, unemployment, inflation, and the federal funds rate.

The early theoretical literature has extensively analyzed the real-option channel as a transmission mechanism of uncertainty shocks to the real economy. Bernanke (1983) and Dixit (1989), for instance, show that real-option effects materialize within the framework of irreversible investment, where uncertainty plays a role in delaying investment decisions. Within this framework, firms defer investment decisions that involve sunk costs whenever facing a highly uncertain environment, because uncertainty increases the option value of waiting (the real-option) until new information about the state of the economy arrives. As a result, increases in uncertainty are typically followed by drops in investment. The real-option channel has also been recently investigated by Bloom (2009). Using a linear VAR, he provides evidence that uncertainty shocks in the U.S. generate a rapid drop, rebound, and overshoot in economic activity. He then replicates this evidence with a model in which firms face a region of inaction in the hiring and investment space. The region of inaction arises from non-convex labor and capital adjustment costs in the model. Under high uncertainty, the region of inaction expands, and in the aggregate firms become less reactive to business conditions and adopt a "wait-and-see" strategy.

Another growing strand of the literature focuses on financial frictions as an additional mechanism by which uncertainty interacts with the business cycle. Intuitively, uncertainty shocks may reduce the expected profitability of firms, which increases their actual or perceived riskiness. Under imperfect financial markets, increased risk raises firms' expected default probabilities, making outside borrowing more expensive. Gilchrist, Sim, and Zakrajšek (2013) explore this hypothesis within a general equilibrium model where heterogeneous

typically defined as the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents".

firms face time-varying uncertainty, non-convex capital adjustment costs, and financial market frictions. They show, both theoretically and empirically (via a SVAR model), that unanticipated increases in uncertainty—based on aggregate idiosyncratic volatility of stock returns—significantly widen corporate credit spreads, which in turn influences investment dynamics. Bonciani and van Roye (2013) set up a Dynamic Stochastic General Equilibrium (DSGE) model featuring a frictional banking sector to analyze uncertainty shocks in the presence of frictions in the supply-side of the credit market. They assume monopolistic competition and sticky retail interest rates in the banking sector, which determine an imperfect pass-through of the central bank interest rate to the private sector. As a result, monetary policy is ineffective in offsetting the dampening effects of uncertainty shocks. Therefore, these frictions considerably amplify the negative effects of uncertainty shocks and make them more persistent than otherwise. Arellano, Bai, and Kehoe (2012); Cesa-Bianchi and Fernandez-Corugedo (2013), and Christiano, Motto, and Rostagno (2014), among others, also find amplification effects of financial frictions in the context of uncertainty shocks. My study adds to this literature by providing empirical evidence on the effects of *financial regulation policy uncertainty* on credit spreads.[2]

Most of the empirical literature employs linear VAR models to investigate uncertainty shocks. A non-exhaustive list includes Alexopoulos and Cohen (2009); Bachmann, Elstner, and Sims (2013); Baker, Bloom, and Davis (2013); Bloom (2009); Gilchrist, Sim, and Zakrajšek (2013); Jurado, Ludvigson, and Ng (2015), and Leduc and Liu (2013). However, to the extent that empirical proxies of uncertainty show extreme values during economic downturns and are rather muted in non-recessionary periods, nonlinearities might be a concern. To deal with this issue, I analyze the effects of FRPU shocks within linear and nonlinear frameworks. As for the linear specification, I estimate a Structural VAR model and appeal to the standard Cholesky approach to identify FRPU shocks. In addition to the linear VAR, I then estimate a nonlinear Smooth Transition VAR (STVAR) model following Caggiano, Castelnuovo, and Groshenny (2014a), who investigate the effects of uncertainty shocks on unemployment dynamics.

[2]Studies investigating the links between financial markets and *overall* economic policy uncertainty include Antonakakis, Chatziantoniou, and Filis (2013); Brogaard and Detzel (2013); Pástor and Veronesi (2012); and Sum (2012). The macroeconomic effects of *policy-specific* uncertainty shocks are assessed by Bauer (2012); Born and Pfeifer (2013), and Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2012b). However, these contributions focus on uncertainty related to fiscal and monetary policies.

Their findings reveal strong asymmetric effects of uncertainty shocks over the business cycle. Bonciani and van Roye (2013) also emphasize the importance of nonlinearities within their DSGE model. To simulate a "distressed" scenario (i.e., a recession) in their model economy, they simultaneously hit the system with a TFP level shock and an uncertainty shock. They then show that the effects of the uncertainty shocks are significantly stronger in times of deep economic downturn.

The results of my linear VAR model show that a one-standard deviation shock to the FRPU index is associated with an increase in the cost of external finance due to a widening in corporate credit spreads. The credit spread measures which I consider in my analysis are the benchmark Baa–Aaa credit spread, the Aaa– and Baa–10 Year Treasury bond spreads, and a new corporate credit spread index constructed by Gilchrist and Zakrajšek (2012), the GZ spread. Gilchrist and Zakrajšek (2012) use an extensive dataset of prices of individual U.S. corporate bonds traded in the secondary market to construct the GZ spread, which is shown to be a highly informative financial indicator in terms of future economic activity. Using an empirical credit-spread pricing framework, they then decompose the GZ into two parts, i.e., a component measuring movements in default risk, and a residual part beyond the compensation for expected defaults—the excess bond premium. I examine the reaction of each component of the GZ spread to FRPU shocks. This exercise shows that FRPU shocks increase the expected probability of firms' default, suggesting that the financial frictions on the demand side of credit markets might matter in the transmission of uncertainty shocks. On the real side of the economy, FRPU shocks considerably and persistently reduce industrial production, whose cumulative growth rate is about 6 percent below its trend one year after the shock. Further, the unemployment rate is estimated to increase by 0.15 percent, while prices fall by more than 1 percent. Thus, FRPU shocks act as negative aggregate demand shocks. This finding lines up with those of Leduc and Liu (2013); Caggiano et al. (2014a); Colombo (2013), and Kamber, Karagedikli, Ryan, and Vehbi (2013), who focus on different definitions of uncertainty. Overall, my linear results are qualitatively robust to richer VAR models that condition the economy's responses to FRPU shocks to movements of additional macroeconomic and uncertainty indicators.

According to the STVAR estimates, the effects of FRPU shocks tend to be larger during recessions than in non-recessionary periods. An exogenous increase in the FRPU index is followed by a positive reaction of the Baa-Aaa spread which is three times larger during a recession than during a non-recessionary phase. The negative impact on unemployment and industrial production is also stronger during recessions. These results provide evidence of the asymmetric effects of FRPU shocks over the business cycle, and corroborate the findings of the above mentioned contributions dealing with nonlinearities of uncertainty shocks. I then compute forecast error variance decompositions to assess the relevance of FRPU shocks for business cycle fluctuations. Within the linear framework, FRPU shocks account for large shares of variations in unemployment and spreads, i.e., respectively more than 19 and 15 percent at a 6 months horizon. As for the nonlinear model, conditional on short-horizons, FRPU shocks tend be more relevant during recessions.

1.2 The FRPU index

The FRPU index is a news-based empirical proxy for U.S. financial regulation policy uncertainty developed by Baker, Bloom, and Davis (2013). It is computed as the monthly number of articles containing jointly references to financial regulation policies, uncertainty, and the economy.[3] The articles are obtained from the NewsBank Access World News, a database covering about 2,000 U.S. newspapers. To deal with changing volumes of articles, Baker et al. (2013) divide the raw counts in each newspaper by the total number of articles in the same newspaper for each given month. They then normalize each newspaper index to have a unit standard deviation over the period 1985-2010 and add up the indices for all newspapers. The monthly index is then rescaled to have an average value of 100. Figure 1.1 shows the evolution of the FRPU index since 1985. The variations of the index are substantial, and capture noticeable financial-related events. Examples are the "Boesky Day" in November 1986, which is considered a defining moment in the history of federal securities law enforcement; the Black Monday in October 1987; the "Friday the 13th minicrash", which refers to a stock market crash dated October 1989; the Japanese Asset Price and the Dot.com bubbles; the WorldCom's collapse in

[3]The key terms are the following: uncertainty, uncertain, economic, economy, regulation, banking supervision, Glass-Steagall, tarp, bank supervision, thrift supervision, Dodd-frank, financial reform, commodity futures trading commission, CFTC, house financial services committee, Basel, capital requirement, Volcker rule, bank stress test, securities and exchange commission, sec, deposit insurance, FDIC, FSLIC, OTS, OCC, Firrea, truth in lending.

July 2002; and more recently, the Great Recession. It is worth stressing that the FRPU index quantifies *perceived* policy uncertainty. Thus, it also shows peaks in correspondence with events not strictly related to financial regulation, such as the 9/11 terrorist attack.

Given the lack of an objective measure of economic uncertainty, it is desirable to evaluate the adequacy of the FRPU index as a proxy for financial regulation policy uncertainty.[4] Figure 1.2 plots the FRPU index along with two indicators of aggregate economic policy uncertainty, namely the "NewsBank" EPU and the EPU indexes (Baker et al., 2013), and a measure of financial markets volatility, i.e., the Chicago Board Options Exchange Volatility index (VIX). The "NewsBank" EPU is constructed in the same way as the FRPU, except that the selected articles contain no terms related to any specific-policy area. Indeed, the FRPU index is a sub-category of the "NewsBank" EPU. The EPU relies on three components: news coverage of economic policy uncertainty, the number U.S. tax code provisions set to expire in future years, and disagreement among economic forecasters.[5] By contrast, the VIX index measures markets' expectations of volatility conveyed by S&P500 index option prices. Many studies have employed the VIX as a proxy for economic uncertainty. Examples are Bloom (2009); Caggiano et al. (2014a); Kamber et al. (2013); Leduc and Liu (2013). Not surprisingly, the four uncertainty indicators show similar patterns.

To analyze the informational content of the FRPU index in comparison with the other uncertainty indexes, I run several Granger-causality tests based on bivariate VARs(6). The results, which are reported in table 1.1 (p-values), show that the FRPU Granger-causes the "NewsBank" EPU and the VIX (first column), but not the EPU index. However, no statistical support is found for the FRPU to be Granger-caused by any of the uncertainty indicators considered (first row). This evidence indicates that the increases in the FRPU index tend to anticipate (or, at least, are not anticipated by) those in the "NewsBank" EPU and in the VIX. As for the comparison between the FRPU and the EPU, I then regress the Baa-Aaa spread on a constant and lagged values of the dependent variable, the two policy uncertainty indexes, and all variables

[4] Few recent papers propose new econometric measures of uncertainty. For example, Jurado, Ludvigson, and Ng (2015) define macro uncertainty as the common variation in the unforecastable component of a large number of economic indicators, which is estimated using a latent factor model and principal component analysis for large datasets. Their broad-based macro uncertainty measure is strongly countercyclical and more persistent than other standard uncertainty proxies, such as the VIX.

[5] The reader is referred to Baker et al. (2013) for further details on the EPU index.

included in the baseline VAR model (i.e., industrial production growth, inflation, unemployment, and the federal funds rate). This specification corresponds to the baseline VAR equation for the spread augmented with the EPU index. Next, I compute two F-tests, one on the exclusion restriction concerning the statistical significance of the FRPU, and another on that of the EPU.[6] The p-values associated with the F-statistics are 0.005 and 0.150, respectively, indicating that the FRPU index contains relevant information on the variation of credit spreads. More important, this information is statistically significant when controlling for the information already conveyed by the aggregate policy uncertainty indicator (EPU).[7]

1.3 The SVAR model

To analyze the effects of a FRPU shock on the U.S. economy, I estimate the following Structural-VAR model:

$$\boldsymbol{B}_0\boldsymbol{X}_t = \sum_{i=1}^{p} \boldsymbol{B}_i\boldsymbol{X}_{t-i} + \boldsymbol{\varepsilon}_t \tag{1.1}$$

The vector $\boldsymbol{X}_t = [frpu_t, \Delta y_t, \pi_t, u_t, i_t, s_t]'$ contains the variables under scrutiny, where $frpu_t$ is the FRPU index, Δy_t denotes the annualized monthly log-difference of real industrial production, π_t stands for the annualized monthly CPI inflation, u_t represents the total civilian unemployment, i_t is the (nominal) federal funds rate, and s_t is the difference between Moody's Baa- and Aaa-rated corporate bond yields. Apart from the FRPU index, the source of these data is the Federal Reserve Bank of St. Louis' database. Conditional on the availability of the FRPU, the sample spans the period 1985:1 – 2012:10. The reduced-form model features a constant and six lags, which are chosen to eliminate residual serial correlation. The VAR satisfies the stability condition, with all roots of the characteristic polynomial being outside the unit circle. The identification of the FRPU shock is achieved by appealing to the commonly used Cholesky approach, with the ordering being the one indicated above. By placing the uncertainty measure first, I assume that the FRPU index responds with a lag to changes

[6] The lag length of six, regarding both the Granger-causality tests and the F-tests, is chosen to match the number of lags subsequently employed in the VAR model.

[7] When conducting robusteness checks, in section 1.5, I also show that the effects of FRPU shocks survive to the addition of the "NewsBank" EPU, the EPU and the VIX indexes to the vector of observables.

in the remaining variables, a very common restriction in the literature (e.g. Alexopoulos and Cohen, 2009; Bachmann et al., 2013; Baker et al., 2013; Bloom, 2009; Caggiano et al., 2014a; Jurado et al., 2015). However, as a robustness check, I allow uncertainty to react contemporaneously to macroeconomic shocks and the results are qualitatively unchanged.

1.4 Results

Figure 1.3 presents the impulse response functions of all six variables in the baseline model. An unanticipated increase in financial regulation policy uncertainty induces long lasting adverse effects on the economy. After the FRPU shock, firms face higher costs of external finance, as documented by the increase in the Baa-Aaa spread. In terms of magnitude, the increase in the spread is not particularly high (7 basis points), although it is statistically significant. It is worth noting that the size of the shock (one-standard deviation) amounts to 90 points increase in the FRPU. To have a sense of this magnitude, the index has increased by more than 700 points in correspondence with the bankruptcy of Lehman Brothers. Such a shock would increase credit spreads by about 50 basis points. According to my SVAR estimates, FRPU shocks also lead to a persistent disinflation of more than 1 percent after two months. The federal funds rate decreases by 0.2 percent, which is in line with a monetary policy easing to counteract adverse economic developments, and return inflation to its target. On the real side of the economy, industrial production bottoms out at about 6 percent below the trend, roughly one year after the shock. The unemployment rate is estimated to increase by about 0.15 percent within the same horizon. Taken together, my results classify FRPU shocks as negative demand shocks, corroborating previous findings in the literature. Leduc and Liu (2013), and Caggiano et al. (2014a), for example, focus their analysis on the impact of uncertainty shocks on the U.S. unemployment rate. Colombo (2013), and Kamber et al. (2013) investigate international spillovers of U.S. uncertainty shocks to the Euro area, and to the New Zealand economy, respectively. All these studies document macroeconomic dynamics similar to those following negative demand shocks, i.e., uncertainty shocks decrease economic activity, and induce a negative co-movement between the responses of inflation and unemployment in the short-run.

Interestingly, FRPU shocks do not induce the "wait and see" effect on industrial production as identified by Bloom (2009). Rather, the adverse effects of FRPU shocks are fairly persistent. Bachmann et al. (2013); Baker et al. (2013), and Jurado et al. (2015) also document a persistent negative reaction of industrial production to uncertainty shocks within a linear framework. As stressed by Bachmann et al. (2013), uncertainty shocks may propagate through other mechanisms in addition to the "wait and see" channel. In this regard, Gilchrist et al. (2013) point to financial distortions as the main mechanism through which fluctuations in uncertainty affect macroeconomic outcomes. They develop a general equilibrium model and show that financial distortions amplify the negative response of aggregate investment to uncertainty shocks by altering the effective supply of credit.

Alternative credit spread indicators To complement the previous results, and shed some light on the financial frictions channel of uncertainty shocks, I re-estimate the baseline SVAR model by replacing the Baa-Aaa spread with alternative credit spread measures. These measures are the yield spread between Aaa- and Baa-rated bonds and the 10-year U.S. Treasury bonds (respectively, the Aaa–GS10 and the Baa-GS10 spreads), and the GZ spread. As previously mentioned, the GZ has been developed by Gilchrist and Zakrajšek (2012). It is a novel credit spread indicator constructed as the yield difference between bonds issued by U.S. non-financial corporations and a hypothetical Treasury security with exactly the same cash flows as the underlying corporate bonds. Interestingly, by employing the "distance to default" framework developed in the seminal work of Merton (1974), Gilchrist and Zakrajšek (2012) decompose the GZ spread into two components, one capturing systematic changes in default risk, and a residual component representing a risk premium beyond expected losses (the excess bond premium). They then show that the excess bond premium fluctuates closely in response to movements in capital and balance sheet conditions of key financial intermediaries. Therefore, both components can be considered as credit market frictions. The default risk component is a proxy for frictions characterizing the demand side, while the excess bond premium represents frictions in the supply side of the credit market. I analyze the effects of FRPU shocks on the differently defined credit spreads as well as on each of the GZ components.[8] Figure 1.4 plots the impulse responses, along with the 90% confidence bands calculated with the bootstrap-after-bootstrap procedure developed by Kilian (1998), to a one-standard deviation FRPU shock. All spreads are estimated to increase in the short-run. The Aaa–GS10 spread follows a pattern similar to the Baa-Aaa, whereas the Baa–GS10 spread and the GZ increase by almost 15 basis points. These results confirm that uncertainty shocks may propagate—at least partially—through the financial frictions channel. Further, the responses of the separated components of the GZ suggest that the frictions related to the demand-side of credit markets are more relevant than those related to the supply side for the transmission of FRPU shocks. Indeed, the FRPU shock leads to a statistically significant increase in default risk perceptions, but does not substantially affect the excess bond premium.

Variance decomposition analysis How important are FRPU shocks for business cycle fluctuations? Table 1.2 reports forecast error variance decompositions for different shocks and horizons. Compared to the other shocks in the model, FRPU shocks account for a non-negligible share of the forecast error variance of the Baa–Aaa spread, i.e., around 18% for all horizons considered (right part of table 1.2). FRPU shocks are also quantitatively relevant for movements in unemployment (≈25%), and in the federal funds rate (≈16%). These findings are robust to the inclusion of additional variables to the vector of observables, such as the S&P500, and the VIX indexes.

Table 1.3 further stresses the contribution of FRPU shocks for the dynamics of credit spreads. It shows that FRPU shocks are responsible for important shares of the forecast error variance of the alternative spread measures considered. For example, financial regulation policy uncertainty picks up about 10, 17 and 13 percent of the variation in the GZ spread, the Baa–GS10, and the Aaa–GS10, respectively, at a 12 month horizon. In comparison, monetary policy shocks account for much smaller fractions, i.e., exogenous variations in the federal funds rate explain just 2, 4, 5 percent of the above spread indicators, respectively, at the same forecast horizon.

[8] Given the availability of data, the models including the GZ spread and its components are estimated over the 1985:1-2010:9 period, while the remaining estimations follow the baseline sample period, i.e., 1985:1-2012:10.

1.5 Sensitivity Analysis

I conduct a sensitivity analysis to verify the robustness of my results. In particular, I estimate a few alternative linear VARs that condition the impact of FRPU shocks to additional macroeconomic variables. I start by controlling for *broad economic conditions in financial markets.* To do so, I add the S&P500 and the VIX indexes as the first two variables, respectively, to the VAR. The inclusion of the S&P500 index enables me to control for the impact of first-moment shocks, i.e., variations in uncertainty may confound variations in the level of the stock market index (Bloom, 2009; Caggiano et al., 2014a).[9] By taking into account also the VIX, which is a proxy for volatility risk (Ang, Hodrick, Xing, and Zhang, 2006) containing important information about economic uncertainty, I control for variations in the FRPU index not necessarily related to financial regulation.

Another concern is that high levels of uncertainty, as proxied by increases in the FRPU, may reflect agent's perceptions of bad economic times rather than an uncertain future. In such a case, FRPU innovations would simply reflect *confidence shocks.* I address this issue by augmenting the baseline VAR with a consumer confidence index placed first in the vector of observables. This index is based on information collected via the Michigan Survey of Consumers, and consists of an average of responses to different questions concerning the future evolution of the business cycle.

Next, to corroborate the results presented in section 1.2—where I show that the FRPU index contains relevant information relatively to other uncertainty indicators—I estimate two VARs, one including the "NewsBank" EPU index, and another including the EPU index. In both specifications, I purge the FRPU shocks from systematic contemporaneous reactions to aggregate economic policy uncertainty by placing the additional indexes first in the Cholesky ordering.

The final two robustness exercises I undertake involve the number of lags, and the Cholesky ordering in the baseline model.[10] My linear baseline VAR features six lags to ensure that there is no serial correlation in the residuals.

[9]Following Bloom (2009), the log of the S&P500 index is HP detrended to capture its cyclical component. However, my results are robust to using the S&P500 index in levels.

[10]In addition to the reported checks, I also performed a subsample analysis by excluding the last part of the sample, i.e., 2008:7-2012:10. The results turned out to be sensitive to including the Great Recession. This suggests that nonlinearities may play an important role in the transmission of uncertainty shocks. To address this issue, I estimate a nonlinear VAR in the next section.

However, I control whether the results are robust to using two lags, as suggested by commonly applied selection criteria (AIC and BIC), and twelve lags. Additionally, to account for the potential criticism to the Cholesky approach, I consider a VAR specification in which the FRPU index is placed last. This alternative ordering allows examining the implications of uncertainty shocks conditional on the information contained in the current level of credit spreads.

Figure 1.5 shows the results of these robustness checks. Overall, the estimated impact of FRPU shocks is qualitatively similar to the baseline scenario, although in most of the cases the effects are quantitatively lower. In particular, FRPU shocks that are orthogonal to the contemporaneous level of credit spreads have a less adverse effect on the real economy. In line with the results of Gilchrist et al. (2013), this suggests that financial distortions are an important transmission mechanism of uncertainty shocks.

1.6 FRPU shocks during recessions

The macroeconomic effects of uncertainty shocks have been typically investigated by employing linear VARs. However, some recent contributions point to the possibility of non-linear effects of such shocks in different phases of the business cycle. Caggiano, Castelnuovo, and Groshenny (2014a) (hereafter CCG) estimate a Smooth Transition VAR model to investigate the effects of uncertainty shocks on unemployment dynamics in the post-WWII U.S. recessions. They find the relevance of uncertainty shocks to be much larger during recessions than in non-recessionary periods. Bonciani and van Roye (2013) provide empirical evidence on the negative impact of uncertainty shocks by estimating a Bayesian VAR (BVAR) model using euro area data. They then analyze the transmission mechanism of the shock by using a DSGE model featuring price rigidities and credit frictions, and find that frictions in the banking sector considerably amplify the effects of uncertainty shocks on economic activity. Interestingly, the magnitude of the responses of macroeconomic aggregates in the data (BVAR model) indicates that uncertainty shocks have a stronger effect in the euro area than predicted by their DSGE model. As Bonciani and van Roye (2013) emphasize, this may be due to strong nonlinear effects associated with the inclusion of the financial crisis of 2007-08 in the data sample. Indeed, they show that the impact of uncertainty shocks in a recession is potentially much larger than in a "normal" macroeconomic environment.[11]

To shed light on the potential asymmetries of FRPU shocks during recessions, I follow CCG and estimate a nonlinear Smooth Transition VAR (STVAR) model. The STVAR framework conveniently allows the isolation of recessionary periods, while retaining enough information to estimate a richly parametrized model.[12] The STVAR is defined as follows:

$$\boldsymbol{X}_t = F(z_{t-1})\boldsymbol{\Pi}_R(L)\boldsymbol{X}_t + [1 - F(z_{t-1})]\boldsymbol{\Pi}_{NR}(L)\boldsymbol{X}_t + \boldsymbol{\varepsilon}_t \tag{1.2}$$

$$\boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{\Omega}_t) \tag{1.3}$$

$$\boldsymbol{\Omega}_t = F(z_{t-1})\boldsymbol{\Omega}_R + [1 - F(z_{t-1})]\boldsymbol{\Omega}_{NR} \tag{1.4}$$

$$F(z_t) = exp(-\gamma z_t)/[1 + exp(-\gamma z_t)] \tag{1.5}$$

where $\boldsymbol{X}_t$ is the same vector of endogenous variables used in the linear model, $\boldsymbol{\Pi}_R$ and $\boldsymbol{\Pi}_{NR}$ are the coefficient matrices capturing the dynamics of the system during recessions and non-recessionary phases. The variance-covariance matrix of reduced-form residuals, $\boldsymbol{\Omega}_t$, varies with the state of the economy as given by (1.3) and (1.4), and $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_{NR}$ are the state-contingent covariance matrices in recessions and non-recessions, respectively. In addition, $F(z_t)$ is the logistic transition function, which is bounded between 0 and 1, and whose smoothness parameter is γ. $F(z_t)$ can be interpreted as the probability of being in a recession given observations on the transition indicator, z_t. Auerbach and Gorodnichenko (2012); Bachmann and Sims (2012) and Berger and Vavra (2014b) estimate nonlinear VAR models with quarterly data, and use a moving average involving seven realizations of GDP growth as the transition indicator. Following these studies, I employ a standardized backward-looking moving average involving twenty-one (monthly) realizations of the growth rate of industrial production. As the mentioned studies, I calibrate γ to match the observed frequencies of U.S. recessions, i.e. 11% in my sample, which implies $\gamma = 2$. A recession is then

[11] Bonciani and van Roye (2013) define a recession as a "distressed scenario" occurring when their DSGE model economy is hit simultaneously by a negative two-standard deviations TFP level shock, and a positive one-standard deviation uncertainty shock.

[12] Given the limited number of recessionary observations in my sample, the STVAR methodology is preferred to alternative ways of modeling nonlinearities in the VAR context, such as Threshold or Markov-Switching VAR models.

defined as a period in which $F(z_t)$ is greater than 0.89, that is $z_t < -1.05\%$.[13] The model is estimated by maximum likelihood, and given its high nonlinearity, I employ Monte Carlo Markov-Chain simulations (Chernozhukov and Hong, 2003). The joint posterior distribution of the parameters is then used for inference.[14] Because of the limited number of observations for the highly parameterized STVAR model, the lag length is set to four.

Figure 1.6 plots the regime-dependent impulse responses to a one-standard deviation FRPU shock. As argued by Ehrmann, Ellison, and Valla (2003), regime-dependent impulse responses are a valid analytical tool given the focus on the short-run dynamics of the system. Moreover, a regime switch from a recession to a non-recessionary phase following a positive uncertainty shock is unlikely in the short-run (see CCG for a discussion). The economy's responses to the shock tend to be much larger during recessions, and for short horizons differences are statistically significant at a 90% confidence level. Importantly, the STVAR predicts that an exogenous increase in the FRPU index is followed by a positive reaction of the Baa-Aaa spread three times larger during a recession than otherwise. Unemployment increases significantly and persistently under recessions, as in CCG. Notably, the short-run difference between the responses of unemployment under recessions and non-recessionary phases is substantial. The short-run reduction of industrial production is also stronger in recessions, but the difference between regimes is not as marked as that for the unemployment rate. Prices react asymmetrically depending on the business cycle phase, i.e., they decrease in recessions, as predicted by the linear VAR model, but slightly increase during non-recessions, although the response in the last case is hardly statistically significant. On the one hand, lower prices following an uncertainty shock may be motivated by downward price adjustments due to a weaker aggregate demand. On the other hand, Mumtaz and Theodoridis (2012) use a DSGE model featuring price and wage rigidities and show that uncertainty shocks can potentially lead to price increases. In their framework, workers faced with higher uncertainty prefer to set higher current wages as an insurance against the possibility of being "locked in" to a contractual agreement to supply

[13]The corresponding threshold value for the non-standardized moving average of the industrial production growth rate is equal to -1.5%. The sample mean of the non-standardized industrial production growth in moving average terms is equal to 2.11, while its standard deviation is 3.43. Then, its corresponding threshold value is obtained by "inverting" the formula I employed to standardize the transition indicator z, i.e., $\bar{z}^{nonstd} = -1.05 * 3.43 + 2.11 = -1.5$.

[14]The estimation procedure of the STVAR is described in Appendix A.

more labor when demand is high. Hence, firms prefer to set higher prices to avoid a similar scenario. Such a mechanism is more likely to be at work during non-recessionary phases, when upward price adjustments—in terms of losses in aggregate demand—are probably less costly than during recessions.

Monetary policy usually plays an important role in offsetting the negative effects of uncertainty shocks. Within their nonlinear framework, CCG show that the federal funds rate is highly sensitive to uncertainty shocks during recessions. Surprisingly, my results show a stronger decrease of the policy rate under non-recessionary periods. This may be justified by the fact that most of the recessionary observations in my sample come from the financial crisis of 2007-08, a period during which the zero lower bound (ZLB) was binding. This could potentially lead to biased estimates concerning the reaction of the federal funds rate to FRPU shocks. To explore this hypothesis, I re-estimate the STVAR model excluding from the sample the period when the federal funds rate was close to zero, i.e., 2008:10 - 2012:10. I then compute the response of the federal funds rate to a FRPU shock conditional on the sub-sample STVAR estimates, which is reported in figure 1.7, along with the baseline responses. This exercise shows that the difference between the two state-dependent impulse response functions is remarkably smaller when excluding the ZLB.

Overall, the impulse responses estimated via the STVAR model support the case for nonlinear dynamics following FRPU shocks. This finding is further reinforced when forecast error variance decompositions within the two regimes are considered (table 1.4).[15] Under recessions, FRPU shocks account for large shares of the variance of industrial production and inflation for all horizons considered. FRPU shocks are more relevant for credit spread dynamics during recessions when considering short horizons (less than six months), and for unemployment dynamics when considering longer horizons (from six to twelve months). Forecast error variances for the policy rate are greater during non-recessionary phases, which is not surprising considering the estimated federal funds rate's reaction to the FRPU shock.

[15]Given the use of regime-dependent impulse responses, forecast error variance decompositions for the nonlinear model are computed for short-run horizons only.

1.7 Conclusions

This Chapter has analyzed the linear and nonlinear macroeconomic effects of financial regulation policy uncertainty in the U.S. economy. To shed light on the financial frictions channel of uncertainty shocks, the investigation has focused on the responses of corporate credit spreads. Financial regulation policy uncertainty has been quantified with the news-based FRPU index recently developed by Baker, Bloom, and Davis (2013). The results based on the linear VAR model show that FRPU shocks trigger an increase in the cost of external finance, documented by the widening in credit spreads. As for the real side of the economy, the shock has a persistent negative impact on industrial production and unemployment. Prices are estimated to fall. The monetary authority reacts to these adverse economic developments by lowering the policy rate. These findings support previous empirical evidence showing that uncertainty shocks act as negative demand shocks. The estimation of a nonlinear (Smooth-Transition) VAR, and the computation of state-dependent impulse response functions, reveal that the impact of FRPU shocks is asymmetric over the business cycle. In particular, the responses of credit spreads, unemployment and industrial production are estimated to be substantially larger when the FRPU shock occurs in a recession than during a non-recessionary phase. This suggests that FRPU shocks can be particularly harmful during times of deep economic downturn.

These findings highlight the importance of modeling financial frictions, and accounting for nonlinearities, when incorporating uncertainty shocks into macro models to analyze their propagation mechanism to the real economy. From a policy perspective, the results suggest that policymakers should pay considerable attention to the design of financial regulation, especially in terms of policy management and credibility. A temporary lack of transparency in economic policy design is very likely to harm the overall economy. As noted by Bloom (2009), a potential trade-off between policy "correctness" and "decisiveness" should be considered. It may be more desirable for governments to act decisively, albeit occasionally incorrectly, than being deliberately ambiguous on policies that many economic agents depend on for purposeful production and spending decisions.

Chapter 2

Uncertainty and Monetary Policy in Good and Bad Times

2.1 Introduction

Bloom's (2009) seminal contribution on the impact of uncertainty shocks has revamped the attention on the role that uncertainty plays for macroeconomic fluctuations. Using a linear VAR, he provides empirical evidence that uncertainty shocks in the U.S., proxied by large stock-market volatility jumps, generate a quick "drop and rebound" in output and employment in the short-run, followed by a temporary "overshoot" in the medium run. The effects of uncertainty shocks are substantial, e.g., industrial production rapidly falls by about 1% within four months. A variety of theoretical and empirical models have further examined the role of uncertainty in affecting agents' decisions and triggering macroeconomic dynamics.[1]

This Chapter looks at nonlinearites, and investigates two questions: Are the effects of uncertainty shocks different in good and bad times? Is the stabilizing power of systematic monetary policy state-contingent? To answer these questions a standard set of macroeconomic variables is modeled within a Smooth Transition Vector AutoRegression (STVAR) framework. This nonlinear

[1]A non-exhaustive list includes the theoretical models by Basu and Bundick (2012); Bloom et al. (2012); Leduc and Liu (2013); Johannsen (2013); Christiano et al. (2014) and the empirical studies by Alexopoulos and Cohen (2009); Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011); Mumtaz and Theodoridis (2012); Stock and Watson (2012); Aastveit, Natvik, and Sola (2013); Baker et al. (2013); Gilchrist et al. (2013); Mumtaz and Surico (2013); Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2014); Nodari (2014); Pellegrino (2014); Jurado et al. (2015), and Furlanetto, Ravazzolo, and Sarferaz (2014).

framework allows to capture the possibly asymmetric macroeconomic responses to an uncertainty shock occurring in different phases of the business cycle. To endogenously account for possible regime-switches due to an uncertainty shock, Generalized Impulse Response Functions (GIRFs) are then computed (Koop et al., 1996). This is important to correctly address the questions indicated above because i) uncertainty shocks occurring in expansions are likely to drive the economy into a recessionary state, and ii) uncertainty shocks occurring in recessions may lead the economy to a temporary expansion in the medium run due to the "volatility effect" as in Bloom (2009).[2]

Our focus on nonlinearities is motivated by the following considerations. First, uncertainty shocks are typically assumed to have symmetric effects over the business cycle. However, some recent evidence points to the asymmetric behavior across the business cycle displayed by a number of macroeconomic indicators (e.g., Caggiano and Castelnuovo, 2011; Morley and Piger, 2012; Abadir, Caggiano, and Talmain, 2013; Morley, Piger, and Tien, 2013). Moreover, uncertainty appears to rise much sharply in bad than in good times. Micro- and macro-evidence of countercyclical uncertainty, with abrupt increases in recessions, is documented by Bloom (2009), Bloom et al. (2012), Jurado et al. (2015), and Orlik and Veldkamp (2014).[3] Different indicators of realized volatility, often taken as a proxy for expected volatility in empirical analysis, are documented to be higher and more volatile in recessions (Bloom, 2014). In light of this evidence, it may very well be that uncertainty shocks have different macroeconomic effects over the business cycle. If this is the case, stabilization policies are most likely to be designed differently depending on whether an uncertainty shock hits during an expansion or a downturn.

Our results provide clear-cut evidence of asymmetric effects of uncertainty shocks over the business cycle. Industrial production and employment follow

[2]In Bloom's (2009) model, the "volatility effect" is due to the fact that an uncertainty shock translates in an increase in the realized volatility of business conditions. The latter leads high productive firms to investing and hiring, and low productive ones to disinvesting and firing. Given that the majority of firms is clustered around the hiring and investing thresholds, a temporary increase in aggregate production and employment occurs. A detailed discussion of the transmission mechanism of uncertainty shocks in Bloom's (2009) model and its relevance for the empirical analysis conducted in this chapter is provided in the next section.

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

a drop, rebound, and overshoot dynamic path when uncertainty rises during recessions. Importantly, these business cycle fluctuations are quantitatively more ample than those predicted by a linear VAR framework modeling the same observables. Turning to expansions, the response of real activity is characterized by a milder drop, a prolonged recovery, and no overshoot. From a theoretical perspective, these results, on the one hand, support the predictions coming from the model put forth by Bloom (2009), in which firms, subject to partial adjustment costs in labor and capital, optimally implement a "wait-and-see" strategy after a sudden increase in the level of uncertainty. Such a strategy gives rise to the drop-rebound-overshoot pattern that we document in recessions. On the other hand, a recent extension of Bloom's (2009) model (Bloom et al., 2012), which includes optimizing consumers, predicts the drop in production – due to an uncertainty shock – to be followed by a *gradual* recovery, with no overshoot. This is exactly what we observe in our estimates during expansions. The absence of a drop-rebound-overshoot of real activity in Bloom et al. (2012) is due to consumption smoothing taking place after the shock. We argue that, during recessions, consumption smoothing may be impeded by harsh financial conditions (Canzoneri, Collard, Dellas, and Diba, 2011). Further, capital and labor adjustment costs may be time-varying as well. If this is the case, our evidence is consistent with both theoretical models mentioned above, and suggests that partial adjustment costs and some form of financial constraints are key elements to understand the effects of uncertainty shocks. Moving to the reaction of nominal variables, uncertainty shocks are found to drive inflation and interest rates down. The policy rate reacts to the shock in both states of the cycle, however, its decrease is much more marked during recessions. This result, combined with that on real activity, suggests that uncertainty shocks behave as "demand" shocks, as advocated by Basu and Bundick (2012) and Leduc and Liu (2013).

Turning to our second question on the role of monetary policy, we simulate a number of counterfactual exercises in which systematic policy remains still in spite of an uncertainty shock. Our results point to policy ineffectiveness in bad times, i.e., the negative peak of real activity remains exactly the same. On the contrary, monetary policy plays an important role during expansions, i.e., in absence of an accommodative policy, the drop in output would have been almost twice as the one observed in the unconstrained scenario. Clearly, monetary policy is likely to work not only via the short-term interest rate, but also through the impact on long-term rates (e.g., Bernanke, 2013, and the literature cited therein). We then re-estimate our STVAR model including a long-term interest rate, and perform counterfactual simulations by alternatively switching off the federal funds rate and the long-term interest rate. Our results, which confirm those from the benchmark counterfactuals, suggest that both the short- and the long-end of the term structure are important for the stabilization of the U.S. business cycle in presence of uncertainty shocks. The ineffectiveness of monetary policy under recessions is consistent, once again, with the predictions of Bloom's (2009) and Bloom et al's (2012) models. In presence of labor and capital adjustment costs, such models predict a weak impact of economic policy owing to the magnified importance of "wait-and-see" effects in presence of heightened uncertainty. Our result is also consistent with Vavra (2014), whose model predicts a link between greater volatility and higher aggregate price flexibility, with the latter harming the central bank's ability to influence aggregate demand. Further, this empirical finding is in line with the prediction coming from Berger and Vavra (2014a), who build up frameworks featuring microeconomic frictions which lead to a decline in the frequency of households' durable adjustment during recessions, a fact implying a procyclical impulse response of aggregate durable spending to macroeconomic shocks.

To the current state of art, the empirical fact established in this chapter, i.e., the statistically relevant, qualitative and quantitative, difference in the response of real variables to an uncertainty shock, is novel in this literature. This result calls for normative studies to understand how macroeconomic policies should optimally react to the state-contingent effects of uncertainty shocks. Blanchard (2009) calls for policies designed to remove tail risks, channel funds towards the private sector, and undo the "wait-and-see" attitudes by creating incentives to spend. Bloom (2014) suggests that stimulus policies should be more aggressive during periods of higher uncertainty. Baker et al. (2013) find that policies that are unclear, hyperactive, or both, may raise uncertainty. Bekaert, Hoerova, and Duca (2013) find that monetary policy shocks have short and medium-term effects on risk aversion and uncertainty. Our results add to this literature by suggesting that policymakers should evaluate the possibility of implementing state-dependent optimal policy responses, possibly closer to first-moment policies in expansions, but clearly different from them in recessions. From a modeling standpoint, our evidence supports the development and use of micro-founded nonlinear frameworks able to replicate both the contractionary effects and the different transmission mechanism of uncertainty shocks over the business cycle (for a recent example, see Cacciatore and Ravenna, 2014). Among the existing models, our results support frameworks pointing to i) the recessionary effects of uncertainty shocks (see, among others, Bloom, 2009; Bloom et al., 2012; Basu and Bundick, 2012; Johannsen, 2013; Leduc and Liu, 2013), ii) the role of "wait-and-see" effects (as in Bloom, 2009, and Bloom et al., 2012), and iii) the (possibly state-dependent) role of financial frictions (Canzoneri et al., 2011), which may offer a rationale to the different ability of agents to smooth consumption over the business cycle and, therefore, to different responses of real activity to uncertainty shocks (Bloom et al., 2012).

2.2 The impact of uncertainty shocks: empirical model

We estimate the impact of uncertainty shocks on real economic outcomes via a nonlinear version of the eight variable-VAR model proposed by Bloom (2009). The vector of endogenous variables $\boldsymbol{X}_t$ includes (from the top to the bottom of the vector): the S&P500 stock market index, an uncertainty dummy based on the VXO, the federal funds rate, a measure of average hourly earnings, the consumer price index, hours, employment, and industrial production. All variables are in logs, except the volatility indicator, the policy rate, and hours.[4] As in Bloom (2009), the uncertainty dummy takes the value of 1 when the HP-detrended VXO level rises 1.65 standard deviations above the mean, and 0 otherwise.[5] Following Bloom (2009), this indicator function is employed

[4]Unlike Bloom (2009), we do not filter these variables with the Hodrick-Prescott (HP) procedure. The reason for not detrending the data is twofold. First, as shown by Cogley and Nason (1995), HP-filtering may induce spurious cyclical fluctuations, which may bias our results. Second, the computation of the GIRFs requires the inclusion of the transition variable z_t, calculated as a moving average of the growth rate of (unfiltered) industrial production in the STVAR. We notice, however, that the choice of not detrending the variables employed in our analysis does not qualitatively affect our results. Some exercises conducted with HP-detrended variables as in Bloom (2009) and based on conditionally linear IRFs computed with our STVAR framework returned results qualitatively in line with those documented in this paper. These results are available upon request and are consistent with the robustness check in Bloom (2009), Fig. A3, p. 679.

[5]As recalled by Bloom (2014), Knight (1921) defined uncertainty as people's inability to form a probability distribution over future outcomes. Differently, he defined risk as people's inability to predict which outcome will be drawn from a known probability distribution. Following most of the empirical literature, we do not distinguish between the two concepts, and use the VXO-related dummy as a proxy for uncertainty, though we acknowledge it is a

to ensure that identification comes from large, and likely to be exogenous, uncertainty shocks and not from smaller, business-cycle related, fluctuations.[6] To ease the comparison of our results with Bloom's (2009), we use the same data frequency and time span, i.e., monthly data from July 1962 to June 2008. Figure 2.1 reports the VXO series used to construct the dummy variable as in Bloom (2009) along with the NBER recessions dates. The sixteen episodes which Bloom identifies as uncertainty shocks are equally split between recessions and expansions. Noticeably, all recessions are associated with significant spikes in the volatility series.

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

$$\boldsymbol{X}_t = F(z_{t-1})\boldsymbol{\Pi}_R(L)\boldsymbol{X}_t + (1 - F(z_{t-1}))\boldsymbol{\Pi}_E(L)\boldsymbol{X}_t + \varepsilon_t, \tag{2.1}$$

$$\varepsilon_t \sim N(0, \boldsymbol{\Omega}_t), \tag{2.2}$$

$$\boldsymbol{\Omega}_t = F(z_{t-1})\boldsymbol{\Omega}_R + (1 - F(z_{t-1}))\boldsymbol{\Omega}_E, \tag{2.3}$$

$$F(z_t) = \exp(-\gamma z_t)/(1 + \exp(-\gamma z_t)), \gamma > 0, z_t \sim N(0, 1). \tag{2.4}$$

In this model, $F(z_{t-1})$ is a logistic transition function which captures the probability of being in a recession, γ is the smoothness parameter, z_t is a transition indicator, $\boldsymbol{\Pi}_R$ and $\boldsymbol{\Pi}_E$ are the VAR coefficients capturing the dynamics of the system in recessions and expansions respectively, ε_t is the vector of reduced-form residuals with zero-mean and time-varying, state-contingent variance-covariance matrix $\boldsymbol{\Omega}_t$, where $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$ are covariance matrices of the reduced-form residuals computed 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 (2014b), 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 et al. (2014a), who focus on the effects of uncertainty shocks on unemployment in recessions.

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mixture of both risk and uncertainty. For an analysis that disentangles the effects of risk and uncertainty, see Bekaert et al. (2013).

[6] Jurado et al. (2015) construct a measure of macroeconomic uncertainty by estimating the common volatility in the unforecastable component of a large number of economic indicators. They document a correlation of about 0.5 the VXO index. For a comparison between these two measures of volatility, see (Jurado et al., 2015, section 5.2).

In short, the STVAR model assumes that the vector of endogenous variables can be described as a combination of two linear VARs, i.e., one suited to describe the economy during recessions and the other to be interpreted as a vector modeling the expansionary phase. Conditional on the standardized transition variable z_t, the logistic function $F(z_t)$ indicates the probability of being in a recessionary phase. The transition from a regime to another is regulated by the smoothness parameter γ. Large values of γ imply abrupt switches, whereas small values of γ enable the economic system to spend some time in each regime before switching to the alternative one. The linear model is a special case of the STVAR, where $\mathbf{\Pi}_R = \mathbf{\Pi}_E = \mathbf{\Pi}$ and $\mathbf{\Omega}_R = \mathbf{\Omega}_E = \mathbf{\Omega}$. Following Bloom (2009), we orthogonalize the residuals of the dummy variable with those of the rest of the system by imposing a Cholesky-decomposition of the covariance matrix of the residuals. Hence, the ordering of the variables admits an immediate response of industrial production and employment, as well as the price index and the federal funds rate, to an uncertainty shock. The inclusion of the SP500 index right before our uncertainty indicator is meant to control for the impact of stock market levels on volatility. Our STVAR model can then be interpreted as a generalization of Bloom's (2009) linear approach, which is included as a special case.

A key-role is played by the transition variable z_t (see eq. (2.4)). Auerbach and Gorodnichenko (2012), Bachmann and Sims (2012), Berger and Vavra (2014b), Caggiano et al. (2014a), and Caggiano et al. (2015) construct their transition indicator using a standardized moving-average of the quarterly real GDP growth rate. Similarly, we employ a standardized backward-looking moving average involving twelve realizations of the month-to-month growth rate of industrial production.[7] Another important feature of the STVAR model is the choice of the smoothness parameter γ. Given that well-known identification issues affect the estimation of this parameter (see the discussion in Teräsvirta et al., 2010), we exploit the dating of recessionary phases produced by the National Bureau of Economic Research (NBER) and calibrate γ to match the frequency and duration of the U.S. recessions, which amounts to 14% in our sample. Consistently, we define as "recession" a period in which $F(z_t) \geqslant 0.86$, and calibrate γ to obtain $\Pr(F(z_t) \geqslant 0.86) \approx 0.14$.[8] This metric

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

[8]This choice is consistent with a threshold value $\bar{z}^{std}$ equal to -1.01%, which corresponds to a threshold value for the non-standardized moving average of the growth rate of industrial

implies $\gamma = 1.8$. Figure 2.2 plots the transition function for the U.S. post-WWII sample and superimposes the NBER recessions dating. As one can see, our transition probability tracks well the downturns of the U.S. economy.[9]

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

We estimate both the linear VAR model and the nonlinear STVAR framework with six lags, a choice supported by standard information criteria. Given the high non-linearity of the model, we estimate it by employing the Markov-Chain Monte Carlo simulation method proposed by Chernozhukov and Hong (2003).[10] The estimated model is then employed to compute GIRFs to an uncertainty shock.[11]

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

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

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

[11]Following Koop et al. (1996), our GIRFs are computed as follows. First, we draw an initial condition, i.e., starting values for the lags of our VARs as well as the transition indicator z, which - given the logistic function (2.4) - gives us the value for $F(z)$. Then, we

We interpret our impulse responses as the reaction of economic variables to an uncertainty shock. Bachmann and Bayer (2013) show that fluctuations in uncertainty may be caused by first-moment shocks like, e.g., aggregate TFP shocks, and are therefore endogenous to the economic system. Bachmann and Moscarini (2012) work with a framework in which strategic price experimentation during recessions (due to first moment shocks) implies a higher dispersion of firms' profits. We check the exogeneity of our uncertainty shocks by running bivariate VARs modeling the vectors $[sp500, VXO]'$, $[indpro, VXO]'$, and $[empl, VXO]'$, where $sp500$, VXO, $indpro$, and $empl$ stand for (respectively) the log of S&P500, the VXO index, the log of industrial production, and the log of employment. All these bivariate VARs point to i) strong evidence (at any conventional level) against the null hypothesis that the VXO does not Granger-cause the other variables, and ii) no evidence (at any conventional level) against the null hypothesis that each of the other variables does not Granger-cause the VXO. These results, based on macroeconomic aggregates, complement those by Bloom et al. (2012), who work with industry-level data and find no significant impact of first-moments shocks on measures of TFP dispersions. They are also consistent with those in Baker and Bloom (2013), who exploit natural disasters and a panel approach to show that exogenous variations in uncertainty are indeed important drivers of the business cycle.

2.3 Results

2.3.1 Nonlinear effects of uncertainty shocks

Are the real effects of uncertainty shocks state-dependent? Figure 2.3 plots the estimated dynamic responses of employment and industrial production to an uncertainty shock obtained with the linear VAR as well as those conditional

simulate two scenarios, one with all the shocks identified with the Cholesky decomposition of the VCV matrix (2.3), and another one with the same shocks plus a $\delta > 0$ corresponding to the first realization of the uncertainty shock. The difference between these two scenarios (each of which accounts for the evolution of $F(z)$ by keeping track of the evolution of industrial production and, therefore, z) gives us the GIRFs to an uncertainty shock δ. Per each given initial condition z, we compute 500 different stochastic realizations of our GIRFs, then store the median realization. We repeat these steps until 500 initial conditions (drawn by allowing for repetitions) associated to recessions (expansions) are considered. Then, we construct the distribution of our GIRFs by considering these 500 median realizations. Appendix A provides details on the algorithm we employed to compute the GIRFs.

on recessions and expansions as described by the STVAR model.[12] The linear model replicates well the drop, rebound, and overshoot of industrial production and employment documented by Bloom (2009). In particular, the peak short-run response of industrial production is about -1.5%, while that of employment reads -1%. Hence, a one-standard deviation shock in uncertainty triggers quantitatively important real effects. Notably, the contractionary effects of uncertainty shocks appear to be mainly driven by what happens in recessions. The short-run responses of industrial production and employment conditional on recessions are larger than what predicted by a linear VAR model. The peak short-run response of industrial production is below -2%, while that of employment is about -1.5% Interestingly, the rebound in industrial production is quicker in recessions than what a linear model would suggest, and the volatility overshoot is larger as well. Overall, a linear model provides a distorted picture of the real effects of uncertainty shocks in terms of: i) the magnitude of the impact over the business cycle, ii) the magnitude of the medium-run overshoot, and iii) the timing of the overshoot.[13]

How relevant is this result from a statistical standpoint? Figure 2.4 contrasts the responses of industrial production and employment obtained in recessions and expansions using 68% (areas identified with dashed and dotted lines) and 95% (grey areas) confidence intervals. The abrupt drop-and-rebound reaction of industrial production in recessions, followed by a persistent overshoot, turns out to be clearly significant even at a 5% level. Quite differently, uncertainty shocks in expansions trigger a hump-shaped, delayed reaction of industrial production, with no evidence of overshoot. Very similar results hold for employment, whose rebound and overshoot is estimated to be slower than that of industrial production, but clearly significant in recessions looking at the 68% confidence intervals. Again, expansions suggest a different conditional path for employment characterized by a much slower return to its trend level and no overshoot.

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

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

2.3.2 Interpreting asymmetries

Our GIRFs suggest a drop, rebound, and overshoot type of response of industrial production and employment only in recessions. Differently, uncertainty shocks occurring in good times induce a hump-shaped response of these variables, and no medium term overshoot. How to interpret such different dynamic paths? We speculate that the different extent to which agents in the economic system may be able to smooth their consumption over the business cycle could be key to understand our impulse responses functions. Bloom et al. (2012) extent Bloom's (2009) model and show that, in an economy in which firms face partial adjustment costs in labor and capital and consumers optimally implement their intertemporal consumption plans, the "wait-and-see" strategy implemented after an uncertainty shock does not lead to a drop-rebound-overshoot in real activities because of the inconsistency of this path of real activity with consumption smoothing. Hence, the presence of consumers willing to smooth their consumption implies that the volatility effect, which is responsible for the temporary "overshoot" in Bloom (2009), is dominated by the consumption smoothing effect. This is so because the overshoot in Bloom's (2009) partial equilibrium economy requires big variations in investment, which imply large changes in consumption. According to Bloom et al.'s (2012) model, after a drop in real activity, a gradual return to the steady state occurs. From a qualitative standpoint, this prediction is clearly supported by our impulse responses when an uncertainty shock hits in expansions. Once consumption smoothing is allowed to play a role, the overshoot in real activity disappears. However, consumption smoothing is intuitively possible if agents can easily access financial markets, something which is likely to occur in expansions. But credit conditions are typically tighter in recessions. Binding credit constraints in recessions could very much prevent (at least to some extent) consumption smoothing, therefore leading to a quick drop and rebound followed by a temporary overshoot in real activity, as predicted by Bloom (2009) (or a version of Bloom et al. (2012) in which consumption smoothing is impeded by some frictions). Interestingly, at least from a qualitative standpoint, this is exactly what our impulse responses predict.[14]

[14] In a different but related context, Canzoneri et al. (2011) show the importance of countercyclical financial frictions in a DSGE model to explain the nonlinear dynamics of real activity indicators after fiscal policy shocks.

2.3.3 Robustness checks

Appendix A discusses at length a battery of robustness checks, which include: i) the employment of an alternative uncertainty dummy, which is constructed by considering just 10 out of 16 extreme realizations of uncertainty, i.e., those which are associated to terror, war, or oil events as in Bloom (2009);[15] ii) different calibrations for the slope parameter γ ranging between 1.4 and 2.2, which imply a frequency of recessionary periods in the sample equal to 10% and 25%, respectively; iii) the use of unemployment as transition indicator z. In particular, following some recent announcements by U.S. policymakers and the modeling choice in Ramey and Zubairy (2014), we classify periods in which the unemployment rate is over (under) 6.5% as recessionary (expansionary);[16] iv) the inclusion in the vector of a measure of credit spread. Caldara et al. (2014) provide empirical evidence in favor of larger real effects of uncertainty shocks in periods of high financial stress. A way to control for the presence of time-varying financial risk is to include a measure of credit spreads in the VAR. We then model the spread between the Baa corporate bonds and the 10-year Treasury yield (the Baa-GS10 spread) along with the baseline observables. The Baa-GS10 spread is highly correlate with the measure of excess bond premium proposed by Gilchrist and Zakrajšek (2012);[17] v) house prices. The housing market is particularly important for us in light of a recent paper by Furlanetto et al. (2014), who show that uncertainty shocks may play a minor role if one controls for housing shocks. We then add the real home price index computed

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

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

[17]Gilchrist and 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. Unfortunately, it is unavailable prior to 1973. Hence, its employment would considerably shorten the sample size, and this would be particularly problematic for the estimation of a richly-parameterized nonlinear VAR as the one modeled in this study. The correlation between the Baa-10-year Treasury yield spread and the Gilchrist and Zakrajŝek's excess bond premium reads 0.67.

by Robert Shiller to our baseline vector.[18] 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 in all the above mentioned robustness exercises.

2.4 Uncertainty shocks and monetary policy

2.4.1 Baseline responses

This section studies the dynamics of prices and the federal funds rate to an uncertainty shock. Figure 2.5 focuses on the differences between recessions and expansions, and plots 68% and 95% confidence bands around the estimated generalized impulse responses. An uncertainty shock triggers a significant negative reaction of prices only in recessions. Inflation goes down and then gradually returns to its initial value. As both quantities and prices fall after an uncertainty shock, and much more markedly in recessions, a central bank following a Taylor-type rule would lower the interest rate. The GIRFs show that, in line with a Taylor-type behavior, the interest rate goes down significantly, both in recessions and expansions. However, in terms of dynamics and quantitative responses, the difference is remarkable. When the uncertainty shock hits the economy in good times, the interest rate goes down by about 0.5 percentage points at its peak, and the reaction is short-lived. When the uncertainty shock hits in a recession, the policy rate goes down up to about two percentage points, and remains statistically significant for a prolonged period of time. These results support the view put forward by Basu and Bundick (2012) and Leduc and Liu (2013) that uncertainty shocks act as demand shocks, and show again that they have different effects over the business cycle.

The VAR estimates policy easings to occur even when uncertainty shocks hit in expansions. A look at some events of recent U.S. economic history suggests that high peaks of uncertainty in expansions did not necessarily lead to recessions. An example is the "Black Monday" in October 1987, which is associated to the highest increase of the volatility index in our sample. While possibly being the responsible of the downturn in industrial production and employment in the following months, this uncertainty shock did not drive

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

the U.S. economy into a recession. However, this "missing recession" may be due to the response of the Federal Reserve, which implemented open market operations that pushed the federal funds rate down to around 7 percent on Tuesday, October 20 from over 7.5 percent on Monday, October 19 (Carlson, 2007).

2.4.2 Counterfactual scenarios

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

We employ our STVAR and run a counterfactual simulation designed to answer these questions. This counterfactual assumes the central bank to stay still after an uncertainty shock, i.e., we shut down the systematic response of the federal funds rate to movements in the economic system due to uncertainty shocks.[19] Given that the federal funds rate is bound to stay fixed to its pre-shock level, the responses obtained are informative as for the costs of "doing nothing" by policymakers.

Figure 2.6 superimposes the dynamic reactions of real activity obtained by muting the systematic policy response to uncertainty shocks (a scenario identified by the label "muted systematic policy") to those obtained in the baseline scenario. Remarkably, the short-run effects of this counterfactual policy response are negligible in recessions. In other words, the recession is estimated to be as severe as the one that realizes when policymakers are allowed to lower the policy rate. The short-run recessionary effect is exactly the same in the two scenarios, and a gap between the baseline responses and those produced with our counterfactual experiment begins realizing only after about one year. Notably, this difference mainly regards the speed with which

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

real activity recovers and overshoots before going back to the steady state. A different picture emerges when our counterfactual monetary policy is run in good times. As Figure 2.6 shows, when the policy rate is kept fixed, industrial production goes down markedly (about -3% at its peak) and persistently, remaining statistically below zero for a prolonged period of time (for all 20 quarters according to 68% confidence bands). The same holds when looking at the response of employment, i.e., the gap between the baseline response and the one associated to the counterfactual exercise is quantitatively substantial.[20]

Are the impulse responses reported in Figure 2.6 statistically different? Figure 2.7 plots the distribution of the difference between the GIRFs obtained under the "muted systematic policy" assumption and the baseline case. In line with the previous discussion, such a difference is hardly significant in recessions according to the 95% confidence bands, while it is significant in expansions when the same confidence level is considered. The 68% confidence bands tell a somewhat different story, and suggest that the short-run effect of different systematic monetary policy may be at work also in recessions. However, it is so for only a few periods, while in expansions such effect is present and significant for a much prolonged period of time (more than four years after the shock).

2.4.3 Interpreting policy (in)effectiveness

How can one interpret the state-dependence of monetary policy effectiveness? As suggested by Bloom (2009) and Bloom et al. (2012), these results might find a rationale in the real option value theory. When uncertainty is high, firms' inaction region expands (Bloom, 2009). Hence, "wait-and-see" behaviour becomes the optimal strategy for a larger number of firms, compared to normal times. These firms become quite insensitive to changes in the interest rate, which explains why the peak recessionary effect is virtually identical regardless of the reaction of monetary policy. When uncertainty starts to drop down, the inaction region shrinks, firms become more willing to invest to face their pent-up demand and hence become more sensitive to the cost of capital. If

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

monetary policy does not react, as in our counterfactual scenario, the higher (with respect to the baseline) cost of borrowing starts playing a role. Hence, firms re-start investing at a lower pace with respect to what happens in our baseline scenario (which is characterized by a strong temporary drop in the nominal interest rate). In equilibrium, firms invest less than in the baseline case in the medium-run, and the overshoot just does not realize. A similar reasoning can be done as for labor demand and, therefore, employment.

Quite differently, higher realizations of the interest rate (at least in the short-run) are found to importantly concur to the downturn triggered by uncertainty shocks in expansions. If the option value of waiting due to uncertainty is less important in expansions, firms are more reactive to stimulus policy. Hence, in presence of a higher nominal interest rate, firms are more likely to invest less and demand a lower quantity of labor. Consequently, a stronger recessionary effect realizes in absence of systematic monetary policy interventions.[21]

Vavra (2014) builds up a model in which monetary policy shocks are shown to be less effective during periods of high volatility. In spite of the presence of an inaction region due to price adjustment costs, in Vavra's (2014) calibrated model second moment shocks push firms, in equilibrium, to adjust their prices more often. This increased price dispersion translates into higher aggregate price flexibility, which dampens the real effects of monetary policy shocks. Given the countercyclicality of price volatilty, monetary policy shocks turn out to be less powerful in recessions. To the extent that uncertainty is higher in recessions (as discussed in the Introduction), our results complement Vavra's (2014), in that they show that the systematic component of monetary policy is less effective when uncertainty is high.

A different mechanism is present in Berger and Vavra (2014a). They build up partial- and general-equilibrium models which focus on the response of aggregate durable expenditures to a variety of macroeconomic shocks. In particular, their model feature 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 across time in the distribution of households'durable holdings, implies a procyclical

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

impulse response of aggregate durabe spending to macroeconomic shocks, a result also documented in Berger and Vavra (2014b). Hence, macroeconomic policies are less effective in stabilizing the business cycle (at least, durable spending) in recessions. Our results can be seen as consistent with those in Berger and Vavra (2014a,b).

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

2.4.4 Short- vs. long-term interest rates

The differences documented in Figures 2.6 are attributed to different policies as captured by different paths of the federal funds rate. As recalled by Bernanke (2013), however, monetary policy is likely to work mainly through the term structure, and in particular via long-term interest rates. Gurkaynak, Sack, and Swanson (2005) argue that the Federal Reserve has increasingly relied on communication strategies to affect agents's expectations over future policy moves to eventually influence long-term rates.[22] Kulish (2007) shows that long-

[22]Such rates are a function of future expected monetary policy and term premia. An overview of the analysis of the term structure of interest rates is provided by Gürkaynak and Wright (2012). It would be of interest to pin down the role played by expectations over future policy moves *per se*. Gertler and Karadi (2014) employ federal funds rate futures as measure of expectations (as in Kuttner (2001)) to investigate the empirical relevance of forward guidance by the Federal Reserve. Unfortunately, federal funds rate futures are available from 1989 only, which would imply a substantial loss in degrees of freedom if we used them in our econometric analysis. Gurkaynak, Sack, and Swanson (2007) find the predictive power of a variety of financial instruments, including federal funds rate futures and short-term Treasury maturity rates, to be very similar when horizons over six months are considered. Attempts

rates may effectively help stabilizing inflation in the context of a new-Keynesian framework featuring a term-structure of interest rate. Following Bagliano and Favero (1998), we then enrich our VAR with the 10-year Treasury constant maturity rate (ordered after the uncertainty dummy), and re-run our estimates. We then compute impulse responses to an uncertainty shock coming from the unconstrained model, as well as two sets of counterfactual responses. The first counterfactual focuses on the response of real activity conditional on a fixed federal funds rate. As before, we conduct this counterfactual to assess the role of systematic monetary policy in this context. The second counterfactual simulates the responses to an uncertainty shock conditional on a fixed long-term interest rate. This exercise is conducted to capture the role that the 10-year rate (again, a combination of expectations over future monetary policy moves and the risk-premium) plays in transmitting the effects of uncertainty shocks.

Figure 2.8 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 the ones obtained with our baseline STVAR (shown in Figure 2.4). 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 results reported in Figure 2.6, the counterfactual recession in this case is milder. In particular, after an uncertainty shock hitting the economy in bad times, real activity goes back much more quickly to the pre-shock level relative to the baseline case (about 12 versus 18 months for industrial production, and 15 versus 24 for employment). This happens because of the role played by the long-term interest rate in this system (possibly, via changes in expectations over future monetary policy moves), which substitutes in part the federal funds rate in influencing the response of real activity. Finally, the 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.

to model short-term interest rates led us to experience multicollinearity-related problems due to their very high correlation with the federal funds rate.

This evidence suggests 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 looking 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.[23]

2.5 Conclusions

After the 2007 financial turmoil and the subsequent deep recession, policymakers have often looked at heightened uncertainty as a major culprit of the slow recovery. This Chapter shows that the state of the business cycle is a crucial element in understanding the transmission of uncertainty shocks to the real economy. Using a nonlinear VAR model, we show that after an uncertainty shock, the drop in real activity is much larger during recessions than what a linear model would predict. Given that uncertainty shocks hit the economy more often during recessions, our findings imply that they may be substantially more costly than what linear frameworks suggest. We also find an asymmetric dynamic path followed by real activity. In bad times, uncertainty shocks trigger a sharp drop, a quick rebound and a medium-term overshoot in economic activity. Differently, the responses in expansions are much more gradual and

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

display no overshoot. Counterfactual simulations conducted to assess the role of systematic monetary policy point to policy ineffectiveness in the short run, especially when uncertainty shocks hit in bad times. Policy effectiveness is found to increase in the medium run, especially in good times.

These findings are informative from a modeling standpoint. Bloom (2009) shows that uncertainty shocks imply a drop, rebound, and overshoot of real activity. This is due to nonconvex adjustment costs that imply the presence of a region of inaction in the hiring and investment space. Our findings suggest that adjustment costs may very well be countercyclical. Another possible interpretation of our results point to state-dependent frictions in credit markets, which may prevent consumption smoothing and, therefore, influence the exit path from a downturn (Bloom et al., 2012). In general, our findings support a research agenda aiming at identifying state-dependent relevant frictions able to induce different dynamic responses to structural shocks in recessions and expansions. From a policy perspective, high uncertainty is found to reduce the sensitivity of output to stimulus policies, above all in recessions. Theoretical models like the one developed by Vavra (2014) and Berger and Vavra (2014a), and empirical investigations as those by Aastveit et al. (2013), Tenreyro and Thwaites (2013), Mumtaz and Surico (2014), and Pellegrino (2014) also offer support to this view as for monetary policy interventions. Our findings call for the design of state-dependent optimal policy responses, possibly closer to first-moment policies in expansions, but clearly different from them in recessions. Blanchard (2009) and Bloom (2014) call for larger policy stimuli in bad times, as well as "second moment policies" like stabilization packages designed to reduce systemic risk. Baker et al.'s (2013) point to the role of clear policy communication and steady policy implementation. Our results confirm that these policy suggestions may be particularly suited to exit phases characterized by particularly severe economics conditions.

Chapter 3

Estimating Fiscal Multipliers: News From a Nonlinear World

3.1 Introduction

How large is the fiscal spending multiplier? Following the lead of Blanchard and Perotti (2002), several VAR models featuring fiscal aggregates have been estimated to answer this question (for a survey, see Ramey, 2011a). However, the quantification of fiscal multipliers with standard VARs is controversial for two reasons. First, as stressed by Parker (2011), the effects of fiscal policy shocks may very well be countercyclical. Fiscal multipliers may be larger in periods of slack because of a milder crowding out of private consumption and investment due to less responsive prices (see the textbook IS-LM-AD-AS model), a constrained reaction of nominal interest rates due to the zero-lower bound (Eggertsson, 2009; Christiano, Eichenbaum, and Rebelo, 2011; Woodford, 2011; Leeper, Traum, and Walker, 2011; Fernández-Villaverde, Gordon, Guerrón-Quintana, and Rubio-Ramírez, 2012a), higher returns from public spending due to countercyclical financial frictions and credit constraints (Canzoneri et al., 2011), and lower crowding out of private employment due to a milder increase in labor market tightness (Michaillat, 2014; Roulleau-Pasdeloup, 2014). Empirical evidence in favor of state-dependent fiscal multipliers is provided by, among others, Tagkalakis (2008), Auerbach and Gorodnichenko (2012, 2013a, 2013b), Bachmann and Sims (2012), Batini, Callegari, and Melina (2012), Mittnik and Semmler (2012), Baum, Poplawski-Ribeiro, and Weber (2012), Fazzari, Morley, and Panovska (2014).[1] Second, anticipation effects are likely to be of great relevance in the transmission of fiscal policy shocks, a phenomenon often referred to as "fiscal foresight" (see, among others, Yang, 2005; Fisher and Peters, 2010; Mertens and Ravn, 2011; Ramey, 2011b; Kriwoluzky, 2012; Favero and Giavazzi, 2012; Leeper et al., 2013). Modeling a standard set of U.S. variables with a medium-scale structural model that allows for foresight up to eight quarters, Schmitt-Grohe and Uribe (2012) find that about sixty percent of the variance of government spending is due to anticipated shocks. Unfortunately, in presence of fiscal foresight, standard VARs - which rely on current and past shocks to interpret the dynamics of the modeled variables - are typically "non-fundamental", in that they do not embed the information related to "news shocks", i.e., future shocks anticipated by rational agents.[2] Leeper et al. (2013) work with a variety of fiscal models and show that the anticipation of tax policy shocks severely affects VAR exercises aiming at identifying fiscal shocks. Forni and Gambetti (2011) and Ramey (2011b) show that government spending shocks estimated with standard fiscal VARs are predictable, i.e., they are non-fundamental.

This Chapter estimates *state-dependent fiscal multipliers* by explicitly addressing the issue of *fiscal foresight*. We tackle the issue of non-fundamentalness by jointly modeling a measure of *anticipated ("news") fiscal spending shocks* along with a set of standard macro-fiscal variables. Such a measure of fiscal news is the *sum of revisions of expectations about future government spending* collected by the Survey of Professional Forecasters. As shown by Gambetti (2012a, 2012b), this measure of fiscal shocks is particularly powerful to capture the effects of fiscal spending shocks when the implementation lag of fiscal policy is larger than one quarter, a very plausible assumption as for U.S. fiscal policy decisions.[3] We include this measure of fiscal news in a nonlinear Smooth Tran-

[1] Other forms of state-dependence have been identified in the literature. Corsetti, Meier, and Müller (2012) investigate the sensitivity of government spending multipliers to different economic scenarios. They find fiscal multipliers to be particularly high during times of financial crisis. Rossi and Zubairy (2011) and Canova and Pappa (2011) show that fiscal multipliers tend to be larger when positive spending shocks are accompanied by a decline in the real interest rate. Perotti (1999) shows that fiscal multipliers may depend on the debt-to-GDP ratio in place when fiscal shocks occur. For a DSGE-based quantification of fiscal multipliers in presence of normal vs. abnormal debt-to-GDP ratios, see Cantore, Levine, Melina, and Pearlman (2013).

[2] For a recent discussion on non-fundamentalness in the VAR context and a survey of the main contributions in this area, see Beaudry and Portier (2013).

[3] Yang (2005) shows that the average implementation lag for major postwar U.S. income tax legislation is about seven months. Mertens and Ravn (2011) find that the median

sition Vector AutoRegressive (STVAR) model, which we use to discriminate dynamic responses to fiscal shocks in bad and good times (i.e., recessions vs. expansions). Following most of the literature, we measure fiscal multipliers in two ways. One measure, which we term "peak", is calculated as the peak response of output divided by the peak response of fiscal expenditure. The second measure, which we term "sum", is the cumulative multiplier given by the integral of the response of output divided by the integral of the response of fiscal expenditure. To assess the effects of public spending shocks on output and estimate fiscal multipliers in recessions and expansions, we compute Generalized Impulse Response Functions (GIRFs), which model the endogeneity of the transition from a state to another after a fiscal shock. Importantly, as explained by Koop et al. (1996), GIRFs allow us to scrutinize the role played by different initial conditions. We then isolate *"extreme" events*, i.e., deep recessions and strong expansions, with the aim of understanding if *fiscal multipliers are larger in very severe economic conditions*. To our knowledge, this key policy-relevant question has not been previously studied in the empirical literature on fiscal multipliers.

Our results are the following: i) anticipated fiscal expenditure shocks trigger a significant reaction of output; ii) such a reaction is not statistically different across different phases (recessions/expansions) of the U.S. business cycle; iii) the reaction becomes statistically different for extreme phases of the business cycle, i.e., deep recessions vs. strong expansions; iv) fiscal multipliers in recessions are statistically larger than one; v) spending shocks in recessions have a noticeable stabilization effect and substantially reduce the probability that the economy will remain slack. These results are robust to a wide battery of checks, including i) the employment of a "purged" measure of fiscal news, which is constructed using information available to survey respondents when they formulate their expectations over future public spending, to account for potential identification issues; ii) the use of the fiscal news constructed by Ramey (2011b), which allows us to extend our sample back to 1947, to control for small-sample biases that may affect our data-intensive estimator; iii) the role of debt, to account for the role played by fiscal strains in computing multipliers; iv) several different VAR specifications.

implementation lag is six quarters. Leeper, Richter, and Walker (2012) calibrate tax foresight and government spending foresight to range between two and eight quarters (the former) and between three and four quarters (the latter).

This analysis represents a novel contribution under several respects. First, our VAR jointly accounts for two relevant issues for the quantification of fiscal multipliers: fiscal foresight and state dependence. Second, we estimate the response of economic aggregates to fiscal shocks via GIRFs, which allow us to endogenize the possibly stabilizing effects of fiscal policy. Third, the use of GIRFs allows us to address a previously unexplored issue, i.e., the role played by business cycle conditions for the quantification of fiscal multipliers, which we investigate by distinguishing between "extreme" and "moderate" business cycle phases. As a result, we are able to establish some new stylized facts about government spending multipliers in the U.S., in particular the fact that firm evidence of state dependence arises only when looking at extreme phases of the business cycle.

The closest papers to ours are Auerbach and Gorodnichenko (2012, 2013a), Owyang, Ramey, and Zubairy (2013), and Ramey and Zubairy (2014). Auerbach and Gorodnichenko (2012, 2013a) employ a STVAR model and find evidence of countercyclical fiscal multipliers.[4] There are substantial differences between Auerbach and Gorodnichenko's contributions and ours. First, they investigate the role of unanticipated fiscal spending shocks. Differently, we focus on anticipated changes in fiscal spending. Second, their impulse responses are conditionally linear, i.e., expansionary fiscal spending shocks are, by construction, not allowed to drive the economy out of a recession. As pointed out by the same authors, this assumption provides an "upper bound" for their estimates of the fiscal multiplier in recessions, because it does not allow the returns from fiscal spending to be decreasing as the economy exits a recession. Our approach links the evolution of the variables in our STVAR to the probability of being in a recession, which is then endogenously modeled. Third, our focus is on "extreme events", i.e., realizations on the tails of the distribution of our business cycle indicator (like the 2007-09 crisis). Our main result is that, while fiscal multipliers may be acyclical when recessions and expansions are considered all alike (i.e., they may be similar when considering the average effect in recessions vs. expansions), they are likely to be large in presence of particularly severe economic conditions. Owyang et al. (2013) and Ramey and Zubairy (2014) employ local-projection methods à la Jordà (2005) to investigate the nonlinearity of fiscal multipliers. They find no evidence of larger fiscal multipliers

[4] For a similar exercise focusing on the role of business confidence, see Bachmann and Sims (2012).

during downturns as for the United States. The comparability between our exercises and theirs is not immediate due to a number of different modeling choices (construction of the news shocks, length of the sample, construction of the impulse responses, among others). We notice that our results are similar to theirs in that we also do not find larger fiscal multipliers in recessions on average. However, when it comes to deep recessions vs. strong expansions, we find such larger multipliers to arise.

Other strands of the literature have dealt with fiscal foresight and anticipated fiscal spending shocks in VARs. Mertens and Ravn (2010) recover the non-fundamental responses to an anticipated fiscal policy shock via economic theory-driven restrictions to gauge information about economic agents' anticipation rate. Such a rate is then used as an input in Blaschke matrices to flip the roots that cause the non-invertibility of the VMA representation of fiscal spending and output. Kriwoluzky (2012) recovers reduced-form innovations by estimating a VARMA model using the Kalman filter. Then, he identifies anticipated fiscal shocks via theoretically-supported sign restrictions. Ramey and Shapiro (1998) follow a narrative approach to identify exogenous changes in military spending related to wars. Ramey (2011b) constructs a measure of changes in the expected present value of government spending. Fisher and Peters (2010) construct a measure of excess returns of large U.S. military contractors which is shown to anticipate future military spending shocks. Ben Zeev and Pappa (2014) identify U.S. defense news shocks as the shocks that best explain future movements in defense spending over a five year horizon and are orthogonal to current defense spending. All these contributions show that, at least qualitatively, anticipated positive fiscal shocks induce a significant increase in output.[5] Perotti (2007, 2011), Ramey (2011b), Gambetti (2012a, 2012b), Blanchard and Leigh (2013), Alesina, Favero, and Giavazzi (2013), and Ricco (2014) work with expectations revisions in different modeling frameworks. Our study complements these

[5]Another interesting approach to account for fiscal foresight rests on the use of municipal bond spreads. This bond spread is well-known to have predictive power for tax changes and can therefore be used to control for anticipated tax changes (see, among others, Poterba (1989), Fortune (1996), and Kueng (2014)). Leeper et al. (2012) show that spreads with maturity lengths of 1 and 5 years are very informative about future tax events. Our investigation deals with anticipated fiscal spending shocks. We leave the analysis of anticipated tax shocks to future research.

contributions, in that it quantifies the effects of anticipated fiscal spending shocks with a nonlinear model focusing on extreme events.[6]

3.2 Non-fundamentalness and expectations revisions

The role of expectations revisions. Standard fiscal VARs may return severely biased impulse responses in presence of news shocks. Consider the model

$$y_t = \delta E_t y_{t+1} + g_t + \omega_t \tag{3.1}$$

$$g_t = \varepsilon_{t-h} + \phi_1 \varepsilon_{t-h-1} + \ldots + \phi_{q-h-1}\varepsilon_{t-(q-1)} + \phi_{q-h}\varepsilon_{t-q} = \Phi(L)\varepsilon_t \tag{3.2}$$

where $|\delta| < 1, \phi_i > 0 \; \forall i, h \geq 0, q \geq h$, and $\phi_0 = 0$. The forward-looking process y_t - say, output measured as log-deviations from its trend - is affected by the exogenous stationary process g_t - say, a fiscal shock - plus a random shock ω_t, which is assumed to capture non-fiscal spending shocks affecting output and which is assumed to be *i.i.d.* with zero mean and unit variance. The process (3.2) features $q - h + 1$ moving average terms. If $h = 0$ and $q > 0$, the process (3.2) features an unanticipated, ε_t, as well as anticipated shocks ε_{t-q} for $q > 0$. For $h > 0$, the process (3.2) would feature only unanticipated shocks, where h is the number of periods of foresights. The process g_t is a news-rich process if $|\phi_i| > 1$ for at least one $i > 0$ (Beaudry and Portier, 2013). In all cases, $\{\varepsilon_{t-j}\}_{j=h}^{q}$ is said to be fundamental for g_t if the roots of the polynomial $\Phi(L)$ lie outside the unit circle (Hansen and Sargent, 1991). Importantly, if the g_t process is non-fundamental, its structural shock is not recoverable by employing current and past realizations of g_t only. Consequently, its impulse response to an anticipated shock as well as the dynamic responses of other variables – in

[6] Admittedly, the theoretical papers modeling nonlinearities cited in this Introduction mainly consider models in which government spending is implemented without lags. As for the zero lower bound, however, Christiano et al. (2011) conduct an exercise in which they model implementation lags in their framework featuring the zero lower bound. They find that a key determinant of the size of the multiplier is indeed the state of the world in which new government spending comes on line. Our conjecture is that such asymmetric effects may be present also when anticipated fiscal shocks hit economic systems characterized by state-dependent financial constraints and labor market downward rigidities.

this example, y_t – will not be correctly recovered by estimating a VAR in y_t and g_t.

We assume that agents have rational expectations and observe news shocks without noise.[7] It can be shown that, if the period of foresight $h \geqslant 1$ is known, the problem of non-fundamentalness in model (3.1)-(3.2) can be solved by alternatively including: i) the h-step-ahead expectation, $E_t g_{t+h}$, if $h = q$; ii) the h-step-ahead expectation revision, $E_t g_{t+h} - E_{t-1} g_{t+h}$, if $h < q$. However, if $h > 1$ is unknown, expectation revisions are not of help. To solve this issue, Gambetti (2012a) proposes to use a news variable defined as

$$\eta^g_{1J} = \sum_{j=1}^{J} (E_t g_{t+j} - E_{t-1} g_{t+j}) = \begin{cases} (1 + \phi_1 + ... + \phi_{J-h})\, \varepsilon_t \text{ if } J < q \\ (1 + \phi_1 + ... + \phi_{q-h})\, \varepsilon_t \text{ if } J \geqslant q \end{cases}, \tag{3.3}$$

which correctly identifies the news shock if $J \geqslant h$.[8] Appendix B provides further discussions and derivations as regards this news variable.

The News13 variable. We will then consider a fiscal VAR augmented with a measure of news constructed by summing up revisions of expectations as follows:

$$\eta^g_{13} = \textstyle\sum_{j=1}^{J} (E_t g_{t+j} - E_{t-1} g_{t+j}) \tag{3.4}$$

where $E_t g_{t+j}$ is the forecast of the growth rate of real government spending from period $t+j-1$ to period $t+j$ based on the information available at time t. Hence, $E_t g_{t+j} - E_{t-1} g_{t+j}$ represents the "news" that becomes available to private agents between time $t-1$ and t about the growth rate of government spending j periods ahead. We use data coming from the Survey of Professional Forecasters (SPF), which collects forecasts conditional on time $t-1$ of variables

[7] Forni, Gambetti, Lippi, and Sala (2013) investigate the case in which economic agents deal with noisy news. Agents are assumed to receive signals regarding the future realization of TFP shocks. Since such signals are noisy, agents react not only to genuinely informative news, but also to noise shocks that are unrelated to economic fundamentals. They find that such noise shocks explain about a third of the variance of output, consumption, and investment. We leave the quantification of the role of noise shocks in the fiscal context to future research.

[8] If $J < h$, the news variable would have no predictive content about fiscal shocks, and would be equal to zero. In our sample, however, this never happens. This is consistent with the evidence in Leeper et al. (2012), who report an average implementation lag of about three quarters. In our example above, h should be interpreted as the minimum temporal gap between the announcement of the implementation of future fiscal spending and the realization of the spending itself (which may take more than one quarter), rather than the mean value. Hence, also the effects of the announcement of future spending whose full implementation would take more than J quarters would be captured by our news, as long as the minimum lag h is less than J.

up to time $t+3$. This is the reason why our baseline analysis will be conducted by considering the variable η^g_{13}.[9]

Information content of expectations revisions. To assess the statistical relevance of our news variable for the dynamics of public expenditure, we regress public spending on a constant and three lags of the dependent variable, public receipts, real GDP, and one lag of the measure of news η^g_{13} (a detailed description of the data is provided in the next Section). This regression augments the public spending equation of a trivariate VAR system modeling the "usual suspects" (public spending, tax receipts, output) with our news variable lagged one period.[10] Public spending shocks are often identified with a Cholesky decomposition of the covariance matrix of the VAR residuals. Hence, the (orthogonalized) residuals of the public spending equation are interpreted as public spending shocks. As shown in table 2.1 - which collects the p-values for our η^g_{13} variable in the equation described above - news shocks are found to carry significant information about the future evolution of public spending. This implies that the trivariate fiscal VAR without news is non-fundamental. Digging deeper, we find that all the three components (forecast revisions) included in η^g_{13} have some predictive power. Overall, this empirical exercise highlights the significant contribution of news revisions regarding *future* realizations of public expenditure. Differently, revisions of expectations based on nowcasting, i.e., $E_t g_t - E_{t-1} g_t$, turn out to be insignificant at the 90% confidence level (see Table 2.1, last column). In line with Ricco (2014), this result suggests that revisions based on "nowcasts" (revision of expectations at time t of contemporaneous public expenditures) are possibly of help in identifying truly *unanticipated* fiscal shocks, rather than *anticipated, news* shocks.[11]

Overall, our results i) show that, from a statistical standpoint, residuals typically employed in a standard trivariate fiscal VAR cannot be interpreted as fiscal shocks; ii) suggest that the components of the variable η^g_{13}, which we interpret as a measure of anticipated fiscal shocks, can augment the information

[9] SPF data are affected by frequent changes in the base years. Forecast errors on the growth rates are not affected by these changes. Hence, they are preferable to forecast errors computed with SPF levels. About this point, see also Perotti (2011).

[10] The regression includes variables in (log-)levels and the news η^g_{13} variable in cumulated sums to preserve the same order of integration. This is consistent with the modeling choices of our baseline VAR analysis (specified in the next Section).

[11] These results are conditional on news variables constructed as revisions of the mean predicted values of the levels of future government spending as collected by the Survey of Professional Forecasters. Similar results were obtained by employing median values of such forecasts, as well as variables expressed in growth rates.

content of our VAR system. These results are consistent with the outcome of the Granger-causality tests conducted by Gambetti (2012b), who shows that η^g_{13} Granger-causes fiscal spending at different horizons.[12]

Extreme realizations of the news spending variable: An interpretation. Figure 3.1 plots our news variable (an updated version of Gambetti's 2012b). The standardized variable η^g_{13} conveys useful information about fiscal policy shocks in the United States. To see this, we isolate the seven realizations which exceed two in absolute value, and provide an interpretation based on the recent U.S. fiscal history. The 1983Q1 positive realization is associated to Ronald Reagan's "Evil Empire" and "Star Wars" speeches, with which the U.S. President announced a forthcoming increase in military spending. The 1986Q1 negative spike reflects the speech given in January 1986 by Mikhail Gorbachev, who proposed decommissioning all nuclear weapons by 2000 in the early stage of the "Perestrojka" period. The 1987Q1 positive forecast revisions might be due to the mid-term Senate elections won by the Democrats in November 1986 plus the questioned constitutionality of the Gramm-Rudman-Hollings Balanced-Budget Act. The 1987Q4 forecast revisions are due to announcements about spending cuts for the Pentagon. The fall of the Berlin Wall in November 1989 is behind the negative spike in 1989Q4. The war in Afghanistan rationalizes the positive peak in 2001Q4. Finally, the upward spike in 2009Q1 can be associated to Obama's stimulus package.

Comparison with Ramey's (2011b) news variable. Figure 3.1 also plots the military spending news variable constructed by Ramey (2011b), and extended up to 2010Q4 by Owyang et al. (2013).[13] It appears that the η^g_{13} variable anticipates changes in Ramey's, or at least it is not anticipated by the latter. To corroborate this statement, we run Granger-causality tests based on an estimated bivariate VAR with one lag involving the military spending news proposed by Ramey (2011b) (as well as its updated version by Owyang,

[12] In a recent paper, Perotti (2011) questions the use of the SPF forecast errors employed by Ramey (2011) to isolate fiscal spending anticipated shocks. In particular, he shows that the one-step-ahead predictive power of the forecast revisions as for federal spending is quite modest, since such revisions are shown to be noisy. Our results are fully consistent with Perotti's (2011) analysis, in that we also reject the relevance of very short-term SPF forecast revisions on future fiscal spending. This evidence suggests the need of searching for anticipation effects beyond one-quarter relative to the moment in which predictions are formulated, and supports the employment of a variable like η^g_{13}.

[13] Ramey (2011b) employs *Business Week* and other newspaper sources to construct an estimate of changes in the expected present value of goverment spending (nominal spending divided by nominal GDP one period before).

Ramey, and Zubairy, 2013) and the η^g_{13} variable. Table 2.2 collects the outcome (p-values associated to testing the null hypothesis that the column variable does not Granger-cause the alternative news measure) of this exercise for our benchmark sample and a shorter sample to account for the fact that, for the first five years in the benchmark sample, Ramey's (2011b) variable is equal to zero. While the contribution of our news shock variable finds large statistical support, Granger-causality running from Ramey's shock to ours is clearly rejected by the data. The same evidence emerges when employing the news variable by Owyang, Ramey, and Zubairy (2013), which includes observations related to the 2007-2009 recession. Again, these results are in line with those reported in Gambetti (2012b), who also finds Ramey's news shock to be predicted by forecast revisions over one quarter.

3.3 Econometric approach: A STVAR macro-fiscal model

Modeling choices. We assess the state-dependence of fiscal spending multipliers to news shocks by estimating a Smooth-Transition VAR model (for an extensive presentation, see Teräsvirta et al., 2010). Our STVAR framework reads as follows:

$$\boldsymbol{X}_t = F(z_{t-1})\boldsymbol{\Pi}_R(L)\boldsymbol{X}_t + (1 - F(z_{t-1}))\boldsymbol{\Pi}_E(L)\boldsymbol{X}_t + \varepsilon_t, \tag{3.5}$$

$$\varepsilon_t \sim N(0, \boldsymbol{\Omega}_t), \tag{3.6}$$

$$\boldsymbol{\Omega}_t = F(z_{t-1})\boldsymbol{\Omega}_R + (1 - F(z_{t-1}))\boldsymbol{\Omega}_E, \tag{3.7}$$

$$F(z_t) = \exp(-\gamma z_t)/(1 + \exp(-\gamma z_t)), \gamma > 0, z_t \sim N(0, 1). \tag{3.8}$$

where $\boldsymbol{X}_t$ is a set of endogenous variables which we aim to model, $F(z_{t-1})$ is a transition function which captures the probability of being in a recession, γ regulates the smoothness of the transition between states, z_t is a transition indicator, $\boldsymbol{\Pi}_R$ and $\boldsymbol{\Pi}_E$ are the VAR coefficients capturing the dynamics of the system during recessions and expansions (respectively), ε_t is the vector of reduced-form residuals having zero-mean and whose time-varying, state-contingent variance-covariance matrix is $\boldsymbol{\Omega}_t$, and $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$ stand for the covariance structure of the residuals in recessions and expansions, respectively.

The modeling assumption is that the variables can be described with a combination of two linear VARs, one suited to describe the economy during recessions and the other during expansions. The transition from a state to another is regulated by the standardized transition variable z_t. The smoothness parameter γ affects the probability of being in a recession $F(z_t)$, i.e., the larger the value of γ, the faster the transition from a state to another. Notably, the model (3.5)-(3.8) allows for nonlinearities to arise from both the contemporaneous and the dynamic relationships of the economic system.

Our baseline analysis refers to the vector $\boldsymbol{X}_t = [G_t, T_t, Y_t, \eta^g_{13,t}]'$, where G is the log of real government (federal, state, and local) purchases (consumption and investment), T is the log of real government receipts of direct and indirect taxes net of transfers to business and individuals, and Y is the log of real GDP.[14] The construction of G and T closely follows Auerbach and Gorodnichenko (2013a).[15] The variable η^g_{13} is the public expenditure news variable (3.4). The variables are expressed in levels because of possible cointegration relationships. Consistently, the variable η^g_{13} is considered in cumulated sums to preserve the same order of integration as the other variables included in the vector. Our sample of U.S. data spans the period 1981Q3-2013Q1, 1981Q3 being the first available quarter to construct the news variable.[16]

The choice of the transition variable z_t and the calibration of the smoothing parameter γ are justified as follows. As in Auerbach and Gorodnichenko (2012), Bachmann and Sims (2012), Caggiano et al. (2014a), and Berger and Vavra (2014b), we employ a standardized moving average of the real GDP quarter-on-quarter percentage growth rate.[17] We calibrate the smoothness parameter γ to match the observed frequencies of the U.S. recessions as identified by the NBER

[14] Our fiscal aggregates are constructed using the Bureau of Economic Analysis' NIPA Table 3.1. Current tax receipts are constructed as the difference between current receipts and government social benefits. Fiscal expenditure is the sum of consumption expenditure and gross government investment from which we subtract the consumption of fixed capital. Data on real GDP and the implicit GDP deflator (which we use to deflate all nominal series) are provided by the Federal Reserve Bank of St. Louis.

[15] Auerbach and Gorodnichenko (2013a) check and verify the robustness of the results in Auerbach and Gorodnichenko (2012) to the employment of a different definition of the net tax series that avoids the double-counting of mandatory Social Security contributions.

[16] Our interpretation of the news variable here is that of an instrument to gauge the real effects of anticipated changes in fiscal spending. We recall that different identification approaches may very well lead to the construction of different, but in principle equally valid, instruments. For an elaboration of this point, see Favero and Giavazzi (2012).

[17] The transition variable z_t is standardized to render our calibration of γ comparable to those employed in the literature. We employ a backward-looking moving average involving four realizations of the real GDP growth rate.

business cycle dates, i.e. 15% in our sample. Then, we define as "recession" a period in which $F(z_t) \geqslant 0.85$, and calibrate γ to obtain $\Pr(F(z_t) \geqslant 0.85) \approx 15\%$. This metric implies a calibration $\gamma = 2.3$. The choice is consistent with the threshold value $\bar{z} = -0.75\%$ discriminating recessions and expansions, i.e., realizations of the standardized transition variable z lower (higher) than the threshold will be associated to recessions (expansions).[18] Figure 3.2 plots the transition function $F(z_t)$. Clearly, high realizations of $F(z_t)$ tend to be associated with NBER recessions. Importantly, our results are robust to the employment of alternative calibrations of the slope parameter γ that imply a number of recessions in our sample ranging from 10% to 20%, where the lower bound is determined by the minimum amount of observations each regime should contain according to Hansen (1999).

Identification of the anticipated fiscal shock. Following Fisher and Peters (2010), we order the news variable η^g_{13} last in our vector and orthogonalize the reduced-form residuals of the VAR via a Cholesky-decomposition of the variance-covariance matrix. We analyze the implications of this versus alternative strategies to identify fiscal news shocks in Section 3.6.

Statistical evidence in favor of nonlinearity. For our vector of endogenous variables $\mathbf{X}_t$, we test and clearly reject the null hypothesis of linearity in favor of the (Logistic) Smooth Transition Vector AutoRegression via the multivariate test proposed by Teräsvirta and Yang (2013) in presence of a single transition variable. Details on this test and its implementation are presented in Appendix A.

Model estimation. Given the high nonlinearity of the model, we estimate it via the Monte-Carlo Markov-Chain algorithm developed by Chernozhukov and Hong (2003). The (linear/nonlinear) VARs include three lags. This choice is based on the Akaike criterion applied to a linear model estimated on the full-sample 1981Q3-2013Q1.

[18]The corresponding threshold value for the non-standardized moving average real GDP growth rate is equal to 0.34%. The sample mean of the non-standardized real GDP growth rate in moving average terms is equal to 0.71, while its standard deviation is 0.50. Then, its corresponding threshold value is obtained by "inverting" the formula we employed to obtain the standardized transition indicator z, i.e., $\bar{z}^{nonstd} = -0.75 \times 0.50 + 0.71 = 0.34$.

3.4 Generalized impulse responses and fiscal multipliers

This Section reports the estimated impulse responses to an anticipated fiscal spending shock. Following Koop et al. (1996), we compute generalized impulse responses to take into account the interaction between the evolution of the variables in the vector $\mathbf{X}_t$ and the transition variable, the latter being directly influenced by the evolution of output. In other words, we model the feedback from the evolution of output in the vector $\mathbf{X}_t$ to the transition indicator z_t and, consequently, the probability $F(z_{t-1})$. Hence, in computing our GIRFs, the probability $F(z)$ is endogenized.[19] Koop et al. (1996) and Ehrmann et al. (2003) show that initial conditions affect the computation of the GIRFs. In our benchmark exercise, we randomize over all possible histories within each state, so to control for the role of initial conditions.[20] We compute the GIRFs by normalizing the news shocks to one.[21]

GIRFs. Figure 3.3 reports the impact of a government spending news shock computed with our linear and nonlinear VARs. The responses obtained with our linear model point to a delayed short-run increase in government expenditure and output, and a decrease in government receipts. Public spending reaches its peak value after about three years. Differently, output increases for the first

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[19] Recall that our transition indicator $z_t \equiv \frac{1}{4}(\Delta Y_t + \Delta Y_{t-1} + \Delta Y_{t-2} + \Delta Y_{t-3})$, i.e., the relationship between z_t and $\Delta Y_{t-i}, i = 0, 1, 2, 3$ features no stochastic elements. Hence, stochastic singularity prevents us from estimating our model jointly with the evolution of z_t. Following Koop et al. (1996), our GIRFs are based on simulations that take into account the link between $\mathbf{X}_t$ and z_t after the estimation of our econometric framework.

[20] Following Koop et al. (1996), our GIRFs are computed as follows. First, we draw an initial condition, i.e., starting values for the lags of our VARs as well as the transition indicator z, which - given the logistic function (3.8) - gives us the value for $F(z)$. Then, we simulate two scenarios, one with all the shocks identified with the Cholesky decomposition of the VCV matrix (3.7), and another one with the same shocks plus a $\delta > 0$ corresponding to the first realization of the news shock. The difference between these two scenarios (each of which accounts for the evolution of $F(z)$ by keeping track of the evolution of output and, therefore, z) gives us the GIRFs to a fiscal news shock δ. Per each given initial condition z, we compute 500 different stochastic realizations of our GIRFs, then store the median realization. We repeat these steps until 500 initial conditions (drawn by allowing for repetitions) associated to recessions (expansions) are considered. Then, we construct the distribution of our GIRFs by considering these 500 median realizations. Appendix B provides details on the algorithm we employed to compute the GIRFs.

[21] The standard deviation of the news variable employed in the sample is 0.19 according to our linear model, 0.21 conditional on our framework under recessions, and 0.18 under expansions. While being theoretically size-dependent, we verified that the sensitivity of our impulse responses to reasonable changes in the size of the shock is negligible.

three quarters after the shock, then gradually goes back to zero, and crosses the zero line about 10 quarters after the shock.

Next, we look at the evidence coming from the nonlinear VAR. Interestingly, the estimated response of output is persistently stronger under recessions. Output increases in expansions in the short-run, but the increase is much milder compared to recessions, and vanishes after about four quarters. Another difference between the two states is the reaction of government spending itself, which is always positive but stronger in recessions. Tax receipts react asymmetrically in the short run, then their patterns become more similar.

Are the reactions of output in recessions and expansions different from a statistical standpoint? Figure 3.4 plots the GIRFs and the associated 90% confidence intervals estimated for both states. Focusing on output, we see that the confidence bands overlap substantially. This result suggests that the reaction of output to a fiscal shock is not necessarily stronger if the economy is slack. This finding is in line with some recent results put forth by Valerie Ramey and coauthors (see Ramey, 2011b; Owyang et al., 2013; Ramey and Zubairy, 2014), which are obtained with a different identification strategy (fiscal spending news shocks constructed following Ramey's (2011b) approach) and methodology (local projections à la Jordà, 2005). At a first glance, the evidence seems to be at odds with the impulse response analysis proposed by Auerbach and Gorodnichenko (2012, 2013a), who find a statistically significant difference between the response of output conditional on different states. However, a subtle difference in the construction of the dynamic responses must be considered. Auerbach and Gorodnichenko (2012, 2013a) assume the economy hit by the fiscal shock to start and remain in a recession/expansion for twenty quarters. Differently, here we allow the economic system to switch from a state to another according to the endogenous evolution of the transition indicator. Moreover, the GIRFs plotted in Figure 3.4 are constructed by integrating over all histories belonging to a given state (recessions, expansions). We elaborate on the role played by initial conditions in the next Section.

Quantifying the multipliers. We now turn to the key issue of computing the multipliers and the associated 90% confidence intervals. Following most of the literature, we measure fiscal multipliers in two ways. One measure, which we term "peak", is calculated as the peak response of output divided by the peak response of fiscal expenditure over the first H horizons, i.e., it is equal to $\frac{max_{h=1,\ldots,H}\{Y_h\}}{max_{h=1,\ldots,H}\{G_h\}}$, where Y_h and G_h represent the impulse responses of output and public spending respectively h-horizon after the shock. Percent changes are then converted into dollars by rescaling such a ratio by the sample mean ratio of the levels of output over public spending.[22] This strategy, popularized by Blanchard and Perotti (2002), has been widely adopted in recent investigations on fiscal multipliers. The second measure, which we term "sum", is the cumulative multiplier computed as the integral of the response of output divided by the integral of the response of fiscal expenditure, i.e., $\sum_{h=1}^{H} Y_h / \sum_{h=1}^{H} G_h$, again rescaled for the sample mean ratio of the levels of Y over G. This latter measure is designed to account for the persistence of fiscal shocks (Woodford, 2011).

Our results are reported in Table 2.3, where multipliers have been computed considering horizons from one to five years. The evidence clearly speaks in favor of larger (short-run) fiscal spending multipliers in recessions, with values between 3.32 after 8 quarters and 2.58 after 20 quarters when we look at the "peak" measure, and between 3.05 after 8 quarters and 1.00 after 20 quarters according to the "sum" measure. The point-estimates of our multipliers in expansions are substantially lower (from 1.24 to 1.09, and from 0.33 to -2.27 after 8 and 20 quarters, respectively, calculated according to the two measures). The multipliers under recession are statistically larger than one at all horizons according to the "peak" measure. This result is confirmed, conditional on the short run (i.e., for the first four quarters), by the "sum" measure.

Are multipliers statistically bigger in recessions? We answer this question by constructing a test based on the difference between the multiplier estimated under recessions and expansions. Such a test is constructed to account for the correlation between the estimated state-dependent multipliers.[23] Figure 3.5 plots the distribution of the difference for both measures of multipliers (peak, sum) and for a range of horizons of our impulse responses along with 90% confidence bands. Evidence in favor of state-dependent multipliers would be

[22] Ramey and Zubairy (2014) warn against this practice by noticing that, in a long U.S. data sample spanning the 1889-2011 period, the output-over-public spending ratio varies from 2 to 24 with a mean of 8. Hence, the choice of a constant value for such ratio may importantly bias the estimation of the multipliers. In our sample, the mean value of such a ratio is 6, and it varies from 5.39 to 6.76. Hence, the commonly adopted *ex-post* conversion from the estimated elasticities to dollar increases does not appear to be an issue for our exercise. The average value of the output-public spending ratio in our sample in 5.81 in NBER recessions, and 6.02 in NBER expansions. Our results are robust to the employment of state-dependent output-public spending ratios.

[23] In short, we compute differences of our multipliers in recessions vs. expansions conditional on the same set of draws of the stochastic elements of our model as well as the same realizations of the coefficients of the vector. The empirical density of the difference between our multipliers is based on 500 realizations of such differences for each horizon of interest.

gained if zero were not included in the confidence bands. In all cases, although marginally, the difference turns out to be not different from a statistical standpoint.[24]

The stabilizing effects of anticipated fiscal shocks. Our STVAR allows also to estimate the impact of government spending shocks on the probability of being in a recession for each given horizon of interest after the shock. Figure 3.6 plots the estimated transition function implied by our model, $\widehat{F(z)}$, along with the 90% confidence bands. The Figure gives interesting information about the estimated impact of a positive government spending shock on the likelihood of remaining in the same phase of the business cycle. Looking at the behavior of the $\widehat{F(z)}$ under recession, we notice that the fiscal shock leads to a clear drop in the probability of remaining in recession. Given the large uncertainty surrounding the response of output to a fiscal shock, different paths of $\widehat{F(z)}$ are admittedly possible. However, the median indication clearly suggests a quick fall of such a probability under the threshold value $\overline{F} = 0.85$ just after five quarters, which is exactly the average duration of a NBER recession in the sample. In terms of the econometric methodology employed to estimate the state-dependent effect of government spending shocks on output, this evidence shows the importance of allowing for the possibility of switching from one phase of the business cycle to another. Unsurprisingly, given its expansionary effect, the probability of falling into a recession after the news shock when starting from an expansions is basically zero, though such a probability is quite imprecisely estimated.

3.5 Fiscal multipliers in presence of "extreme" events

Extreme events analysis. So far, our analysis has focused on the possible state-dependence of output reactions to fiscal news shocks and fiscal multipliers, finding weak evidence in favor of countercyclical spending multipliers. The

[24]Importantly, our results are not driven by the systematic component of our STVAR *per se*. In other words, in absence of fiscal interventions, our model economy does not deliver large negative accumulated multipliers at longer forecast horizons when starting in expansions. This was verified by simulating a deterministic version of the STVAR, in which only initial conditions are responsible for the different evolution of the variables in recessions and expansions. Our simulations confirm that our cumulated multipliers are indeed driven by the interaction between fiscal shocks and the systematic component of our STVARs.

next question we address is whether evidence of nonlinearities might arise when recessions and expansions are "extreme" events. We then re-compute the GIRFs by randomizing over different subsets of histories associated to recessions and expansions. We label "deep" recessions/"strong" expansions the histories associated to realizations of the transition variable which are below/above two standard deviations. Given that our transition variable is standardized, this amounts to saying that all historical realizations of z above two are associated to a strong expansion, while all realizations below minus two are associated to a deep recession. This criterion leads us to isolate four realizations in deep recessions corresponding to the recent great recession (2008Q4-2009Q3) and three realizations which belong to the "strong" expansions category (1983Q4-1984Q2). In a complementary fashion, mild recessions/weak expansions are associated to histories consistent with realizations of the transition variable below/above the threshold value $\overline{z} = -0.75$ but within the range $[-2, 2]$. We then re-compute the GIRFs by randomizing over histories within each of these four sub-categories.

Figure 3.7 shows the GIRFs obtained by distinguishing between "deep" and "mild" recessions and "strong" and "weak" expansions. The estimated GIRFs show that the response of output is roughly proportional to the strength of the recession (expansion). Although in the short-run the response of output in the case of a "mild" recession is very similar to the response of output in a "deep" recession, the response of output is much more persistent at longer horizons when conditioning on the latter case. This, however, cannot be immediately turned into evidence about multipliers, since the persistence in output response might be driven by the persistence of government spending.

Table 2.4 reports the fiscal multipliers estimated in the four different cases under scrutiny. Interestingly, multipliers are still larger in recessions relative to expansions, regardless of the strength of the recession (expansion). When the economy is in a deep recession, we find 4-year horizon multipliers around 2.3 and 1.6 according to the peak and the sum measure, respectively. Similar figures can be gauged for mild recessions, where government spending is found to be expansionary after up to four years. In strong expansions, short-run (one-year) multipliers are slightly above one, but they take values lower than one (and negative according to the "sum" measure) at longer horizons. Interestingly, while the difference between mild recessions and weak expansions might seem minimal, the impact of fiscal policy in these two states is much more dramatic.

Such a difference may be interpreted in light of the different response of fiscal revenues in the two states (at least in the short-run). In good times, government receipts are found to increase after the shock, while in bad times they are found to decrease. In other words, our VAR suggests that recessions are associated to deficit-financed increases in public spending, while expansions are associated to increases in fiscal spending which are readily financed via an increase in revenues. Hence, recessions are associated with a higher net present value of the fiscal deficit relative to expansions. This can justify the large and positive real effects of fiscal news on the output multiplier if, during recessions, the Ricardian equivalence does not hold because of, say, binding liquidity constraints during recessions, of rule-of-thumb consumers. It can also offer a rationale for the negative multipliers in strong expansions, which is a state associated with a clearly positive response of revenues to fiscal spending shocks.[25]

Turning to multipliers in expansions, while our point estimates suggest values above one in the short-run, 90% confidence bands imply that we cannot reject values lower than unity. A possible interpretation of large short-run multipliers in expansions relates to the zero lower bound, which has been in place even after the end of the 2007-09 recession, hence in a period classified as ("weak") expansion in our sample. As shown by Leeper et al. (2011), multipliers may be larger than one when an active fiscal policy is accompanied by a passive monetary policy.[26]

When we turn to statistical difference, a comparison between the multipliers in the case of "deep" recessions and those conditional on "strong" expansions suggests that the confidence bands do not overlap, and point to a strong evidence in terms of nonlinear responses of the economy to an expansionary fiscal shock. Our results are confirmed also by looking at the distribution of the difference between the estimated state-dependent multipliers. As shown in Figure 3.8, the countercyclicality of fiscal multipliers conditional on extreme realizations of the business cycle is supported regardless of the way in which we calculate the multipliers and regardless of the horizon.

[25] See Barro and Redlick (2011) for a discussion of deficit-financed versus balanced-budget fiscal multipliers.

[26] In our sample, the number of quarters associated to expansions by the NBER in which the zero lower bound is in place is 15, i.e., some 14% of all the quarters in expansions according to the NBER, which is a non-negligible share. For an analysis pointing to lower fiscal spending multipliers in a liquidity trap caused by a self-fulfilling state of low confidence in a model with nominal rigidies and a Taylor-type interest rate rule, see Mertens and Ravn (2014).

In our context, it might be more appropriate to test for the null hypothesis of equal multipliers versus the one-sided alternative of multipliers larger in recessions relative to expansions. Table 2.5 collects the fraction of multipliers that are larger in recessions for both "Normal" (recessions/expansions) and "Extreme" (deep recessions/strong expansions) phases of the business cycle. As before, these numbers are estimated by referring to different initial conditions, all else being equal. Hence, any entry greater than or equal to 90 might be interpreted as evidence in favor of larger multipliers in recessions at a 90% confidence level in the context of a one-sided test. The figures corresponding to the exercises conducted so far refer to the "Baseline" scenario. Under the "Normal" (i.e. all recessions vs. all expansions) case, evidence in favor of countercyclical multipliers is borderline, and it depends on how the multiplier is calculated. Differently, the analysis of extreme events robustly points towards larger multipliers during recessions. We postpone the analysis of the robustness of this result to a number of perturbations of the baseline framework to the next Section.

How does the economic system evolve after a fiscal shock hitting during an extreme phase of the business cycle? Figure 3.9 plots the estimated value of the $\widehat{F(z)}$ conditional on the four scenarios. For deep recessions, a sizeable decrease of the probability of remaining in such a state occurs as a consequence of the government spending shock: after about five quarters, the value of $\widehat{F(z)}$ decreases from 1 (the economy is in a recession with probability one) to about 0.5 (the economy is unlikely to be in a recession). This drop is quicker and more substantial than the one estimated in presence of mild recessions, and it is also more precisely estimated. Importantly, this suggests that government spending can be effective in lifting the U.S. economy from a deep recession to an expansionary path. The probability of moving away from a strong expansion is low, and more precisely estimated than the one of drifting away from a weak expansion. However, none of the two suggests a high likelihood of falling into a recession.

Estimated multipliers: Comparison with the literature. Our evidence points to larger multipliers in recessions (around 2.3 and 1.6 for the 4-year horizon, according to the peak and sum measures respectively), and smaller ones, but still somewhat high in the short-run (slightly larger than 1 after one year), in expansions. Are these multipliers in line with what suggested by the literature? A close look at some recent contributions suggests a positive answer. Auerbach and Gorodnichenko (2012, 2013a) deal with unexpected fiscal shocks in a nonlinear VAR framework and find multipliers in recessions of about 2.5. Bachmann and Sims (2012) control for the effects of business confidence and find the sum and peak multipliers in recessions to be 2.7 and 3.3, respectively. Corsetti et al. (2012) work with a flexible panel of OECD countries that allow them to study the effects of fiscal spending shocks under different scenarios. Conditional on periods of financial strains, they find fiscal spending multipliers to be 2.3 on impact, 2.9 at the peak, and larger than 2 in the medium run.[27] Christiano et al. (2011) work with a medium-scale DSGE model and find a multiplier of 2.3 conditional on the zero-lower bound being in place for one year. Evidence of large multipliers can be found also in linear frameworks which deal with the issue of fiscal foresight. Using Bayesian prior predictive analysis for a battery of closed- and open-economy DSGE models featuring different frictions and policy conducts, Leeper et al. (2011) rationalize fiscal spending multipliers of two or larger. Ben Zeev and Pappa (2014) find a peak multiplier larger than 4. Fisher and Peters (2010), using their measure of excess returns of large U.S. military contractors, find a multiplier of 1.5. The same figure is found by Ricco (2014), who employes a measure of news which accounts for the changes in the composition of the pool of forecasters compiling the SPF questionnaires. Depending on the set of restrictions imposed in their sign restriction-VAR analysis, Canova and Pappa (2011) find the U.S. fiscal multipliers to range between 2 and 4.

Our findings qualify those by Auerbach and Gorodnichenko (2012, 2013a), who suggest that recessions are associated with larger fiscal spending multipliers. As already pointed out, their general conclusion might be driven by the implicit assumption that all recessions are treated like "extreme events" when conducting their impulse response analysis. Our analysis suggests that this may very well be the case. This finding has important implications from a policy perspective too, given that a fiscal stimulus may be needed exactly in correspondence to deep recessions.

Overall, our analysis based on "disaggregated" recessions and expansions shows that nonlinearities are likely to arise when we look *within* each of the two states typically investigated in a business cycle context, i.e., recessions and

[27] As reported in the minutes of the *Economic Policy* Panel Discussion, Giancarlo Corsetti pointed out that financial crises, in their study, are not meant to represent recessions. However, he also added that the multipliers are even larger when one uses macro crisis episodes alone in their panel approach. See *Economic Policy*, 2012, 27(72), p. 562.

expansions. In particular, we find support in favor of a larger fiscal multiplier when deep recessions are considered.

3.6 Further investigations

Our baseline analysis suggests that evidence in favor of countercyclical fiscal multipliers is borderline when we condition upon recessions vs. expansions, while it becomes much clearer and solid when conditioning upon extreme events. This Section discusses the solidity of our results to the employment of i) alternative identification strategies; ii) a longer sample; iii) debt; iv) several different VAR specifications.

3.6.1 Identification

Exogeneity of the change in government spending expectations. Our baseline analysis rests on revisions of government spending expectations. Such revisions may in principle be due to shocks other than merely fiscal ones. Suppose that $g_t = \boldsymbol{\delta} \boldsymbol{z}_t + \xi_t$, where $\boldsymbol{z}_t$ is a vector of m indicators of the business cycle (say, output, unemployment, inflation, interest rates), $\boldsymbol{\delta}$ is the vector of loadings relating $\boldsymbol{z}_t$ to g_t, and $\xi_t = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + ... + \phi_n \varepsilon_{t-n}$ is a moving average process modeling the unexpected fiscal shock ε_t as well as the expected ones $\varepsilon_{t-j}, j = 1, ..., n$. Then, $\eta_{13}^g = \sum_{j=1}^{3} (E_t g_{t+j} - E_{t-1} g_{t+j}) = \boldsymbol{\delta} \sum_{j=1}^{3} (E_t \boldsymbol{z}_{t+j} - E_{t-1} \boldsymbol{z}_{t+j}) + \widetilde{\eta}_{13}^g$, where $\widetilde{\eta}_{13}^g = \sum_{j=1}^{3} \phi_j \varepsilon_{t-j}$. In words, systematic revisions of fiscal spending forecasts might be due not only to anticipated fiscal shocks, but also to revisions of other variables' forecasts possibly due to other shocks (technology, financial). We deal with this issue by regressing our measure of fiscal news η_{13}^g on a number of macroeconomic indicators available to professional forecasters when they are asked to form expectations about G: (the sums of forecasts revisions of) real GDP growth, unemployment, GDP deflator inflation, the 3-month Treasury bill rate, and the 10-year Treasury bond rate.[28] Figure 3.10 displays the raw and purged versions of the news

[28] Forecasts of the debt-to-GDP ratio are not included in the SPF survey. We run further regressions by adding lagged realizations of debt-to-GDP ratio to the regression described in the text. Such measures turn out to be insignificant. The choice of not including the contemporaneous realizations of the debt-to-GDP ratio on the right-hand side of the regression is due to the timing of the Survey of Professional Forecasters (SPF). The questionnaire of such survey is sent to the pool of respondents after the advance report of the national income and product accounts by the Bureau of Economic Analysis (BEA) is released to the public. Hence,

variable, denoted by η_{13}^{g} and $\widetilde{\eta}_{13}^{g}$ respectively. Two considerations are in order. First, the correlation between these two variables is quite high (0.95). Second, the most extreme realizations, documented in Figure 3.1 and reproposed here, are clearly captured by both variables. Hence, most of the information content of the (unpurged version of the) η_{13}^{g} variable is likely to come from its genuinely exogenous component. To corroborate this statement, we replace the η_{13}^{g} variable with its purged version $\widetilde{\eta}_{13}^{g}$ in our VAR, and re-run our estimations and simulations. Table 2.6 ("$\widetilde{\eta}_{13}^{g}$ last") collects the results of this exercise for our extreme events analysis.[29] These results, as well as those in Table 2.5 on the difference of the multipliers in extreme business cycle phases, confirm our baseline findings

Contemporaneous effects of fiscal spending shocks. Another issue affecting our baseline analysis regards the timing of the impact of the news shocks. The baseline vector features a recursive identification scheme in which the news variable is ordered last. This choice aims at purging the movements of the η_{13}^{g} fiscal variable by accounting for its systematic response to government spending, tax revenues, and output. However, such a choice has an obvious limitation, i.e., output is not allowed to move immediately after the realization of the news shock. We then perform a robustness check by focusing on the four-variate VAR $\boldsymbol{X}_t^{\widetilde{\eta}^g} = [\widetilde{\eta}_{13,t}^{g}, G_t, T_t, Y_t]'$, which enables fiscal news shocks to affect output on impact.[30] We run this exercise with our purged measure of anticipated fiscal shocks to control for the systematic movements of fiscal news due to news hitting other macroeconomic indicators, as explained above. Table 2.6 ("$\widetilde{\eta}_{13}^{g}$ first") documents slightly different, but statistically equivalent, multipliers relative to the baseline. Most importantly, as also documented by Table 2.5, we find again larger multipliers in deep recessions than in strong expansions.

the questionnaire contains the first estimate of GDP and its components for the *previous* quarter. Thus, in formulating and submitting their projections, the information sets of the SPF panelists include the data reported in the advance report and related to quarter $t-1$ but not data regarding quarter t. For information on the variables included in the survey and the information set possessed by respondents, see http://www.philadelphiafed.org/research-and-data/real-time-center/survey .

[29]Multipliers computed by considering a four-year time span. Similar results are obtained when considering a two-year time span.

[30]An alternative, not pursued here, would be to work with sign restrictions. For an analysis of sign restrictions in fiscal VARs and their implications for the implied fiscal elasticities, see Caldara and Kamps (2012).

3.6.2 Longer sample

The nonlinear estimator we employ is data intensive. Because of limited data availability for the SPF forecast revisions, our baseline analysis rests on a relatively short sample, i.e., 1981Q3-2013Q1. Hence, small-sample issues may lead to distortions of our estimated coefficients, which could then lead us to obtain biased multipliers. We then conduct a robustness check by employing a much longer sample, i.e., 1947Q1-2013Q1. To do so, we use an updated version of Ramey's (2011b) widely known fiscal news variable (available at Valerie Ramey's website), and put it first in a VAR including fiscal spending, fiscal revenues, and output. Following Ramey (2011b), we estimate a VAR with four lags and a quadratic trend. Table 2.6 ("Long sample, Ramey's news") collects the outcome of our estimations. Reassuringly, this exercise produces multipliers very much in line with our baseline ones, and it offers support to the importance of looking at extreme events to find nonlinearities in the fiscal multipliers even in long samples.

3.6.3 The role of debt

Our baseline VAR does not feature debt. However, controlling for debt fluctuations in our regressions is important to better understand the drivers of our countercyclical multipliers. The reason is simple. Recent panel-data studies have shown that countries with "high" levels of debt have smaller multipliers than countries with lower levels of debt (see, e.g., Corsetti et al., 2012; Ilzetzki, Mendoza, and Végh, 2013). Hence, it could in principle be possible that the nonlinearities we have found are driven by different levels of debt rather than different phases of the business cycle. It is then of interest to check if the relevant initial conditions could be related to different degrees of fiscal distress. To this aim, we modify our baseline vector along two dimensions. First, we include the debt/GDP ratio in our VAR. Following a common modeling choice in the literature (see, among others, Leeper et al., 2011, 2012; Corsetti et al., 2012; Leeper et al., 2013), we assume the debt/GDP ratio to affect the fiscal instruments with a lag, and put it last in the vector. Second, we employ our debt/GDP ratio as the variable which dictates the switch from a regime to another. This second modification is exactly aimed at capturing the idea of different "debt-contingent" regimes. To discriminate between "high" vs. "low" realizations of debt, we focus on the cyclical component of the debt/GDP ratio, which is extracted from the raw series (in log) by applying a standard Hodrick-Prescott filter with smoothing weight equal to 1,600. Realizations of the debt/GDP ratio one standard deviation above (below) the HP-trend are interpreted as phases of "high" ("low") debt. Positive (negative) realizations within one standard deviation are classified as "moderately high" ("moderately low"). A possible interpretation of this series is that of a "debt/GDP gap" computed by considering a time-varying debt/GDP target, which may be consistent with the clear upward-trending behavior displayed by this ratio in our sample.

Table 2.6 ("Debt/GDP ratio") collects the multipliers produced by this exercise. We distinguish between extreme phases of "high" and "low" fiscal distress, as well as intermediate ones, i.e. "moderately high" and "moderately low", which we indicate with "$Mod.^{+}$ *debt*" and "$Mod.^{-}$ *debt*", respectively. Our results point to fairly similar fiscal multipliers when computed conditional on "high" vs. "low" debt levels. Hence, countercyclical fiscal multipliers do not seem to be guided by the "fiscal cycle".[31] Our results echo those by Favero and Giavazzi (2012), who also find no major empirical differences in a fiscal model for the U.S. when adding debt. It is important to stress, however, that this conclusion is not inconsistent with cross-country studies which point to relevant nonlinearities of fiscal policy effects due to different levels of debt, in particular for developing countries.

3.6.4 Further robustness checks

Our results are robust to a variety of further perturbations of our baseline model, which include: i) a "FAST-VAR" (Factor Augmented Smooth Transition-VAR) version of our VAR model, which we estimate to further control for nonfundamentalness as suggested by Forni and Gambetti (2014); ii) the estimation of a five-variate VAR featuring the sum of forecast revisions regarding future real GDP as first variable in the vector, again to control for revisions of real GDP forecasts; iii) the employment of revisions over total spending forecasts (as opposed to Federal spending only); iv) a measure of news which accounts for the changes in the composition of the pool of forecasters compiling the SPF questionnaires as in Ricco (2014). The solidity of our baseline results is

[31] An analysis conducted by adding the debt-to-GDP ratio to our otherwise baseline framework while keeping the moving average of real GDP as our transition indicator returned multipliers very similar to our baseline ones.

confirmed also by this battery of robustness checks, which is available upon request.

3.7 Conclusions

This Chapter quantifies the fiscal spending multiplier in the U.S. and tests the theoretical prediction of a larger reaction of output to fiscal shocks in economic downturns. Following Gambetti (2012a,b), we tackle the issue of non-fundamentalness due to fiscal foresight by identifying anticipated government spending shocks via sums of forecasts revisions collected by the Survey of Professional Forecasters. We show that such a measure of fiscal spending news carries relevant information to predict the future evolution of fiscal expenditures and Granger-causes other measures of fiscal news recently proposed in the literature. Then, we augment a macro-fiscal nonlinear VAR with this measure of fiscal news and estimate the size of fiscal spending multipliers across different phases of the business cycle.

Our empirical investigation points to fiscal multipliers larger than one in recessionary periods. However, conditional on a standard "recession vs. expansion" classification of the phases of the U.S. business cycle, our results do not support the idea of a countercyclical fiscal multiplier. Differently, when we condition the estimates of the fiscal multipliers on the *strength* of the business cycle (namely, when we distinguish between deep and mild recessions, and weak and strong expansions), we find that fiscal multipliers are statistically larger in deep recessions relative to strong expansionary periods.

The results of our analysis highlight the relevance of the different initial economic conditions *within* each of the two states typically considered for classifying the U.S. business cycle. Fiscal multipliers may very well be larger when a fiscal shock occurs in presence of a deep recession like that of 2007-09 than when it occurs in presence of milder economic downturns. Our results imply that a correct measurement of the fiscal multipliers can be performed just if flexible-enough econometric models are put at work.

Chapter 4

Credit Supply Shocks in U.S. Bond Markets: Are There Nonlinearities?

4.1 Introduction

Credit crunches have not been rare events during the last decades. However, the severity of the 2007-08 crisis, which saw a sharp reduction in the availability of credit, have renewed interest in understanding to what extent credit constraints shape the business cycle. This Chapter investigates this question by studying the *asymmetric propagation* of U.S. credit supply shocks across the business cycle. Credit supply shocks may very well be asymmetric due to intensified financial frictions during downturns. Although this conjecture is a very natural one, few empirical studies take into account nonlinearities. My results show that credit supply shocks originating in bond markets induce a drop-rebound-overshoot pattern for real activity when hitting the economy in recessions. Differently, a long-lasting, hump-shaped reaction is found in upward phases of the business cycle. The nonlinear transmission of financial shocks has key implications for policymakers and academic researchers. On the policy side, it favors the introduction of nonlinear macroprudential rules to deal with financial instability, which possibly take into account the persistent effects of credit shocks during expansions. On the research side, the evidence of significant asymmetric effects of credit supply shocks i) complements empirical studies, within a linear context, that document an independent role of credit (in addition to real factors) in driving the path of the economy, ii) supports the development of structural macro models featuring a role for financial intermediation that goes beyond that of a merely conduit, and iii) favors the theoretical modeling of nonlinearities.

In this Chapter, I adopt an empirical perspective and estimates linear and nonlinear local projection models (Jordà, 2005) to study the real effects of credit supply shocks in the U.S., where the latter is proxied by the *excess bond premium* (EBP) developed by Gilchrist and Zakrajšek (2012) (GZ hereafter). The choice of using the EBP as a proxy of credit shocks originating from the supply side of bond markets can be firstly motivated by the way in which this indicator is developed (details are presented in section 4.3). In short, the EBP is a measure of marketwide corporate bond spreads net of expected default losses. Thus, by construction, the EBP is orthogonal to variations in expected default risk of borrowers. Secondly, GZ offer extensive evidence showing that EBP movements are strictly linked to balance sheet conditions of key financial intermediaries that operate in corporate bond markets. They estimate a linear VAR and show that an adverse shock to the returns on assets of primary dealers, major banks, and securities broker-dealers, leads to a sustained increase in the EBP.[1] They also document a comovement between the EBP and changes in credit standards on commercial and industrial (C&I) loans at U.S. commercial banks.[2] To measure real activity, I then consider standard macro indicators, i.e., industrial production, employment, and the unemployment rate. Due to the availability of the EBP, I work with a sample from 1973:1 to 2012:12. To identify the states of the business cycle, I simply use the U.S. business cycle dates, as defined by the National Bureau of Economic Research (NBER), which is less controversial than relying on single indicators of economic activity.

The local projection estimates enable me to compute two sets of impulse response functions to an EBP shock: one conditional on a linear view of the world, and the other allowing (but not forcing) the economy to react differently in recessions vs. normal times. The linear estimates provide evidence that the financial sector may very well be an originator, other than propagator, of

[1] Gilchrist and Zakrajšek (2012) also examine the macroeconomic consequences of shocks to the EBP within a VAR model, showing that they are a potential source of recessions. However, their analysis is confined to a linear framework.

[2] López-Salido, Stein, and Zakrajšek (2015) define the EBP as "credit market sentiment", i.e., an economic indicator that forecasts future returns to bearing credit risk. This definition is not necessarily in contrast with the view that the EBP measures credit supply conditions.

shocks. All indicators of economic activity are shown to negatively react to the shock, e.g., a 1% increase in the EBP is associated to a 4% fall in output. When economic activity is allowed to respond asymmetrically to the EBP shock, evidence of nonlinearities across the business cycle robustly emerges. Specifically, adverse effects materialize much faster in recessions, and die out within a 1 year horizon. A mild overshoot in real activity also emerges in the medium run. Contrarily, when the shock hits in normal times/upward phases of the cycle, its effects are far more persistent, with no signs of economic recovery in the subsequent 2 years.

I subject the above results to a few robustness checks. In particular, given that my results echo recent findings in the business cycle literature as for uncertainty shocks, which tend to generate the same pattern of real activity across the two states of the economy (Bloom, 2009; Caggiano, Castelnuovo, and Nodari, 2014b), I estimate impulse response functions to an uncertainty shock à la Jurado et al. (2015) conditional on the same nonlinear local projection model used for the EBP shock, and compare the results of the two shocks. I also re-estimate the effects of the EBP shock by taking into account the level of uncertainty in the economy. This check is a very relevant one: as stressed by Stock and Watson (2012), and Caldara et al. (2014), increases in financial stress are frequently associated with heightened uncertainty, making it hard to distinguish between the two. Additional robustness checks aim at controlling that the results are not driven by the Great Recession or by volatility in stock markets. All these checks deliver the same kind of asymmetric responses across states.

Finally, I provide an interpretation of my results based on Dow, Gorton, and Krishnamurthy (2005) and Philippon (2006), who develop theoretical models augmented with corporate governance frictions, in which empire-building managers overinvest when the economy is booming, leading to amplification and persistence of otherwise i.i.d. shocks during upward economic phases. Linking the predictions of their models with insights from real option theory, I argue that increased manager misbehavior and increased value of growth options during expansions, may lead firms to overinvest in irreversible investment projects, which may explain the sluggish recovery observed after the credit supply shock during this state of the economy.

This Chapter contributes to the literature in a number of ways. First, I focus on nonlinearities relating to business cycle phases, whereas most of the previous research has dealt with financial shocks within a linear context (see, among others, Abildgren, 2012; Adrian, Moench, and Shin, 2010; Barnett and Thomas, 2014; Caldara et al., 2014; Favara and Imbs, 2015; Gilchrist and Zakrajšek, 2012) or relating nonlinearities to credit market conditions rather than recessions and expansions (e.g., Calza and Sousa, 2006; Hubrich and Tetlow, 2012; Hubrich, D'Agostino, Červená, Ciccarelli, Guarda, Haavio, Jeanfils, Mendicino, Ortega, Valderrama, and Valentinyiné Endrész, 2013). Second, my study differs substantially in terms of methodology from existing nonlinear investigations of financial shocks. Almost all empirical studies dealing with nonlinearities use Vector Autoregression (VAR) models, whereas I compute the effects of credit supply shocks using local projection methods, which, in contrast to VARs, do not impose restrictions on the relationship between aggregates. Third, I focus on credit shocks originating in bond markets, as opposed to the majority of previous studies which investigate "broad" financial shocks. Opening the "financial black-box" to look at different market segments may be useful to provide guidance to the ongoing macroprudential regulation debate.

The remainder of the Chapter is organized as follows. In section 4.2 I summarize the main theoretical studies considering financial shocks within macro-models, and discuss the related empirical literature. I present the econometric approach and briefly describe the data in section 4.3. Section 4.4 summarizes the results and offers an interpretation of the main findings. A number of robustness checks are presented in section 4.5. Conclusions appear in section 4.6.

4.2 Related literature

The literature exploring how financial frictions influence the aggregate response of economic activity to *non-financial shocks* is large and well established. Leading theoretical research on this topic includes Bernanke and Gertler (1989); Carlstrom and Fuerst (1997); Kyiotaki and Moore (1997), and Bernanke, Gertler, and Gilchrist (1999). Despite the heterogeneity of micro-foundations giving rise to frictions (e.g., agency costs, collateral constraints), these models explain the persistence and amplitude of small, temporary shocks through the financial accelerator mechanism: exogenous shocks that reduce the net worth of borrowers lead to adverse feedback loops between the external finance premium and financial conditions. These contributions abstract from financial shocks as such, focusing mostly on frictions affecting end borrowers. However, the most recent U.S. recession has cast doubt on the traditional sources of business cycles, pointing to *financial shocks* as potential drivers of economic fluctuations.[3] The lack of analytical frameworks to investigate events such as the Great Recession induced many researchers to consider model economies where financial intermediaries play a non-trivial role.[4] Building on DSGE models incorporating a financial sector subject to frictions, recent theoretical studies suggest that credit shocks are harmful for economic activity. Gerali, Neri, Sessa, and Signoretti (2010); Gertler and Karadi (2011); Jermann and Quadrini (2012), among others, show that exogenous disturbances that reduce intermediaries' capital cause a contraction in credit supply, decreasing in turn output and investment.[5] Importantly, these disturbances are quantitatively relevant for business cycle dynamics. Iacoviello (2015) estimates that financial shocks accounted for two-thirds of the output collapse during the Great Recession.

Notably, a few recent theoretical contributions account for nonlinearities in the attempt to better capture the role of the financial sector for macro dynamics. He and Krishnamurthy (2013) study intermediary asset pricing, and model financial frictions as a constraint on intermediaries' ability to raise outside equity financing. During constrained states of their model economy, sudden reductions in intermediaries' capital cause large increases in risk premia. Conversely, under unconstrained states risk premia are not affected by changes in intermediaries' equity ownership. Their model does not address the implications of financial shocks for economic activity. However, to the extent that risk premia influence investment, one can expect shocks to the balance sheet of intermediaries to propagate asymmetrically to the real economy. Brunnermeier and Sannikov (2014) offer another example of nonlinear interactions between financial frictions and the macroeconomy. Their model underlines a sharp distinction between crisis and normal times as for the system's reaction to shocks that affect agents' balance sheets. In normal times, agents absorb shocks to their net worth easily by adjusting payouts. During crisis episodes, macro shocks induce fire sales of

[3]Another strand of business cycle research also emphasizes *news*, *noise* and *confidence* shocks as potential drivers of economic activity fluctuations, (e.g., among others, Barsky and Sims, 2011; Blanchard, L'Huillier, and Lorenzoni, 2013; Beaudry and Portier, 2006).

[4]For a comprehensive survey on the interaction between macroeconomics and financial frictions, see Brunnermeier, Eisenbach, and Sannikov (2012).

[5]The literature remains elusive on the effects of financial shocks on labor demand, consumption and prices, whose responses seem to be "financial frictions-type" dependent.

capital, which leads to highly nonlinear amplification effects caused by leverage and feedback effects from asset prices.

On the empirical side, early attempts to address nonlinearities relating financial frictions to the macroeconomy include, among others, McCallum (1991); Galbraith (1996); Balke (2000); Atanasova (2003) and Calza and Sousa (2006). While all these studies share the same dimension along with nonlinearities are investigated, i.e., credit cycles, only Calza and Sousa (2006) explicitly analyze credit shocks.[6] They use a Threshold VAR (TVAR) model and investigate how Euro area macro variables respond to aggregate loan shocks. Allowing for regime-switching after the shock, they find the reactions of output and inflation to be significant only when the economy is in a low credit growth state. More recently, Gambetti and Musso (2012) investigate the effects of loan supply shocks in the Euro Area, the U.K. and the U.S. using a time-varying VAR model. Shock identification is achieved via sign-restrictions. Their impulse response functions, and historical decompositions, show that these shocks have been particularly important during recessions. Hubrich, D'Agostino, Červená, Ciccarelli, Guarda, Haavio, Jeanfils, Mendicino, Ortega, Valderrama, and Valentinyiné Endrész (2013) investigate the effects of financial shocks in the Euro area using a Markov-Switching (MS-VAR) model. They identify (broad) financial shocks by relying on the Composite Indicator of Systemic Stress (CISS) introduced by Holló, Kremer, and Lo Duca (2012) Their results show that shocks to the level of financial stress have much more pronounced effects for the macroeconomy in high stress episodes than in normal times. Hubrich and Tetlow (2012) also use an aggregate index of financial stress within a MS-VAR model and draw similar conclusions for the U.S. economy.

I depart from the above literature along several dimensions. First, I focus on nonlinearities relating to business cycle phases rather than credit market conditions. Second, I compute the effects of credit supply shocks using local projections (Jordà, 2005), which, in contrast to nonlinear VARs, do not impose restrictions on the relationship between aggregates.[7] Third, I focus on credit shocks originating in bond markets, whereas most of the mentioned studies either investigate bank loan shocks or simply do not try to identify any specific type of financial shock. Opening the "financial black-box", by evaluating shocks

[6] The other studies are mainly concerned with monetary policy shocks.
[7] A detailed description of local projection methods, and relative advantages compared to VARs, is provided in section 4.3.

to different financial market segments, may be a very useful exercise that can help addressing issues in the macroprudential regulation debate. Fourth, I appeal to a well defined measure of credit supply shocks, i.e., the excess bond premium developed by Gilchrist and Zakrajšek (2012), which relieves me from imposing identification restrictions that could mask the correlations present in the data. My study shares some similarities with Avdjiev (2014), who also investigate how credit shock effects differ along the U.S. business cycle. I differ from them in terms of i) methodology, as they use a TVAR model; ii) classification of states: they use GDP growth as an indicator of business cycles, whereas I adopt a less controversial approach by relying on official (NBER) recession dates;[8] iii) shock identification: they analyze credit quantity and credit spread shocks, while I focus on excess bond premium shocks; iv) data and sample: they use quarterly data and consider only GDP as a measure of economic activity, whereas I use different indicators at a higher frequency (monthly), which is relevant when studying such a dynamic sector as the financial system.

4.3 The empirical approach

4.3.1 Credit supply shocks and the excess bond premium

My analysis uses the excess bond premium (EBP) developed by GZ as a proxy for credit supply shocks in U.S. bond markets, which is plotted in Figure 4.1.[9] The EBP displays substantial time-series variation, with the highest positive spike occurring in correspondence of the Great Recession. Sizeable increases occur also during normal times, possibly indicating that credit supply shocks are not exclusively associated with recessions. The correlations of the EBP with industrial production growth and the unemployment rate are equal to, respectively, -0.37 and 0.13 over the full sample, i.e., 1973-2012. Further, I estimate the half-life of an EBP innovation, based on a univariate AR(1) model,

[8] It has to be noticed, however, that their approach enables them to study 3 regimes: subpar, moderate, and high growth. In this Chapter I focus only on recessions and normal times.

[9] The excess bond premium data is available on Gilchrist's website: http://people.bu.edu/sgilchri/research/research.htm

to be approximately 9 months. Such persistence suggests that the EBP might contribute to explain business cycle fluctuations.

To derive the EBP, GZ first construct a corporate bond credit spread index based on micro-level data. They collect data on secondary market prices of outstanding bonds of a panel of U.S. nonfinancial firms. For each corporate bond, they then construct a corresponding synthetic risk-free security that mimics exactly the same cash flows (and whose price is based on the U.S. Treasury yield curve). The micro level credit spread is calculated as the yield difference between the risk free and the corporate bond security. Their dataset is fairly large, comprising 1,112 U.S. nonfinancial issuers, and 5,982 bond issues. To obtain a macro credit spread index (the GZ spread), the authors simply calculate the cross-sectional average of all individual credit spreads. Next, they regress the GZ spread on the components of Merton's (1974) distance-to-default model. The residuals of this regression are then classified as the average price of bearing exposure to U.S. corporate credit risk, above and beyond the compensation for expected defaults, i.e., the excess bond premium. Thus, the EBP represents effective "risk-bearing capacity" of the financial intermediary sector.

4.3.2 Local projections: linear specification

The macroeconomic effects of credit supply shocks are estimated by means of impulse response functions, computed using the Local Projections (LP) method advocated by Jordà (2005). This methodology consists of a single-equation approach, which simply requires the estimation of separated regressions for each horizon, h, of interest. The linear specification is the following:

$$y_{t+h} = \alpha_h + \beta_h(L)\boldsymbol{x}_{t-1} + \phi_h \varepsilon_t + u_{t+h} \tag{4.1}$$

where y_t is the time series of interest, $\boldsymbol{x}_t$ is a vector of control variables, $\beta_h(L)$ is a polynomial in the lag operator, and ε_t is the structural shock whose effects one wants to estimate. The vector of controls, $\boldsymbol{x}_t$, helps ensuring that the shock ε_t is exogenous. In addition to the control variables, equation (4.1) includes lags of y_t to control for serial correlation. The coefficient ϕ_h gives the response of y at time $t+h$ to the shock ε at time t. Thus, the dynamics of y_t, conditional on the shock, are constructed as the sequence of the ϕ_h's estimated in a series of h single regressions. The standard error estimates of ϕ_h are then used to display error bands around the impulse responses.[10]

4.3.3 Local projections and nonlinearities

Local projections can conveniently accommodate nonlinearities in the response function of the variable under scrutiny. To examine whether the effects of credit supply shocks differ over business cycle phases, one can consider a dummy variable, I_t, which takes the value of 1 if the economy is, say, in recession, and 0 otherwise. The state-dependent specification of equation (4.1) is then:

$$\begin{aligned} y_{t+h} = \ & I_{t-1}[\alpha_h^R + \beta_h^R(L)\boldsymbol{x}_{t-1} + \phi_h^R \varepsilon_t] \\ & + (1 - I_{t-1})[\alpha_h^E + \beta_h^E(L)\boldsymbol{x}_{t-1} + \phi_h^E \varepsilon_t] + u_{t+h} \end{aligned} \tag{4.2}$$

Based on equation (4.2), the dynamics of y_t following a shock ε_t, conditional on recessions, is given by the sequence of the ϕ_h^R's, whereas under normal times/expansions, the responses are the sequence of the ϕ_h^E's, both estimated in a series of h single regressions, where h denotes the forecast horizon.

In contrast to the predominant SVAR method for empirically studying the effects of macro structural shocks, local projections do not impose any pattern for the impulse response functions; asymmetries can be addressed in a simple, and linear way; and the estimation of equations for dependent variables other than the variable of interest is unneeded. Thus, local projections are less sensitive to misspecification, allow to specify a more parsimonious model, and have relatively a higher number of degrees of freedom.[11]

[10] The successive leading of the dependent variable leads to serial correlation in the error terms, u_{t+h}. Thus, standard error estimates are produced using the Newey-West variance estimator (Newey and West, 1987).

[11] Along these benefits come some disadvantages of local projections. As discussed in Ramey and Zubairy (2014), local projections i) do not impose any restrictions that link the impulse responses at h and $h+1$, so the estimates can show irregular patterns; ii) as h increases, one loses observations from the end of the sample; iii) the impulse responses may display large oscillations at long horizons (Ramey (2012) compares impulse responses estimated using Jordà's method to those derived from a standard VAR, and show that results are qualitatively similar up to $h = 16$, where the horizon is expressed in quarters). This study focuses on short-run dynamics, and therefore reliability of long horizons is not a concern.

4.3.4 Data and estimation

In light of the theoretical literature discussed in section 4.2, I compute impulse response functions to an EBP shock for the following U.S. indicators of real activity: log industrial production in manufacturing, log employment (total nonfarm payroll), and the civilian unemployment rate.[12] The regimes in equation (4.2) are defined according to the U.S. business cycle dates, as identified by the National Bureau of Economic Research (NBER). Thus, the dummy I_t equals 1 when the corresponding month is a NBER recession. The baseline vector of controls includes: all the three macro aggregates mentioned above; average hours in manufacturing, and log average hourly earnings for production workers (manufacturing), to control for labor market dynamics; the log of the consumer price index (all urban consumers), the (effective) federal funds rate to control for the stance of monetary policy, and the log of the S&P500 stock-market index. Including the S&P500 index is important to control for general trends in stock markets, and for news about future firm's aggregate cash flows. Therefore, $x_t = [ip_t, emp_t, unrate_t, hours_t, wages_t, cpi_t, ffr_t, sp_t]$. The data is considered at a monthly frequency, and spans the period 1973:1–2012:12, whose choice is dictated by the availability of the excess bond premium. For all regressions I consider a lag polynomial, i.e., $\beta_h(L)$, $\beta_h^R(L), \beta_h^E(L)$, of order 6, whose length is intended to be large enough to control for exogeneity concerns related to the shock. The estimates for industrial production and employment also include a linear trend.

4.4 Results

Figure 4.2 plots the estimated effects of a 1% increase in the excess bond premium under the assumption of a linear world. The figure reports the responses of each variable up to 2 years after the shock—a forecast horizon typically associated with business cycle fluctuations—along with the $\pm$ one standard error confidence bands. All measures of economic activity are shown to decrease substantially after the shock. Output reaches a negative peak of about 4% after 12 months, whereas the fall in employment is estimated to be more contained, i.e., about -1.5% within the same horizon. It is worth noting

[12] The source of the data, which is seasonally adjusted, is the Federal Reserve Bank of St. Louis' database.

that these results line up with previous studies. For example, Caldara et al. (2014) show that a one-standard deviation shock to the EBP (about 25 basis points) leads to a 1% reduction of industrial production, and a 0.4% fall in employment. My estimates are quantitatively very similar to theirs, since I compute responses to a shock which is four times bigger. The negative impact of an increase in the EBP is also confirmed by the response of the unemployment rate, which is shown to increase by 1% within the first 15 months. Another remark on these linear estimates concerns the persistent effects of the shock. The economy shows no signs of recovery within the short-run, with all variables below their normal trends even at a 2 years horizon after the shock.

Nonlinear estimates. How different are the effects of credit supply shocks if the economy is experiencing a phase of downturn? Figure 4.3 displays the responses of the same macroeconomic time series to a 1% increase in the EBP, distinguishing between a shock that realizes during a recession and one (of the same magnitude) that occurs during normal times or upward phases of the cycle. The estimated differences are striking if one considers the timing with which the shock propagates to the real economy. During recessions, the negative impact of increases in the EBP materializes much faster than in normal times, and the peak response of unemployment is much larger. However, the economy recovers quickly from the shock, i.e., within a 12 months horizon. Interestingly, all the three measures of real activity display a somewhat overshoot in the medium term.[13] Differently, a long-lasting, hump-shaped reaction is found in normal times. In terms of magnitude, the peak fall in industrial production is very similar between the two states, whereas the fall in employment is twice the one that occurs in recessions.

4.4.1 Interpreting asymmetries

How one can explain the long-lasting effects of credit supply shocks during expansionary phases of the business cycle? At a first glance, this evidence may seem counterintuitive if we think that in good times the economy, in aggregate,

[13]The same drop-rebound-overshoot pattern for real activity is found by Bloom (2009), and Caggiano, Castelnuovo, and Nodari (2015) in response to uncertainty shocks. This might suggest some similarities between financial and uncertainty shocks. I account for the potential role of uncertainty by running some robustness checks, which are presented in the next section.

is more resilient to shocks. Disentangling the transmission mechanism of EBP shocks would require a structural model of the economy. Here, I provide an interpretation of my results by discussing theoretical models that can potentially explain the asymmetries found in the data. In particular, I discuss the models by Dow et al. (2005) and Philippon (2006), which provide a complementary view to the financial accelerator mechanism (Bernanke et al., 1999), with the main difference that shocks here are amplified and propagated during booms rather than in recessions.

Dow et al. (2005) develop a dynamic equilibrium model featuring a financial friction in the form of imperfect corporate control, and study its implications for investment and asset pricing. In the model, the separation of ownership and control allows managers to use their discretion over free cash flow. Because managers are empire-building, they always invest as much as they can, implying that they may choose projects that do not maximize firm value. This means that when free cash flow is high, as in a cyclical peak, investment may be higher than shareholders would optimally prefer. Dow et al. show then that the variation in the corporate control problem over the business cycle has implications for interest rates and risk premia. But most importantly, they show that this type of friction generates amplification and persistence of otherwise i.i.d. shocks through large firms and during boom phases. Similarly, Philippon (2006) presents a model with corporate governance conflicts in which firms overinvest because of managerial tendencies to build empires. What matters for aggregate dynamics in his model is whether these deviations from profit maximization are more likely to happen in booms or in recessions. Because the relative costs and benefits of monitoring firms' decisions change with the state of the economy, shareholders leave more discretion to managers in good times, when the costs of missing a profit opportunity (due to time consuming monitoring) are higher. Therefore, also his models predicts that corporate governance conflicts amplify aggregate fluctuations, especially during upward phases of the business cycle.

To interpret the evidence provided here on the effects of credit supply shocks, with the predictions coming from the above models, I make the following additional considerations: insights from the real option theory and irreversible investment suggest that the value of exercising a growth option is high during booms; to the extent that managerial misbehavior is also more likely in this state of the economy, one can expect a higher number of irreversible investment projects to be undertaken in upward phases of the cycle. When the shock hits in normal times/expansions, the relatively high share of irreversible projects may make it difficult for firms to recover quickly from the funding shortage, explaining thus the slower recovery period compared to recessions. As for the delayed initial drop in economic activity, it may be explained by the fact that during normal times, firms may have a liquidity buffer since the economy is functioning well. And therefore they may initially be able to counteract the adverse effects of the shock.

4.5 Robustness checks

In this section I conduct a sensitivity analysis to verify the robustness of my results. I start by focusing on the potential interaction between changes in the excess bond premium and movements in uncertainty. A few recent papers have raised concerns about the distinction between financial and uncertainty shocks. Stock and Watson (2012), and Caldara et al. (2014) emphasize the high positive correlation between indicators of financial stress and commonly used proxies for economic uncertainty. I tackle this issue in three different ways. First, I compute impulse response functions to an uncertainty shock for the macro variables considered in my analysis, conditional on the very same scenario as my baseline estimates. Thus, the only element that differs is the shock: I substitute the EBP with an uncertainty measure recently proposed by Jurado, Ludvigson and Ng (2015) (JLN uncertainty hereafter). The JLN uncertainty is computed as the common component of the volatility of the one-step-ahead forecast errors of a large number of economic indicators.[14] This measure of macro uncertainty features big spikes only in correspondence of the 1973-74, the 1981-82, and the 2007-09 recessions, while being much more stable in the rest of the sample. This makes the identification of the shock complicated during normal times. For this reason, I present the results only for recessions. Figure 4.4 plots the estimated responses to the JLN uncertainty shock, along with those to the EBP shock computed in the baseline model.[15] Uncertainty shocks seem to have larger quantitative effects in recessions than

[14] Jurado et al. (2015) develop uncertainty measures for different forecast horizons. Here I focus on the one based on one-step-ahead forecast errors. Exercises conduct with alternative measures, i.e., three- and twelve-step-ahead uncertainty, did not change my results.

[15] To easy comparison, I have rescaled all the responses by the standard deviation of the shocks, which are 0.10 for the JLN uncertainty, and 0.51 for the EBP. This is because the two indicators are expressed in different unit measures.

EBP shocks do. However, the drop-rebound-overshoot pattern found after an EBP shock is not replicated by the uncertainty shock. This is clearly evident for employment. The economy reacts differently to the two shocks, all else being equal. Secondly, in addition to the above exercise, I also re-estimate the effects of EBP shocks including the JLN uncertainty indicator in the vector of controls. The baseline results continue to hold, i.e., conditional on this specification, real activity displays a even larger overshoot in the medium term. The impulse responses of this check are reported in Figure 4.5 ("uncertainty"). Figure 4.5 shows also the other two robustness checks I undertake. One consists of replacing the S&P500 index with the VXO in the vector of controls. The purpose of this check is twofold: further controlling for uncertainty, given that the VXO is a commonly used proxy for economic uncertainty; and accounting for second-moment developments in stock markets (the VXO is an index of percentage implied volatility on a hypothetical at the money S&P100 option 30 days to expiration).[16] Finally, I also re-compute the effects of the EBP shock excluding the Great Recession. I find asymmetric responses of industrial production, employment and unemployment over the business cycle in all the above mentioned robustness exercises.

4.6 Conclusions

The recent turmoil in global financial markets, together with the severity of the 2008-2009 crisis and subsequent slow recovery, led researchers and policymakers alike to search for alternative drivers of business cycle fluctuations, shifting their attention to financial shocks. This Chapter empirically investigates the effects of credit supply shocks originating in bond markets, and shows that the state of the business cycle is a key element to understand the transmission of these shocks to the real economy. Using nonlinear local projections, I show that aggregate indicators of economic activity react asymmetrically to credit supply shocks in recessions and normal times. My findings evidence that in bad times, credit supply shocks induce a drop-rebound-overshoot pattern in output, employment, and unemployment. Differently, a long-lasting, hump-shaped reaction is found in normal times. This result echoes recent findings in the business cycle literature as for uncertainty shocks, which tend to generate the

[16]The results for the VXO check are conditional on regressions featuring 3 lags. Impulse response functions conditional on 6 lags, as the baseline model, displayed excessive oscillation.

same pattern of real activity across the two states of the economy. I show that my findings are robust to considering macroeconomic uncertainty within the empirical model, in addition to other few robustness checks.

From a modeling standing point, the evidence of asymmetries highlights the importance of accounting for nonlinearities when incorporating a financial sector into macro models. From a policy perspective, the results suggest the implementation of nonlinear macroprudential rules to properly deal with the asymmetric response of the economy to financial instability. One question that this Chapter does not address is whether credit supply shocks are ultimately supply or demand shocks, which is key to determine the optimal response of monetary policy to disturbances affecting the financial system. I leave this question for future research.

Tables

Table 1.1: Granger causality tests

	FRPU	NewsBank EPU	EPU	VIX
FRPU	–	0.42	0.17	0.47
NewsBank EPU	0.01	–	0.01	0.11
EPU	0.20	0.01	–	0.08
VIX	0.00	0.12	0.19	–

Notes: The table reports the p-values of Granger causality tests based on bivariate VARs(6) estimated over the period 1985:1 - 2012:10. Null hypothesis: Row variable does not Granger cause column variable.

Table 1.2: FEVD: macro aggregates - linear VAR

Horizon	shock: ε^{frpu}				Baa-Aaa spread					
	Δy	π	u	i	ε^{frpu}	$\varepsilon^{\Delta y}$	ε^{π}	ε^{u}	ε^{i}	ε^{s}
6	7.96	7.21	19.64	16.14	17.99	6.15	2.32	0.87	0.13	72.54
12	8.26	7.21	26.88	17.11	17.82	7.05	5.25	1.04	2.43	66.40
36	8.53	7.25	29.57	18.37	18.29	7.24	7.54	0.99	6.35	59.59
60	9.08	7.55	29.70	17.79	18.51	7.61	7.52	1.26	6.63	58.46

Notes: The left part shows the percentages of the total forecast error variance of the variables due to FRPU shocks, calculated within the linear VAR. The right part displays the total forecast error variance decomposition of the spread, i.e., the percentage explained by each shock within the baseline VAR.

Table 1.3: FEVD: credit spreads - linear VAR

Horizon	GZ spread		Baa–GS10 spread		Aaa–GS10 spread	
	ε^{frpu}	ε^{i}	ε^{frpu}	ε^{i}	ε^{frpu}	ε^{i}
6	14.46	1.89	20.49	0.43	15.42	1.60
12	9.76	1.72	17.08	3.89	13.15	4.75
36	11.52	4.59	14.00	11.94	9.97	9.51
60	14.96	3.79	14.01	12.26	9.66	10.06

Notes: The table shows the percentages of the total forecast error variance of alternative credit spread measures due to FRPU shocks, ε^{frpu}, and monetary policy shocks, ε^{i}. Estimates are based on the linear specification of the VAR.

Table 1.4: FEVD: macro aggregates - nonlinear (STVAR) model

Horizon	Non-recessions					Recessions				
	Δy	π	u	i	s	Δy	π	u	i	s
1	2.15	3.54	15.10	9.08	1.79	2.64	7.29	2.83	4.63	9.02
4	2.28	3.51	15.21	14.30	6.19	13.14	9.20	13.39	7.06	16.11
6	2.38	3.49	13.89	17.53	12.40	12.45	7.62	16.99	6.53	12.85
12	2.88	3.67	11.79	19.65	16.03	12.78	7.86	16.75	5.27	10.87

Notes: The table shows the percentages of the total forecast error variance – of the variables of interest – explained by FRPU shocks, calculated using the nonlinear (Smooth Transition) VAR model.

Table 2.1: Anticipated fiscal spending shocks: statistical relevance

$News$	$(1,3)$	$(1,1)$	$(2,2)$	$(3,3)$	$(0,0)$
$p-value$	**0.00**	**0.00**	**0.00**	**0.00**	0.11

Notes: P-values related to the exclusion Wald-test of one period-lagged News variables entering (one at a time) a regression involving government spending (dependent variable), a constant, three lags of government spending, three lags of fiscal receipts, and three lags of real GDP. Figures in bold are associated to a predictive power of news found to be significant at a 10 percent confidence level. News are expressed in cumulated terms to have an order of integration comparable to that of the other variables. Estimation conducted by considering Newey-West standard errors robust to heteroskedasticity and serial correlation.

Table 2.2: News à la Ramey vs. forecast revisions: Granger-causality tests

Sample	*Ramey*	η_{13}^{g}	*ORZ*	η_{13}^{g}
1981:III-2008:IV	0.44	**0.06**		
1986:IV-2008:IV	0.28	**0.02**		
1981:III-2010:IV			0.71	**0.06**
1986:IV-2010:IV			0.59	**0.02**

Notes: 'Ramey' stands for the news variable employed by Ramey (2011), 'ORZ' stands for its updated version employed by Owyang, Ramey, and Zubairy (2013). P-values related to the exclusion Wald-test of one period-lagged covariate of interest. Figures in bold are associated to a predictive power of news found to be significant at a 10 percent confidence level. Results based on a bivariate VAR with one lag. Null hypothesis: Column variable does not Granger cause the alternative news measure.

Table 2.3: Fiscal spending multipliers

	Peak		*Sum*	
Horizon/State	*Expansion*	*Recession*	*Expansion*	*Recession*
4	1.68 [1.12,3.49]	3.38 [1.77,4.70]	1.73 [0.52,3.50]	3.15 [1.71,4.27]
8	1.24 [0.80,3.19]	3.32 [1.55,4.91]	0.33 [−1.05,2.77]	3.05 [0.68,4.70]
12	1.11 [0.74,2.69]	2.77 [1.40,4.28]	−0.57 [−2.24,1.54]	2.13 [0.13,3.82]
16	1.09 [0.71,2.43]	2.60 [1.38,3.96]	−1.41 [−3.96,0.74]	1.54 [−0.42,2.95]
20	1.09 [0.71,2.41]	2.58 [1.38,3.90]	−2.27 [−6.23,−0.01]	1.00 [−0.94,2.47]

Notes: Figures conditional on the baseline VAR analysis. Log-values of the impulse response of output rescaled by the sample mean of output over public spending (both taken in levels) to convert percent changes in dollars.

Table 2.4: Fiscal spending multipliers: extreme events

	Peak			
Hor./State	*Strong exp.*	*Deep rec.*	*Weak exp.*	*Mild rec.*
4	1.24 [0.78,1.88]	3.57 [2.14,4.73]	1.68 [1.15,3.44]	3.23 [1.74,4.69]
8	0.86 [0.53,1.25]	3.58 [1.94,4.75]	1.24 [0.82,3.16]	3.24 [1.56,4.72]
12	0.79 [0.48,1.10]	2.39 [1.48,3.30]	1.11 [0.75,2.56]	2.88 [1.32,4.20]
16	0.79 [0.45,1.09]	2.27 [1.45,2.93]	1.09 [0.72,2.31]	2.72 [1.32,3.96]
20	0.79 [0.43,1.08]	2.24 [1.44,2.90]	1.09 [0.72,2.29]	2.71 [1.31,3.94]

	Sum			
Hor./State	*Strong exp.*	*Deep rec.*	*Weak exp.*	*Mild rec.*
4	1.03 [−0.51,2.03]	3.42 [2.05,4.35]	1.69 [0.64,3.40]	3.09 [1.71,4.14]
8	−0.26 [−2.01,0.84]	3.42 [1.22,5.14]	0.30 [−0.87,2.83]	2.94 [0.56,4.46]
12	−1.32 [−3.68,−0.03]	2.21 [0.61,3.54]	−0.62 [−2.15,1.48]	2.06 [0.03,3.78]
16	−2.26 [−5.63,−0.78]	1.60 [0.18,2.63]	−1.40 [−3.91,0.65]	1.38 [−0.48,3.02]
20	−3.28 [−7.00,−1.56]	1.09 [−0.31,2.07]	−2.37 [−6.08,0.01]	0.83 [−0.97,2.54]

Notes: Figures conditional on the VAR analysis with GIRFs conditional on four different sets of initial conditions. Log-values of the impulse response of output rescaled by the sample mean of output over public spending (both taken in levels) to convert percent changes in dollars.

Table 2.5: Shares of fiscal multipliers larger in recessions

		Peak				
Scenario/Horizon	*Cycle*	h=4	h=8	h=12	h=16	h=20
Baseline	*Normal*	87.8	90.8	90.0	90.6	90.2
	Extreme	100	100	100	100	100
$\tilde{\eta}^{g}_{13}$ *last*	*Normal*	84.0	87.0	87.8	88.8	89.2
	Extreme	100	100	100	100	100
$\tilde{\eta}^{g}_{13}$ *first*	*Normal*	69.0	76.2	76.8	79.8	80.6
	Extreme	86.4	96.4	96.2	96.0	96.0
Long sample (Ramey's news)	*Normal*	96.8	98.2	98.0	98.0	98.0
	Extreme	99.0	100	100	100	100
		Sum				
Scenario/Horizon	*Cycle*	h=4	h=8	h=12	h=16	h=20
Baseline	*Normal*	84.8	91.6	93.6	95.4	96.6
	Extreme	100	100	100	100	100
$\tilde{\eta}^{g}_{13}$ *last*	*Normal*	78.2	86.4	89.4	90.6	92.6
	Extreme	100	100	100	100	100
$\tilde{\eta}^{g}_{13}$ *first*	*Normal*	58.2	76.2	82.2	89.8	92.0
	Extreme	71.6	93.0	97.8	98.8	99.2
Long sample (Ramey's news)	*Normal*	82.8	89.6	87.6	86.4	86.6
	Extreme	90.2	92.8	92.8	93.0	93.6

Notes: Normal scenarios: fraction of multipliers which are larger in recessions than expansions out of 500 draws from their empirical distributions. Extreme scenarios: fraction of multipliers which are larger in deep recessions than strong expansions out of 500 draws from their empirical distributions. 'h' identifies the number of quarters after the shock.

Table 2.6: Fiscal spending multipliers: extreme events - different scenarios

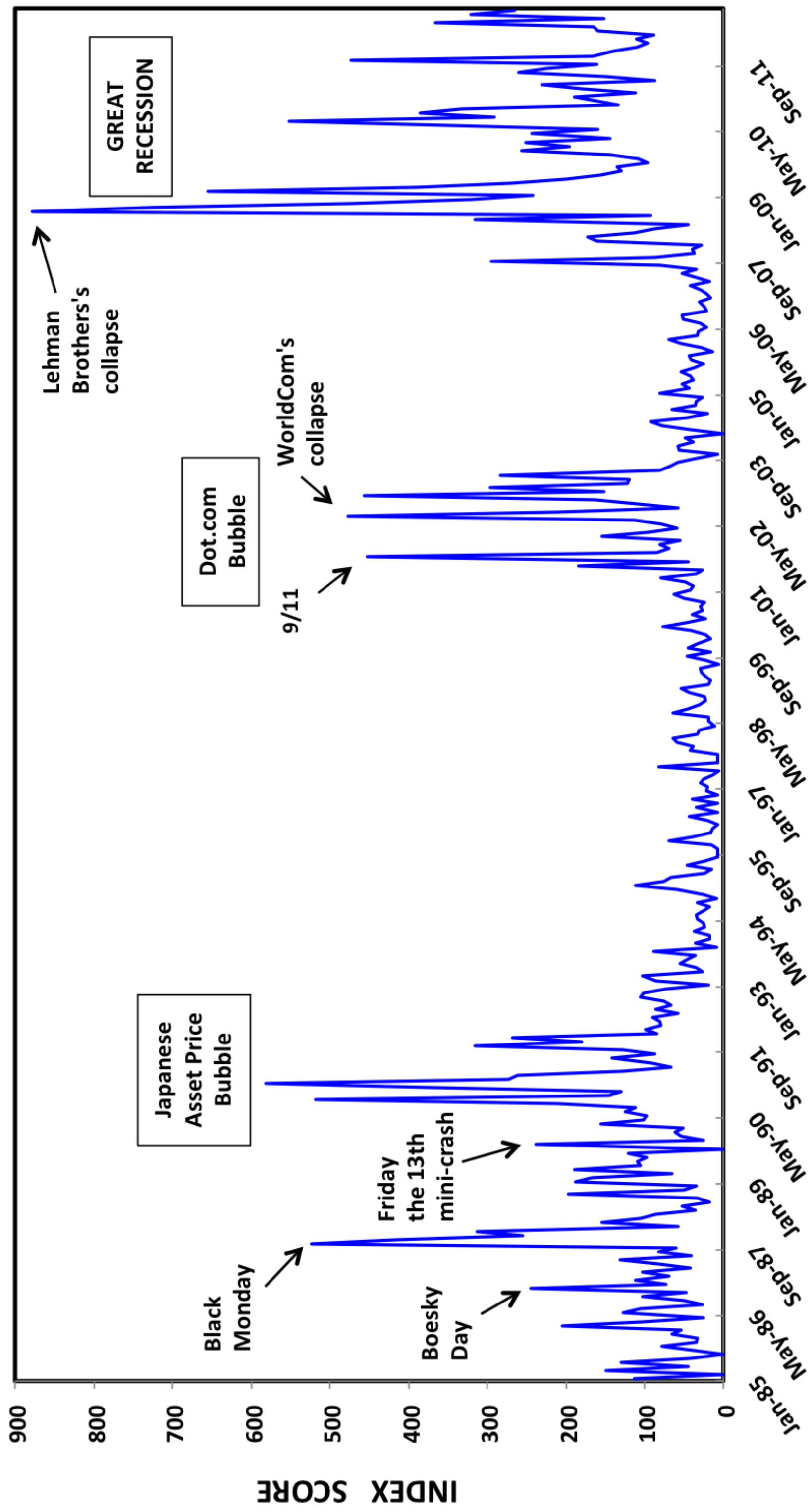
	Peak			
Scenario/State	*Strong exp.*	*Deep rec.*	*Weak exp.*	*Mild rec.*
Baseline	0.79 [0.45,1.09]	2.27 [1.45,2.93]	1.09 [0.72,2.31]	2.72 [1.32,3.96]
$\widetilde{\eta}^g_{13}$ *last*	0.43 [0.19,0.61]	2.55 [1.66,3.34]	0.97 [0.45,3.01]	2.88 [1.44,3.72]
$\widetilde{\eta}^g_{13}$ *first*	1.14 [0.24,1.82]	2.74 [1.65,4.48]	1.91 [0.85,3.72]	3.23 [1.51,5.14]
Long sample (Ramey's news)	0.49 [0.20,0.81]	2.61 [1.55,4.62]	0.77 [0.28,1.50]	2.51 [1.21,5.31]
	High debt	*Mod.$^+$ debt*	*Mod.$^-$ debt*	*Low debt*
Debt/GDP ratio	1.35 [1.15,1.54]	1.22 [0.58,1.81]	1.56 [1.31,2.00]	1.66 [1.24,2.55]

	Sum			
Scenario/State	*Strong exp.*	*Deep rec.*	*Weak exp.*	*Mild rec.*
Baseline	−2.26 [−5.63,−0.78]	1.60 [0.18,2.63]	−1.40 [−3.91,0.65]	1.38 [−0.48,3.02]
$\widetilde{\eta}^g_{13}$ *last*	−1.57 [−2.92,−0.91]	2.28 [1.23,3.10]	−0.44 [−1.97,2.29]	2.16 [0.22,3.00]
$\widetilde{\eta}^g_{13}$ *first*	−0.70 [−2.50,0.43]	2.36 [0.99,4.29]	0.66 [−1.04,2.90]	2.50 [0.59,4.39]
Long sample (Ramey's news)	0.15 [−0.24,0.53]	1.74 [0.08,3.92]	0.07 [−1.23,0.96]	1.52 [0.60,4.62]
	High debt	*Mod.$^+$ debt*	*Mod.$^-$ debt*	*Low debt*
Debt/GDP ratio	0.68 [0.15,1.37]	0.74 [−1.02,1.15]	1.33 [0.95,1.66]	1.33 [0.81,1.97]

Notes: Four-year integral multipliers. Figures conditional on the VAR analysis with GIRFs conditional on four different sets of initial conditions. Log-values of the impulse response of output rescaled by the sample mean of output over public spending (both taken in levels) to convert percent changes in dollars.

Figures

Figure 1.1: The FRPU index



Notes: Evolution of the news-based U.S. financial regulation policy uncertainty index for the period 1985:1-2012:10.

Figure 1.2: U.S. Uncertainty measures

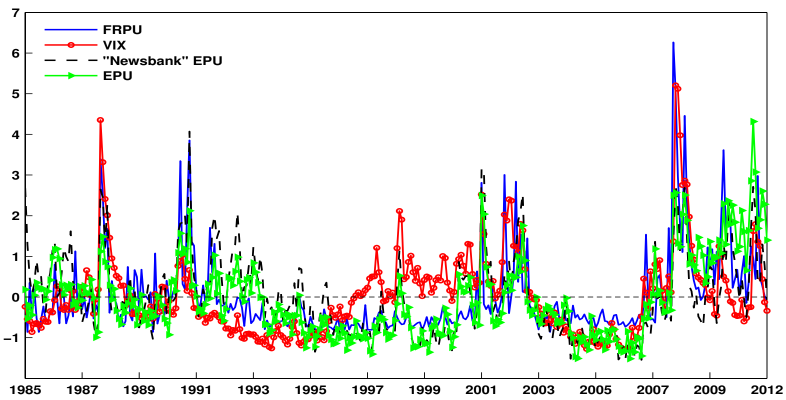
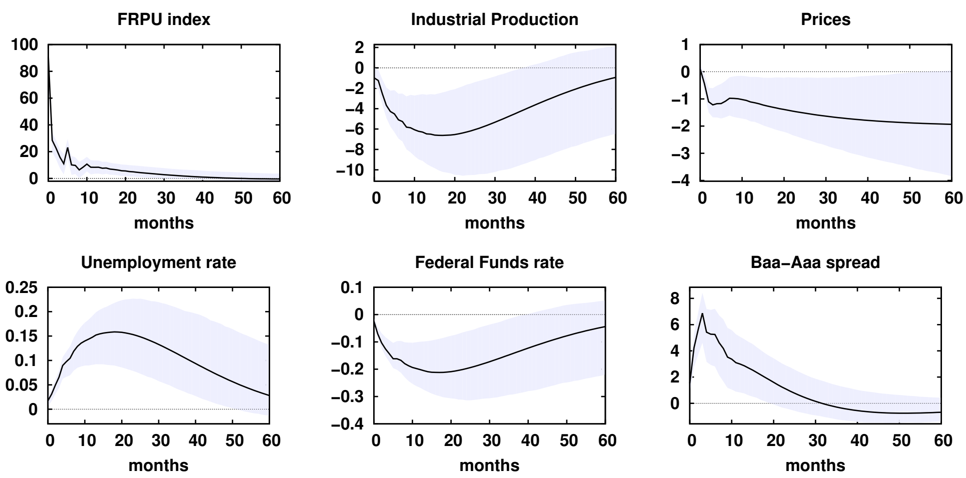
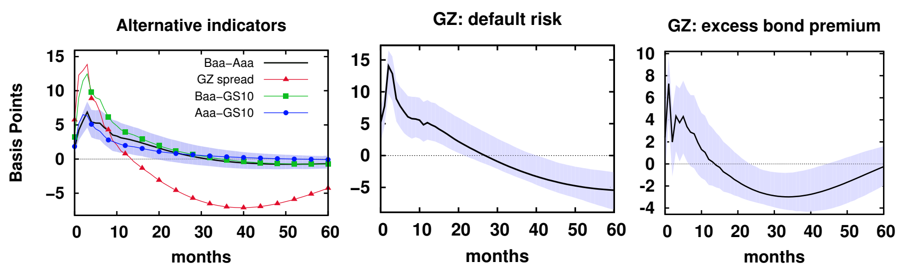


Figure 1.3: Macroeconomic effects of FRPU shocks: linear model



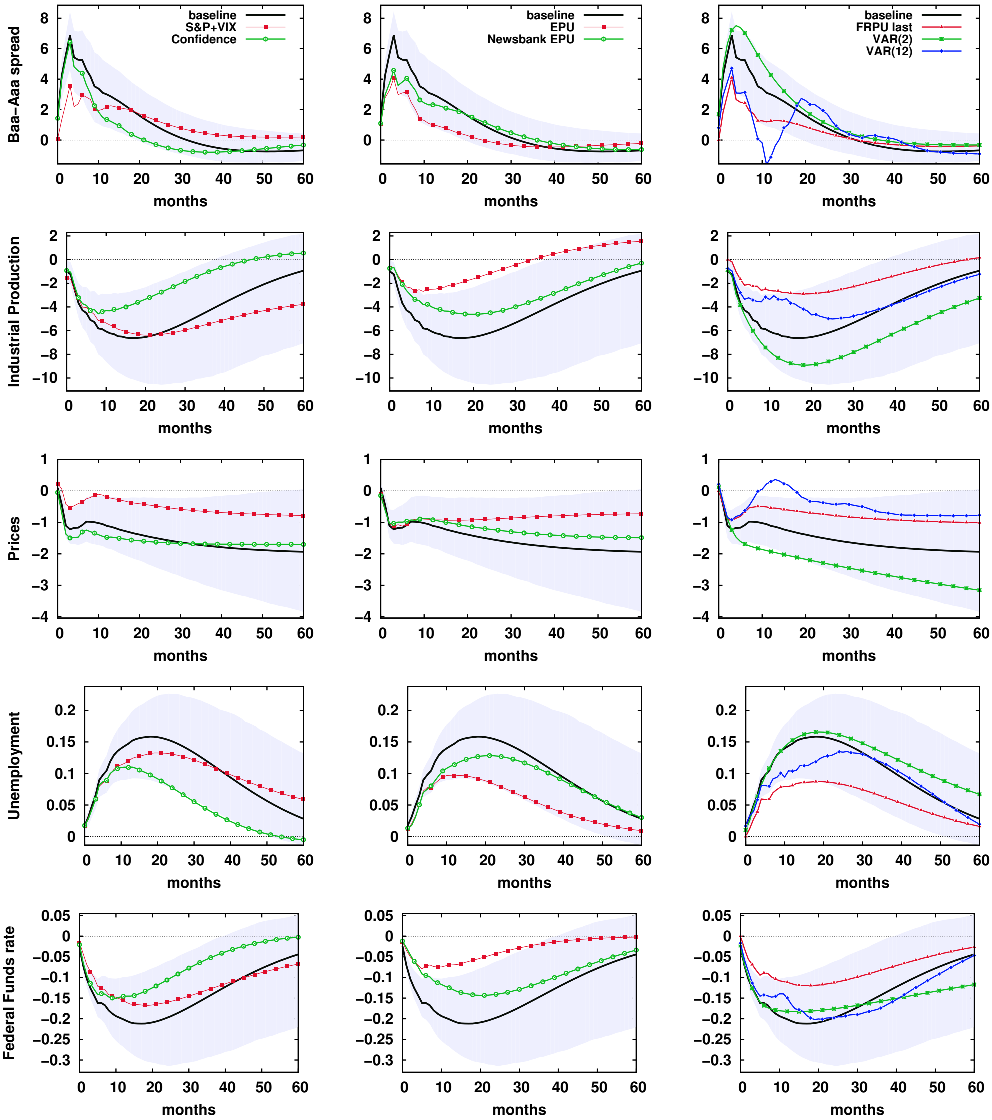
Notes: Impulse responses to a one-standard deviation shock to the FRPU index, calculated with the baseline (linear) VAR. The responses of industrial production growth and the inflation rate have been cumulated. Gray areas: 90% confidence bands, calculated with the bootstrap-after-bootstrap procedure by Kilian (1998).

Figure 1.4: Credit spreads and FRPU shocks



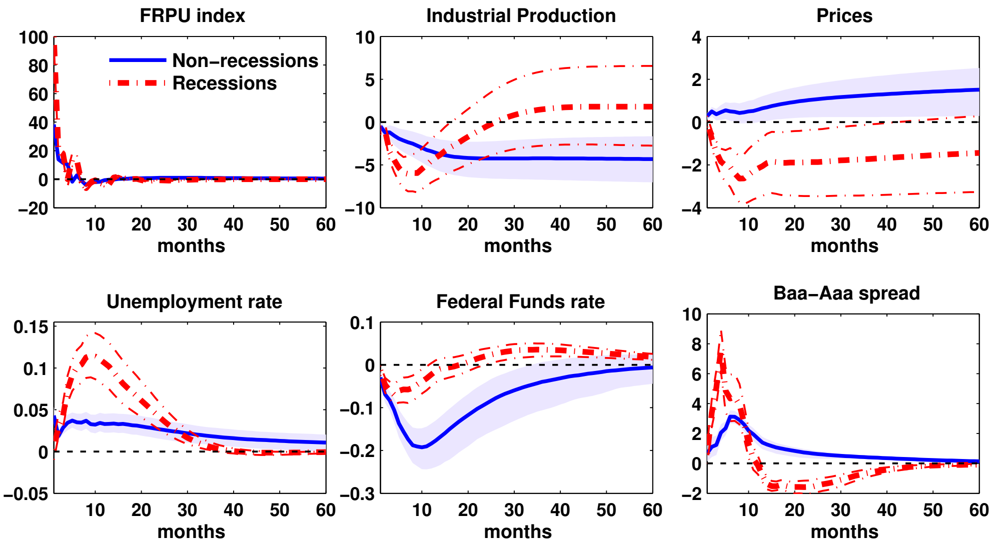
Notes: Impulse responses of credit spreads to a one standard shock to the FRPU index, calculated with the baseline (linear) VAR. Gray areas: 90% confidence bands.

Figure 1.5: Robustness checks of FRPU shocks



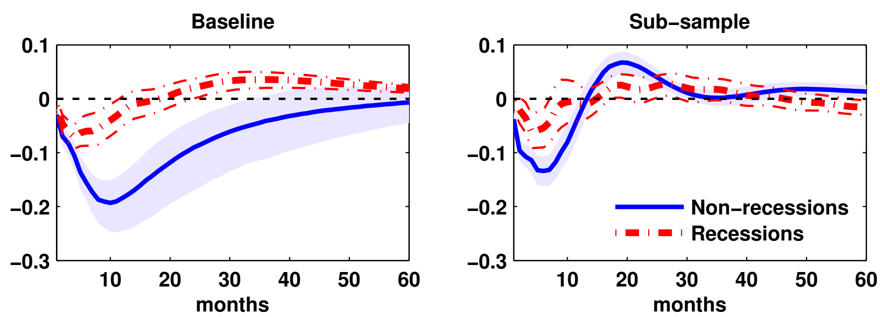
Notes: Macroeconomic effects of a one-standard deviation FRPU shock. The responses of industrial production growth and the inflation rate have been cumulated. Gray areas: 90% bootstrapped confidence intervals in the baseline model.

Figure 1.6: Macroeconomic effects of FRPU shocks: nonlinear model



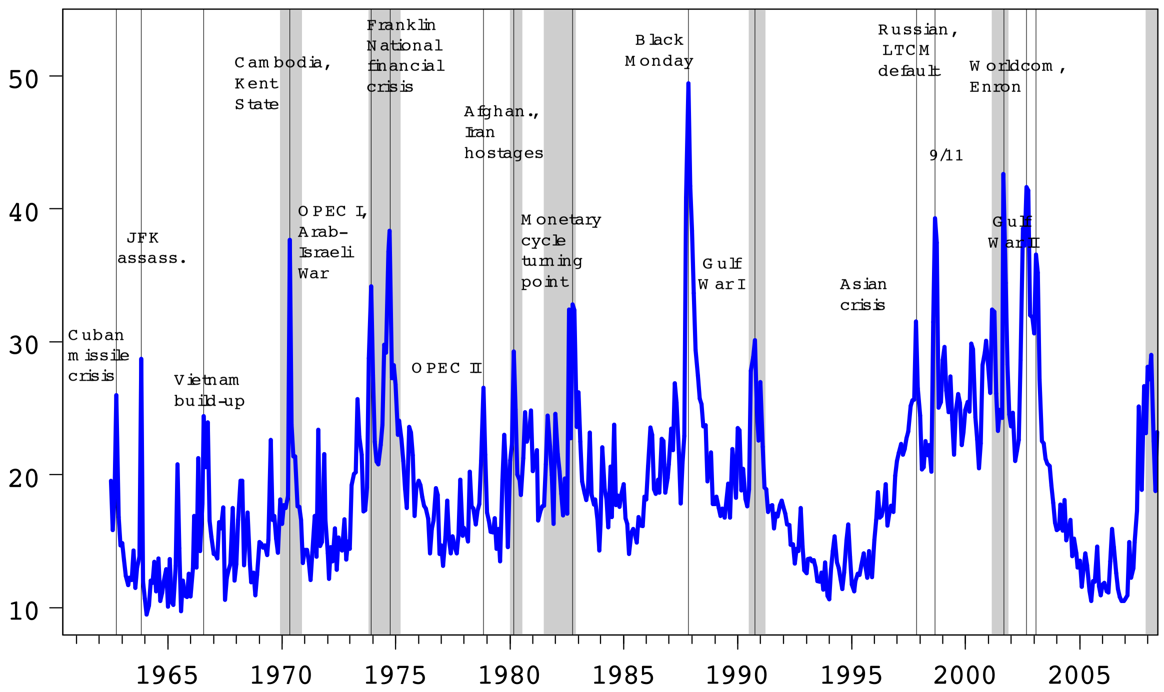
Notes: Impulse responses to a one-standard deviation shock to the FRPU index, calculated with the nonlinear (Smooth-Transition) VAR. The responses of industrial production growth and the inflation rate have been cumulated. Gray areas: 90% confidence bands.

Figure 1.7: Interest rate's reaction to FRPU shocks



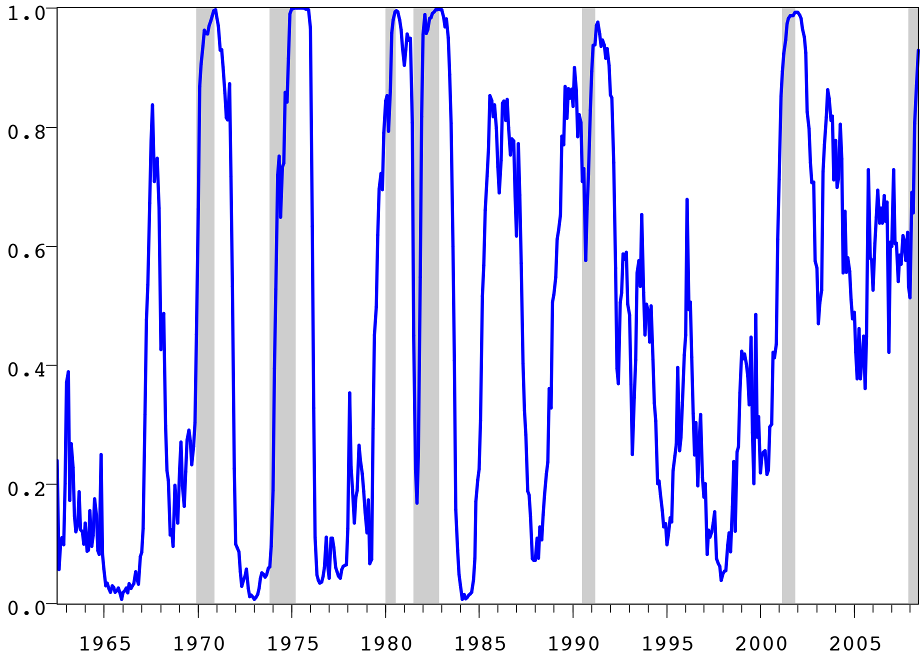
Notes: The left panel plots the reaction of the federal funds rate to a one standard deviation FRPU shock, computed with the nonlinear STVAR model, estimated over the full sample, i.e. 1985:1–2012:10. The right panel shows the same responses calculated with the STVAR model estimated over a subsample period, i.e., 1985:1–2008:9, to exclude the potential effects of the Zero Lower Bound.

Figure 2.1: Uncertainty shocks and the business cycle



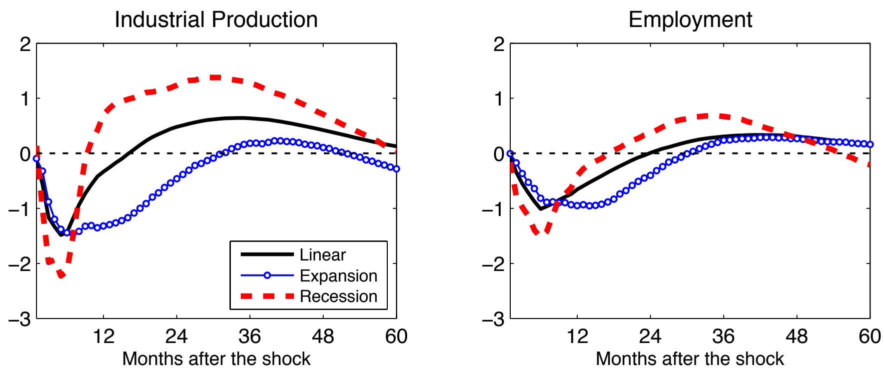
Notes: Blue line: Chicago Board of Options Exchange VXO index. Vertical black lines: uncertainty episodes identified as realizations over 1.65 times the standard deviation of the HP filtered VXO. Shaded areas: NBER recessions.

Figure 2.2: Probability of being in a recessionary phase



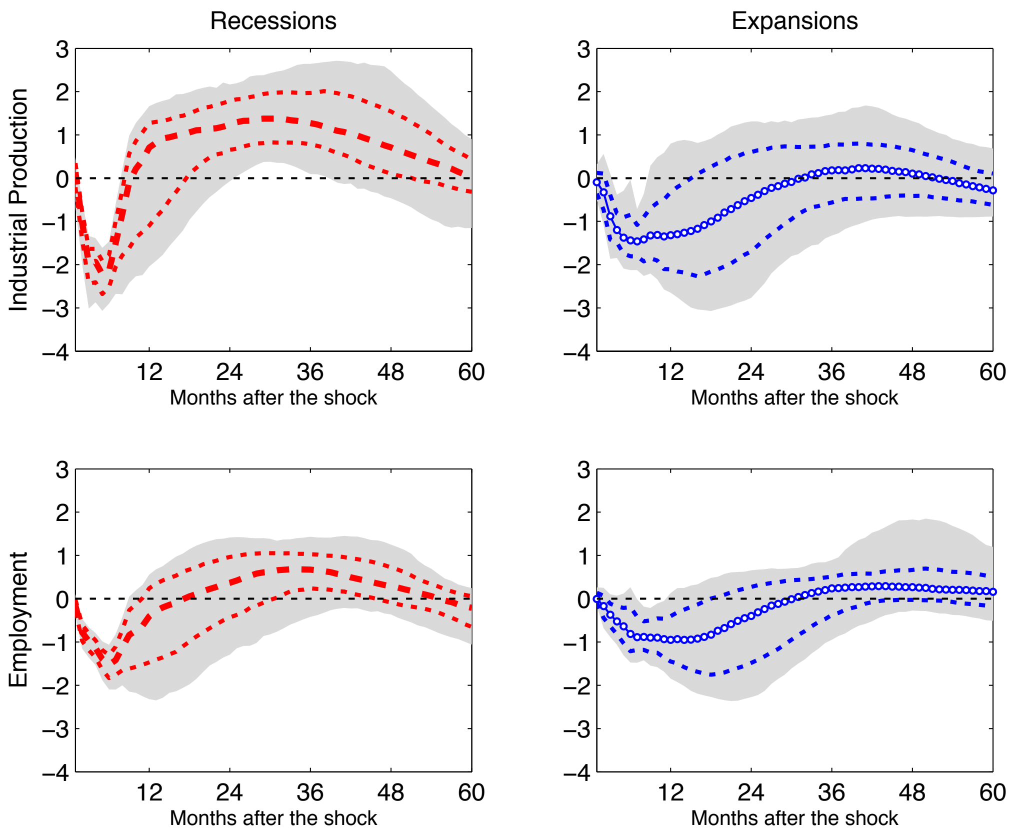
Notes: Blue line: Transition function $F(z)$. Shaded columns: NBER recessions. Transition function computed by employing the standardized moving average (12 terms) of the month-on-month growth rate of industrial production.

Figure 2.3: Real effects of uncertainty shocks: nonlinearities



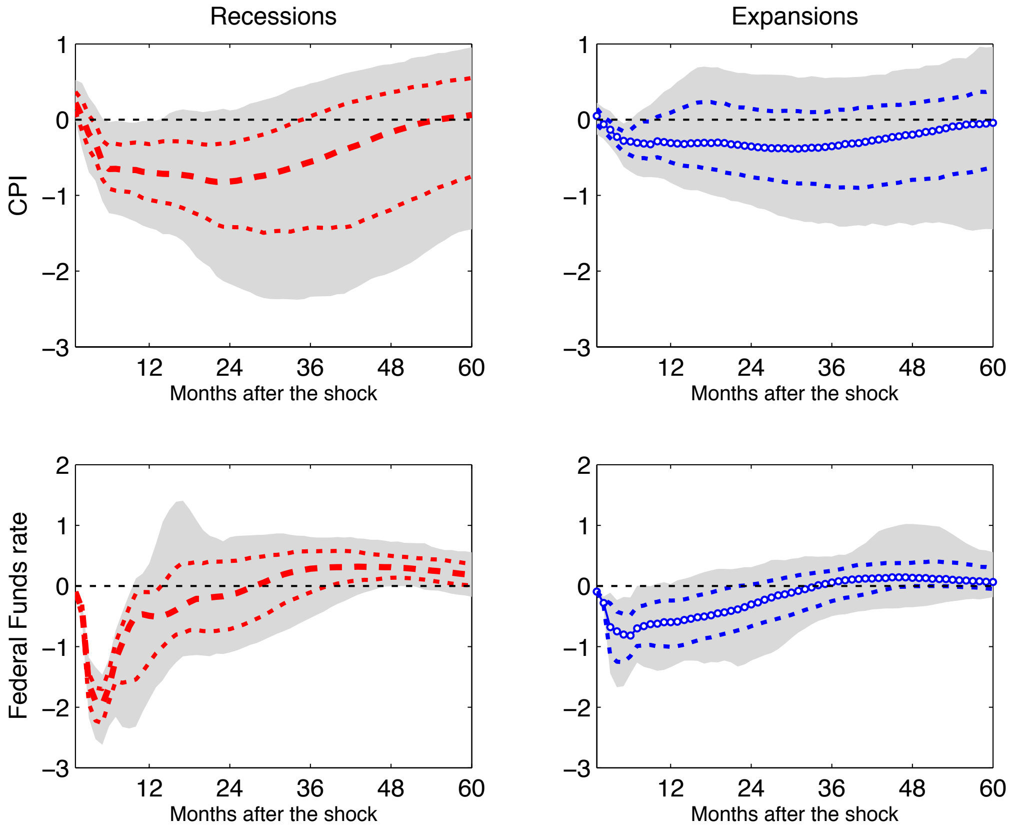
Notes: Impulse responses (median values) to a one-standard deviation uncertainty shock identified as described in Chapter 2. Solid black lines: Responses computed with the linear VAR. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions).

Figure 2.4: Real effects of uncertainty shocks: good and bad times



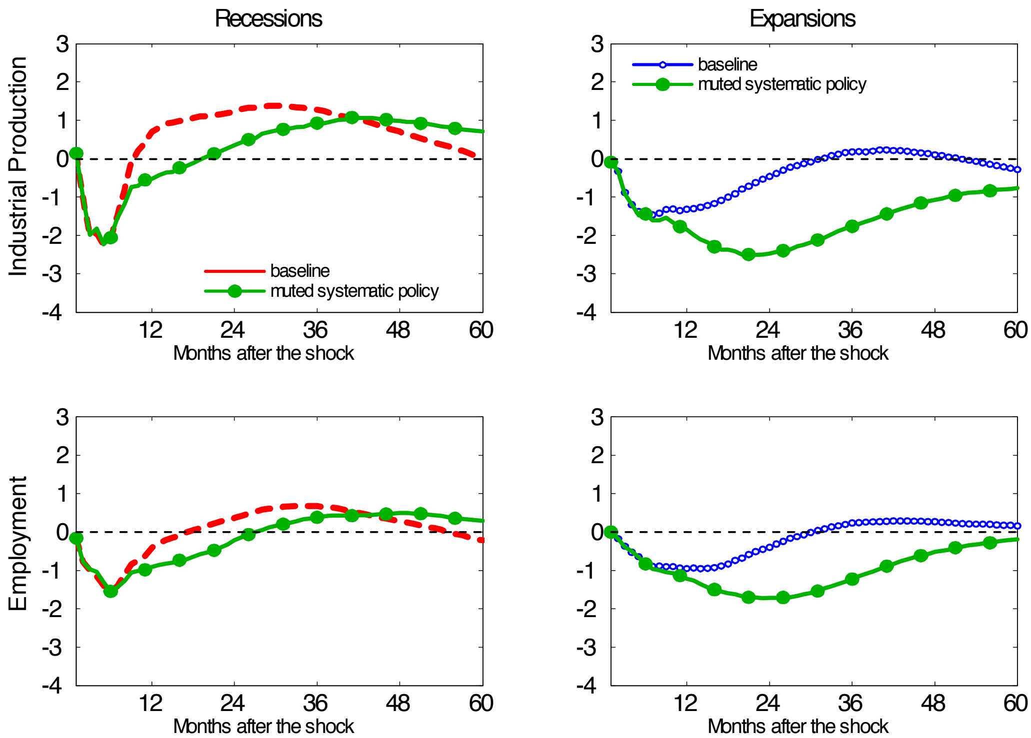
Notes: Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified as described in Chapter 2. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands. Gray areas: 95% confidence bands.

Figure 2.5: Nominal effects of uncertainty shocks: good and bad times



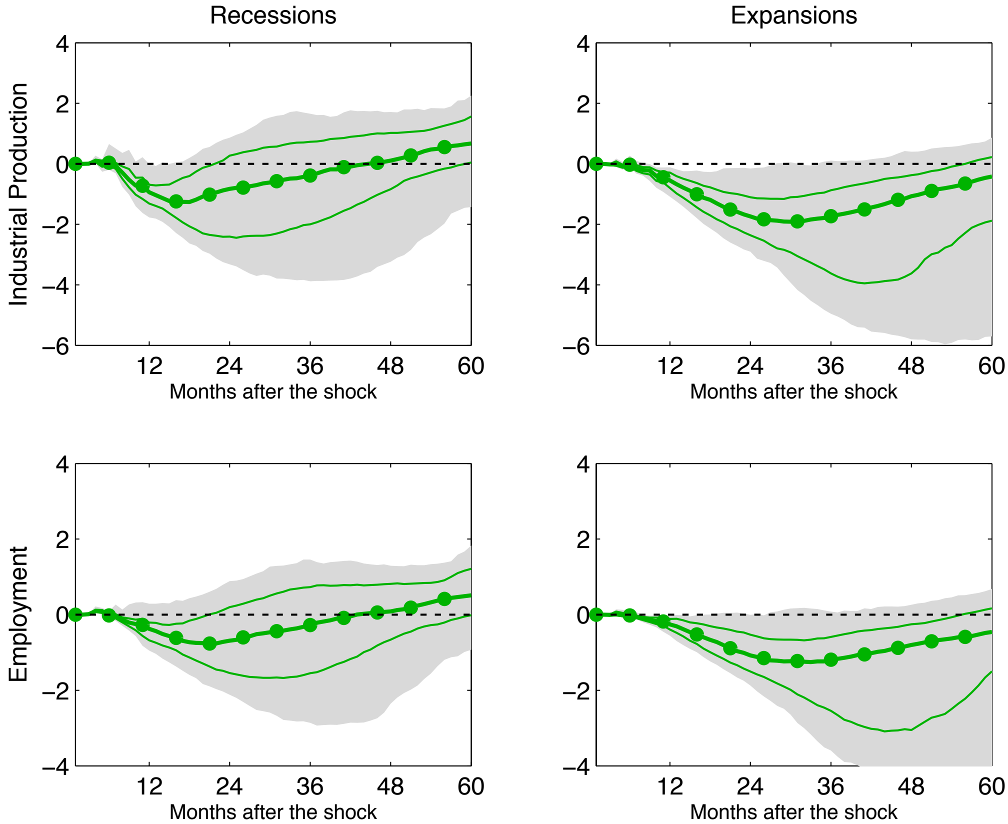
Notes: Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified as described in Chapter 2. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands. Gray areas: 95% confidence bands.

Figure 2.6: Uncertainty shocks and systematic monetary policy



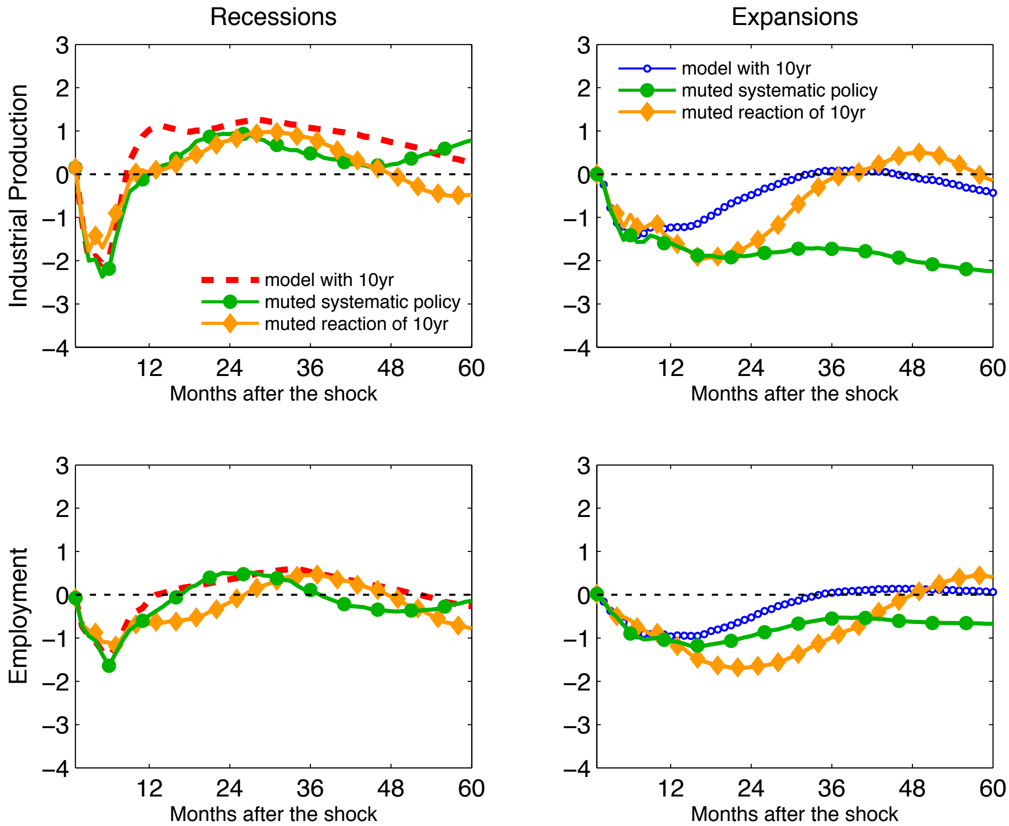
Notes: Median impulse responses to a one-standard deviation uncertainty in scenarios with unconstrained/constrained monetary policy. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Counterfactual responses computed conditional on a muted systematic policy (fixed federal funds rate) in green-circled lines.

Figure 2.7: Role of monetary policy: statistical difference



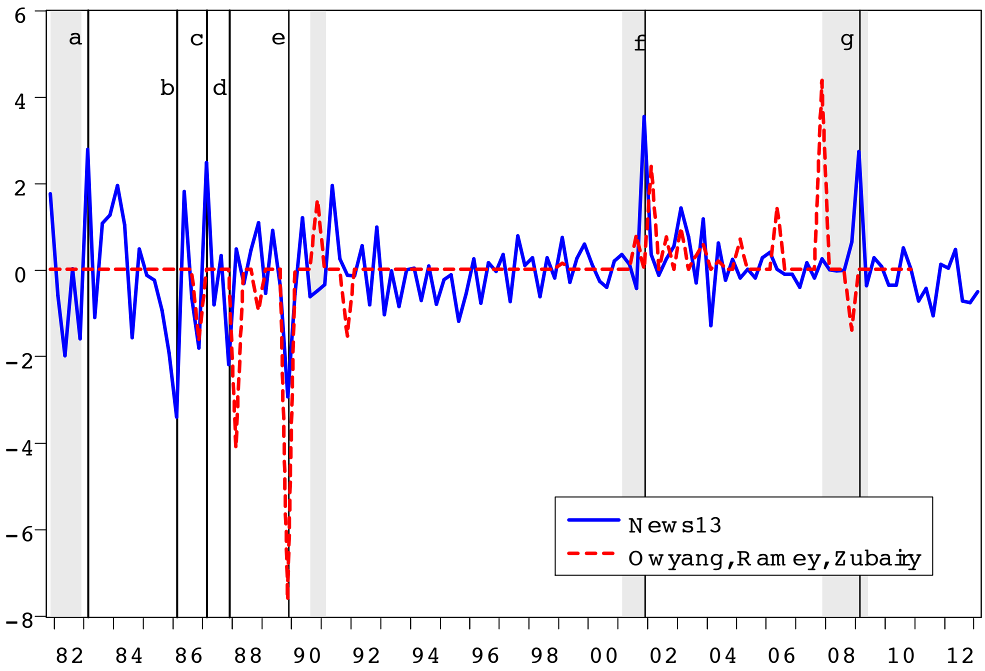
Notes: Difference between "baseline" minus "muted monetary policy" impulse responses to a one-standard deviation uncertainty shock identified as described in Chapter 2. Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Green circled-lines: Median of the distribution of the differences. Solid green lines: 68% bands of the distribution of the differences. Gray areas: 95% bands of the distribution of the differences.

Figure 2.8: Uncertainty shocks and short- vs. long-term interest rates



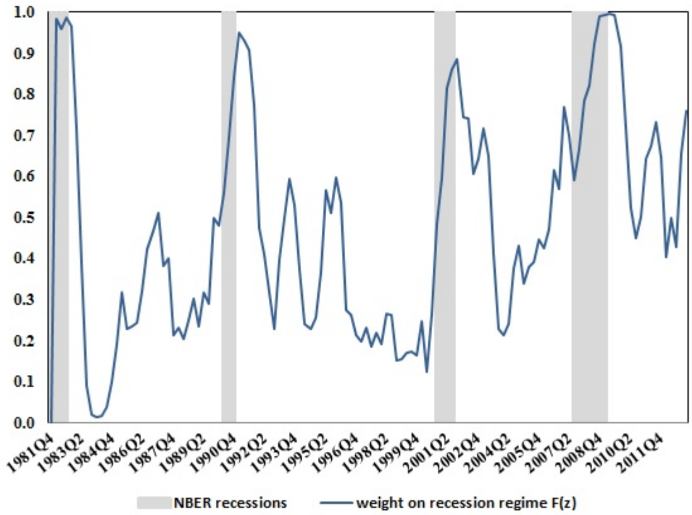
Notes: Median impulse responses to a one-standard deviation uncertainty in scenarios with unconstrained/constrained monetary policy. Red dashed (blue dashed-circled) lines: Responses computed with the estimated nine-variate STVAR with the 10 year Treasury yield (unrestricted model). Counterfactual responses 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 3.1: News13 vs. Ramey's news



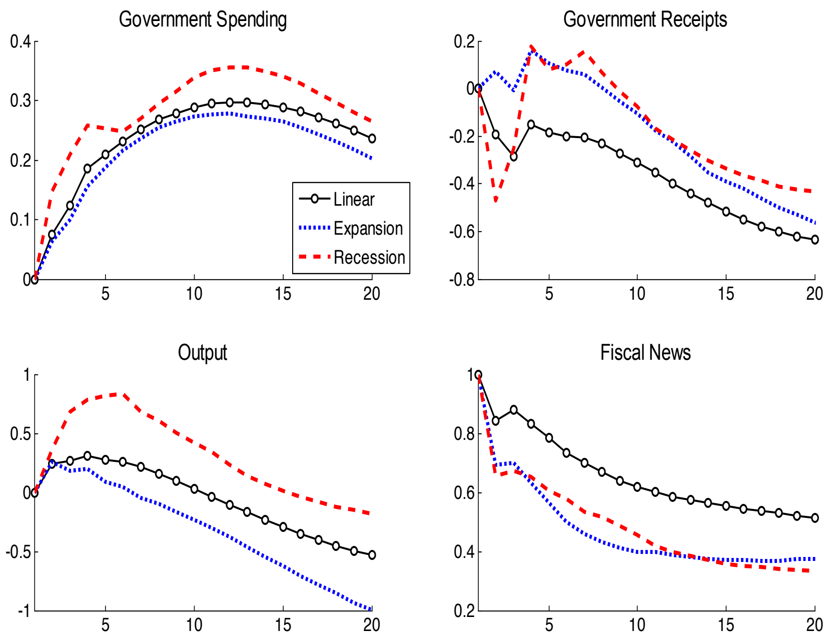
Notes: Blue, solid line: News variable constructed by considering the sum of Survey of Professional Forecasters' forecast revisions regarding future public spending from one-to-three quarter-ahead. Extreme values, interpretation: (a) 1983Q1: Reagan's "Evil Empire" and "Star Wars" speeches; (b) 1986Q1: Perestrojka; (c) 1987Q1: Senate elections won by the Democrats a quarter before; (d) 1987Q4: Spending cuts as for the Pentagon; (e) 1989Q4: Berlin wall; (f) 2001Q4: War in Afghanistan; (g) 2009Q1: Obama's stimulus package. Red, dashed line: News variable constructed by Owyang, Ramey, and Zubairy (2013), who extended Ramey's (2011) news variable up to 2010Q4. Ramey's (2011) variable is constructed by considering the present discounted value of expected changes in defense spending (nominal spending divided by nominal GDP one period before). Both news measures in this Figure are standardized.

Figure 3.2: Transition function



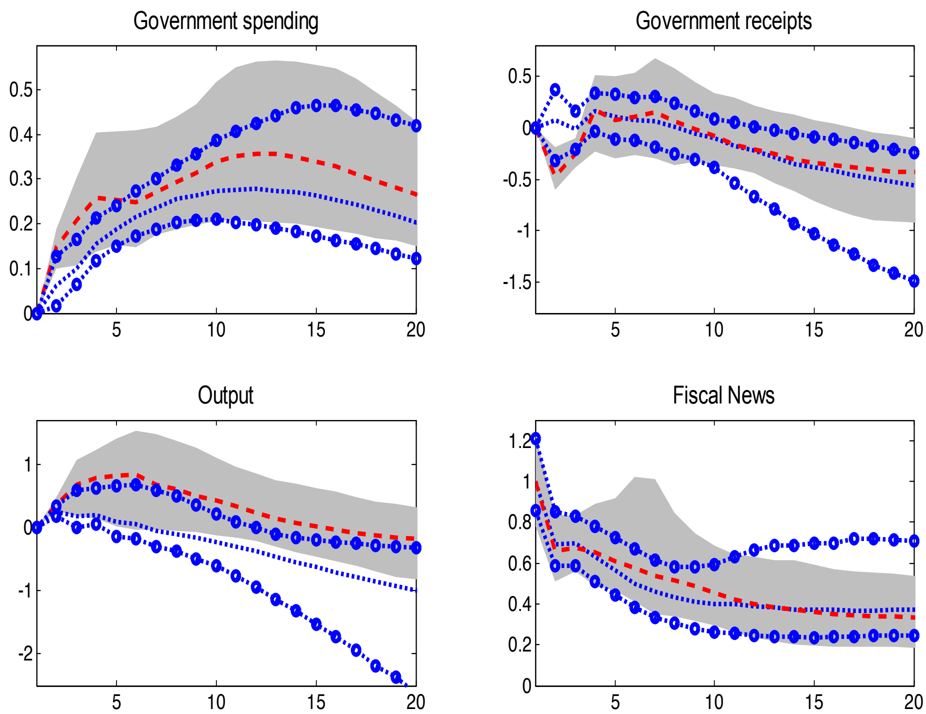
Notes: Transition variable: standardized backward-looking moving average constructed with four realizations of the quarter-on-quarter real GDP growth rate. Value of the slope parameter: 2.3.

Figure 3.3: Impulse responses to a fiscal news shock: linear vs. nonlinear



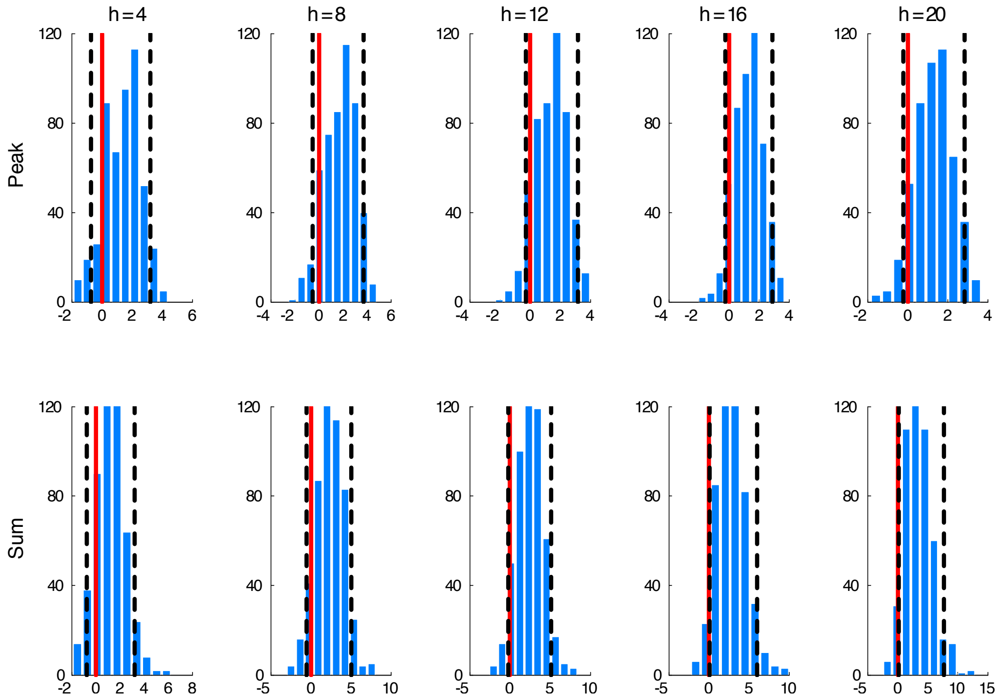
Notes: Median responses to a fiscal news shock normalized to one. News variable constructed as the sum of the revisions of the one, two, and three step-ahead expectation values over future fiscal spending growth. News variable expressed in cumulated terms to have the same order of integration as the one of the log-real variables in the vector. Log-values of the impulse response of output rescaled by the sample mean of output over public spending (both taken in levels) to convert percent changes in dollars.

Figure 3.4: Impulse responses to a fiscal news shock: recessions vs. expansions



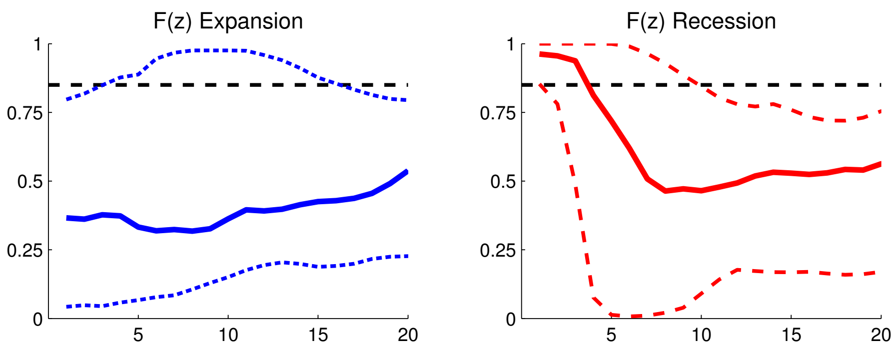
Notes: Median responses to a fiscal news shock normalized to one. 90 percent confidence intervals identified with gray areas (recessions) and circled lines (expansions). Red dashed lines: Recessions. Dotted blue lines: Expansions. News variable constructed as the sum of the revisions of the one, two, and three step-ahead expectation values over future fiscal spending growth. News variable expressed in cumulated terms to have the same order of integration as the one of the log-real variables in the vector. Sample 1981Q3-2013Q1. VAR models estimated with a constant and three lags. Log-values of the impulse response of output rescaled by the sample mean of output over public spending (both taken in levels) to convert percent changes in dollars.

Figure 3.5: Difference in multipliers between recessions and expansions



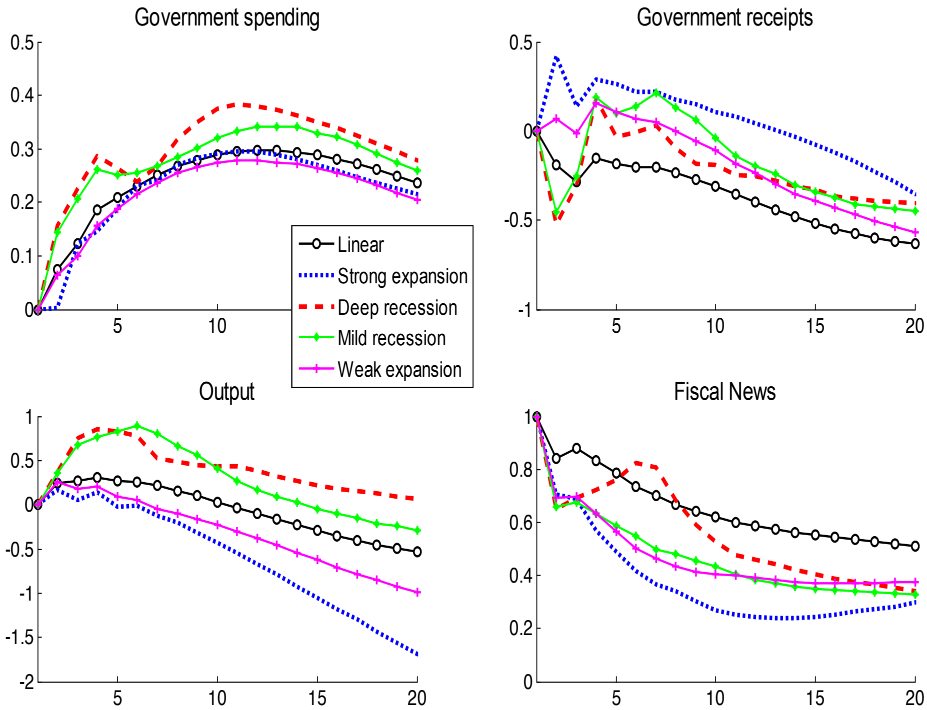
Notes: Empirical densities of the differences computed as multipliers in recessions minus multipliers in expansions. Densities constructed by considering all recessions and expansions (initial conditions) present in the sample. Multipliers conditional on the same set of draws of the stochastic elements of our STVAR model as well as the same realizations of the coefficients of the vector. Densities based on 500 realizations of such differences per each horizon of interest. 'h' identifies the number of quarters after the shock.

Figure 3.6: Evolution of the probability of being in a recession



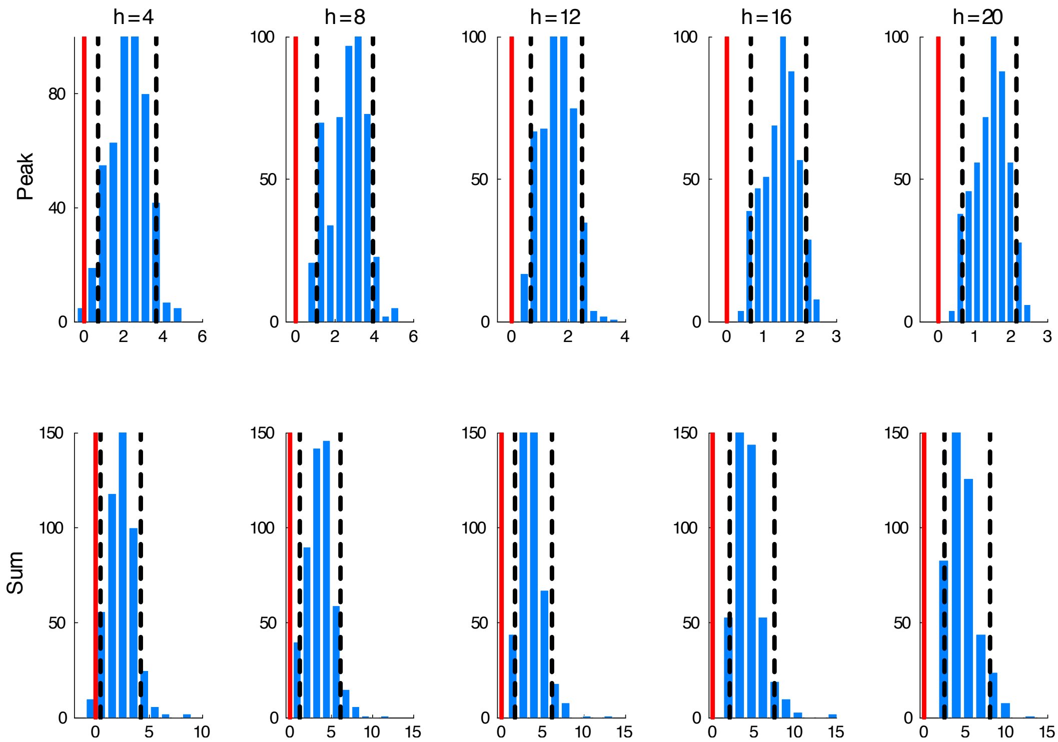
Notes: Solid lines: Median reactions. Blue dotted/red dashed lines: 90 percent confidence intervals. Black dashed horizontal line: Threshold value to switch from a regime to another. Probability computed according to the logistic function presented in the text and the evolution of output conditional on a fiscal news shock. Transition variable: Standardized backward-looking moving average constructed with four realizations of the quarter-on-quarter real GDP growth rate. Value of the slope parameter: 2.3.

Figure 3.7: Impulse responses to a fiscal news shock: extreme events



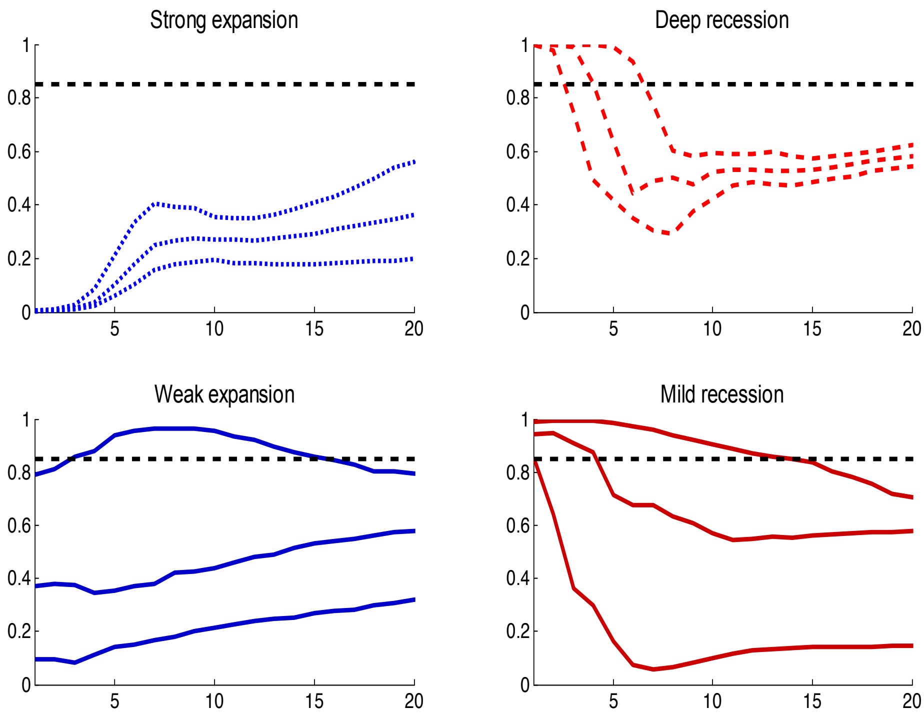
Notes: Deep recessions/strong expansions associated to histories consistent with realizations of our transition variable which are below/above two standard deviations. Mild recessions/weak expansions associated to histories consistent with realizations of our transition variable below/above -0.75 but within the range [-2,2]. Median responses to a fiscal news shock normalized to one. News variable constructed as the sum of the revisions of the one, two, and three step-ahead expectation values over future fiscal spending growth. News variable expressed in cumulated terms to have the same order of integration as the one of the log-real variables in the vector. VAR models estimated with a constant and three lags. Log-values of the impulse response of output rescaled by the sample mean of output over public spending (both taken in levels) to convert percent changes in dollars.

Figure 3.8: Difference in multipliers: extreme events



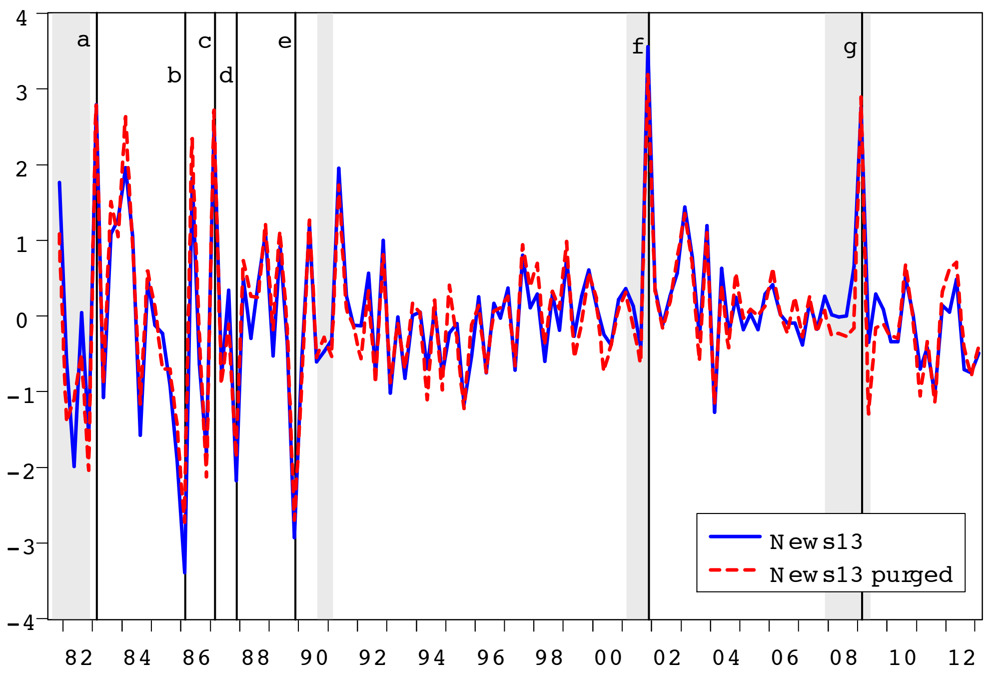
Notes: Empirical densities of the differences computed as multipliers in recessions minus multipliers in expansions. Densities constructed by considering just extreme realizations of recessions and expansions (initial conditions) present in the sample. Multipliers conditional on the same set of draws of the stochastic elements of our STVAR model as well as the same realizations of the coefficients of the vector. Densities based on 500 realizations of such differences per each horizon of interest. 'h' identifies the number of quarters after the shock.

Figure 3.9: Probability of being in a recession: extreme events



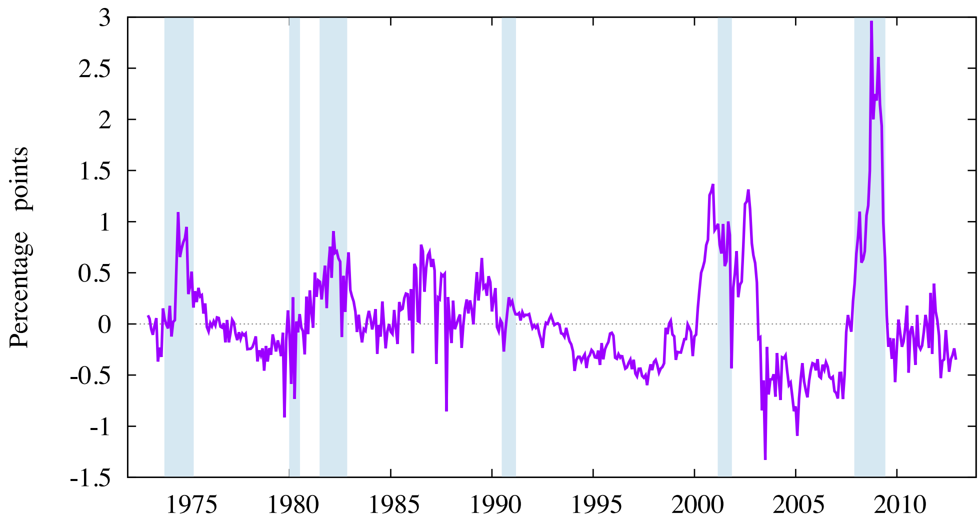
Notes: Median reactions and 90 percent confidence intervals. Black dashed horizontal line: Threshold value to switch from a regime to another. Deep recessions/strong expansions associated to histories consistent with realizations of our transition variable which are below/above two standard deviations. Mild recessions/weak expansions associated to histories consistent with realizations of our transition variable below/above -0.75 but within the range [-2,2]. Probability computed according to the logistic function presented in the text and the evolution of output conditional on a fiscal news shock. Transition variable: Standardized backward-looking moving average constructed with four realizations of the quarter-on-quarter real GDP growth rate. Value of the slope parameter: 2.3.

Figure 3.10: News13 vs. News13 purged



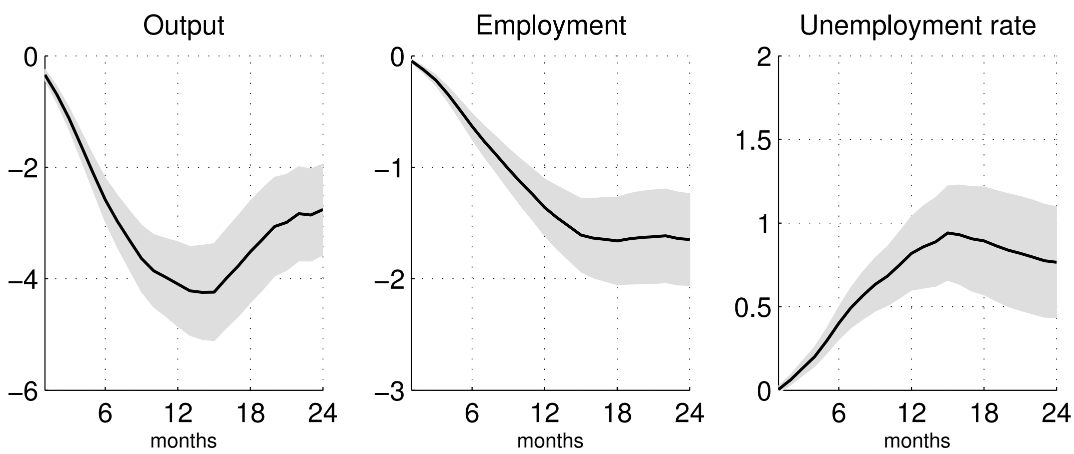
Notes: Blue, solid line: News variable constructed by considering the sum of Survey of Professional Forecasters' forecast revisions regarding future public spending from one to three period-ahead. Red, dashed line: News variable constructed by regressing News13 over a constant and the sums of the forecasts revisions of real GDP growth, unemployment, GDP deflator inflation, the three-month Treasury bill rate, and the 10-year Treasury bond rate. Extreme values, interpretation: (a) 1983Q1: Reagan's "Evil Empire" and "Star Wars" speeches; (b) 1986Q1: Perestrojka; (c) 1987Q1: Senate elections won by the Democrats a quarter before; (d) 1987Q4: Spending cuts as for the Pentagon; (e) 1989Q4: Berlin wall; (f) 2001Q4: War in Afghanistan; (g) 2009Q1: Obama's stimulus package. Both news measures in this Figure are standardized.

Figure 4.1: Excess bond premium



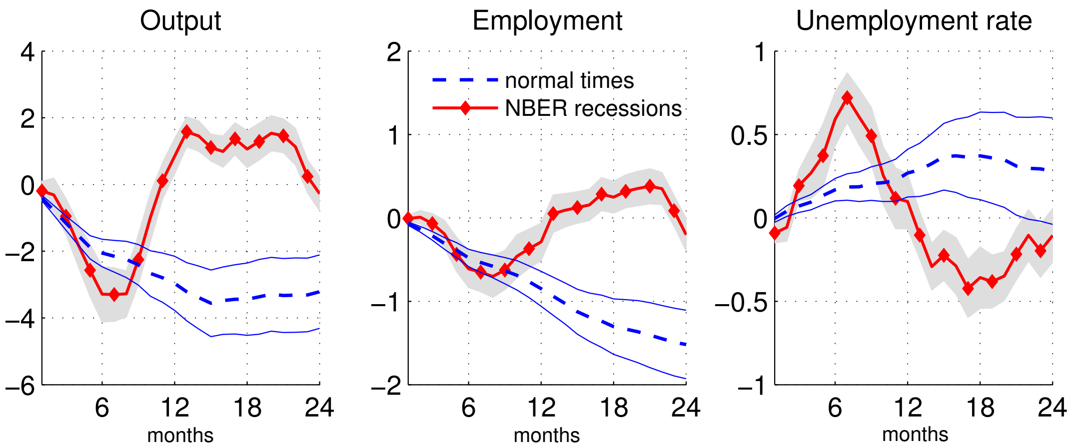
Notes: The figure plots the monthly excess bond premium developed by Gilchrist and Zakrajšek (2012), from 1973:1 to 2012:12. Shaded areas denote NBER recession dates.

Figure 4.2: Baseline results: linear model



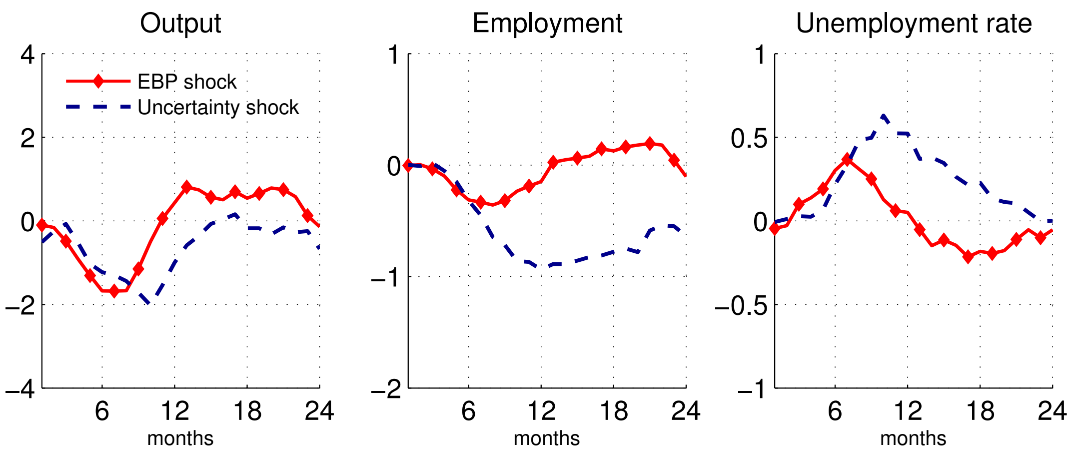
Notes: Impulse responses to a one-percent increase in the excess bond premium, calculated with linear local projection methods à la Jordà (2005). Gray areas: ± one standard error confidence bands.

Figure 4.3: Baseline results: nonlinear model



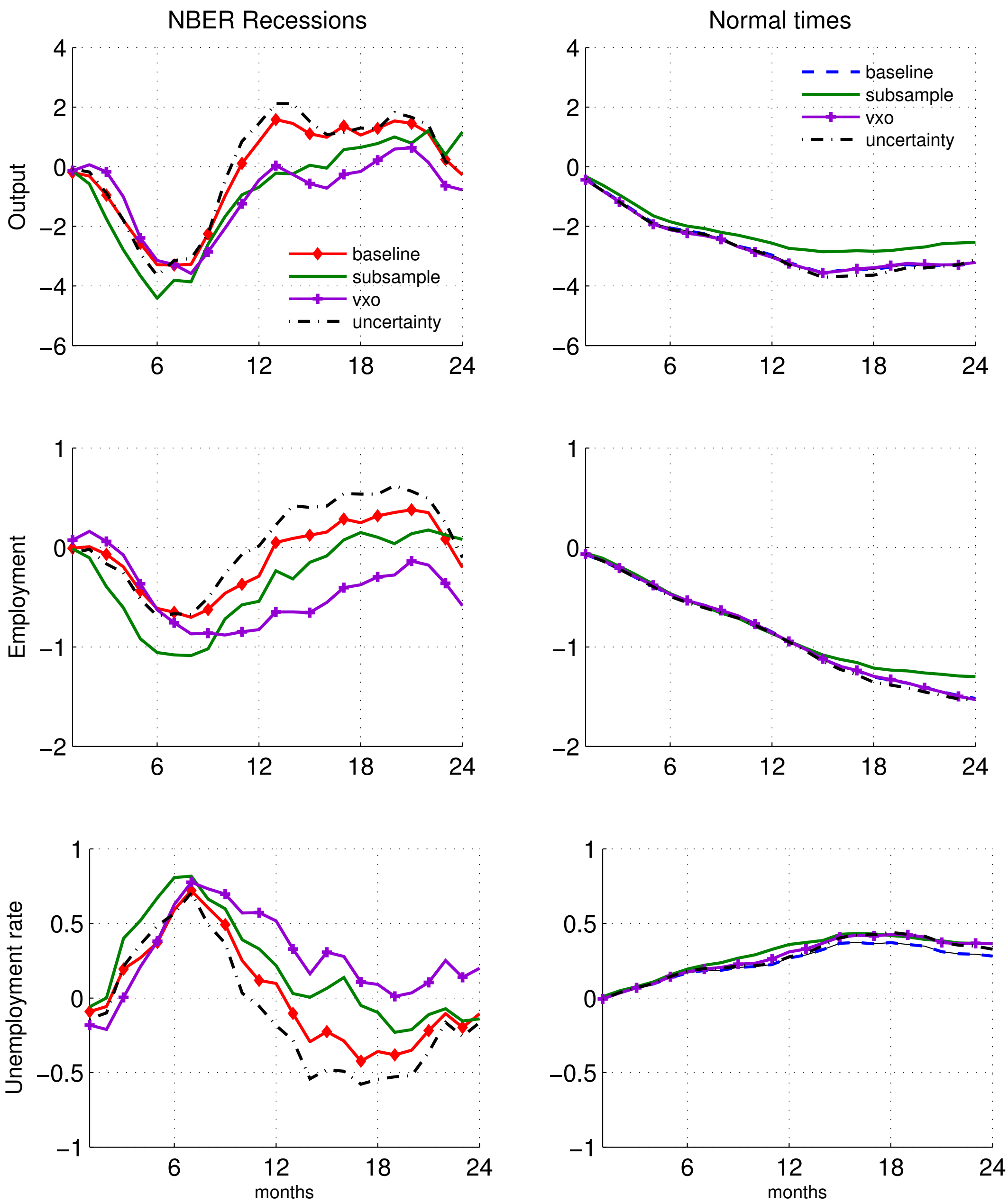
Notes: Impulse responses to a one-percent increase in the excess bond premium, calculated with nonlinear local projection methods à la Jordà (2005). Gray areas, and blue lines represent ± one standard error confidence bands in recessions and normal times, respectively.

Figure 4.4: Financial vs. Uncertainty shocks



Notes: Red lines: impulse responses to a one-standard deviation increase in the excess bond premium, calculated with nonlinear local projection methods. Blue-dashed lines: impulse responses to a one-standard deviation increase in the uncertainty indicator developed by Jurado et al. (2015), calculated with nonlinear local projection methods

Figure 4.5: Robustness checks



Notes: Impulse responses to a one-percent increase in the excess bond premium, calculated with nonlinear local projection methods. *Subsample*: estimates calculated over the sample 1973:1-2007:12. *VXO*: estimates calculated by substituting the S&P500 index with the VXO in the baseline vector of controls. *Uncertainty*: estimates calculated by adding the uncertainty indicator by Jurado et al. (2015) to the baseline vector of controls.

Appendix A

This Appendix refers to Chapter 2. First, it documents statistical evidence in favor of a nonlinear relationship between the endogenous variables included in the STVAR used to analyze uncertainty shocks. Next, it offers details on the estimation procedure of non-linear VARs. It then reports details on the computation of the GIRFs. Finally, it documents our robustness checks.

Statistical evidence in favor of non-linearities

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

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

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

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

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

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

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

3. Compute the test-statistic

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

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

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

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

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

Estimation of the non-linear VARs

Our model (2.1)-(2.4) is estimated via maximum likelihood.[17] Its log-likelihood reads as follows:

$$\log L = const + \frac{1}{2}\sum\nolimits_{t=1}^{T} \log|\boldsymbol{\Omega}_t| - \frac{1}{2}\sum\nolimits_{t=1}^{T} \boldsymbol{u}'_t\boldsymbol{\Omega}_t^{-1}\boldsymbol{u}_t \qquad \text{(A.2)}$$

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

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

Conditional on $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$, the model is linear in $\{\boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$. Then, for a given guess on $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$, the coefficients $\{\boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$ can be estimated by minimizing $\frac{1}{2}\sum_{t=1}^{T} \boldsymbol{u}_t' \boldsymbol{\Omega}_t^{-1} \boldsymbol{u}_t$. This can be seen by re-writing the regressors as follows:

$$\boldsymbol{W}_t = \left[\begin{array}{cccccc} F(z_{t-1})\boldsymbol{X}_{t-1} & (1 - F(z_{t-1}))\boldsymbol{X}_{t-1} & ... & F(z_{t-1})\boldsymbol{X}_{t-p} & 1 - F(z_{t-1}))\boldsymbol{X}_{t-p} \end{array} \right]$$

be the extended vector of regressors, and $\boldsymbol{\Pi} = \left[\begin{array}{cc} \boldsymbol{\Pi}_R(L) & \boldsymbol{\Pi}_E(L) \end{array} \right]$. Then, we can write $\boldsymbol{u}_t = \boldsymbol{X}_t - \boldsymbol{\Pi}\boldsymbol{W}_t'$. Consequently, the objective function becomes

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

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

$$vec\boldsymbol{\Pi}' = \left(\sum_{t=1}^{T} \left[\boldsymbol{\Omega}_t^{-1} \otimes \boldsymbol{W}_t'\boldsymbol{W}_t\right]\right)^{-1} vec\left(\sum_{t=1}^{T} \boldsymbol{W}_t'\boldsymbol{X}_t\boldsymbol{\Omega}_t^{-1}\right). \qquad \text{(A.3)}$$

This procedure iterates over different sets of values for $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$. For each set of values, $\boldsymbol{\Pi}$ is obtained and the $logL$ (A.2) computed.

Given that the model is highly non-linear in its parameters, several local optima might be present. Hence, it is recommended to try different starting values for $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$. To ensure positive definiteness of the matrices $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$, we focus on the alternative vector of parameters:

$$\boldsymbol{\Psi} = \{\gamma, chol(\boldsymbol{\Omega}_R), chol(\boldsymbol{\Omega}_E), \boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$$

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

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

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

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

The starting value $\boldsymbol{\Theta}^{(0)}$ is computed by working with a second-order Taylor approximation of the model (2.1)-(2.4), so that the model can be written as regressing $\boldsymbol{X}_t$ on lags of $\boldsymbol{X}_t$, $\boldsymbol{X}_t z_t$, and $\boldsymbol{X}_t z_t^2$. The residuals from this regression are employed to fit the expression for the reduced-form time-varying variance-covariance matrix of the VAR (see our paper) using maximum likelihood to estimate $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$. Conditional on these estimates and given a calibration for γ, we can construct $\boldsymbol{\Omega}_t$. Conditional on $\boldsymbol{\Omega}_t$, we can get starting values for $\boldsymbol{\Pi}_R(L)$ and $\boldsymbol{\Pi}_E(L)$ via equation (A.3).

The initial (diagonal matrix) $\boldsymbol{\Omega}_{\Psi}$ is calibrated to one percent of the parameter values. It is then adjusted "on the fly" for the first 3,000 draws to generate an acceptance rate close to 0.3. We employ $N = 10,000$ draws for our estimates, retaining 70% for inference.

As shown by CH, $\overline{\boldsymbol{\Psi}} = \frac{1}{N}\sum_{n=1}^{N} \boldsymbol{\Psi}^{(n)}$ is a consistent estimate of $\boldsymbol{\Psi}$ under standard regularity assumptions on maximum likelihood estimators. Moreover, the covariance matrix of $\boldsymbol{\Psi}$ is given by $\boldsymbol{V} = \frac{1}{N}\sum_{n=1}^{N}(\boldsymbol{\Psi}^{(n)} - \overline{\boldsymbol{\Psi}})^2 = var(\boldsymbol{\Psi}^{(n)})$, 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 et al. (1996). The algorithm features the following steps.

1. Consider the entire available observations, with sample size $t = 1962M7$, $\ldots, 2008M6$, with $T = 552$, and construct the set of all possible histories $\mathbf{\Lambda}$ of length $p = 13$:[18] $\{\lambda_i \in \mathbf{\Lambda}\}$. $\mathbf{\Lambda}$ 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 $z_{\lambda_i} \leq \overline{z} = -1.01\%$, then $\lambda_i \in \mathbf{\Lambda}^R$, where $\mathbf{\Lambda}^R$ is the set of all recessionary histories; if $z_{\lambda_i} > -\overline{z} = -1.01\%$, then $\lambda_i \in \mathbf{\Lambda}^E$, where $\mathbf{\Lambda}^E$ is the set of all expansionary histories.

3. Select at random one history λ_i from the set $\mathbf{\Lambda}^R$. For the selected history λ_i, take $\widehat{\mathbf{\Omega}}_{\lambda_i}$ obtained as:

$$\widehat{\mathbf{\Omega}}_{\lambda_i} = F\left(z_{\lambda i}\right)\widehat{\mathbf{\Omega}}_R + \left(1 - F\left(z_{\lambda_i}\right)\right)\widehat{\mathbf{\Omega}}_E, \tag{A.4}$$

   where $\widehat{\mathbf{\Omega}}_R$ and $\widehat{\mathbf{\Omega}}_E$ are obtained from the generated MCMC chain of parameter values during the estimation phase.[19] z_{λ_i} is the transition variable calculated for the selected history λ_i.

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

$$\widehat{\mathbf{\Omega}}_{\lambda_i} = \widehat{\mathbf{C}}_{\lambda_i}\widehat{\mathbf{C}}'_{\lambda_i} \tag{A.5}$$

   and orthogonalize the estimated residuals to get the structural shocks:

$$\mathbf{e}^{(j)}_{\lambda_i} = \widehat{\mathbf{C}}^{-1}_{\lambda_i}\widehat{\varepsilon}. \tag{A.6}$$

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

$$\mathbf{e}^{(j)*}_{\lambda_i} = \left\{\mathbf{e}^*_{\lambda_i,t}, \mathbf{e}^*_{\lambda_i,t+1}, \ldots, \mathbf{e}^*_{\lambda_i,t+h}\right\}, \tag{A.7}$$

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

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

[19] We consider the distribution of parameters rather than their mean values to allow for parameter uncertainty, as suggested by Koop et al. (1996).

6. Form another set of bootstrapped shocks which will be equal to (A.7) except for the k_{th} shock in $\mathbf{e}_{\lambda_i,t}^{(j)*}$ which is the shock we want to perturbate by an amount equal to δ. Denote the vector of bootstrapped perturbated shocks by $\mathbf{e}_{\lambda_i}^{(j)\delta}$.

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

$$\widehat{\varepsilon}_{\lambda_i}^{(j)*} = \widehat{\mathbf{C}}_{\lambda_i}\mathbf{e}_{\lambda_i}^{(j)*} \tag{A.8}$$

and

$$\widehat{\varepsilon}_{\lambda_i}^{(j)\delta} = \widehat{\mathbf{C}}_{\lambda_i}\mathbf{e}_{\lambda_i}^{(j)\delta}. \tag{A.9}$$

8. Use (A.8) and (A.9) to simulate the evolution of $\mathbf{X}_{\lambda_i}^{(j)*}$ and $\mathbf{X}_{\lambda_i}^{(j)\delta}$ and construct the $GIRF^{(j)}\left(h, \delta, \lambda_i\right)$ as $\mathbf{X}_{\lambda_i}^{(j)*} - \mathbf{X}_{\lambda_i}^{(j)\delta}$.

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

10. Calculate the GIRF conditional on history λ_i as

$$\widehat{GIRF}^{(i)}\left(h, \delta, \lambda_i\right) = B^{-1}\sum_{j=1}^{B} GIRF^{(i,j)}\left(h, \delta, \lambda_i\right). \tag{A.10}$$

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

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

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

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

Robustness analysis

Exogenous uncertainty shocks. Following Bloom (2009), our baseline analysis is conducted by working with 16 extreme realizations of uncertainty, identified as all the spikes which are 1.65 standard deviations above the mean of the HP-detrended VXO. Some of them, however, might be related to changes in the business cycle, e.g., the 1987 black Monday, or the 1982 economic recession. Hence, endogeneity may be at work and affect our impulse responses. To control for this possible endogeneity, we define an alternative volatility dummy by focusing on just 10 out of 16 extreme realizations of uncertainty, i.e., those which are associated to terror, war, or oil events as in Bloom (2009).[20] Figure A.1 reports the estimated GIRFs for industrial production and employment to this possibly more "exogenous" shock, along with the 68% and 95% confidence bands. As in the baseline case, our results show that the drop, rebound and overshoot path is present only when uncertainty shocks hits during recessions (though it is only marginally significant for employment).

Different calibration of the slope parameter. One potential drawback of our empirical exercise is that the slope parameter γ of the logistic function of our STVAR, which drives the smoothness with which the economy switches from one regime to another, is calibrated. Our baseline estimation uses a value of $\gamma = 1.8$, selected so that the economy spends 14% of the time in recessions, which is the frequency observed in our sample according to the NBER definition of recessions. To check the robustness of the baseline results to different values of γ, we have re-estimated the model using values of γ between 1.4 and 2.2, which imply a frequency of recessionary periods in the sample equal to 10% and 25%, respectively. Following Hansen (1999), we set to 10% the frequency corresponding to the minimum amount of observations each regime should contain to be identified. Our results are reported in Figure A.2, which plots our baseline GIRFs along with the GIRFs obtained with alternative calibrated values for γ. This robustness check clearly confirms our baseline results.

Unemployment as transition indicator. In our baseline exercise, the transition indicator z, which regulates the probability of being in a recession, is a

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

twelve-term moving average of the month-by-month growth rate of the industrial production index. An alternative indicator of the business cycle often considered by policymakers and academics is the unemployment rate. We then estimate a version of our STVAR model in which our baseline vector is augmented with the unemployment rate (ordered after the uncertainty dummy). Following some recent announcements by U.S. policymakers and the modeling choice in Ramey and Zubairy (2014), we classify periods in which the unemployment rate is over (under) 6.5% as recessionary (expansionary).[21] Figure A.3 documents our GIRFs, which deliver the same stylized facts as in our baseline analysis, i.e., a marked drop followed by a quick rebound and a temporary overshoot in industrial production and employment when uncertainty shocks occur in recessions, and a hump-shaped response of real activity in good times.

Uncertainty and financial risk. Stock and Watson (2012) point out that financial strains lead to higher uncertainty, which in turn increases financial risk. An implication of this relationship for our analysis is that the transmission of uncertainty shocks to the real economy might not be due to uncertainty *per se* but it might rather be driven by the level of financial stress in the economy. Caldara et al. (2014) provide empirical evidence in favor of larger real effects of uncertainty shocks in periods of high financial stress. A way to control for the presence of time-varying financial risk is to include a measure of credit spread in our VAR. Gilchrist and 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. Unfortunately, it is unavailable prior to 1973. Hence, its employment would considerably shorten our sample size, and this would be particularly problematic for the estimation of a richly-parameterized nonlinear VAR like ours. To circumvent this issue, we consider a large set of credit spread measures available for our full sample, as in Stock and Watson (2012), and choose the one which correlates the most with Gilchrist and Zakrajsek's measure of excess bond premium in the

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

sample 1973-2008. The selected credit spread measure is the difference between the Baa corporate bonds and the 10-year Treasury yield, whose correlation with Gilchrist and Zakrajsek's excess bond premium reads 0.67. We then add the Baa-10yr spread to our 8-variate VAR. Figure A.4 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 et al. (2013), who show that uncertainty shocks induce business cycle fluctuations even when controlling for indicators of time-varying risk aversion. Our results are also consistent with those in Caldara et al. (2014), who show that uncertainty shocks working via credit frictions may lead to a persistent decline in real and financial variables.

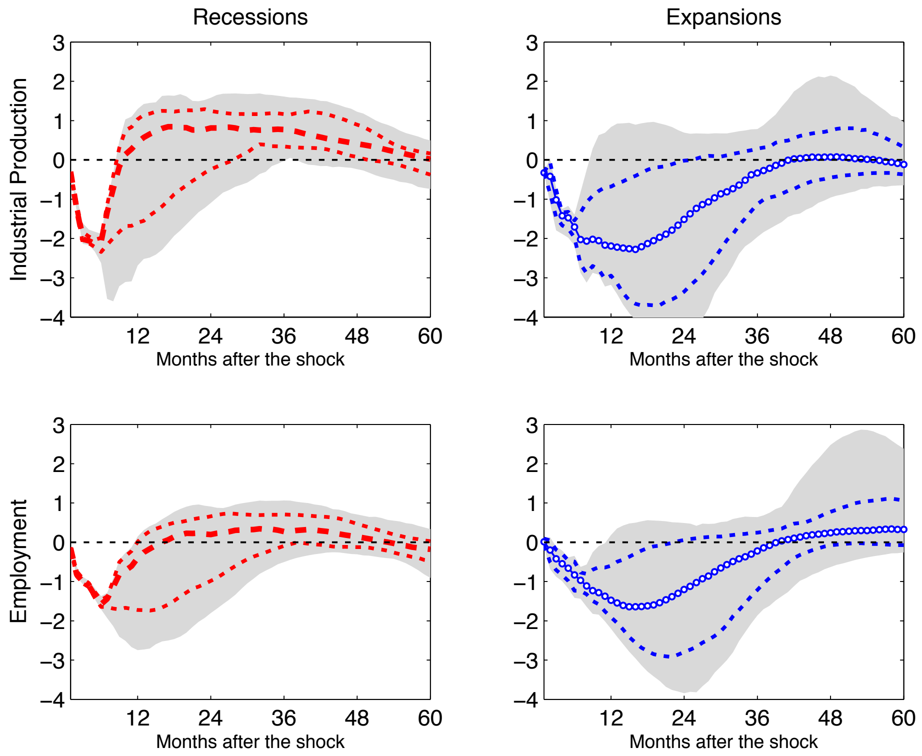
Uncertainty and housing. Since Iacoviello (2005),, there has been a revamped attention toward the relationship between housing market dynamics and the business cycle, attention which has intensified after the 2007-09 financial and real crisis. The housing market is particularly important for us in light of a recent paper by Furlanetto et al. (2014), who show that uncertainty shocks may play a minor role if one controls for housing shocks. We then add the real home price index computed by Robert Shiller to our baseline vector.[22] 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 A.5 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

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

variables in expansions, house prices do appear to moderate the response of real activity also in the short-run. These results are consistent with those in with Furlanetto et al. (2014), who show that part of the effects often attributed to uncertainty shocks may be an artifact due to the omission of house prices from VAR analysis. However, even when controlling for house prices, we find asymmetric responses of industrial production and employment (in terms of severity of the recession, speed of the recovery, and overall dynamics) over the business cycle.

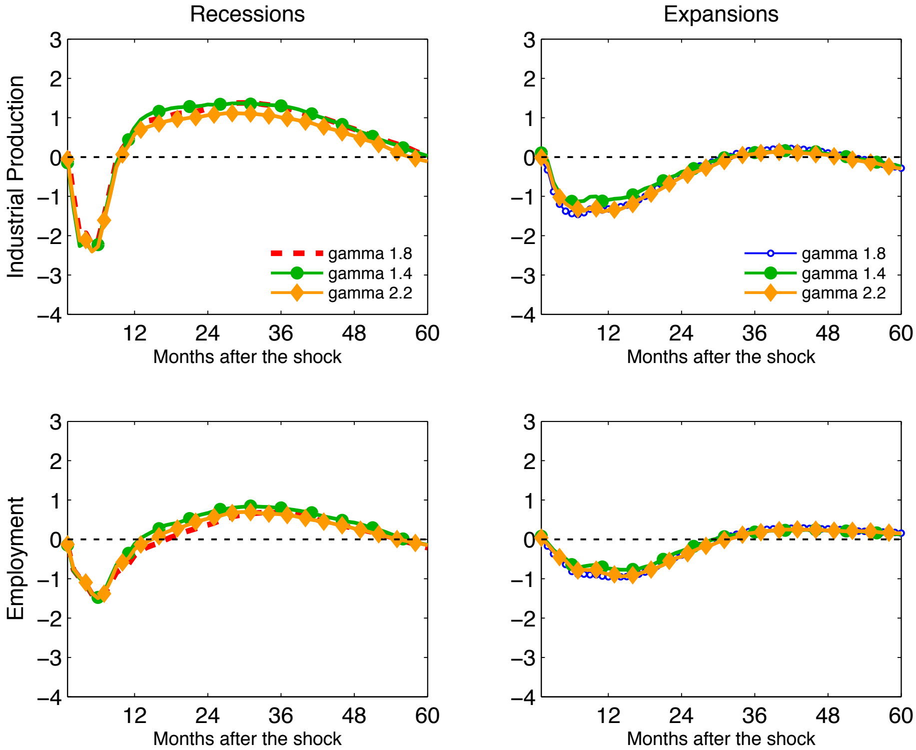
We propose an extra Figure to complement those presented in Chapter 2. Figure A.6 shows that a muted systematic policy response to our uncertainty dummy *per se* (via switching off only the systematic component related to uncertainty in the federal funds rate equation) would have a negligible impact on our baseline results obtained by allowing for an unconstrained response of the federal funds rate to an uncertainty shock.

Figure A.1: Effects of uncertainty shocks: exogenous dummy



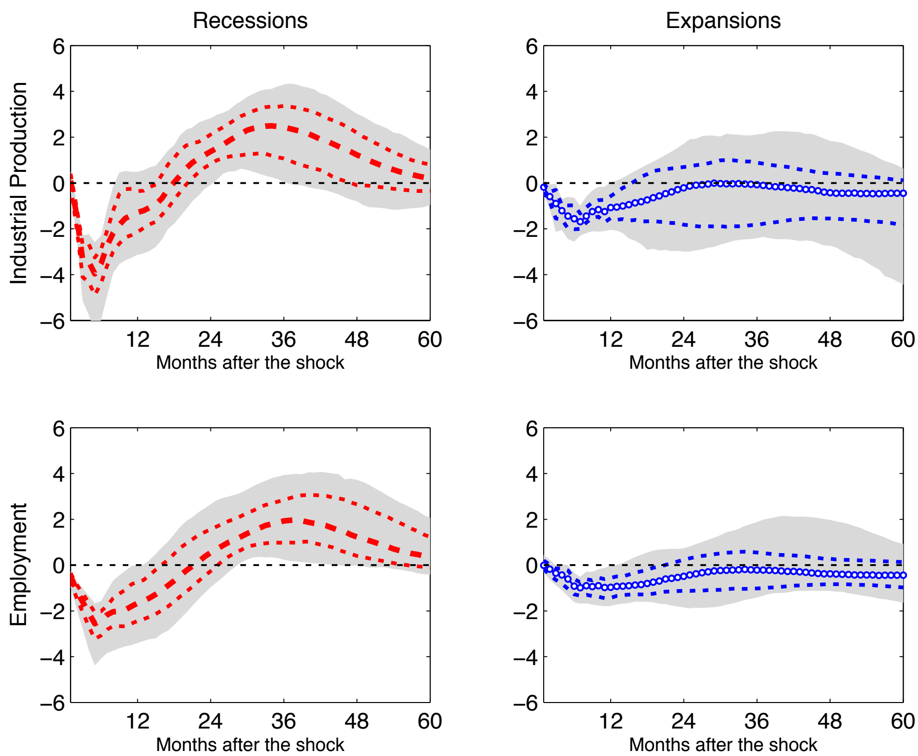
Notes: Uncertainty dummy constructed by considering extreme realizations of the VXO index related to terror, war, and oil events only. Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands. Gray areas: 95% confidence bands.

Figure A.2: Effects of uncertainty shocks: different calibrations



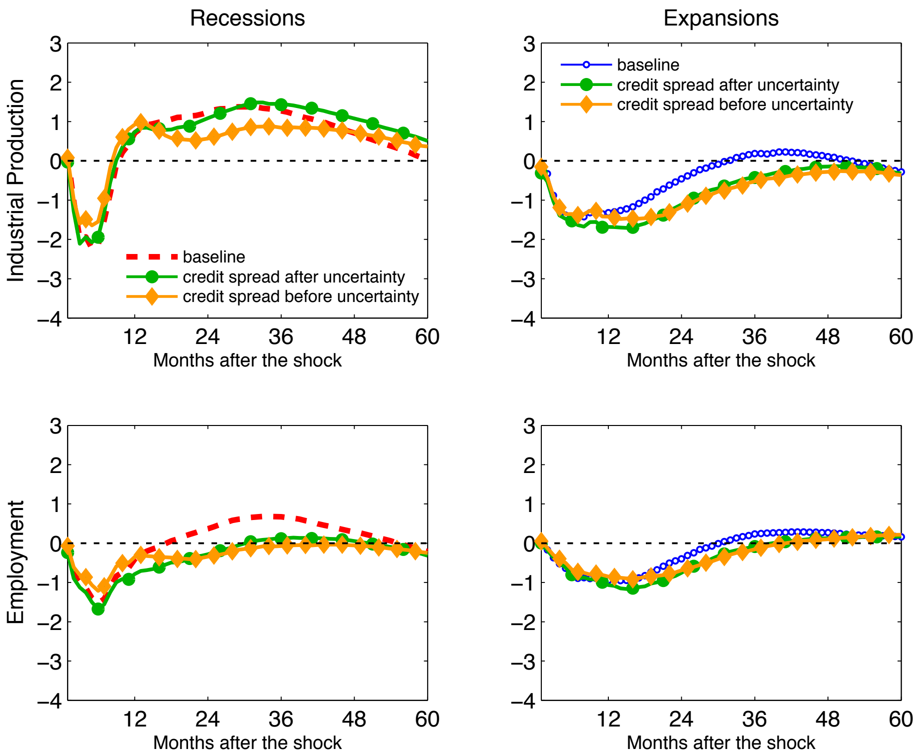
Notes: Impulse responses (median values) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed/blue dashed-circled lines: GIRFs conditional on $\gamma = 1.8$. Green lines: GIRFs conditional on $\gamma = 1.4$. Black lines: GIRFs conditional on $\gamma = 2.2$.

Figure A.3: Effects of uncertainty shocks: unemployment as transition variable



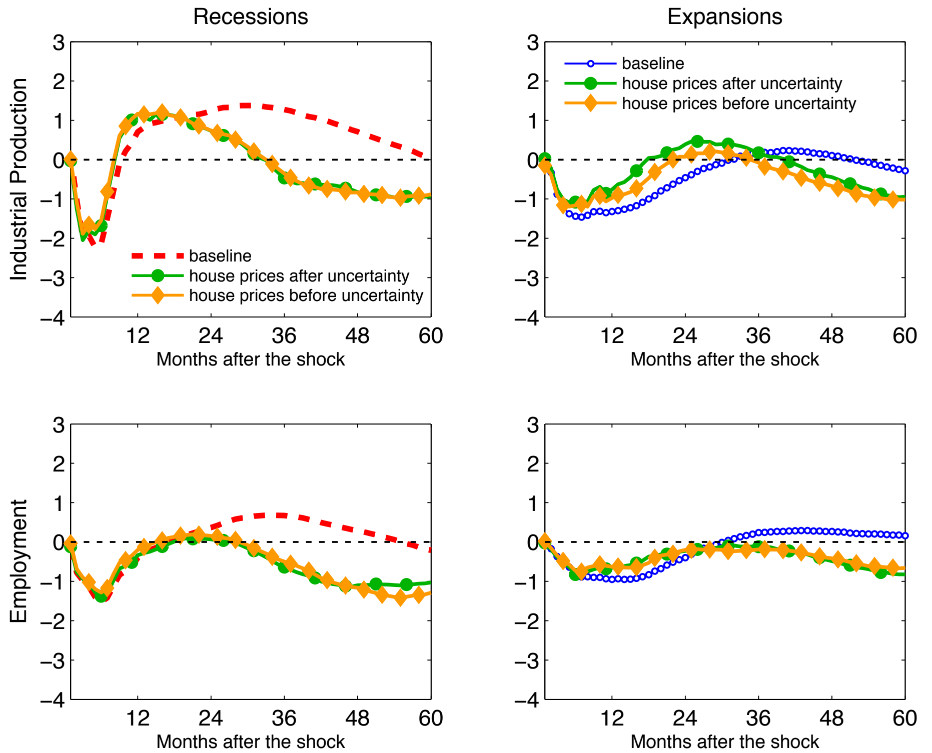
Notes: Unemployment added to our baseline model and employed and transition indicator. Realizations of unemployment above (below) 6.5% are associated to recessions (expansions). Impulse responses (median values and confidence bands) to a one-standard deviation uncertainty shock identified as described in the paper. Red dashed (blue dashed-circled) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (expansions). Dashed-dotted lines: 68% confidence bands. Gray areas: 95% confidence bands.

Figure A.4: Effects of uncertainty shocks: role of credit spreads



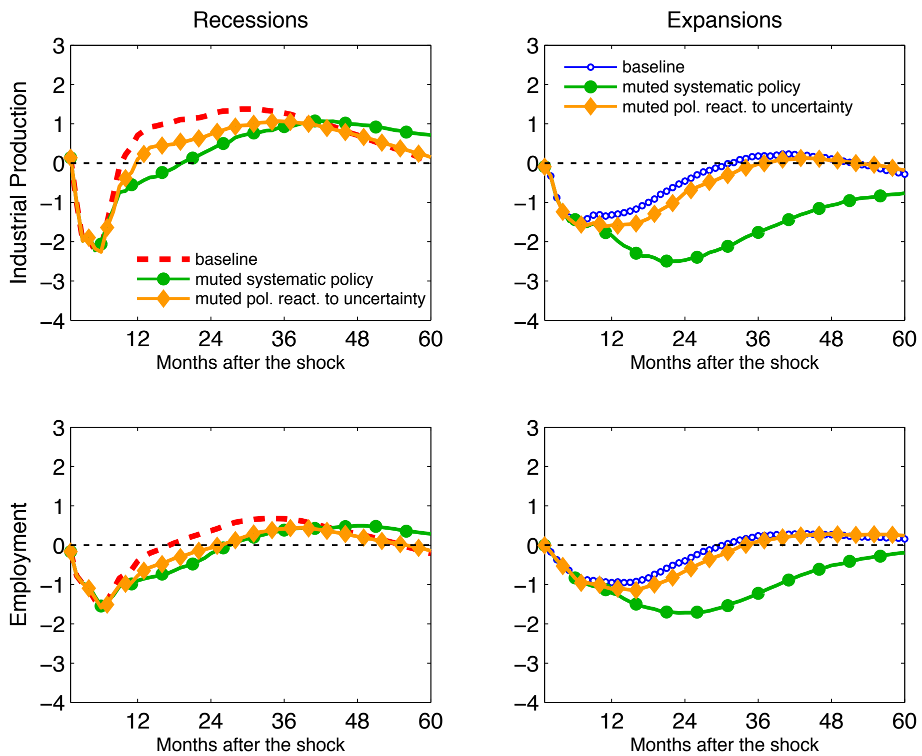
Notes: Median impulse responses to a one-standard deviation uncertainty in scenarios without/with credit spreads. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Responses of the models estimated with credit spreads are in green (when the spread is ordered after uncertainty) and orange (when the spread is ordered before uncertainty).

Figure A.5: Effects of uncertainty shocks: role of house prices



Notes: Median impulse responses to a one-standard deviation uncertainty in scenarios without/with real house price index. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Responses of the models estimated with the real house price index in green (when the index spread is ordered after uncertainty) and orange (when the index is ordered before uncertainty).

Figure A.6: Effects of uncertainty shocks: systematic monetary policy



Notes: Median impulse responses to a one-standard deviation uncertainty in scenarios with unconstrained/constrained monetary policy. Red dashed-dotted (blue dashed) lines: Responses computed with the Smooth-Transition VAR and conditional on recessions (non-recessionary phases). Counterfactual responses computed conditional on a muted systematic policy (fixed federal funds rate) in green-circled lines. Counterfactual responses computed conditional on a systematic policy not responding to the uncertainty indicator in orange-diamonded lines.

Appendix B

This Appendix refers to Chapter 3. It reports details on non-fundamentalness in fiscal SVARs and the role of expectations revisions. A number of robustness checks is also presented, in addition to those reported in the main text (Chapter 3, Section 3.6). Details on the computation of the factors employed in one of our robustness checks are provided as well. For the estimation of our nonlinear VARs, and the computation of the Generalized Impulse Responses, the reader is referred to Appendix A.

Non-fundamentalness and the role of expectations revisions

Structural VARs have been extensively employed to recover the impulse responses of key macroeconomic variables to fiscal shocks. The implicit assumption when working with SVARs is that their VMA representations are invertible in the past, or in other words that they are fundamental Wold representations of the vector of interest. When such conditions are met, the econometrician has the same information set as the economic agents and can recover the structural shocks by conditioning the VAR estimates on past and current observables.

Fiscal foresight and non-fundamentalness. It is well known, however, that in presence of fiscal foresight (and news shocks in general), this assumption may not hold and fundamental shocks to fiscal policy cannot be recovered from past and current observations. The non-fundamentalness is due to the different discount patterns employed by agents and the econometrician: while the agents attach a larger weight to realizations of the shock occurring in the past, the econometrician discounts in the usual way, and attach lower weights to past observations compared to more recent ones, the reason being that the econometrician's information set lags that of the agents (Leeper et al. (2013)). Hence, in presence of a non-fundamental process, an econometrician not endowed with a large enough information set will not be able to correctly recover the impulse response function of a variable of interest to the structural shock.

How severe is the non-fundamentalness problem? As pointed out by Sims (2012) and Beaudry and Portier (2013), the answer to this question depends on the very same process(es) one wants to model. In terms of fiscal shocks, Leeper et al. (2013) convincingly show that when non-fundamentalness holds the magnitude of the error is quite severe. They employ two DSGE models of the business cycle - a calibrated RBC model and an estimated DSGE model with a number of nominal and real frictions à la Smets and Wouters (2007) - to quantify the mistake an econometrician makes when failing to model fiscal foresight. They show that fiscal multipliers may turn out to be off by hundreds of percent, and can even get the wrong sign.[23] Moreover, Forni and Gambetti (2011) and Ramey (2011b) show that government spending shocks estimated with standard fiscal VARs can be predicted, evidence supporting the case for non-fundamentalness.

VAR analysis in presence of anticipated shocks. In this section, we propose a framework to fix ideas about the relationship between fiscal foresight and non-fundamentalness and to discuss how the problem can be tackled. To this aim, consider the model

$$y_t = \delta E_t y_{t+1} + g_t + \omega_t \tag{B.1}$$

$$g_t = \varepsilon_{t-h} + \phi_1 \varepsilon_{t-h-1} + \ldots + \phi_{q-h} \varepsilon_{t-q} = \Phi(L)\varepsilon_t \tag{B.2}$$

where $|\delta| < 1, \phi_i > 0 \ \forall i, h \geq 0, q \geq h$. The forward-looking process y_t - say, output measured as log-deviations from its trend - is affected by the exogenous stationary process g_t - say, a fiscal shock - plus a random shock ω_t, which is assumed to capture non-fiscal spending shocks affecting output and which is assumed to be *i.i.d.* with zero mean and unit variance. The process (B.2) features an unanticipated contemporaneous shock ε_t as well as anticipated shocks ε_{t-h} for $h > 0$, where h is the number of foresight periods. The latter are known in advance by rational agents, i.e., agents foresee fiscal moves

[23] Leeper et al. (2013) model fiscal foresight associated to tax policies. Schmitt-Grohe and Uribe (2012) find government spending shocks anticipated up to eight quarters to be responsible of about 60% of the overall variability of government spending.

occurring h-periods ahead. The process g_t is a news-rich process if $|\phi_i| > 1$ for at least one $i > 0$ (Beaudry and Portier (2013)). In all cases, $\{\varepsilon_{t-j}\}_{j=h}^{q}$ is said to be fundamental for g_t if the roots of the polynomial $\Phi(L)$ lie outside the unit circle (Hansen and Sargent (1991)). Importantly, if the g_t process is non-fundamental, its structural shock is not recoverable by employing current and past realizations of g_t only. Consequently, its impulse response to an anticipated shock as well as the dynamic responses of other variables – in this example, y_t – will not be correctly recovered by estimating a VAR in y_t and g_t.

For simplicity, and without loss of generality, consider the case in which the unanticipated component is zero, i.e., $h > 0$. We assume that agents have rational expectations and observe news shocks without noise.[24] To begin with, consider the case $h = q = 1$, so that[25]

$$g_t = \varepsilon_{t-1}$$

Under rational expectations, the solution for the process y_t reads

$$y_t = \delta\varepsilon_t + \varepsilon_{t-1} + \omega_t \tag{B.3}$$

The VMA representation of the vector (y_t, g_t) is:

$$\begin{bmatrix} y_t \\ g_t \end{bmatrix} = \underbrace{\begin{bmatrix} \delta & 1 \\ 0 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix} \tag{B.4}$$

The VMA representation (B.4) is fundamental if all the roots of $|\sum_{i=0}^{q} A_i z^i|$ in absolute value lie outside the unit circle. It is easy to verify that in this case the condition is not met, since one gets $|z| = 0$. Hence, in this economic system, inference based on an estimated VAR which includes y_t and g_t only would be incorrect.

[24]Forni et al. (2013) investigate the case in which economic agents deal with noisy news. Agents are assumed to receive signals regarding the future realization of TFP shocks. Since such signals are noisy, agents react not only to genuinely informative news, but also to noise shocks that are unrelated to economic fundamentals. They find that such noise shocks explain about a third of the variance of output, consumption, and investment. We leave the quantification of the role of noise shocks in the fiscal context to future research.

[25]This process is termed "degenerated news-rich process" by Beaudry and Portier (2013). For an application, see Fève, Matheron, and Sahuc (2009).

Importantly, if a variable η_t added to the econometrician's information set contains "enough" information about the structural shock ε_t, then the VMA representation becomes invertible and the non-fundamentalness issue is circumvented (Giannone and Reichlin (2006), Sims (2012), Beaudry and Portier (2013), and Forni and Gambetti (2014)). Based on this argument, a way to tackle the issue of non-fundamentalness is to include in the VAR a variable which is informative about the effects that news shocks exert on the endogenous variables of interest.[26] In the case of fiscal foresight, then, one has to find a measure of anticipated fiscal spending shocks to correctly gauge the reaction of output to such shocks. It is easy to show that, in the context of model ($B.4$), replacing g_t with its one-step-ahead forecast, i.e. $E_t g_{t+1}$, leads to a fundamental VMA representation for the vector $(y_t, E_t g_{t+1})$:

$$\begin{bmatrix} y_t \\ E_t g_{t+1} \end{bmatrix} = \underbrace{\begin{bmatrix} \delta & 1 \\ 1 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix}$$

This can be seen by verifying that $|A_0 + A_1 z| \neq 0$, $\forall z$.

It is important to notice that expectations *per se* do not necessarily provide a correct measure of fiscal shocks. Consider the case $h = 1$ and $q = 2$, so that

$$g_t = \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} \tag{B.5}$$

The VMA representation for (y_t, g_t) is:

$$\begin{bmatrix} y_t \\ g_t \end{bmatrix} = \underbrace{\begin{bmatrix} \delta(1+\delta\phi_2) & 1 \\ 0 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} 1+\delta\phi_2 & 0 \\ 1 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} \phi_2 & 0 \\ \phi_2 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} \varepsilon_{t-2} \\ \omega_{t-2} \end{bmatrix}$$

[26] Alternative ways of dealing with this issue have been proposed in the literature. Lippi and Reichlin (1993) propose to use Blaschke matrices to "flip" the roots that are outside the unit circle in order to recover the fundamental representation of the process of interest. Alessi, Barigozzi, and Capasso (2011) and Forni and Gambetti (2014) propose to augment the VAR with information coming from factors extracted from large datasets. However, in the context of fiscal foresight, non-fundamentalness has a clearly detectable cause, i.e., omitted information due to the absence in the VAR of an informative measure regarding (variations concerning) future fiscal spending moves (Leeper et al. (2013), Beaudry and Portier (2013)). Hence, a direct, fiscal-related way of tackling the presence of foresight appears to be desirable.

which is non-fundamental since the roots of $|A_0 + A_1 z + A_2 z^2|$ are $z_1 = 0$ and $|z_2| = \phi_2^{-1}$. In this case, adding the one-step-ahead forecast of g_t does not solve the problem. The VMA representation for the vector $(y_t, E_t g_{t+1})$ is given by:

$$\begin{bmatrix} y_t \\ E_t g_{t+1} \end{bmatrix} = \underbrace{\begin{bmatrix} \delta(1+\delta\phi_2) & 1 \\ 1 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} 1+\delta\phi_2 & 0 \\ \phi_2 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} \phi_2 & 0 \\ 0 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} \varepsilon_{t-2} \\ \omega_{t-2} \end{bmatrix}$$

which is non-fundamental if $|\phi_2| > 1$.

The role of forecast revisions. Expectation *revisions* help solving the problem. Consider the variable $\eta_t = E_t g_{t+1} - E_{t-1} g_{t+1}$. The VMA representation for the vector (y_t, η_t) is given by:

$$\begin{bmatrix} y_t \\ \eta_t \end{bmatrix} = \underbrace{\begin{bmatrix} \delta(1+\delta\phi_2) & 1 \\ 1 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} 1+\delta\phi_2 & 0 \\ 0 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} \phi_2 & 0 \\ 0 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} \varepsilon_{t-2} \\ \omega_{t-2} \end{bmatrix}$$

which is fundamental, since $|A_0 + A_1 z + A_2 z^2| \neq 0$, $\forall z$. It can recursively be shown that expectations revisions of the form $E_t g_{t+1} - E_{t-1} g_{t+1}$ help tackling the issue of non-fundamentalness for any $q > h = 1$.

However, when $h > 1$ is unknown, even expectation revisions are not of help. Consider for example the process:

$$g_t = \varepsilon_{t-2} + \phi_3 \varepsilon_{t-3}.$$

This is not an unlikely case, given that typically the implementation lag for fiscal policy decisions is longer than one quarter. The VMA representation for the vector (y_t, g_t) is:

$$\begin{bmatrix} y_t \\ g_t \end{bmatrix} = \underbrace{\begin{bmatrix} \delta^2(1+\delta\phi_3) & 1 \\ 0 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} \delta(1+\delta\phi_3) & 0 \\ 0 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix}$$
$$+ \underbrace{\begin{bmatrix} 1+\delta\phi_3 & 0 \\ 1 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} \varepsilon_{t-2} \\ \omega_{t-2} \end{bmatrix} + \underbrace{\begin{bmatrix} \phi_3 & 0 \\ \phi_3 & 0 \end{bmatrix}}_{A_3} \begin{bmatrix} \varepsilon_{t-3} \\ \omega_{t-3} \end{bmatrix}$$

and the roots of $|A_0 + A_1 z + A_2 z^2 + A_3 z^3|$ are $z_{1,2} = 0, |z_3| = \phi_3^{-1}$. Using expectations revisions as before is in this case uninformative, since $E_t g_{t+1} - E_{t-1} g_{t+1} = 0$.

Knowing exactly the number of anticipation periods h would solve the problem, since $E_t g_{t+2} - E_{t-1} g_{t+2} = \varepsilon_t$. However, h is typically unknown. To solve this issue, Gambetti (2012a) proposes to use an alternative, more general measure of expectations revisions, i.e., the news variable defined as:

$$\eta_{1J}^g = \sum_{j=1}^{J} \left(E_t g_{t+j} - E_{t-1} g_{t+j} \right),$$

with J large enough to ensure that $J \geq h$. It can be shown that setting $J \geq 2$ leads to a fundamental representation associated with the vector (y_t, η_{1J}^g), since $\eta_{12}^g = \varepsilon_t$, $\eta_{13}^g = (1+\phi_3)\,\varepsilon_t$ and so on. In our example, if $J = 2$, the VMA representation for (y_t, η_{12}^g) is:

$$\begin{bmatrix} y_t \\ \eta_{12}^g \end{bmatrix} = \underbrace{\begin{bmatrix} \delta^2(1+\delta\phi_3) & 1 \\ 1 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} \delta(1+\delta\phi_3) & 0 \\ 0 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix}$$
$$+ \underbrace{\begin{bmatrix} 1+\delta\phi_3 & 0 \\ 0 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} \varepsilon_{t-2} \\ \omega_{t-2} \end{bmatrix} + \underbrace{\begin{bmatrix} \phi_3 & 0 \\ 0 & 0 \end{bmatrix}}_{A_3} \begin{bmatrix} \varepsilon_{t-3} \\ \omega_{t-3} \end{bmatrix},$$

where the determinant of $|A_0 + A_1 z + A_2 z^2 + A_3 z^3| \neq 0$, $\forall z$.[27]

In general, when the period of foresight h is unknown or uncertain, the solution would be to include in the VAR a measure of expectations revisions

[27] It is important to notice that, though related in spirit, Perotti's (2011) variable $(E_t g_t - E_{t-1} g_t) + (E_t g_{t+1} - E_{t-1} g_{t+1})$ is uninformative in a case like this, because it does not contain any valuable information about ε_t, i.e., it is equal to zero. The reason is that the forecast horizon covered by such a variable is too short.

taken over a long enough horizon:

$$\eta_{1J}^{g} = \sum_{j=1}^{J} \left(E_t g_{t+j} - E_{t-1} g_{t+j} \right) = \begin{cases} \left(1 + \phi_1 + ... + \phi_{J-h}\right) \varepsilon_t \text{ if } J < q \\ \left(1 + \phi_1 + ... + \phi_{q-h}\right) \varepsilon_t \text{ if } J \geqslant q \end{cases} \tag{B.6}$$

(where $\phi_0 = 0$), which correctly identifies the news shock if $J \geqslant h$.

Further robustness checks

Our baseline analysis suggests that evidence in favor of countercyclical fiscal multipliers is borderline when we condition upon recessions vs. expansions, while it becomes much clearer and solid when conditioning upon extreme events. Chapter 3 presents the robustness checks conducted by considering a different measure of fiscal spending news (obtained by regressing the baseline fiscal news variable on a constant and a number of controls), a different ordering of the variables in our VAR, the debt/GDP ratio as an extra-variable in our VAR as well as the transition indicator, and a longer sample (an analysis that we conducted by working with Ramey's (2011) indicator of fiscal spending news). Table 2.6 documents the robustness of our results by collecting multipliers computed over a 4-year horizon. Table B.1 in this Appendix confirms the solidity of our results conditional on a 2-year horizon.

We then conduct a variety of robustness checks to verify the solidity of our results. We present the robustness checks below and discuss our results by referring to Table B.2, which summarizes the outcome.

FAVAR. Our baseline VAR is meant to parsimoniously model a set of key macroeconomic indicators crucial to quantify fiscal spending multipliers. A further reason to prefer a parsimonious VAR is the somewhat limited number of observations available to construct the measures of forecast revisions we deal with, as well as the nonlinearity of our framework, in which a large number of VAR coefficients is estimated. Despite its advantages, a parsimonious model might suffer from an omitted-variable problem, which may bias the results of our baseline scenario. In particular, reactions of variables like the real interest rate and the real exchange rate may be important for the computation of the fiscal spending multipliers. Interactions between financial variables and real aggregates may also be at work conditional on our fiscal news shock. We tackle this informational insufficiency issue by adding to our VAR a factor extracted from a large dataset, so to purge the (possibly bias-contaminated) estimated shocks. This strategy leads us to deal with a nonlinear version of the Factor-Augmented VAR (FAVAR) model popularized, in the monetary policy context, by Bernanke, Boivin, and Eliasz (2005). In particular, we consider a large dataset composed of 150 time-series, all reported in Table B.3, along with their respective transformations, and extract the common factors which maximize the explained variance of such series. Following Stock and Watson (2012) in their recent analysis on the drivers of the post-WWII U.S. economy, we extract six common factors and then focus on the fiscal FAVAR $\boldsymbol{X}_t^{favar} = [f_t^1, G_t, T_t, Y_t, \eta_{13,t}^g]'$, where "$f_t^1$" is the factor explaining the largest share of variance of the series in our enlarged database. Due to the limited number of degrees of freedom, we focus on a VAR model with two lags, a choice that we will keep for all the five-variate VARs we estimate to check the robustness of our baseline results. Results on the difference of the fiscal multiplier in different states of the economy are collected in Table B.2 under the label "FAVAR".

Expectation revisions of output. Our baseline results rests on the identifying assumption that our fiscal news variable carries valuable information regarding fiscal shocks which may have led economic agents to revise their expectations of future public spending. However, such revisions may have been undertaken because of "news" about some other shocks. Suppose news about the future evolution of technology become part of agents' information sets between time $t-1$ and t. This might induce agents to revise their expectations regarding future realizations of output. Given the link between output and public spending (due to, e.g., automatic stabilizers), such revisions may induce agents to further revise their expectations of future fiscal spending as well. Hence, revisions of future fiscal spending may be triggered not only by anticipated fiscal shocks, but also by anticipated shocks of a different nature (say, news concerning technology). We tackle this issue by modeling the five-variate VAR $\boldsymbol{X}_t^Y = [\eta_{13,t}^Y, G_t, T_t, Y_t, \eta_{13,t}^g]'$, where η_{13}^Y stands for the sum of forecast revisions regarding future real GDP. The construction of this variable replicates the construction of η_{13}^g explained in Chapter 3, section 3.2, eq.(3.4). We put η_{13}^Y before η_{13}^g in the vector to control for the effects exerted by contemporaneous movements in η_{13}^Y on η_{13}^g.[28] Notice that one can interpret this robustness check as pointing to the role of an identified factor omitted in the baseline analysis,

[28]Given the choice of a Cholesky-identification scheme, the ordering of the variables before η_{13}^g is irrelevant for the computation of our impulse responses to a fiscal news shock.

i.e., the role of expectation revisions on output. Table B.2 collects our results under the label "η_{13}^{Y}".

Contemporaneous effects of η_{13}^{g} shocks. Our approach features a recursive identification scheme. Our choice aims at purging the movements of the η_{13}^{g} fiscal variable by accounting for its systematic response to government spending, tax revenues, and output. However, such a choice has an obvious limitation, i.e., output is not allowed to move immediately after the realization of the news shock. We then perform a robustness check by focusing on the five-variate VAR $\boldsymbol{X}_t^{\eta^g} = [\eta_{13,t}^{g}, \eta_{13,t}^{Y}, G_t, T_t, Y_t]'$, which enables fiscal news shocks to move output immediately. We keep the measure of news on output to control for the systematic movements of fiscal news due to output news. Notice that this VAR allows for (without forcing) an immediate response of fiscal spending G, which would however be inconsistent with the idea of a news shock. Interestingly, a look at our GIRFs (available upon request) suggest that public spending moves in neither of the two states. This result confirms the potential of the measure of fiscal news shocks employed in this paper to capture anticipated fiscal shocks, i.e., shocks which do not exert an immediate impact on public spending but, possibly, trigger an immediate reaction of output.[29] As for the difference in fiscal multipliers, the results are presented in Table B.2 under "η_{13}^{g} first".

Expectation revisions of total government spending. Our baseline analysis hinges upon a η_{13}^{g}, which is based on revisions of forecasts over the growth rates of federal spending only. However, expectations concerning levels of future fiscal spending regarding state and local expenditures are also available. We then construct levels of expected total spending and compute the growth rates of such expected realizations. We use this variable as a proxy of the expected growth rates of total fiscal spending that are not readily available in the SPF dataset. We then use this proxy as an alternative to our η_{13}^{g} variable in our vector. Our results are collected in Table B.2 under the label "η_{13}^{g} total".

Ricco's news indicator. In a recent paper, Ricco (2014) shows that the news variable we employ in our study to account for fiscal foresight may

[29]Interestingly, our impulse responses suggest that output moves immediately in recessions, while its contemporaneous response is not significant when expansions are considered (IRFs not shown for the sake of brevity, but available upon request). The contemporaneous zero reaction of public spending to changes in output is consistent with the evidence on the zero contemporaneous output elasticity of government spending in the U.S. surveyed by Caldara and Kamps (2012).

be affected by aggregation bias. Our measure is based on forecast revisions constructed by appealing to location measures (e.g., mean, median) of the distribution of the forecasts (across forecasters). However, since the composition of the pool of respondents to the SPF changes over time, one problem related with our measure is that use of measures of central tendency might induce a non negligible bias if the distribution of forecast revisions is skewed. The resulting aggregation bias may in principle imply important quantitative effects for the computation of fiscal multipliers. Ricco (2014) circumvents this problem by constructing a measure of news based on the revisions of expectations of each individual forecaster in the pool, whose forecast is available for at least two consecutive quarters. Ex-post aggregation of such revisions gives rise to a "microfounded" measure of aggregate news. Even though the correlation between the two measures of fiscal anticipation in our sample is quite high (it reads 0.84), it is of interest to repeat our exercise by employing Ricco's news measure as an alternative to our η^g_{13}.[30] Results are documented in Table B.2 under "η^g_{13} à la Ricco".

Overall, two main messages arise by from the results reported in Table B.2. First, the "Normal" scenarios generally points to a rather fragile evidence of countercyclical fiscal multipliers. The most evident exception is the case of the news variable *à la* Ricco, which leads to larger multipliers in recessions. This is in line with the fact that, in presence of a skewed distribution of forecast revisions, our measure of news would downward-bias the estimated fiscal multipliers (see Ricco (2014) for a detailed explanation of the sources of this bias). Second, our extreme events analysis robustly supports larger multipliers in recessions. Hence, our results corroborate a recent statement by Blanchard and Leigh (2013) on the magnitude of fiscal multipliers and the effectiveness of fiscal stabilization policies in periods of substantial economic slack. These results lend support also to Parker's (2011) call for empirical models able to capture the possible countercyclicality of fiscal multipliers.

Computation of the factors for the FAVAR approach

We follow Stock and Watson (2012) to estimate the factors from a large unbalanced data set of US variables. Let $\boldsymbol{X}_t = (X_{1t}, \dots, X_{nt})'$ denote a vector of n macroeconomic time series, with $t = 1, \dots, T$. X_{it} is a single time series

[30] We thank Giovanni Ricco for providing us with his measure of fiscal news.

transformed to be stationary and to have mean zero. The dynamic factor model expresses each of the n time series as the sum of a common component driven by r unobserved factors $\boldsymbol{F}_t$ plus an idiosyncratic disturbance term e_{it}:

$$\mathbf{X}_t = \mathbf{\Lambda}\mathbf{F}_t + \mathbf{e}_t \tag{B.7}$$

where $\boldsymbol{e}_t = (e_{1t}, \ldots, e_{nt})'$ and $\mathbf{\Lambda}$ is the $n \times r$ matrix of factor loadings.

The factors are assumed to follow a linear and stationary vector autoregression:

$$\mathbf{\Phi}(L)\,\boldsymbol{F}_t = \boldsymbol{\eta}_t \tag{B.8}$$

where $\mathbf{\Phi}(L)$ is a $r \times r$ matrix of lag polynomials with the vector of r innovations $\boldsymbol{\eta}_t$. Stationarity implies that $\mathbf{\Phi}(L)$ can be inverted and $\boldsymbol{F}_t$ has the moving average representation:

$$\boldsymbol{F}_t = \mathbf{\Phi}(L)^{-1}\,\boldsymbol{\eta}_t. \tag{B.9}$$

With n large, under the assumption that there is a single-factor structure, simple cross-sectional averaging provides an estimate of $\boldsymbol{F}_t$ good enough to treat $\widehat{\boldsymbol{F}}_t$ as data in a regression without a generated regressor problem. With multiple factors, Stock and Watson (2002) show that a consistent estimate of $\boldsymbol{F}_t$ is obtained using principal components.

Our data set is standard in the recent literature on factor models (see Stock and Watson, 2012, and Forni and Gambetti, 2014). It contains an unbalanced panel of 150 quarterly series, with starting date 1947Q1 and end date 2012Q3. The data are grouped into 12 categories: NIPA variables (31); industrial production (16); employment and unemployment (14); housing starts (6); inventories, orders and sales (12); prices (15); earnings and productivity (13); interest rates (10); money and credit (12); stock prices (5); exchange rates (7); and other (9). Earnings and productivity data include TFP-adjusted measures of capacity utilization introduced by Basu, Fernald, and Kimball (2006). The category labeled "other" includes expectations variables.

The transformation implemented for the series to be stationary with zero mean are reported in Table B.3. The factors were estimated using principal components as in Stock and Watson (2012). The assumption that the factors can be estimated with no breaks over the period 1947Q2-2012Q3 is motivated by the findings of Stock and Watson (2002), who show that the space spanned by the factors can be estimated consistently even if there is instability in $\mathbf{\Lambda}$.

Table B.1: Fiscal spending multipliers: Extreme events. Different Scenarios

	Peak			
Scenario/State	*Strong exp.*	*Deep rec.*	*Weak exp.*	*Mild rec.*
Baseline	0.79 [0.45,1.09]	2.27 [1.45,2.93]	1.09 [0.72,2.31]	2.72 [1.32,3.96]
$\widetilde{\eta}_{13}^{g}$ *last*	0.45 [0.20,0.63]	3.37 [2.03,4.34]	1.05 [0.48,3.77]	3.15 [1.50,4.21]
$\widetilde{\eta}_{13}^{g}$ *first*	1.21 [0.25,1.94]	3.05 [1.84,6.72]	2.17 [0.93,4.97]	3.64 [1.58,6.80]
Long sample (Ramey's news)	0.47 [0.19,0.80]	2.83 [1.56,5.92]	0.68 [0.23,1.56]	2.59 [1.22,6.60]
	High debt	*Mod.$^{+}$ debt*	*Mod.$^{-}$ debt*	*Low debt*
Debt/GDP ratio	1.79 [1.62,2.00]	1.35 [0.68,2.15]	1.95 [1.68,2.44]	2.08 [1.54,2.78]

	Sum			
Scenario/State	*Strong exp.*	*Deep rec.*	*Weak exp.*	*Mild rec.*
Baseline	-2.26 [-5.63,-0.78]	1.60 [0.18,2.63]	-1.40 [-3.91,0.65]	1.38 [-0.48,3.02]
$\widetilde{\eta}_{13}^{g}$ *last*	-0.42 [-1.56,0.13]	3.65 [2.09,4.99]	0.76 [-0.62,3.86]	3.17 [0.99,4.43]
$\widetilde{\eta}_{13}^{g}$ *first*	0.76 [-1.02,2.20]	3.95 [1.59,8.72]	2.35 [0.38,5.43]	3.95 [1.27,8.17]
Long sample (Ramey's news)	0.43 [0.06,0.85]	2.49 [0.19,8.66]	0.02 [-1.77,1.08]	2.21 [-0.68,9.72]
	High debt	*Mod.$^{+}$ debt*	*Mod.$^{-}$ debt*	*Low debt*
Debt/GDP ratio	2.43 [2.13,2.72]	0.99 [0.36,1.77]	2.29 [1.93,2.59]	2.07 [1.43,2.54]

Notes: Two-year integral multipliers. Figures conditional on our VAR analysis with GIRFs conditional on four different sets of initial conditions. Log-values of the impulse response of output rescaled by the sample mean of output over public spending (both taken in levels) to convert percent changes in dollars.

Table B.2: Fiscal spending multipliers: Shares of multipliers larger in recessions

		Peak				
Scenario/Horizon	*Cycle*	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Baseline	*Normal*	87.80	90.80	90.00	90.60	90.20
	Extreme	99.60	100.00	100.00	100.00	100.00
FAVAR	*Normal*	87.40	91.00	93.20	93.40	93.40
	Extreme	100.00	99.80	99.60	99.60	99.60
η_{13}^{Y}	*Normal*	62.60	80.60	82.20	84.00	84.80
	Extreme	93.00	99.20	99.40	99.20	99.20
η_{13}^{g} *first*	*Normal*	81.00	86.80	88.60	90.00	90.00
	Extreme	97.60	99.20	99.40	99.60	99.60
η_{13}^{g} *total*	*Normal*	94.60	92.60	92.60	93.20	93.40
	Extreme	100.00	100.00	100.00	100.00	100.00
η_{13}^{g} *à la Ricco*	*Normal*	95.00	94.00	94.00	94.20	94.40
	Extreme	100.00	100.00	100.0	100.00	100.00
		Sum				
Scenario/Horizon	*Cycle*	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Baseline	*Normal*	84.80	91.60	93.60	95.40	96.60
	Extreme	100.00	100.00	100.00	100.00	100.00
FAVAR	*Normal*	89.80	85.20	85.60	88.20	89.80
	Extreme	100.00	100.00	100.00	100.00	100.00
η_{13}^{Y}	*Normal*	36.80	73.00	79.80	83.00	86.40
	Extreme	86.20	100.00	100.00	100.00	100.00
η_{13}^{g} *first*	*Normal*	74.20	84.60	88.20	90.40	91.40
	Extreme	96.20	99.80	100.00	100.00	100.0
η_{13}^{g} *total*	*Normal*	89.80	86.60	85.40	85.80	87.00
	Extreme	98.60	95.20	99.00	100.00	100.00
η_{13}^{g} *à la Ricco*	*Normal*	93.00	90.80	90.60	90.20	90.40
	Extreme	99.80	99.80	99.80	99.80	99.80

Notes: Figures conditional on our VAR analysis with GIRFs conditional on four different sets of initial conditions. Log-values of the impulse response of output rescaled by the sample mean of output over public spending (both taken in levels) to convert percent changes in dollars.

Table B.3: Time series employed for the computation of the factors

N	Series	Mnemonic	Tr.	Start	End
1	Real Gross Domestic Product, 1 Decimal	GDPC1	5	1947Q1	2012Q3
2	Real Gross National Product	GNPC96	5	1947Q1	2012Q3
3	Real National Income	NICUR/GDPDEF	5	1947Q1	2012Q3
4	Real Disposable Income	DPIC96	5	1947Q1	2012Q3
5	Real Personal Income	RPI	6	1959Q1	2012Q3
6	Nonfarm Business Sector: Output	OUTNFB	5	1947Q1	2012Q3
7	Real Final Sales of Domestic Product, 1 Decimal	FINSLC1	5	1947Q1	2012Q3
8	Real Private Fixed Investment, 1 Decimal	FPIC1	5	1995Q1	2012Q3
9	Real Private Residential Fixed Investment, 1 Decimal	PRFIC1	5	1995Q1	2012Q3
10	Real Private Nonresidential Fixed Investment, 1 Decimal	PNFIC1	5	1995Q1	2012Q3
11	Real Gross Private Domestic Investment, 1 Decimal	GPDIC1	5	1947Q1	2012Q3
12	Real Personal Consumption Expenditure	PCECC96	5	1947Q1	2012Q3
13	Real Personal Consumption Expenditure: Nondurable Goods	PCNDGC96	5	1995Q1	2012Q3
14	Real Personal Consumption Expenditure: Durable Goods	PCDGCC96	5	1995Q1	2012Q3
15	Real Personal Consumption Expenditure: Services	PCESVC96	5	1995Q1	2012Q3
16	Real Gross Private Saving	GPSAVE/GDPDEF	5	1947Q1	2012Q3
17	Real Federal Consumption Expenditures, Gross Investment, 1 Decimal	FGCEC1	5	1995Q1	2012Q3
18	Federal Goverment: Current Expenditures, Real	FGEXPND/GDPDEF	5	1947Q1	2012Q3
19	Federal Goverment: Current Receipts, Real	FGRECPT/GDPDEF	5	1947Q1	2012Q3
20	Net Federal Government Saving	FGDEF	2	1947Q1	2012Q3
21	Government Current Expenditures/GDP Deflator	GEXPND/GDPDEF	5	1947Q1	2012Q3
22	Government Current Receipts/GDP Deflator	GRECPT/GDPDEF	5	1947Q1	2012Q3
23	Government Real Expenditures minus Real Receipts	GDEF	2	1947Q1	2012Q3
24	Real Government Consumption Expenditures, Gross Investment, 1 Decimal	GCEC1	5	1947Q1	2012Q3
25	Real Change in Private Inventories, 1 Decimal	CBIC1	1	1947Q1	2012Q3

Classification of the series: 1-31: "NIPA"; 32-47: "Industrial Production"; 48-61: "Employment and Unemployment"; 62-67: "Housing Starts"; 68-79: "Inventories", "Orders and Sales"; 80-94: "Prices"; 95-107: "Earnings and Productivity"; 108-117: "Interest Rates"; 118-129: "Money and Credit"; 130-134: "Stock Prices"; 135-141: "Exchange Rates"; 142-150: "Others". The column labeled "Tr." indicates the transformation applied to the series (1 = level, 2 = first difference, 3 = logarithm, 4 = second difference, 5 = first difference of logarithm, 6 = second difference of logarithm). Data source: Federal Reserve Bank of St. Louis' website.

N	Series	Mnemonic	Tr.	Start	End
26	Real Exports of Goods and Services, 1 Decimal	EXPGSC1	5	1947Q1	2012Q3
27	Real Imports of Goods and Services, 1 Decimal	IMPGSC1	5	1947Q1	2012Q3
28	Corporate Profits After Tax, Real	CP/GDPDEF	5	1947Q1	2012Q3
29	Nonfinancial Corporate Business: Profits After Tax, Real	NFCPATAX/GDPDEF	5	1947Q1	2012Q3
30	Corporate Net Cash Flow, Real	CNCF/GDPDEF	5	1947Q1	2012Q3
31	Net Corporate Dividends, Real	DIVIDEND/GDPDEF	5	1947Q1	2012Q3
32	Industrial Production Index	INDPRO	5	1947Q1	2012Q3
33	Industrial Production: Business Equipment	IPBUSEQ	5	1947Q1	2012Q3
34	Industrial Production: Consumer Goods	IPCONGD	5	1947Q1	2012Q3
35	Industrial Production: Durable Consumer Goods	IPDCONGD	5	1947Q1	2012Q3
36	Industrial Production: Final Products (Market Group)	IPFINAL	5	1947Q1	2012Q3
37	Industrial Production: Materials	IPMAT	5	1947Q1	2012Q3
38	Industrial Production: Nondurable Consumer Goods	IPNCONGD	5	1947Q1	2012Q3
39	Capacity Utilization: Manufacturing	MCUMFN	4	1972Q1	2012Q3
40	Industrial Production: Manufacturing	IPMAN	5	1972Q1	2012Q3
41	Industrial Production: Durable Manufacturing	IPDMAN	5	1972Q1	2012Q3
42	Industrial Production: Mining	IPMINE	5	1972Q1	2012Q3
43	Industrial Production: Nondurable Manufacturing	IPNMAN	5	1972Q1	2012Q3
44	Industrial Production: Durable Materials	IPDMAT	5	1947Q1	2012Q3
45	Industrial Production: Electric and Gas Utilities	IPUTIL	5	1972Q1	2012Q3
46	ISM Manufacturing: PMI Composite Index	NAPM	1	1948Q1	2012Q3
47	ISM Manufacturing: Production Index	NAPMPI	1	1948Q1	2012Q3
48	Average Weekly Hours of Production and Nonsupervisory Employees: Manuf.	AWHMAN	1	1948Q1	2012Q3
49	Average Weekly Overtime Hours of Prod. and Nonsupervisory Employees: Manuf.	AWOTMAN	2	1948Q1	2012Q3
50	Civilian Labor Force Participation Rate	CIVPART	2	1948Q1	2012Q3

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N	Series	Mnemonic	Tr.	Start	End
51	Civilian Labor Force	CLF160V	5	1948Q1	2012Q3
52	Civilian Employment	CE160V	5	1948Q1	2012Q3
53	All Employees: Total Private Industries	USPRIV	5	1947Q1	2012Q3
54	All Employees: Goods-Producing Industries	USGOOD	5	1947Q1	2012Q3
55	All Employees: Service-Providing Industries	SRVPRD	5	1947Q1	2012Q3
56	Unemployed	UNEMPLOY	5	1948Q1	2012Q3
57	Average (Mean) Duration of Unemployment	UEMPMEAN	2	1948Q1	2012Q3
58	Civilian Unemployment Rate	UNRATE	2	1948Q1	2012Q3
59	Index of Help-Wanted Advertising in Newspapers	A0M046	1	1959Q1	2012Q3
60	HOANBS/CNP160V	HOANBS/CNP160V	4	1948Q1	2012Q3
61	Initial Claims	ICSA	5	1967Q3	2012Q3
62	Housing Starts: Total: New Privately Owned Units Started	HOUST	5	1959Q1	2012Q3
63	Housing Starts in Northeast Census Region	HOUSTNE	5	1959Q1	2012Q3
64	Housing Starts in Midwest Census Region	HOUSTMW	5	1959Q1	2012Q3
65	Housing Starts in South Census Region	HOUSTS	5	1959Q1	2012Q3
66	Housing Starts in West Census Region	HOUSTW	5	1959Q1	2012Q3
67	New Private Housing Units Authorized by Building Permits	PERMIT	5	1960Q1	2012Q3
68	US Manufacturers New Orders for Non Defense Capital Goods	USNOIDN.D	5	1959Q2	2012Q3
69	US New Orders of Consumer Goods and Materials	USCNORCGD	5	1959Q2	2012Q3
70	US ISM Manufacturers Survey: New Orders Index SADJ	USNAPMNO	1	1950Q2	2012Q3
71	Retail Sales: Total (Excluding Food Services)	RSXFS	5	1992Q1	2012Q3
72	Value of Manufacturers' Total Inventories for All Manufacturing Industries	UMTMTI	5	1992Q1	2012Q3
73	Value of Manufacturers' Total Inventories for Durable Goods	AMDMTI	5	1992Q1	2012Q3
74	Value of Manufacturers' Total Inventories for Nondurable Goods Industries	AMNMTI	5	1992Q1	2012Q3
75	ISM Manufacturing: Inventories Index	NAPMII	1	1948Q1	2012Q3

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N	Series	Mnemonic	Tr.	Start	End
76	ISM Manufacturing: New Orders Index	NAPMNOI	1	1948Q1	2012Q3
77	Value of Manufacturers' New Orders for Cons. Goods: Cons. Dur. Goods Ind.s	ACDGNO	5	1992Q1	2012Q3
78	Manuf.s' New Orders: Durable Goods	DGORDER	5	1992Q1	2012Q3
79	Value of Manuf.s' New Orders for Dur. Goods Ind.: Transp. Equipment	ANAPNO	5	1992Q1	2012Q3
80	Gross Domestic Product: Chain-type Price Index	GDPCTPI	5	1947Q1	2012Q3
81	Gross National Product: Chain-type Price Index	GNPCTPI	5	1947Q1	2012Q3
82	Gross Domestic Product: Implicit Price Deflator	GDPDEF	5	1947Q1	2012Q3
83	Gross National Product: Implicit Price Deflator	GNPDEF	5	1947Q1	2012Q3
84	Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	6	1947Q1	2012Q3
85	Consumer Price Index for All Urban Consumers: All Items Less Food	CPIULFSL	6	1947Q1	2012Q3
86	Consumer Price Index for All Urban Consumers: All Items Less Energy	CPILEGSL	6	1957Q1	2012Q3
87	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	CPILFESL	6	1957Q1	2012Q3
88	Consumer Price Index for All Urban Consumers: Energy	CPIENGSL	6	1947Q1	2012Q3
89	Consumer Price Index for All Urban Consumers: Food	CPIUFDSL	6	1947Q1	2012Q3
90	Producer Price Index: Finished Goods: Capital Equipment	PPICPE	6	1947Q1	2012Q3
91	Producer Price Index: Crude Materials for Further Processing	PPICRM	6	1947Q1	2012Q3
92	Producer Price Index: Finished Consumer Goods	PPIFCG	6	1947Q1	2012Q3
93	Producer Price Index: Finished Goods	PPIFGS	6	1947Q1	2012Q3
94	Spot Oil Price: West Texas Intermediate	OILPRICE	6	1947Q1	2012Q3
95	Nonfarm Business Sector: Hours of All Persons	HOANBS	5	1947Q1	2012Q3
96	Nonfarm Business Secotr: Output Per Hour of All Persons	OPHNFB	5	1947Q1	2012Q3
97	Nonfarm Business Sector: Unit Nonlabor Payments	UNLPNBS	5	1947Q1	2012Q3
98	Nonfarm Business Sector: Unit Labor Cost	ULCNFB	5	1947Q1	2012Q3
99	Compensation of Employees: Wages and Salary Accruals, Real	WASCUR/CPI	5	1947Q1	2012Q3
100	Nonfarm Business Sector: Compensation Per Hour	COMPNFB	5	1947Q1	2012Q3

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N	Series	Mnemonic	Tr.	Start	End
101	Nonfarm Business Sector: Real Compensation Per Hour	COMPRNFB	5	1947Q1	2012Q3
102	Growth in utilization-adjusted TFP	dtfp_util	1	1947Q2	2012Q3
103	Growth in business sector TFP	dtfp	1	1947Q2	2012Q3
104	Utilization in producing investment	du_invest	1	1947Q2	2012Q3
105	Utilization in producing non-investment business output	du_consumption	1	1947Q2	2012Q3
106	Utilization-adjusted TFP in producing equipment and consumer durables	dtfp_I_util	1	1947Q2	2012Q3
107	Utilization-adjusted TFP in producing non-equipment output	dtfp_C_util	1	1947Q2	2012Q3
108	Effective Federal Funds Rate	FEDFUNDS	2	1954Q3	2012Q3
109	3-Month Treasury Bill: Secondary Market Rate	TB3MS	2	1947Q1	2012Q3
110	1-Year Treasury Constant Maturity Rate	GS1	2	1953Q2	2012Q3
111	10-Year Treasury Constant Maturity Rate	GS10	2	1953Q2	2012Q3
112	Moody's Seasoned Aaa Corporate Bond Yield	AAA	2	1947Q1	2012Q3
113	Moody's Seasoned Baa Corporate Bond Yield	BAA	2	1947Q1	2012Q3
114	Bank Prime Loan Rate	MPRIME	2	1949Q1	2012Q3
115	GS10-FEDFUNDS Spread	GS10-FEDFUNDS	1	1954Q3	2012Q3
116	GS1-FEDFUNDS Spread	GS1-FEDFUNDS	1	1954Q3	2012Q3
117	BAA-FEDFUNDS Spread	BAA-FEDFUNDS	1	1954Q3	2012Q3
118	Non-Borrowed Reserves of Depository Institutions	BOGNONBR	5	1959Q1	2012Q3
119	Board of Gov. Total Reserves, Adjusted for Changes in Reserve Requirements	TRARR	5	1959Q1	2012Q3
120	Board of Gov. Monetary Base, Adjusted for Changes in Reserve Requirements	BOGAMBSL	5	1959Q1	2012Q3
121	M1 Money Stock	M1SL	5	1959Q1	2012Q3
122	M2 Less Small Time Deposits	M2MSL	5	1959Q1	2012Q3
123	M2 Money Stock	M2SL	5	1959Q1	2012Q3
124	Commercial and Industrial Loans at All Commercial Banks	BUSLOANS	5	1947Q1	2012Q3
125	Consumer Loans at All Commercial Banks	CONSUMER	5	1947Q1	2012Q3

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N	Series	Mnemonic	Tr.	Start	End
126	Bank Credit at All Commercial Banks	LOANINV	5	1947Q1	2012Q3
127	Real Estate Loans at All Commercial Banks	REALLN	5	1947Q1	2012Q3
128	Total Consumer Credit Owned and Securitized, Outstanding	TOTALSL	5	1947Q1	2012Q3
129	St. Louis Adjusted Monetary Base	AMBSL (CHNG)	5	1947Q1	2012Q3
130	US Dow Jones Industrials Share Price Index (EP)	USSHRPRCF	5	1950Q2	2012Q3
131	US Standard & Poor's Index of 500 Common Stocks	US500STK	5	1950Q2	2012Q3
132	US Share Price Index NADJ	USI62...F	5	1957Q2	2012Q3
133	Dow Jones/GDP Deflator	DOW Jones/GDPDEF	5	1950Q2	2012Q3
134	S&P/GDP Deflator	S&P/GDPDEF	5	1950Q2	2012Q3
135	Trade Weighted U.S. Dollar Index: Major Currencies	TWEXMMTH	2	1973Q1	2012Q3
136	Euro/U.S. Foreign Exchange Rate	EXUSEU(-1)	5	1999Q1	2012Q3
137	Germany/U.S. Foreign Exchange Rate	EXGEUS	5	1971Q1	2001Q4
138	Switzerland/U.S. Foreign Exchange Rate	EXSZUS	5	1971Q1	2012Q3
139	Japan/U.S. Foreign Exchange Rate	EXJPUS	5	1971Q1	2012Q3
140	U.K./U.S. Foreign Exchange Rate	EXUSUK(-1)	5	1971Q1	2012Q3
141	Canada/U.S. Foreign Exchange Rate	EXCAUS	5	1971Q1	2012Q3
142	US The Conference Board Leading Economic Indicators Index SADJ	USCYLEADQ	5	1959Q1	2012Q3
143	US Economic Cycle Research Institute Weekly Leading Index	USECRIWLH	5	1950Q2	2012Q3
144	University of Michigan Consumer Sentiment: Personal Finances, Current	USUMPFNCH	2	1978Q1	2012Q3
145	University of Michigan Consumer Sentiment: Personal Finances, Expected	USUMPFNEH	2	1978Q1	2012Q3
146	University of Michigan Consumer Sentiment: Economic Outlook, 12 Months	USUMECO1H	2	1978Q1	2012Q3
147	University of Michigan Consumer Sentiment: Economic Outlook, 5 Years	USUMECO5H	2	1978Q1	2012Q3
148	University of Michigan Consumer Sentiment: Buying Conditions, Durables	USUMBUYDH	2	1978Q1	2012Q3
149	University of Michigan Consumer Sentiment Index	USUMCONSH	2	1991Q1	2012Q3
150	University of Michigan Consumer Sentiment - Current Conditions	USUMCNSUR	2	1991Q1	2012Q3

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