Estimating the effects of uncertainty over the business cycle

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Abstract

In this paper I provide empirical evidence that uncertainty shocks have strong asymmetric effects on economic activity depending on the phase of the business cycle. In particular, the impulse responses estimated with the local projection method on a smooth-transition model show that in recessions uncertainty shocks strongly dampen industrial production, increase unemployment and reduce prices. In an expansion the effects are reversed, and uncertainty shocks appear to have positive macroeconomic effects. One possible explanation is that during expansions uncertainty fosters investments and economic activity through the "growth options" channel, while in recessions it reduces investments via the "wait-and-see" channel.

Keywords: Uncertainty Shocks, Local Projection Methods, Real Options, Growth Options, wait-and-see.

JEL classification: E21, E32.

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1 Introduction

> *"The most recent GDP data confirm that the recovery in the euro area remains uniformly weak, with subdued wage growth even in non-stressed countries suggesting lackluster demand. In these circumstances, it seems likely that uncertainty over the strength of the recovery is weighing on business investment and slowing the rate at which workers are being rehired."*
>
> Speech by Mario Draghi, President of the ECB, Annual central bank symposium in Jackson Hole, 22 August 2014

The 2008 global financial crisis has led to a sharp increase in fiscal deficits that has dragged Europe into a debt crisis. We have therefore witnessed to a surge in the perceived risk over the sustainability of the debts of several European member states. This crisis has also casted doubts on the stability of the banking system and on the sustainability of the monetary union itself. Forseeing when the recession is going to end appears to be particularly difficult in this environment. As the recent quotation of Mario Draghi shows, high uncertainty on the economic outlook is seen by economists and policy makers as a major factor holding back the European economy to recover from the cyclical downturn. In times of high uncertainty firms postpone investment decisions, reduce hirings (Bertola and Caballero, 1994) and consumers increase their savings for precautionary reasons (Leland, 1968).

Explaining how uncertainty affects business cycle fluctuations is a relevant question from both theoretical and policy perspectives. A growing literature studies the effects of uncertainty shocks on economic activity. This literature has been initiated by the seminal contribution by Bloom (2009). The analysis of uncertainty shocks is a challenging task both from an empirical and a theoretical point of view. The latent nature of uncertainty has led the empirical literature to investigate its effects on the economy using various proxies, such as survey data (e.g., Leduc and Liu, 2014; Bachmann, Elstner, and Sims, 2013) and stock market's implied and realized volatility (Bloom, 2009; Caggiano, Castelnuovo, and Groshenny, 2014). This literature has found that shocks increasing uncertainty have significant contractionary effects on the economy and act like negative demand shocks, by increasing unemployment and reducing inflation (Leduc and Liu, 2014).

The ways uncertainty can affect economic activity have been widely analyzed in the theoretical literature. In particular, four key channels have been identified: (*i*) the real options channel, that can lead firms to increase ("growth options") or decrease ("wait-and-see") their investment (Bernanke, 1983); (*ii*) the Hartman-Abel effect that leads firms to expand in response to increases in demand or cost uncertainty and contract after decreases in uncertainty, under the assumption that profits are convex in demand or costs (Hartman, 1976; Abel, 1983); (*iii*) the precautionary savings channel that makes risk-averse agents reduce their consumption when uncertainty increases (Leland, 1968) and (*iv*) the risk-premium effect that increases the cost of financing when uncertainty rises (Christiano, Motto, and Rostagno, 2014; Gilchrist, Sim, and Zakrajsek, 2014). These four channels have potentially contrasting effects and in a general equilibrium (GE) context they may offset each other. For this reason the macroeconomic literature has provided mixed evidence on the importance of uncertainty shocks in determining business cycle fluctuations in a GE framework[1]. Basu and Bundick (2012) show that uncertainty shocks are able to generate business cycle fluctuations only in sticky-prices (New-Keynesian) frameworks. In flexible-prices models instead, the precautionary savings and precautionary labor channels lead consumption to fall and labor supply to increase. The rise in labor supply increases total output, which (in a closed economy) implies an increase in investment, given the fall in consumption. Furthermore they show that the effects of uncertainty shocks strongly depend on how effective the response of monetary policy is.

[1] Relevant contributions have been provided by Bachmann and Bayer (2013), Born and Pfeifer (2014), Fernandez-Villaverde, Guerron-Quintana, Kuester, and Rubio-Ramirez (2011).

If the nominal rates have approached the zero lower bound and monetary authority cannot further reduce its policy rate, then the effects of uncertainty shocks on economic activity are strongly amplified. Gilchrist, Sim, and Zakrajsek (2014) and Bonciani and van Roye (2015) highlight the importance of financial and banking frictions as a mechanism through which idyosincratic and aggregate uncertainty affect macroeconomic activity.

As the statement by Mario Draghi in the foreword shows, uncertainty is considered to have particularly severe effects when the economy is in a recessionary phase. The present paper extends the literature by providing evidence of the asymmetric effects of aggregate uncertainty on economic activity. I use the local projection method developed by Jorda (2005) to estimate the response of economic activity to uncertainty shocks during recessions and expansions. The econometric framework is similar to Auerbach and Gorodnichenko (2012) and Tenreyro and Thwaites (2013), that adapt the local projection method to the Smooth Transition regression used and discussed in Anderson and Vahid (1998) and Terasvirta, Tjostheim, and Granger (2010). This methodology easily accomodates state dependence and does not impose the dynamic restrictions involved in vector autoregressive models (VARs). I find that in times of recession uncertainty shocks act like negative demand shocks, reducing industrial production, increasing unemployment and pushing down prices. In times of expansion instead, uncertainty shocks appear to have the opposite effect on macroeconomic activity. In particular, when an economy is in an upturn, an increase in uncertainty acts like a positive demand shock. This result is quite surprising and needs further empirical and theoretical investigation. One possible interpretation of this result is that during economic upturns uncertainty acts through the "growth options" channel. An example of "growth options" is the "dot.com" boom of the late 1990's. Firms were uncertain about the potential gains from the internet, but that extreme uncertainty fostered investments. Empirical evidence of growth options effects is for example provided by Segal, Shaliastovich, and Yaron (2014) and Rossi and Sekhposyan (2015), who decompose uncertainty into "good" and "bad" type of uncertainty. They find that the former increases in expansions and fosters investment and demand, while instead bad uncertainty is predominant in recessions and dampens economic activity.

The analysis of the impulse responses estimated by Local Projection Method shows that production falls three times as much during recessions than a linear (state-independent) model would imply. Similarly the increase in unemployment is three times larger in the recessionary phase than the state-independent model predicts. Related work are those by Caggiano, Castelnuovo, and Groshenny (2014) and Caggiano, Castelnuovo, and Nodari (2015), who estimate a Smooth Transition Vector Autoregressive (STVAR) model as in Auerbach and Gorodnichenko (2013) and Bachmann and Sims (2012) and, coherently with my results, find that in recessions, uncertainty shocks increase unemployment more than a linear VAR would imply. The use of local projection method compared to the standard VARs allows to more robustly estimate the effects of uncertainty shocks during the two states of the business cycle, as it naturally allows for possible transitions from one state to the other and it is more robust to model misspecifications. Another point that is worth mentioning is that with the full sample, I do not find the typical rebound and "overshooting" effect as in Bloom (2009), neither with the uncertainty measure estimated by Jurado, Ludvigson, and Ng (2015), nor with the stock market volatility variable used by Bloom (2009). When I exclude the period in which the federal funds rate approaches the Zero Lower Bound, there is an overshoot that occurs after 12 to 15 months.

The remainder of this paper is organized as follows: section 2 presents the econometric framework and the local projection method; section 3 presents the empirical evidence on the asymmetric macroeconomic effects of uncertainty shocks and a possible interpretation of the results; section 4 concludes the paper with some final remarks.

2 Empirical evidence: a LPM analysis

2.1 Econometric framework

In this section I present empirical evidence on the asymmetric effects of uncertainty shocks on economic activity. I follow Auerbach and Gorodnichenko (2012) and Owyang, Ramey, and Zubairy (2013), who adapt the local projection tecnique developed by Jorda (2005) to a Smooth Transition regression and to a Threshold regression respectively, in order to allow the impulse response functions (IRFs) to depend on the state of the business cycle. The calculation of the IRFs involves the estimation of a set of regressions for each horizon $h = 0, 1, \ldots, H$:

$$
\begin{aligned}
Y_{t+h} = {} & (1 - F(v_{t-1})) \left[A^{EXP}(L) Y_{t-1} + B^{EXP}(L) X_t + \gamma_h^{EXP} Z_t + C^{EXP}(L) Z_{t-1} \right] \\
& + F(v_{t-1}) \left[A^{REC}(L) Y_{t-1} + B^{REC}(L) X_t + \gamma_h^{REC} Z_t + C^{REC}(L) Z_{t-1} \right] + \varepsilon_{t+h}
\end{aligned} \tag{1}
$$

$$
F(v_t) = \frac{\exp(-\alpha v_t)}{1 + \exp(-\alpha v_t)} = \frac{1}{1 + \exp(\alpha v_t)}, \quad \alpha > 0 \tag{2}
$$

$$
\mathbb{E}[v_t] = 0 \text{ and } \operatorname{var}(v_t) = 1 \tag{3}
$$

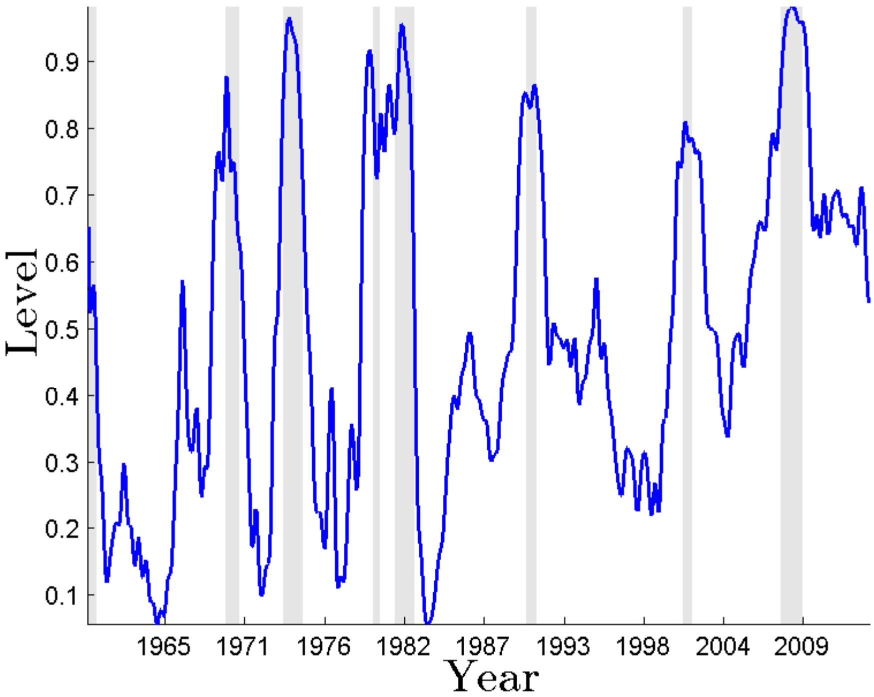
where Y is the response variable of interest, X are controls and Z is the variable we are shocking. $F(\cdot)$ is a logistic function and v_t is the variable that defines the transition from one state to the other. The matrices $A^{EXP}(L)$, $A^{REC}(L)$, $B^{EXP}(L)$, $B^{REC}(L)$, $C^{EXP}(L)$ and $C^{REC}(L)$ are lag polynomials, whose coefficients depend on the state of the business cycle (EXP stands for expansion and REC stands for recession). The coefficients γ_h^{EXP} and γ_h^{REC} are the state-dependent impulse response of Z_t upon Y in h steps ahead. The vector ε_{t+h} is the error term at time $t + h$. These errors are assumed to be normally distributed.

Similarly as in Auerbach and Gorodnichenko (2013) and Bachmann and Sims (2012), the transition variable v is defined as a standardized centered seven-quarter moving average of the growth rate of real gross domestic output (GDP). The logistic function $F(v_t)$ is bounded between 0 and 1 and can be interpreted as the probability of being in a recession, given observations on v_t. If $F(v_t) \approx 1$, v_t must be very negative , while if $F(v_t) \approx 0$, v_t is very positive. As in Auerbach and Gorodnichenko (2013), a recession is defined as a period in which $F(v_t) > 0.8$. The parameter α is calibrated to match the observed frequency of recessions in the United States since 1960 according to the NBER business cycles dates (approximately 14%). Thus $\Pr(F(v_t) > 0.8) \approx 0.14$ yields $\alpha = 1.32$. When α is equal to 0 the logistic function becomes constant and the model (1) collapses into a linear (state-independent) model. When $\alpha \to \infty$, the function $F(\cdot)$ becomes a Dirac function and the model (1) becomes a two regime Threshold model as in Tong (1983). Figure 1 compares the cyclical indicator $F(v_t)$ with the recessions as dated by the NBER (grey shaded areas). Given that the GDP is measured at a quarterly frequency, while the rest of our data are monthly, I perform a spline interpolation of the transition variable, in order to obtain the missing observations.

2.2 Local Projection Method (LPM)

In the standard VAR literature impulse responses are estimated from the Wold representation of the VAR process. This involves a two steps procedure. First the model needs to be estimated and secondly, the estimates need to be inverted. As Jorda (2005) points out, this is only justified if the model is not misspecified, i.e. the VAR under consideration is actually the true data generating process (DGP). The projection technique combines the two steps mentioned above into one and is more to robust to model misspecifications. More specifically, consider the definition of impulse response by Koop, Pesaran, and Potter (1996), that abstracts from any reference to the

Figure 1: *Probability of being in a recessionary state*



Notes: The blue line is the probability of being in a recession, $F(v_t)$; the grey shaded areas are the recessionary phases as dated by the NBER; black line is threshold value I used to define a recession.

DGP:

$$IRF(t,h,d_i) \equiv \mathbb{E}\left[Y_{t+h}|v_t = d_i; S_t\right] - \mathbb{E}\left[Y_{t+h}|v_t = 0; S_t\right] \tag{4}$$

where: $E[\cdot|\cdot]$ is conditional expectation function; y_t is a vector of dimension $n \times 1$; S_t is the vector of lags of Y_t and other controls; v_t is the vector of reduced form errors; d_i is the identified structural shock. The IRF as defined in equation (4) is the best multi-step prediction of Y_{t+h} given S_t. Best, in the sense that it minimizes the mean squared error. Unless the VAR is the DGP, recursively iterating on the estimated VAR model is not an optimal way of computing the IRFs. Direct forecasting models, reestimated for each h, produce better multi-step predictions.

As an illustration of the LPM, consider to estimate the following linear regression (5):

$$Y_{t+h} = A\left(L\right)Y_{t-1} + B\left(L\right)X_t + \gamma_h Z_t + C\left(L\right)Z_{t-1}. \tag{5}$$

For example, projecting Y_{t+2} onto the variables on the right hand side, we obtain the estimate $\hat{\gamma}_2$. This is the effect of an increase in Z_t on Y two-months ahead, that is orthogonal to the other variables on the right hand-side of the equation. Estimating H regressions for each response variable Y of interest gives us the sequence of "*local projections*". The estimated IRFs are given by the sequence $(\hat{\gamma}_h)_{h=0}^{H}$. The IRFs can be therefore estimated by univariate regression methods with a heteroskedasticity and autocorrelation (HAC) robust estimator. In order to make as little assumptions on the DGP as possible, it is important to use HAC robust standard errors. Error bands can then be computed for various confidence levels simply as:

$$\begin{aligned}
&68\% \text{ confidence:} && 0.9945 \pm \left(d_i' \hat{\Sigma}_{HAC} d_i\right) \\
&90\% \text{ confidence:} && 1.6449 \pm \left(d_i' \hat{\Sigma}_{HAC} d_i\right) \\
&95\% \text{ confidence:} && 1.96 \pm \left(d_i' \hat{\Sigma}_{HAC} d_i\right) \\
&99\% \text{ confidence:} && 2.5758 \pm \left(d_i' \hat{\Sigma}_{HAC} d_i\right)
\end{aligned} \tag{6}$$

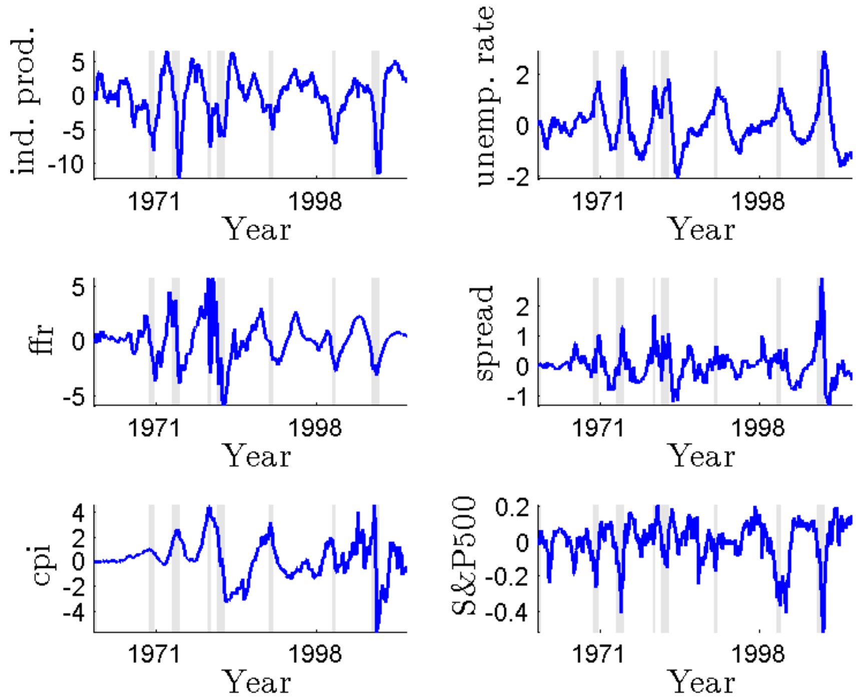
where $\hat{\Sigma}_{HAC}$ is the estimate matrix of HAC robust standard errors. An example of such estimator is that suggested by Newey and West (1987).

The LPM as defined by equation (1) has several advantanges over the STVAR considered by Caggiano, Castelnuovo, and Groshenny (2014). First, it involves only linear estimations and is therefore computationally less cumbersome. Second, it does not impose the dynamic restrictions on the IRFs implicit in a VAR. As a result the IRFs given by the two tecniques will be the same only if the SVAR is correctly specified. Third, the methodology conveniently accomodates for nonlinearities in the response function. Fourth, the IRFs computed with the LPM are much less sensitive to lag order misspecification. Last but not least, the impulse responses computed with this methodology incorporate the average transitions of the economy from one state to another, since the set regressors in (1) does not vary with h. In the STVAR used by Caggiano, Castelnuovo, and Groshenny (2014) instead, the impulse responses were computed under the assumption that the regime was fixed.

2.3 Data

The model is estimated with monthly data for the United States. The time span considered is July 1960 to December 2014. I collect the data on industrial production, real gross domestic product, unemployment rate, consumer price index, the federal funds rate, the spread between the yield on BAA corporate bonds relative to yield on 10-year treasury bonds from the FRED database of the Federal Reserve of St.Louis. The series of the $S\&P500$ index is taken from Datastream. I take the logarithm of the series for production,$S\&P500$ index and uncertainty (described below). Similarly as Bloom (2009) I remove trends with the Hoddrick-Prescott (HP) filter with smoothing parameter $129,600$. Given the dynamic procedure used to estimate the impulse responses, I opt for the one-sided HP filter. Figure 2 displays the series of the variables used in the baseline estimation.

Figure 2: *Variables used for the estimation*



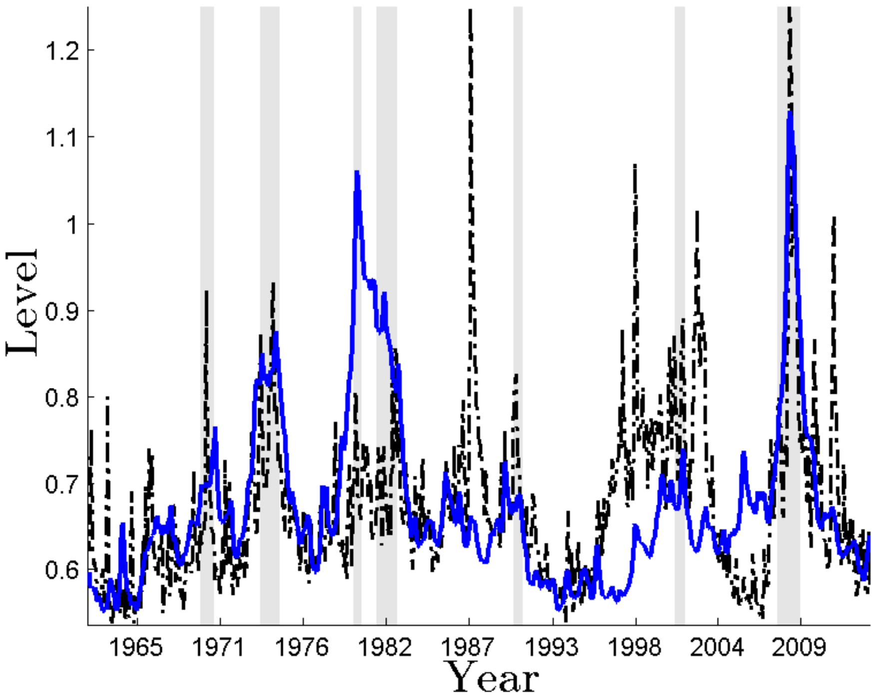
Notes: The variables displayed are the variables used for the estimation of the Smooth Transition LPM model. The series of industrial production, cpi and S& P500 index are in logs percent and filterd with a one-sided HP filter with smoothing parameter equal to $129,600$.

The measurement of uncertainty has been widely discussed in the literature (see e.g., Bloom, 2009; Baker, Bloom, and Davis, 2013; Jurado, Ludvigson, and Ng, 2015). Economic uncertainty refers to an environment in which little or nothing is known about the future state of the economy. Economic uncertainty can stem from various sources such as economic and financial policies, dispersion in future growth prospects, productivity movements, wars, terrorist attacks, and natural disasters (Bloom, 2009). The latent nature of uncertainty makes this variable difficult to quantify. Macroeconomic uncertainty has been often proxied by the VIX and VXO indeces. These indeces are measures of the implied volatility respectively of the S&P 500 and S&P 100 option prices. In other words, they represent measures of the market's expectation of stock market volatility over the next 30 days. As it has been pointed out by Jurado, Ludvigson, and Ng (2015) and Bekaert, Hoerova, and Lo Duca (2013), stock market volatility may be a poor proxy for macroeconomic uncertainty, as it is driven also by other factors such as risk aversion, leverage and sentiments. For this reason in this paper I will use the uncertainty measure estimated by Jurado, Ludvigson, and Ng (2015) that is available at a monthly frequency from July 1960 to December 2014. This measure of macroeconomic uncertainty is defined as the common dispersion in the unforecastable component of a large number of economic indicators. Figure 3 displays the aforementioned uncertainty measure and compares it to the stock market volatility index used in Bloom (2009), which is based on the VXO[2]. Since the VXO is available only from 1986 onward, the observations prior 1986 are calculated as the monthly standard deviation of the daily S&P500 index normalized to the same mean and variance as the VXO index. As it is clear from the figure, uncertainty tends to be relatively high during economic downturns. The measure by Jurado, Ludvigson, and Ng (2015) reveals three periods of high uncertainty in the considered sample, namely the recessions in 1973-74, 1981-1982 and the Great Recession in 2007-2009. The VXO instead reveals 17 periods of high uncertainty, which may not all be related to macroeconomic fundamentals. For example, the index reaches a larger value during the Black Monday (19th October 1987) than during the

[2] For comparison purposes, in figure 3 the stock market volatility index has been rescaled to have same mean and variance as the uncertainty measure by Jurado, Ludvigson, and Ng (2015)

Great Recession in 2007, although the changes in macroeconomic activity that occured during the last crisis are uncomparably larger than those in the late 1980's.

Figure 3: *Macroeconomic Uncertainty*



Notes: The blue line is the macroeconomic uncertainty measure estimated by Jurado, Ludvigson, and Ng (2015), $\bar{\mathcal{U}}_t^y(1)$. The black dash-dotted line is the VXO series used by Bloom (2009). Grey shaded areas are the NBER recession dates.

3 Results

In this section I discuss the impulse responses (IRFs) obtained from the linear (state-independent) model as in equation (5) and compare them to those obtained with the Smooth Transition model given by equation (1) for the two different states, i.e. Recession and Expansion.

Figures 4 and 5 display the state-independent and state-dependent IRFs to a 1 percent increase in uncertainty to two real macroeconomic variables, namely industrial production and unemployment. Using the same notation as in equation (5), we have that Y is given by industrial production (unemployment), X_t is a vector consisting of the lagged federal funds rate r_{t-1}, the lagged spread s_{t-1}, lagged value of the log $S\&P500$ index, $sp500_{t-1}$[3], lagged unemployment u_{t-1} (industrial production, y_{t-1}). The Z_t is given by the lagged value of the log of the uncertainty variable σ_{t-1}. The IRFs of the nominal variables, i.e. the federal funds rate and the spread between the yield on BAA corporate bonds relative to yield on 10-year treasury bonds, are displayed in figures A1 and 6. In this case Y is given by r (or s), and X_t is the vector $[y_t, u_t, s_t, sp500_t]'$ (or $[y_t, u_t, r_t, sp500_t]'$). The Z_t is now the uncertainty variable at time t, σ_t. Implicitly I am assuming that the real variables respond with a lag to uncertainty, while the response of the nominal variables, i.e. the federal funds rate and the spread, is immediate. I believe this identification strategy is plausible given the monthly frequency of the data. Nevertheless, the results are very similar if we assume that also industrial production and unemployment respond immediately to uncertainty shocks. The order of the lag-polynomials is 6, as suggested by the AIC.[4]

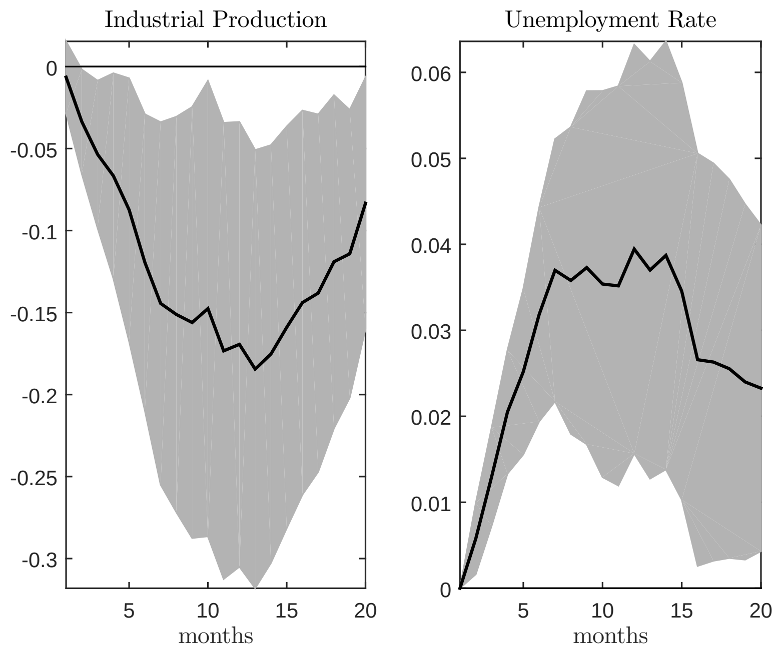
The IRFs of the linear model displayed in figure 4 show that a 1 percent increase in uncertainty worsens macroeconomic activity, reducing industrial production and increasing unemployment in a fairly persistent way. These effects are significant at a 68% significance level[5]. This result confirms what has been found previously in the literature (see e.g., Bloom, 2009; Jurado, Ludvigson, and Ng, 2015; Caggiano, Castelnuovo, and Groshenny, 2014). An important difference is that the quick rebound and "overshoot" that has

[3] This follows Bloom (2009), who includes the $S\&P500$ index to control for movements in the stock market.

[4] The local projection method guarantees more robust results in case of lag-order misspecification than the VARs.

[5] The fall in industrial production is not significant at a 90% significance level

Figure 4: *State-independent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

been found in Bloom (2009) is not present in this case. As I will discuss in subsection 3.1, this result is not driven by the choice of the uncertainty variable as the overshoot is not present even when I use stock market volatility as a proxy for macroeconomic uncertainty.

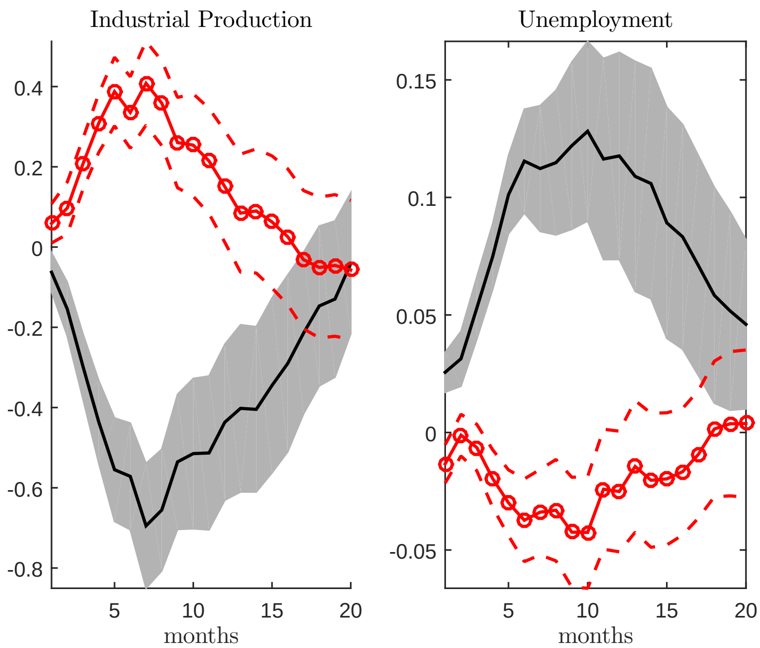
The IRFs of the Smooth-Transition model, displayed in figure 5, show that a 1 percent increase in uncertainty significantly worsens macroeconomic activity during recessions (black line). This confirms the results in Caggiano, Castelnuovo, and Groshenny (2014), that find that uncertainty shocks lead to a larger increase in unemployment during recessions than a linear model would predict. Perhaphs more surprisingly, (red circled line) an increase in uncertainty during expansions appears to raise industrial production and sluggishly reduce unemployment. Moreover, in recessions an increase in uncertainty tends to reduce prices (federal funds rate) and increase the spread between the BAA corporate bond yield relative to the yield on the 10-year Treasury bond. The fall in macroeconomic activity and in the federal funds rate (see figure 6) confirms (partially) the result in Basu and Bundick (2012) and Leduc and Liu (2014) that uncertainty shocks act as negative demand shocks. On the contrary, uncertainty shocks in expansions appear to act as positive demand shocks, increasing macroeconomic activity and raising prices. In subsections 3.1 and 3.2 I discuss how sensitive the results are to various changes to the baseline specifications and a possible interpretation. Furthermore I explain how my results relate to existing theoretical and empirical findings in the literature.

3.1 Robustness checks

In this subsection I discuss the robustness of the results described above. First, I replace the uncertainty measure with the stock market volatility. Figure A2 displays the result. The main difference is in the response of the federal funds rate, while for the real variables, the results seem to be confirmed, i.e. uncertainty seems to have positive effects on macroeconomic activity in expansions and negative effects in recessions.

Second, I check whether my results are sensitive to the inclusion in the sample of the period where the federal funds rate has approached the zero lower bound (ZLB). Figure A3 in the appendix displays the IRFs when the sample considered is July 1960 to November 2008. As the figure shows, the main result does not change. Uncertainty affects negatively economic activity during recession, and positively during expansions. Two points need be mentioned: (i) the exclusion of the period with the ZLB notably mitigates the effects uncertainty. In particular, in recessions the fall in industrial production is only 1/3 as strong than in the baseline case. Also unemployment rises more

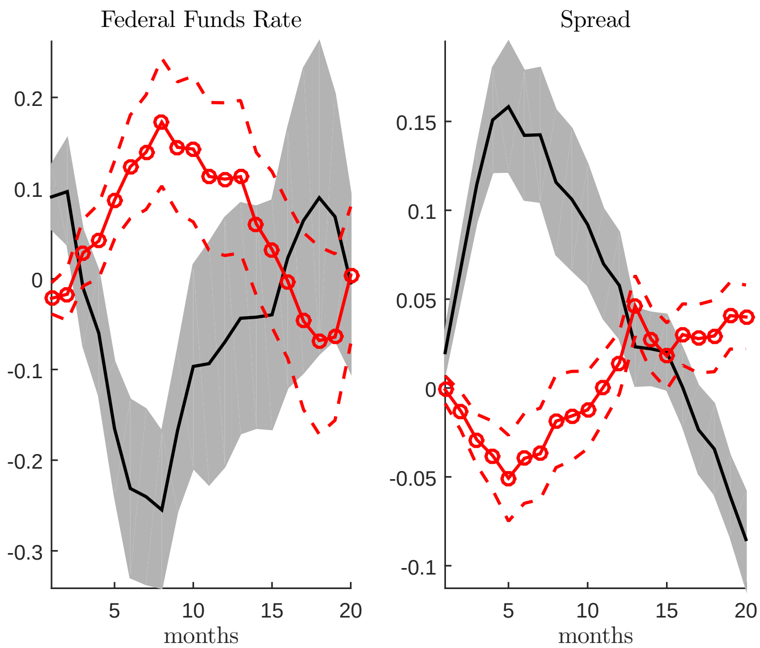
Figure 5: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The red circled line is the IRF of the response variable in an expansionary regime. The red dashed line and the grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

mildly than the in the baseline case. (ii) The fall (rise) in economic activity in recession (expansion) is less persistent when the ZLB is omitted. In particular, after an increase in uncertainty the fall (rise) in industrial production last only 10 months approximately and displays an overshoot. Both results are in line with Basu and Bundick (2012) and Bonciani and van Roye (2015), who explained with New-Keynesian Dynamic Stochastic General Equilibrium models that the monetary authority plays a crucial role in mitigating the effects of uncertainty shocks. Moreover they show that the effects of these shocks is strongly amplified if the central bank is constrained by the ZLB or if its policy is not perfectly passed-through by the banking sector. However, what should be noted is that by removing the sample from November 2008 onwards, we are also removing some observations from the relatively short

Figure 6: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The red circled line is the IRF of the response variable in an expansionary regime. The red dashed line and the grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

sample of recession dates, which might affect the estimation of the IRFs.

Third, I check for sensitivity of the results with respect to the α parameter in equation (1) (see figure A4). For any variable that I considered, results do not seem to vary much if I increase α from 1.32 to 2. Fourth, I control for consumer confidence by adding the OECD confidence indicator to X_t in equation (1). As figure A5 shows, results are robust to this type of variation. Finally, I check whether varying the order of the lag polynomials in equation (1) may significantly affect the results. Both for a lag order of 3 (figure A6) and lag order of 10 (figure A7), results remain stable. This is not very surprising, since with the local projection method, the parameters in the lag polynomials should not affect the dynamics of the IRF. Overall, the results are stable to various changes to the baseline analysis. The main difference is due to the change in the uncertainty variable. Nevertheless, as discussed above, the choice of the Jurado, Ludvigson, and Ng (2015)'s uncertainty measure seems to be more appropriate to analyze the effects of macroeconomic uncertainty.

3.2 Explaining the asymmetric effects

The results of the linear model and of the recessionary regime are in line with what had been found previously in most of the empirical literature. Increases in uncertainty strongly dampen economic activity through various channels such as the *"wait-and-see"* channel and precautionary savings. Moreover, uncertainty shocks can be strongly amplified by financial frictions (see e.g., Gilchrist, Sim, and Zakrajsek, 2014; Bonciani and van Roye, 2015) that may be especially stringent in recessionary times and lead the stabilizing effects of monetary policy to be less effective than in expansion. With the methodology adopted in this paper, the fall in economic activity after an increase in uncertainty can be very persistent. The rebound and overshoot in industrial production that is usually found in the literature is not present in the baseline case but only once I omit the period in which the nominal rates approached the ZLB. The rebound and overshoot effects have been explained in Bloom (2009) through the wait-and-see channel in a partial equilibrium framework. More specifically, under uncertainty, firms have an option of delay when investment is partially or completely irreversible. Uncertainty shocks lead in the short-run to a drop in investment and hiring, while in the medium run they generate a rebound and an overshoot. As discussed in subsection 3.1, the results in my paper suggest that a prompt response by the monetary authority may be necessary to obtain the effects mentioned above.

Why do uncertainty shocks have positive effects on economic activity during expansions? The theoretical literature does not usually distinguish between the two regimes. According to the channels mentioned above (i.e. the wait-and-see and the precautionary savings channels), we would expect uncertainty shocks to have similar (at least qualitatively) effects on the macroeconomy regardless of the state of the business cycle. One possible explanation is related to the fact that during expansions uncertainty spurs investment and therefore econominc activity via the *"growth options"* channel. More specifically, according to the "growth options" channel, initial investment can often be seen as the purchase of a call option to expand in the future. If the value of such option is large enough to compensate for the initial investment, then the firm may be willing to undertake it. The value of such option is positively related to uncertainty if this (uncertainty) increases the potential return. Therefore, if uncertainty in expansions is mostly associated with increases in the potential returns on investments, while in recessions uncertainty is mainly associated with reduction in returns, then real options effects ("growth-options" and "wait-and-see") can explain the opposite effects of uncertainty during the different states of the business cycle. Two recent works by Segal, Shaliastovich, and Yaron (2014) and Rossi and Sekhposyan (2015) provide empirical support that uncertainty affects economic activity via the growth options channel by decomposing total uncertainty into two components: *"Good"* (or *"Upside"*) and *"Bad"* (*or "Downside"*) uncertainty. Good or Upside uncertainty consists in uncertainty associated with news or outcomes that are unexpectedly positive (e.g. higher GDP than expected). An example of an upside uncertainty shock is the high-tech revolution of the 1990's, that with the introduction of the *world wide web* led to the common view that the new technology would give rise to persistent growth, yet it was uncertain by how much and for how long. Bad or downside uncertainty instead consists in uncertainty that stems from news or outcomes that are unexpectedly negative (e.g. lower GDP than expected). An example of a downside uncertainty shock is the large surge in uncertainty after the collapse of Lehman Brothers in 2008. After this event people expected the economy to be hit negatively, but they did not know by how much and for how long. Segal, Shaliastovich, and Yaron (2014) estimate good and bad uncertainty following Barndorff-Neilsen, Kinnebrouk, and Shephard (2010) and Patton and Sheppard (2013) decomposing the realized variance into two components that separately capture positive (good) and negative (bad) movements in the underlying variable[6]. Rossi and Sekhposyan (2015) instead propose new uncertainty indeces for upside and downside uncertainty based on the percentile in the historical distribution of forecast errors associated with the realized error[7]. Both papers find good uncertainty to have positive effects on economic activity, while bad uncertainty affects it negatively, acting as a negative demand shock. Moreover, in recessions uncertainty is predominantly downside uncertainty, while upside uncertainty is more frequent in expansions.

4 Concluding remarks

Uncertainty is considered to have particularly severe effects when the economy is in a recessionary phase. The present paper provides empirical evidence on the asymmetric macroeconomic effects of uncertainty shocks depending on the state of the business cycle. To this end, I estimate state-dependent impulse responses for the US economy with the local projection method developed by Jorda (2005). I find that during recessions positive uncertainty shocks have significant dampening effects on economic activity and act as negative demand shocks. In expansions instead uncertainty shocks have a positive effect on economic activity. In line with the theoretical literature (Basu and Bundick, 2012), I find that by excluding from the sample the period in which the federal funds rate approached the Zero Lower Bound, the effects of uncertainty on the macroeconomy are strongly mitigated in both phases of the business cycle. One potential interpretation for the asymmetric effects of uncertainty during expansions and recessions is that in upturns uncertainty is mostly driven by "good" uncertainty and positively affects

[6]Good and bad uncertainty are estimated by projecting the logarithm of the positive realized semivariance, RV^P, and negative realized semivariance, RV^N of the underlying macroeconomic variable (such as industrial production) onto a set of predictors X_t.

[7]Let e_{t+h} be the $h-$ step ahead forecast error of y_{t+h} defined as $y_{t+h} - E_t[y_{t+h}]$ and let $f(e)$ be its forecast error distribution. Uncertainty is then defined as the cumulative distribution $U_{t+h} = \int_{-\infty}^{e_{t+h}} f(e)de$. Upside and downside uncertainty are defined respectively as $U^+_{t+h} = \frac{1}{2} + max\left\{U_{t+h} - \frac{1}{2}, 0\right\}$ and $U^-_{t+h} = \frac{1}{2} + max\left\{\frac{1}{2} - U_{t+h}, 0\right\}$

economic activity through the "growth options" channel. During downturns instead, uncertainty is mostly "bad" and tends to affect negatively the economy via other channels such as the "wait-and-see" effect.

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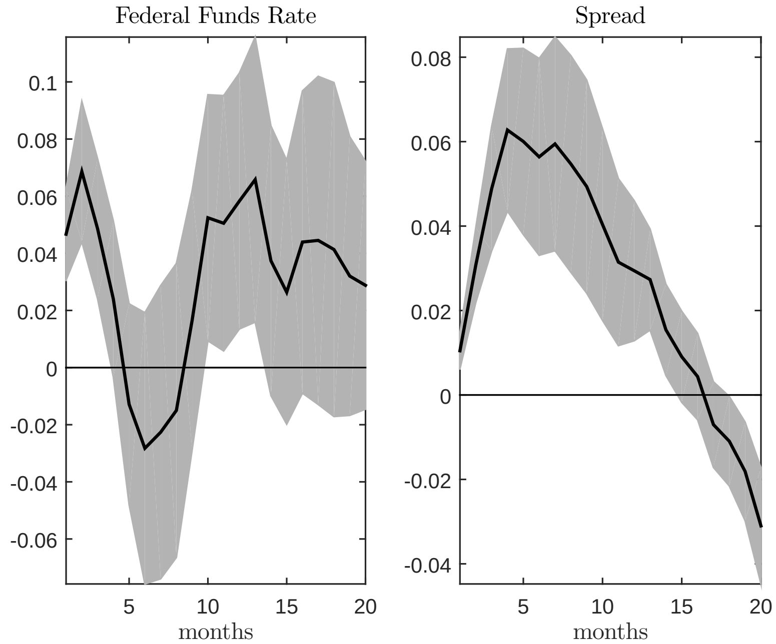
A Appendix

A.1 Additional Figure

Figure A1: *State-dependent IRFs after an uncertainty shock*

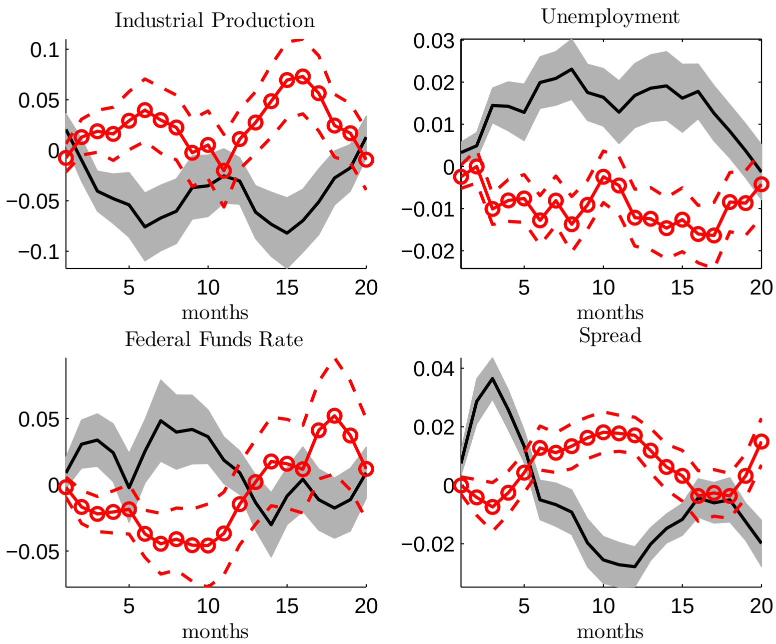


Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

A.2 Robustness Checks

A.2.1 VXO as measure of uncertainty

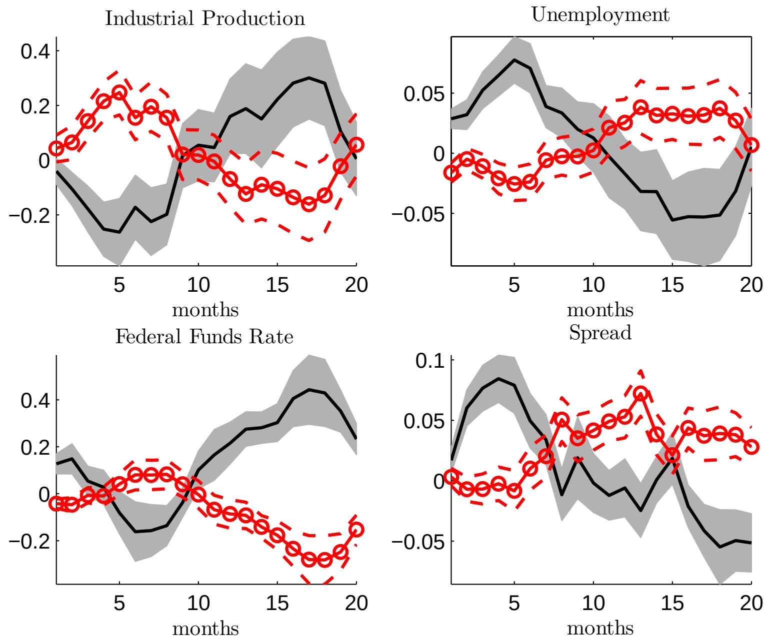
Figure A2: *State-dependent IRFs after an uncertainty shock*



NOTES: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

A.2.2 Excluding the Zero Lower Bound period

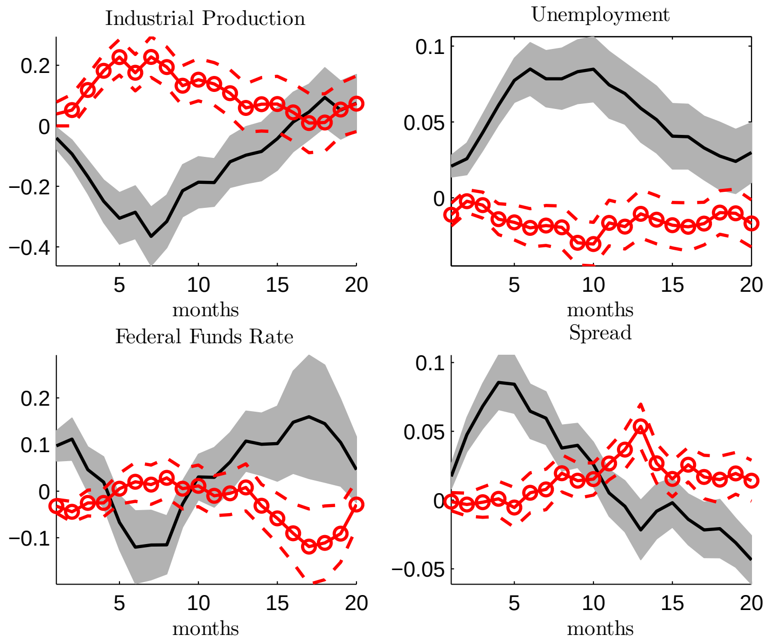
Figure A3: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

A.2.3 Sensitivity of α: $\alpha = 2$

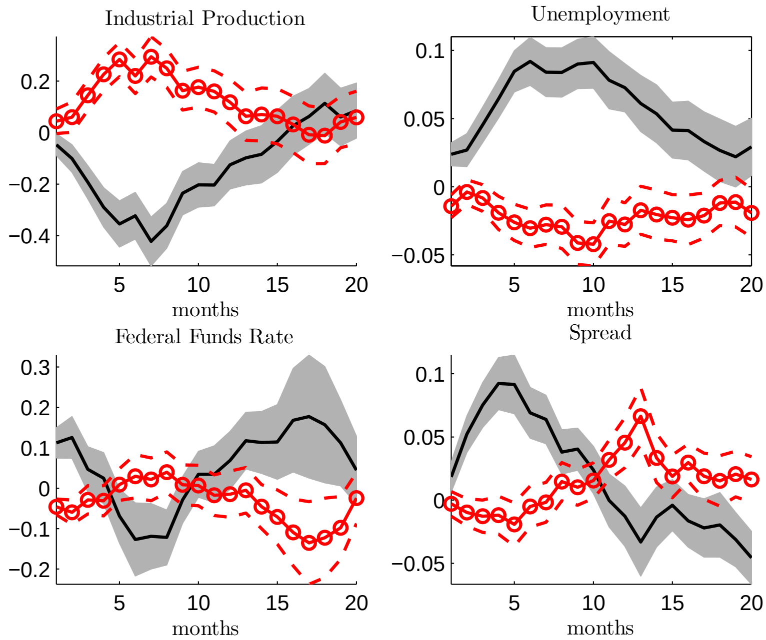
Figure A4: *State-dependent IRFs after an uncertainty shock*



NOTES: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

A.2.4 Controlling for consumer confidence

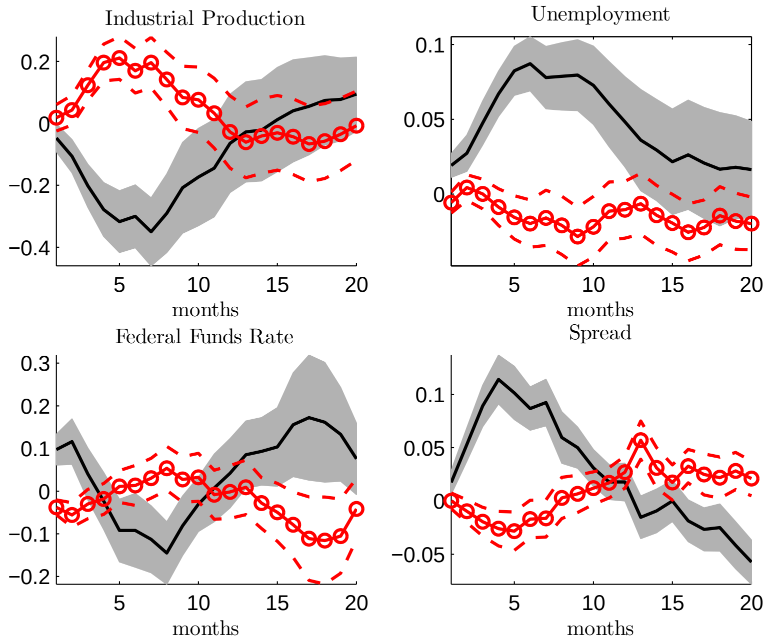
Figure A5: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

A.2.5 Reducing order of lag polynomials to 3

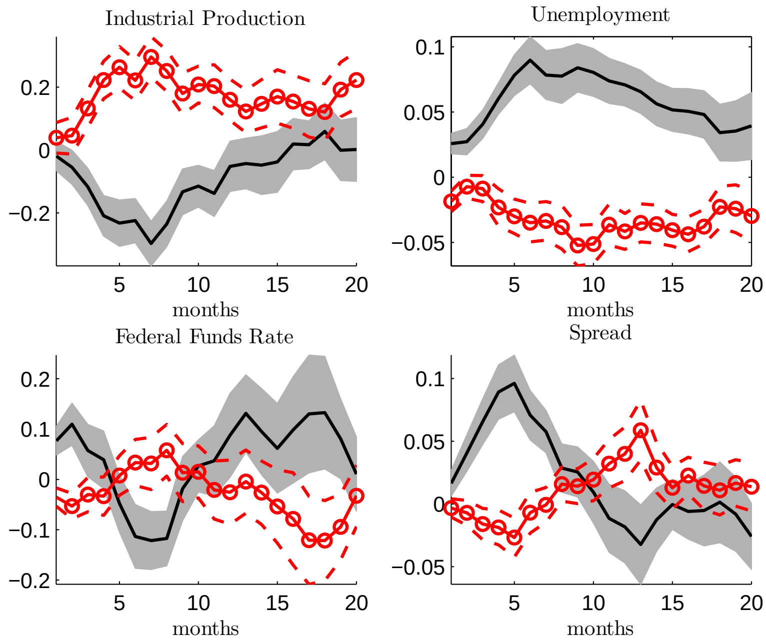
Figure A6: *State-dependent IRFs after an uncertainty shock*



NOTES: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

A.2.6 Increasing order of lag polynomials to 10

Figure A7: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.