The Nonlinear Effects of News through Uncertainty[*]

Mario Forni[†]

Università di Modena e Reggio Emilia, CEPR and RECent

Luca Gambetti[‡]

Collegio Carlo Alberto, Università di Torino, UAB and Barcelona GSE

Luca Sala

Università Bocconi, IGIER and Baffi CAREFIN

Abstract

We put forward the idea that news and uncertainty are closely connected. More specifically, news about future events, whose effects are not perfectly predictable, generate uncertainty. The combination of news and uncertainty makes the effects of news shocks nonlinear. We propose a simple procedure based on linear Structural Vector Autoregressions to estimate nonlinear impulse response functions. Big bad news tend to have higher effects on real variables than positive news since uncertainty exacerbates the negative first moment effect of bad news and mitigates the positive first moment effects of positive news.

1 Introduction

News shocks and uncertainty shocks have been in recent years at the heart of the business cycle debate. In the "news shock" literature, news about future fundamentals affect the current behavior of consumers and investors by changing their expectations, see Jaimovic and Rebelo (2009), Den Haan and Kaltenbrunner (2009) and Schmitt-Grohé and Uribe (2012). A partial list of major empirical contributions in this stream of literature includes Beaudry and Portier (2004, 2006), and Barsky and Sims (2011). By contrast, in the "uncertainty shock" literature, exogenous shocks change the "confidence" of economic agents about their expectations. An increase in uncertainty induces agents to defer private expenditure, thus producing a temporary downturn of economic activity. Since Bloom (2009), a vast literature studying the link between uncertainty and economic fluctuations has grown up. A non-exhaustive list of contributions includes Bachmann, Elstner and Sims (2013), Rossi and Sekhposyan (2015), Jurado et al. (2015), Ludvigson et al. (2015) and Baker et al., (2016) Caldara et al. (2016), Carriero et al. (2016).

Somewhat surprisingly, uncertainty and news are usually regarded as distinct, if not completely independent, sources of business cycle fluctuations[1]. But where does uncertainty stem from? The starting point of the present work is the idea that, to some extent, *uncertainty arises from news*. Economic agents live in a world with imperfect information, observe new important events, but cannot predict exactly their effects on economic activity. This affects the forecast error variance, i.e. uncertainty.

Our main point is that news have both a "first-moment" effect on the expected values and a "second-moment" effect on the variance of the forecast error. Of course, it is conceivable that some news affect uncertainty without affecting expectations, or vice-versa. But it is quite reasonable to assume that first-moment and second-moment effects are most often closely related to each other. The more important the event, the higher the uncertainty originating from news. If nothing new happens,

---

[1]Only very recently, two independent and parallel works have been studying the link between news and uncertainty, see Berger, Dew-Becker and Giglio (2107) and Cascaldi-Garcia and Galvao (2018)

expectations do not change and uncertainty reduces. By contrast, when important events occur, expectations change substantially (either positively or negatively) and, given that the true magnitude of the event is unknown, uncertainty increases.

The empirical evidence supports this idea. We identify a news shock with an informationally sufficient VAR along the lines of Forni, Gambetti and Sala (2014) and Beaudry and Portier (2014) and show that the square of the estimated shock is positively correlated with existing measures of uncertainty. We present a very stylized theoretical framework of limited information that can rationalize this fact. In the model, the conditional forecast error variance depends on the squared news shock. The main implication is that, as long as uncertainty is important for economic fluctuations, the effects of news shock will be non linear. Indeed uncertainty, proxied by the square of the shock, acts as asymmetric propagator.

We propose a new empirical procedure to estimate nonlinear effects of news using linear Structural Vector Autoregressions. The method involves two steps. First, as mentioned above, a VAR is employed to estimate the news shock. Second, the news shock and the squared news shock are added in a VAR which includes a set of variables of interest. The impulse response functions of the news shock are derived using the Generalized Impulse Response functions definition of Koop, Pesaran and Potter (1994).

When the quadratic effect is taken into account, the business-cycle consequences of news appear more complex than usually believed. First, squared news shocks above average, i.e. news shocks larger than one standard deviation, increase uncertainty, producing a temporary downturn of economic activity. On the contrary, squared shocks below average reduce uncertainty triggering a temporary upturn. A zero news shock, for instance, implies a zero first-moment effect, but a positive uncertainty effect since uncertainty reduces. In this sense, no news is good news. Second, the response of output to positive and negative news is generally asymmetric. For small shocks the uncertainty effect, being positive, mitigates the negative first moment effect of bad news and reinforces the positive effect of good news. For large shocks, the asymmetry is reversed. The uncertainty effect is negative; it therefore exacerbates the negative

first moment effect of bad news and reduces the positive impact of good news.

The forecast error variance of GDP accounted for by squared news is sizable on average (about 20% at the 1-year horizon in the benchmark specification). The distribution of squared news shocks is characterized by a large number of small shocks and a small number of large shocks. These large shocks are typically negative, the distribution of news shocks being left skewed. As a consequence, most of the time the effect of square news is relatively small, but in a few episodes of large negative news it is not.

The reminder of the paper is structured as follows: section 2 discusses some evidence about news and uncertainty and a simple theoretical model; section 3 discusses the empirical model; section 4 presents the empirical results; section 5 concludes.

2   The link between news and uncertainty

In this section we report some *prima facie* evidence on the link between news and uncertainty and present a simple framework of limited information where uncertainty arises from news.

2.1   Preliminary evidence

We start off our analysis by estimating the effects of news shocks. We use quarterly US data from 1963:Q4 to 2015:Q2 to estimate a Bayesian VAR[2] with diffuse priors and 4 lags which includes the following variables: (log) TFP[3], (log) stock prices (the S&P500 index divided by the GDP deflator), the Michigan Survey confidence index component concerning business conditions for the next five years (E5Y), (log) real consumption of nondurables and services (Consumption), the 3-month Treasury Bill secondary market rate (TB3M), the 10-year Treasury constant maturity rate (GS10),

---

[2]A frequentist VAR yields the same results.

[3]Following Beaudry and Portier, 2006, we use total factor productivity (TFP) corrected for capacity utilization. The source is Fernald's website. TFP is cumulated to get level data.

the Moody's Aaa interest rate (AAA) and the Michigan Survey's News variable[4]. We denote this model as VAR 1.

To identify the news shock, denoted by s_t, we follow Forni, Gambetti and Sala (2014) and Beaudry et al. (2016) and we impose the following restrictions: (i) the news shock has no effects on TFP contemporaneously and (ii) has a maximal effect in the long-run (48 quarters). This identification scheme is standard in the news shock literature and is very similar to the one used in Barsky and Sims (2011).[5]

Figure 1 shows the effects of the news shock on the variables in VAR 1. The impulse-response function of TFP exhibits the typical S-shape which is usually found in the literature. Stock prices, E5Y and the news variable jump on impact, as expected, while consumption increases more gradually. All interest rates reduce on impact, albeit the effect is barely significant. All in all, the effects of the news shock are qualitatively very similar to those found in the literature.

Next, we investigate the link between the news shocks and various existing measures of uncertainty. We focus on the squared news shock, which we interpret as a rough measure of the one-step ahead forecast error variance attributable to news

---

[4]We add the News variable to enhance VAR information sufficiency. The variable is constructed as follows. Question A.6 of the Michigan Consumers Survey questionnaire asks: "During the last few months, have you heard of any favorable or unfavorable changes in business conditions?". The answers are summarized into three time series, Favorable News, Unfavorable News, No Mentions, which express the percentage of respondents which select that particular answer. We build a "Consumers' News" variable by taking the difference between "Favorable News" and "Unfavorable News". This variable takes on positive values when most consumers mention good news and negative values when most consumers mention bad news.

[5]The VAR specification is chosen in order to make the VAR informationally sufficient (Forni and Gambetti, 2014). Under informational sufficiency, the news shock can be recovered from a VAR and it is invariant to the inclusion of other variables. To evaluate whether we are neglecting relevant variables in our VAR specification, we use the testing procedure suggested in Forni and Gambetti (2014). We regress the news shock, s_t onto the past values of a number of macroeconomic variables, taken one at a time and test for significance of the coefficients using a F-test. For all of the regressions, the null that all coefficients are zero cannot be rejected (See Table A.1 in the Appendix). We conclude that the model incorporates enough information to identify the news shock.

shocks.[6] We first compute the correlation between the squared news shock and a number of uncertainty measures used in the literature, namely the (i) extended VXO index of implied volatility in option prices, see Bloom (2009); (ii) the Jurado, Ludvigson and Ng, 2015 macroeconomic uncertainty index, at the 3-months and 12-months horizon (denoted respectively JLN3 and JLN12 henceforth); (iii) the Ludvigson, Ma and Ng, 2015, financial and real uncertainty indexes 3-months ahead (denoted respectively, LMN3 Fin. and LMN3 Real). The correlation between s_t^2 and the VXO, JLN3, JLN12, LMN3 Fin. and LMN3 Real are respectively 0.3, 0.5, 0.4, 0.3 and 0.4. The squared news shock is positively correlated with all recent measures of uncertainty.

As a second check, we identify an uncertainty shock as the first shock in a Cholesky decomposition in a VAR which includes the VXO, GDP, consumption, investment, hours worked, CPI inflation and new orders with this order and compute impulse responses.[7] The correlation between the uncertainty shock and the news shock estimated above is -0.377. We then add the news shock and the squared news shock as the first and second variable to the specification above and study the effects of an uncertainty shock identified as the third shock in a Cholesky identification and compute impulse responses. If the standard uncertainty shock has nothing to do with squared news, the impulse response functions in the VAR models with and without s_t and s_t^2 should be very similar. It turns out that impulse responses are significantly different (see Figure A.1). When the uncertainty shock is cleaned from the effects of the news and squared news, its effects basically vanish. We interpret this as meaning that a large part of the uncertainty shock is associated with news and squared news.[8]

The above evidence is obviously only suggestive, but points to a close link between squared news and uncertainty. Not only, the result seems to suggests that a part of

---

[6]We will see in the following sections that this variable might be seen as the time-varying uncertainty generated by the news shock.

[7]The VAR specification is fairly standard, see Bloom (2009).

[8]We have also replaced the VXO with LMN3 Fin. and LMN3 Reak and computed impulse responses, see Figures A.2 and A.3 in the Appendix. The change in the responses is milder, suggesting that the type of uncertainty captured by LMN3 Fin. and LMN3 Real is not entirely related to the news shock.

measured uncertainty arises from news.

2.2 A simple and consistent informational framework

In this section, for illustrative purposes, we discuss a very stylized framework to understand how uncertainty, defined as the conditional forecast error variance, can arise from news. Let the fundamental of the economy a_t follow

$$\Delta a_t = \epsilon_{t-1} \tag{1}$$

where $\epsilon_t \sim N(0, \sigma_\epsilon^2)$ is shock with delayed effects.[9] Agents have imperfect information and cannot observe ϵ_t, but rather have access to news that report the events underlying the shock. For instance natural disasters, scientific and technological advances, institutional changes and political events.[10] At each point in time, agents form an expectation, $s_t = E_t \varepsilon_t$ of the true shock. The shock and the expectation however, because information is imperfect, do not coincide. We assume that there is a random factor v_t that creates a wedge between the two

$$\varepsilon_t = s_t v_t.$$

The shock v_t has the following properties: the conditional mean is $E_t v_t = 1$, so to satisfy $E_t \varepsilon_t = s_t$, and the conditional variance is $E_t(v_t - 1)^2 = \sigma_v^2$. The above equation can be rewritten as $\varepsilon_t = s_t + s_t(v_t - 1)$, so that ε_t is made up by the sum of two components: the observed component s_t and an unobserved component which is proportional to s_t.

This multiplicative noise structure, to our knowledge, has not been employed before in the literature of limited information. However we find it particularly attractive since, despite being very simple, can describe relevant economic situations. A few examples can provide a better intuition. Suppose that a diplomatic crisis takes place

---

[9]For the sake of simplicity, we assume one period delay but it is possible to consider a more general model.

[10]Models of limited information has been recently developed by Angeletos and La'O (2010), Lorenzoni (2009) and Blanchard, L'Huillier and Lorenzoni (2013) among others.

at time t and is reported by the media. The crisis can lead to a war ($\varepsilon_t = 1$) or not ($\varepsilon_t = 0$) with equal probabilities, so that agents' expectation is $s_t = 0.5$. The president decides at time t to go to war ($v_t = 2$) or not ($v_t = 0$), but the decision is not made public until time $t+1$ for security reasons. As a second example, suppose the agents observe that a big bank goes bankrupt. The value of the shock, however, is unknown because with some probability, say 0.5, there will be a domino effect and other banks will go bankrupt ($\varepsilon_t = -3$), but with probability 0.5 the government will intervene to rescue them ($\varepsilon_t = -1$). In this case $s_t = -2$ and v_t can be either 1.5 or 0.5 with equal probabilities.

The forecast error in this model is simply

$$
\begin{aligned}
u_{t+1} &= \Delta a_{t+1} - E(\Delta a_{t+1}|s_t) \\
&= \epsilon_t - E(\varepsilon_t|s_t) \\
&= (v_t - 1)s_t.
\end{aligned}
$$

As in Ludvigson, Jurado and Ng, 2015, we define uncertainty as the conditional variance of the forecast error, which is

$$
E((v_t - 1)^2|s_t)s_t^2 = \sigma_v^2 s_t^2.
$$

Thus, that the conditional variance, i.e. uncertainty, depends on the news shock squared.[11] Going back to the previous example, the bigger is the war, i.e. the larger the value of ε_t, the larger will be the uncertainty, since the larger is s_t.

As long as s_t corresponds to the news shock estimated with the SVAR in the previous section, this simple theoretical framework is consistent with the empirical feature discussed in the previous section: existing measures of uncertainty are correlated with the news shock squared.[12] It is easy to see that the news shock estimated

---

[11]In the former example above $\sigma_v^2 = 1$ and uncertainty is 0.25; in the latter, $\sigma_v^2 = 0.25$ and uncertainty is 1.

[12]Here the correlation between s_t^2 and uncertainty is one, but it is possible to break the perfect correlation by adding an exogenous component to uncertainty.

from a VAR indeed corresponds to s_t. In fact, the representation of Δa_t and s_t is[13]:

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} 1 & L \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}, \tag{2}$$

and s_t satisfies the restrictions used above to identify the news shock: positive long run effect and zero impact effect. Under this simple limited information framework, the news shock identified in the empirical literature corresponds to s_t. The other shock, u_t, is what the VAR would identify as a surprise shock.[14]

Summing up, if uncertainty has any effects on the economy, then the news shock will have non linear effects: a first moment effect through s_t and a second moment effect through s_t^2.

3 Nonlinear IRF from linear VAR

If s_t^2 has any effect on the economy, then the effects of news shocks will be nonlinear, a feature of the propagation mechanism of news which has been largely neglected in the literature. By nonlinear here we mean that positive and negative, as well as large and small news, might generate different effect because uncertainty acts, through the square term, as an asymmetric amplifier.

In this section we discuss the empirical approach we use to study the effects of news shocks. We estimate the nonlinear effects of news shocks using a linear VAR. Let Y_t be a vector of m variables of interest.[15] Using the news shock obtained in section 2, we estimate a VAR which includes s_t, $s_t^2 - 1$[16] and Y_t and derive the Cholesky

---

[13]ε_t cannot be obtained from a VAR. The only shock that is recoverable from a VAR is s_t

[14]The fact that under limited information the shock estimated with a VAR is not the structural shock, ε_t is not surprising. Indeed it was been pointed out for the first time by Blanchard et al. (2013). In this setting the shock identified by the VAR is simply the part of the structural shock observed by the agents.

[15]See section 4 for a detailed description of the variables used in the empirical analysis.

[16]We use $s_t^2 - 1$ instead of s_t^2 because we normalize s_t^2 so to have $Es_t^2 = 1$ and demean it. Results would be identical by using s_t^2.

representation

$$\begin{pmatrix} s_t^2 - 1 \\ s_t \\ Y_t \end{pmatrix} = \begin{pmatrix} \sigma_{s^2} & 0 & \mathbf{0} \\ 0 & 1 & \mathbf{0} \\ & A(L) & \end{pmatrix} \begin{pmatrix} \frac{s_t^2 - 1}{\sigma_{s^2}} \\ s_t \\ w_t \end{pmatrix}, \tag{3}$$

where $A(L)$ is a $m \times m + 2$ matrix of polynomials in the lag operator, w_t is a m-dimensional vector of (unidentified) structural shocks and $\mathbf{0}$ is a $1 \times m$ vector of zeros. We follow standard conventions by standardizing the structural shocks.

The effects of news shocks can be obtained using a version of the Generalized Impulse Response Functions (GIRF, henceforth), see Koop, Pesaran and Potter (1996). More specifically, we define the GIRFs at the horizon j as

$$E(Y_{i,t+j}|s_t = \bar{s}, \mathcal{I}_{t-1}) - E(Y_{i,t+j}|\mathcal{I}_{t-1}) = A_{i1}(L)\bar{s} + A_{i2}(L)\frac{(\bar{s}^2 - 1)}{\sigma_{s^2}} \tag{4}$$

where $\mathcal{I}_{t-1}$ represents the information set at time $t-1$. The first term of the right-hand side represents the linear effect of news, while the second term represents the effect of uncertainty. Notice that in our set-up the non-linear responses simply correspond to the sum of the coefficients of the moving average representation obtained from the linear VAR weighted by $\bar{s}$ and $(\bar{s}^2 - 1)/\sigma_{s^2}$.

A few remarks about our econometric procedure are in order. First, s_t is well estimated as long as the first VAR is informationally sufficient, and it is (see Table A.1 in the Appendix). Second, as s_t is iid, then $s_t^2 - 1$ is also iid and s_t and $s_t^2 - 1$ are jointly white noise. This implies that the OLS estimator of the VAR associated to the above MA representation will have the standard properties including consistency. Third, if s_t has a symmetric distribution, then s_t^2 is also orthogonal to s_t. In this case, the ordering of s_t and s_t^2 in the first two positions is irrelevant in the Cholesky decomposition. In practice, the correlation, although small, -0.2, is not zero. Nonetheless it turns out that the ordering of s_t and s_t^2 is irrelevant since the impulse responses are very similar.[17]

---

[17]Notice that instead of estimating a VAR, direct projections or a VARX can be used. We have explored these alternatives: the main results are similar across different procedures.

3.1 Simulations

Before going to the data, we use two simulations to assess our econometric approach. The first simulation is designed as follows. Consider the simple model of Section 2.2. Assume that $[v_t \quad s_t]' \sim N(0, I)$.[18] Under the assumption $\Delta a_t = \epsilon_{t-1}$, and recalling that $s_t = E_t a_{t+1}$ and that $u_t = s_{t-1} v_{t-1}$ is the forecast error, the invertible representation for Δa_t is $\Delta a_t = s_{t-1} + u_t$. We assume that there are two variables, $z_t = [z_{1t} \ z_{2t}]'$, following an MA process, which are affected by s_t and s_t^2. By putting together the fundamental representation for Δa_t and the processes for z_t, the data generating process is given by the following MA:

$$\begin{pmatrix} \Delta a_t \\ z_{1t} \\ z_{2t} \end{pmatrix} = \begin{pmatrix} 1 & L & 0 \\ 1 + m_1 L & 1 + n_1 L & 0 \\ 1 + m_2 L & 1 + n_2 L & 1 + p_2 L \end{pmatrix} \begin{pmatrix} u_t \\ s_t \\ w_t \end{pmatrix} \tag{5}$$

where $w_t = \frac{s_t^2 - 1}{\sigma_{s^2}}$.

Simple MA(1) impulse response functions are chosen for the sake of tractability, but more complicated processes can be also considered. Using the following values $m_1 = 0.8$, $m_2 = 1$, $n_1 = 0.6$, $n_2 = -0.6$, $p_1 = 0.2$, $p_2 = 0.4$, and drawing $[v_t \ s_t]$, we generate 2000 artificial series of length $T = 200$. For each set of series, we estimate a VAR for $[\Delta a_t \ z_{1t} \ z_{2t}]'$ and identify s_t as the second shock of the Cholesky representation. We define $\hat{s}_t$ as the estimate of s_t obtained from the VAR. In a second step, using the same 2000 realizations of $[u_t \ s_t \ s_t^2]'$, we generate another variable Δy_t (which in the simulation plays the role of any variables in the vector Y_t) as[19]

$$\Delta y_t = u_t + [L + (1 - L)(1 + g_1 L)]s_t - (1 - L)(1 + f_1 L)w_t,$$

where $g_1 = 0.7$ and $f_1 = 1.4$. We estimate a VAR with $[\hat{s}_t^2 \ \hat{s}_t \ \Delta y_t]'$ and apply a Cholesky identification. The first shock is the squared news shock, the second shock is the news shock.

The second simulation is similar to the first, the only difference being that w_t is an exogenous shock which does not depend on s_t, which implies that the squared

---

[18]This also allows us to generate $\epsilon_t = s_t + s_t v_t$.

[19]This is the corresponding row of the VAR in equation (3)

news shock has no effects on z_t and Δy_t. The values of the parameters are the same as before and $[v_t \ \ s_t \ \ w_t]' \sim N(0, I)$. We estimate a VAR with $[\hat{s}_t^2 \ \hat{s}_t \ \Delta y_t]'$ and apply a Cholesky identification.

Results of simulation 1 are reported in the left column of figure 2, while those of simulation 2 on the right column. The solid line is the mean of the 2000 responses, the gray area represents the 68% confidence bands, while the dashed red lines are the true theoretical responses. In both simulations, and in all of the cases, our approach succeeds in correctly estimating the true effects of news and uncertainty shock, the theoretical responses essentially overlapping with the mean estimated effects. When none of the variables is driven by uncertainty, our procedure consistently estimates a zero effect.

4   Empirical results

In this section we report and discuss the empirical results.

4.1   News and squared news

The news shock, and therefore the squared shock, exhibits very large values (more than two standard deviations larger than average) in seven quarters. Five of them correspond to periods associated to negative shocks and two are period associated to positive shocks. The news shock is therefore left skewed, with skewness of -0.36. The seven quarters are the following (in parenthesis the sign of the shock): 1974:Q (-) Stock Market Oil Embargo Crisis; 1982:Q1 (-) Loan Crisis; 1982:Q4 (+) End of early 80s recession; 1987:Q1 (+) Oil price collapse; 2002:Q3 (-) WorldCom Bankruptcy; 2008:Q3 (-) Lehman Brothers Bankruptcy; 2008:Q4 (-) Stock Market Crash. Most of these dates correspond to well identified historical events and/or cycle phases.

4.2 The effect of news

The VAR we employ to study the effects of nws on the economy includes: the estimated squared news shock (estimated with the VAR 1 of section 2.1), the news shock, (log) real GDP, (log) real consumption of non-durables and services, (log) real investment plus consumption of durables, (log) hours worked, CPI inflation and the ISM new orders index. We call this model VAR 2.

We organize the discussion as follows. First we present the results relative to the estimated impulse response functions of s_t and s_t^2 (for magnitudes $s_t = 1$ and $\frac{(\bar{s}^2-1)}{\hat{\sigma}_{s^2}} = 1$) separately. Then, we focus on the nonlinearities implied by equation (3). Results are reported in Figure 3. The numbers on the vertical axis can be interpreted as yearly percentage variations. The news shock, Figure 3 (left column) has a large, permanent, positive effect on real activity, with maximal effect after about 2 years. The results are in line with what already found in the literature.[20] The squared news shock (Figure 3, right column) has a significant negative effect on all variables on impact. The maximal effect on GDP is reached after 4 quarters and is about -1.5% in annual terms. Afterwards, the effect reduces and vanishes after about 3 years. By using different identification schemes and different specifications for the VAR in equation (3) we find similar results, the maximal effect on GDP ranging between -1.5% and -2% at the 1-year horizon (see Figures A.6 and A.5 in the Appendix.). Let us stress that the shock has essentially the nature of a demand shock: both new orders and prices jump down on impact.

In terms of variance decomposition (see Table 1), the squared news shock explains a sizable fraction of output, investment and hours volatility at the 1-year horizon (19%, 16.8% and 10.4%, respectively). The effects on consumption are smaller, about 5%.

Recall that the response to the squared news shock is given by $\hat{A}_{i2}(L)\frac{(\bar{s}^2-1)}{\hat{\sigma}_{s^2}}$. The size and the sign of the effect depends on the size of s_t. This implies that the uncertainty effects of news shocks might be positive. Indeed this happens when the

---

[20]Barsky and Sims, 2011, Forni, Gambetti and Sala, 2011.

squared news shock is below its mean, that is, when $-1 < s_t < 1$. No news (or small news) produce a temporary upturn of economic activity since a level of uncertainty below its average stimulates the economy. When the news shock is equal to 1 or -1, i.e. equal to its standard deviation in absolute value (equivalently, when the uncertainty shock is equal to its mean), there are no uncertainty effects. On the contrary, a news shock in absolute value larger than its standard deviation (equivalently, an uncertainty shock larger than its mean) produces negative uncertainty effects. For instance, a news shock equal to twice its standard deviation produces a reduction in GDP of around 7-8% on an yearly basis (see box (1,2) of Figure 4).

With these premises, we investigate the total effect of news estimated using equation (4). We consider shocks of dimension $\bar{s} = \pm 0.5, \pm 2$. Results for are reported in Figure 4.[21] Let us focus on real variables first. The responses of GDP, consumption, investment and hours are quite similar. The main common feature is that the effects of news are generally asymmetric. When s_t is small in absolute value (equivalently, s_t^2 is smaller than its mean), the uncertainty effect is positive. In the short run, the effect of s_t^2 mitigates the negative first moment effect of bad news and reinforces the positive effect of good news (upper panels). For large shocks (as in Fugure 3) when s_t is larger, in absolute value, then its standard deviation and s_t^2 is larger than its mean, the asymmetry is reversed: the uncertainty effect is negative. Also, interestingly, for negative shocks the response of real variable is quicker than for positive shocks. Real variables respond more and more quickly to big bad news than big positive news. Real Uncertainty exacerbates the negative first moment effect of bad news and mitigates the positive effect of good news.

As for inflation, large positive shocks have large effects than large negative shocks which essentially have no effects on inflation. On the other hand small negative shocks have larger effects than small positive shocks.

---

[21]The effect of a shock such that $\bar{s} = \pm 1$ is actually displayed in the left column of Figure 3. When $\bar{s} = \pm 1$, the nonlinear effect is zero and the response of the economy is driven only by the news shock.

4.3 News, uncertainty and financial variables

In order to analyze the effects of news on financial variables and uncertainty, we estimated an additional VAR where we included again the squared news shock and the news shock, along with stock prices, the 10-year government bond yield (GS10), the spread between Baa and Aaa corporate bonds, which may be regarded as a measure of the risk premium, the stock of commercial and industrial loans, the extended VXO index, see Bloom (2009), and the macroeconomic uncertainty index JLN3.

Results are reported in Figure 5. The mid column reports the linear case, a shock of size ± 1. Good news have a large, positive and persistent effect on stock prices. Moreover, good news reduce significantly the risk premium, the VXO index and the JLN3 index. The effects are symmetric for negative news, being absent the uncertainty channel.

For small and large shocks, respectively ± 0.5 (left column) and ± 2 (right column), nonlinearities kick in and uncertainty becomes an asymmetric propagator. Let us consider first the shock of magnitude ± 2 . For all of the variables, negative shocks have larger (absolute value) effects than positive shocks. The reason is that the sign of the first and second moment effects tend to coincide. The only exception is the long rate. Despite different magnitudes, the responses of loans and stock prices are reltivey similar for positive and negative shocks. On the contrary the spread, the long rate and the VIX display very different dynamics. The long rate significantly reduces as also found in Kurmann and Otrock (2013) following positive news but is barely affected by negative news. The spread and the VIX, on the other hand, react only to negative shocks. The opposite results hold for small shocks.

5 Conclusions

News about future events, whose effects are not predictable with certainty, increase economic uncertainty. As a consequence, the effects of news become nonlinear since uncertainty acts as an asymmetric amplifier. Big bad news have larger effects than big good news. Large news shocks increase uncertainty above its expected value.

Given that the effects of uncertainty are contractionary for the economy, uncertainty amplifies the effects of bad news and mitigates those of good news. For small shocks the results are reversed.

References

[1] Angeletos G., M. and J. La'O (2010), "Noisy Business Cycles", NBER Chapters, in: NBER Macroeconomics Annual 24, 319-378.

[2] Bachmann R., S. Elstner and E. R. Sims (2013), ''Uncertainty and economic activity: Evidence from business survey data", American Economic Journal: Macroeconomics, 5(2), 21749.

[3] Baker, S. R., N. Bloom, N., and S. J. Davis (2016), ''Measuring economic policy uncertainty", The Quarterly Journal of Economics, 131(4), 15931636.

[4] Barsky, R. and E. Sims (2012), "Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence", American Economic Review 102, 1343-77.

[5] Barsky, R. and E. Sims (2011), "News shocks and business cycles", Journal of Monetary Economics 58, 273-289.

[6] Beaudry, P. and F. Portier (2004), "Exploring Pigou's Theory of Cycles", Journal of Monetary Economics 51, 1183-1216.

[7] Beaudry, P. and F. Portier (2006), "Stock Prices, News, and Economic Fluctuations", American Economic Review 96, 1293-1307.

[8] Beaudry, P. and F. Portier (2014), "The News View of Business Cycles: Insights and Challenges", Journal of Economic Literature, 52(4), pp. 993-1074.

[9] Beaudry, P., D. Nam and J. Wang (2011), "Do Mood Swings Drive Business Cycles and is it Rational?", NBER working paper 17651.

[10] Berger, D., I. Dew-Becker, and S. Giglio (2017),''Uncertainty Shocks as Second-Moment News Shocks", NBER Working Paper 23796.

[11] Blanchard O.J., G. Lorenzoni and J.P. L'Huillier (2013), "News, Noise, and Fluctuations: An Empirical Exploration", American Economic Review, vol. 103(7), pp. 3045-70,

[12] Bloom, N. (2009), "The Impact of Uncertainty Shocks", Econometrica 77, pp. 623-685.

[13] Cascaldi-Garcia, D. and A. Beatriz Galvao (2018), '' News and Uncertainty Shocks", Board of Governors of the Federal Reserve System, International Finance Discussion Papers, Number 1240.

[14] Caldara, D., C. Fuentes-Albero, S., Gilchrist and E. Zakrajsek, (2016), ''The macroeconomic impact of financial and uncertainty shocks", European Economic Review, 88 , 185207.

[15] Carriero, A., T., Clark, and M. Marcellino (2016), ''Measuring uncertainty and its impacts on the economy'',forthcoming: The Review of Economics and Statistics.

[16] Den Haan, W.J. and G. Kaltenbrunner (2009). "Anticipated growth and business cycles in matching models", Journal of Monetary Economics 56, pp. 309-327. eds. Boulder: Westview, pp.77-119.

[17] Forni, M. and L. Gambetti (2014), "Sufficient information in structural VARs", Journal of Monetary Economics 66, pp. 124-136.

[18] Forni, M., Gambetti, L., Lippi, M. and L. Sala (2014),"Noise bubbles", Baffi Center Research Papers no. 2014-160, forthcoming in *Economic Journal*.

[19] Forni, M., L. Gambetti and L. Sala (2014), "No news in business cycles", The Economic Journal 124, pp. 1168-1191.

[20] Forni, M., Gambetti, L. and L. Sala (2016), "VAR information and the empirical validation of macroeconomic models", CEPR Discussion Papers no. 11178.

[21] Forni, M., D. Giannone, M. Lippi and L. Reichlin (2009), "Opening the black box: structural factor models with large cross-sections", Econometric Theory 25, pp. 1319-1347.

[22] Jaimovich, N. and S. Rebelo, (2009), "Can news about the future drive the business cycle?", American Economic Review, 99(4): 1097-1118

[23] Jurado, K., Ludvigson, S.C. and S. Ng (2015), "Measuring uncertainty", American Economic Review 105, pp. 1177-1216.

[24] Koop, G., H. Pesaran, H.M. and S. M.Potter (1996), ''Impulse response analysis in nonlinear multivariate models", Journal of Econometrics 74(1): 119-147.

[25] Kurmann, A., and C. Otrock (2013), ''News Shocks and the Slope of the Term Structure of Interest Rates", American Economic Review 103(6): 2612-32.

[26] Leduc, S., and Z. Liu (2016), ''Uncertainty shocks are aggregate demand shocks", Journal of Monetary Economics, 82(C), 2035.

[27] Leeper, E. M., Walker, T. B. and Yang, S. C. (2013), "Fiscal foresight and information flows", Econometrica, 81: 1115-1145

[28] Lippi, M. and L. Reichlin (1993), "The dynamic effects of aggregate demand and supply disturbances: comment", American Economic Review 83, 644-652.

[29] Lippi, M. and L. Reichlin (1994), "VAR analysis, non fundamental representation, Blaschke matrices", Journal of Econometrics 63, 307-325.

[30] Lorenzoni, G., (2009), "A theory of demand shocks", American Economic Review, 99, 2050-84.

[31] Ludvigson, S., Ma, S., and Ng, S. (2015), "Uncertainty and business cycles: exogenous impulse or endogenous response?," NBER Working Papers 21803, National Bureau of Economic Research.

[32] Schmitt-Grohé, S. and Uribe, M. (2012), "What's News in Business Cycles", Econometrica, 80: pp. 2733-2764.

Variable	Horizon				
	Impact	1-Year	2-Years	4-Years	10-Years
	Squared news shock				
GDP	10.6	19.3	11.6	5.7	3.1
Consumption	4.8	4.8	2.4	1.0	0.5
Investment	9.8	16.8	9.9	5.6	4.5
Hours Worked	3.1	11.5	10.4	6.2	4.3
CPI inflation	2.0	3.7	3.3	3.2	3.1
ISM New Orders Index	5.9	7.2	8.9	9.8	9.7
	News shock				
GDP	1.7	18.0	28.8	34.9	38.4
Consumption	12.9	38.8	46.4	48.9	48.9
Investment	0.1	15.9	25.7	30.6	32.8
Hours Worked	2.0	14.0	26.3	35.6	32.5
CPI inflation	1.2	4.0	3.5	3.4	3.3
ISM New Orders Index	0.5	14.7	11.4	11.4	11.5

Table 1: Variance decomposition for s_t and s_t^2. The entries are the percentages of the forecast error variance explained by the shocks.
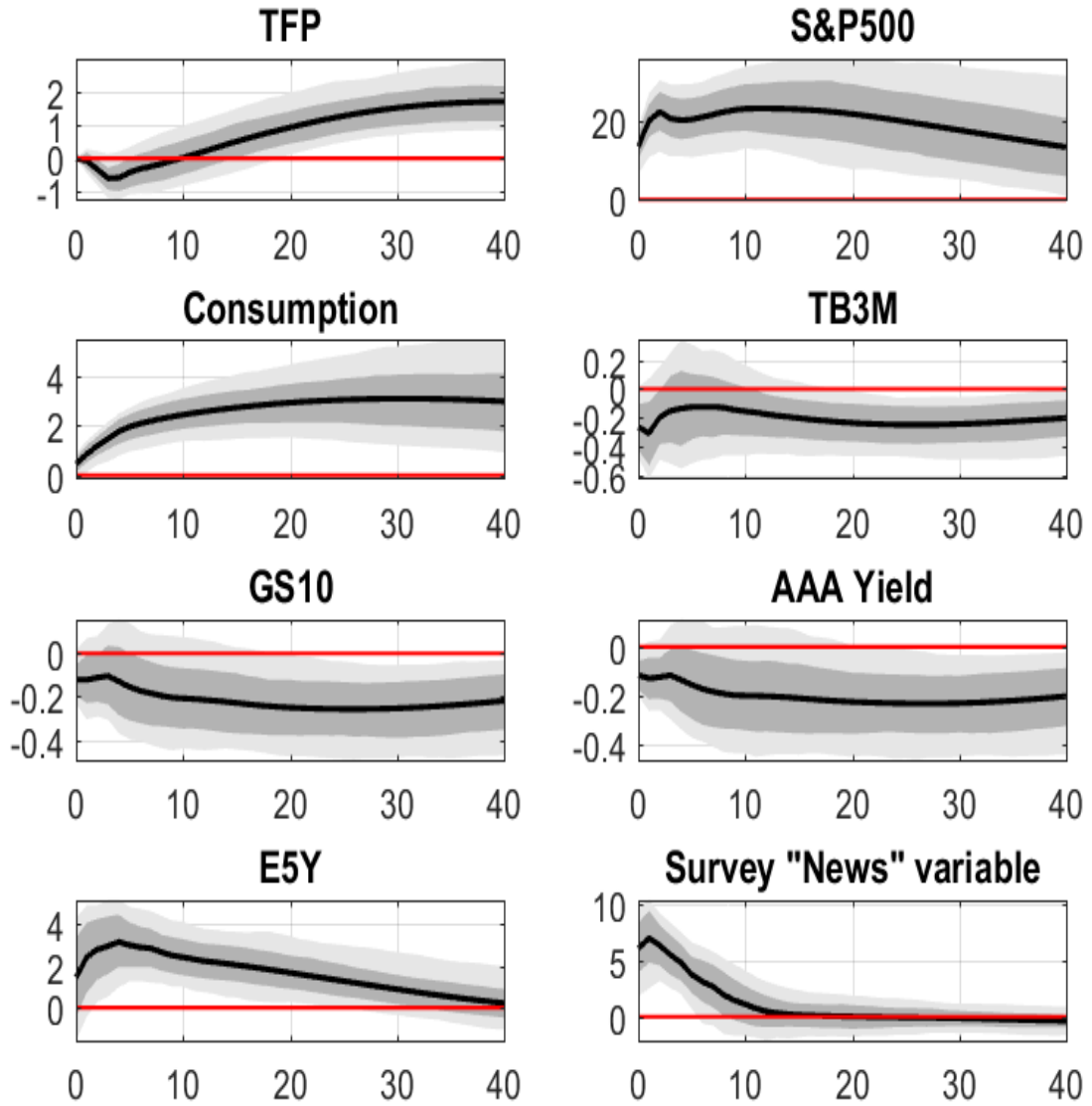
Figure 1: Impulse response functions to the news shock (VAR 1). Solid line: point estimate. Light grey area: 90% credible bands. Dark grey area: 68% credible bands.
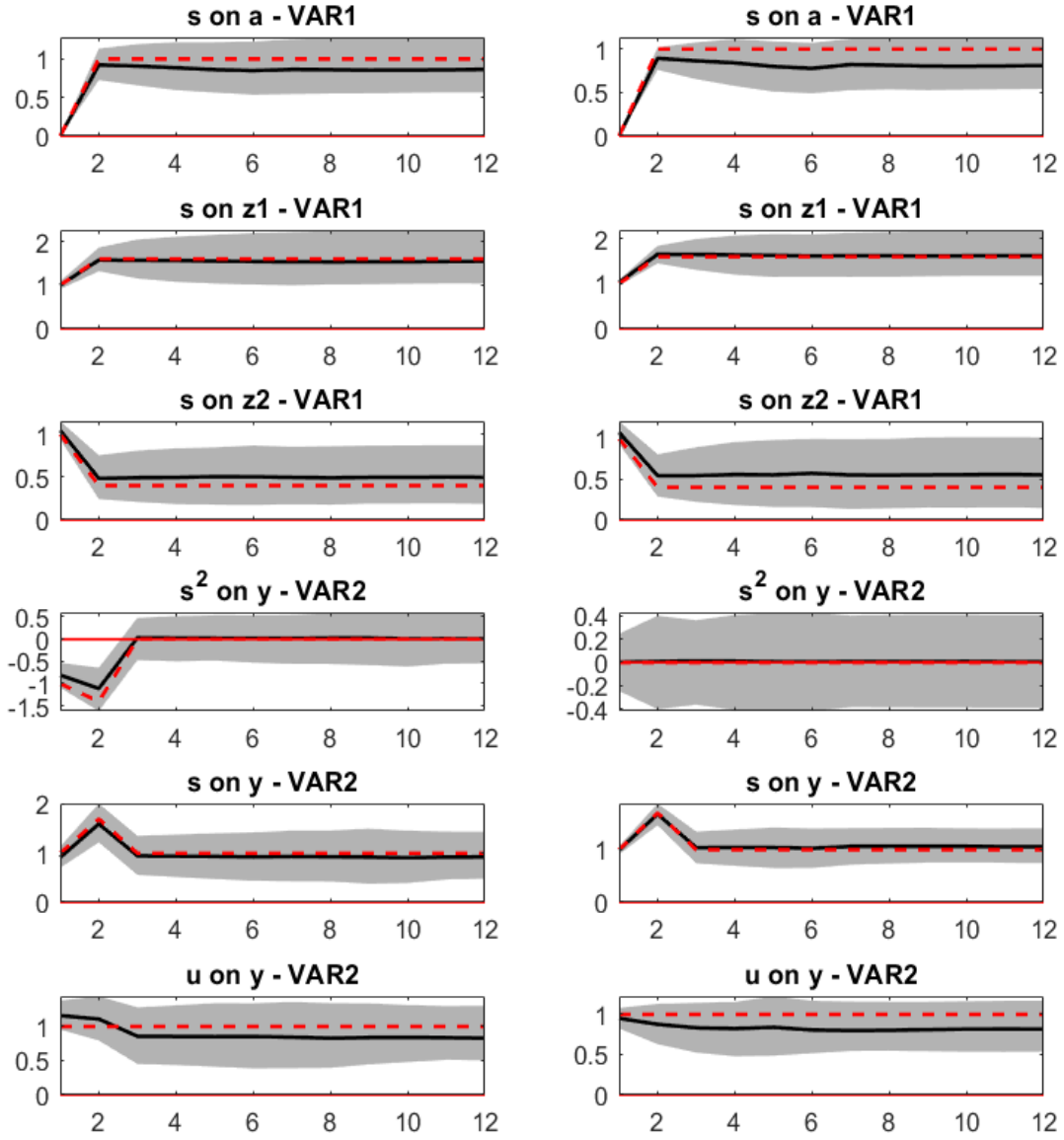
Figure 2: Impulse response functions functions of the two simulations. Left column: simulation 1. Right column: simulation 2. Solid line: point estimate. Grey area: 90% confidence bands. Red dashed line: true theoretical responses.
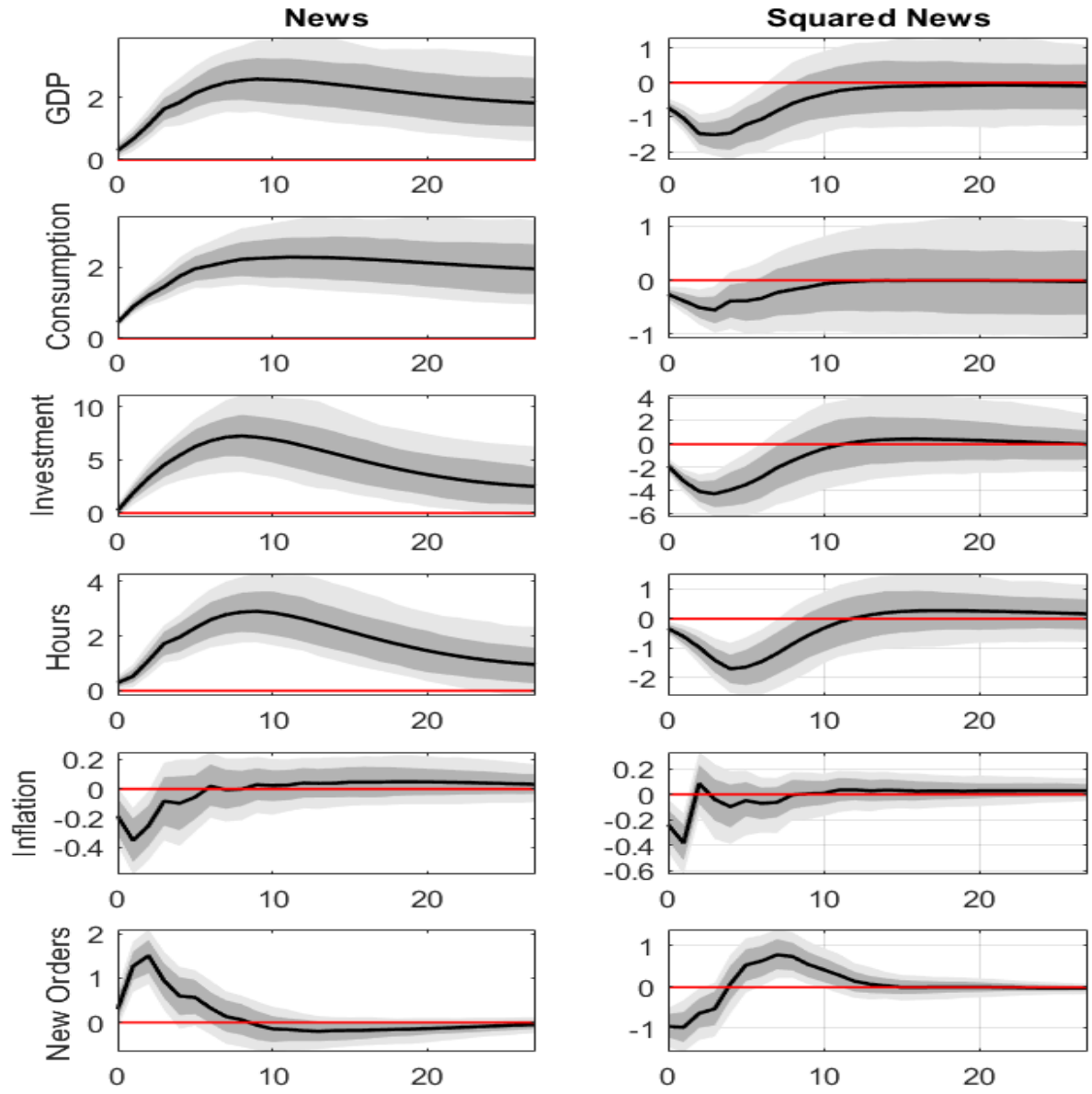
Figure 3: Impulse response functions to the news (left column) and the squared news shocks (right column) obtained with VAR 2. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.
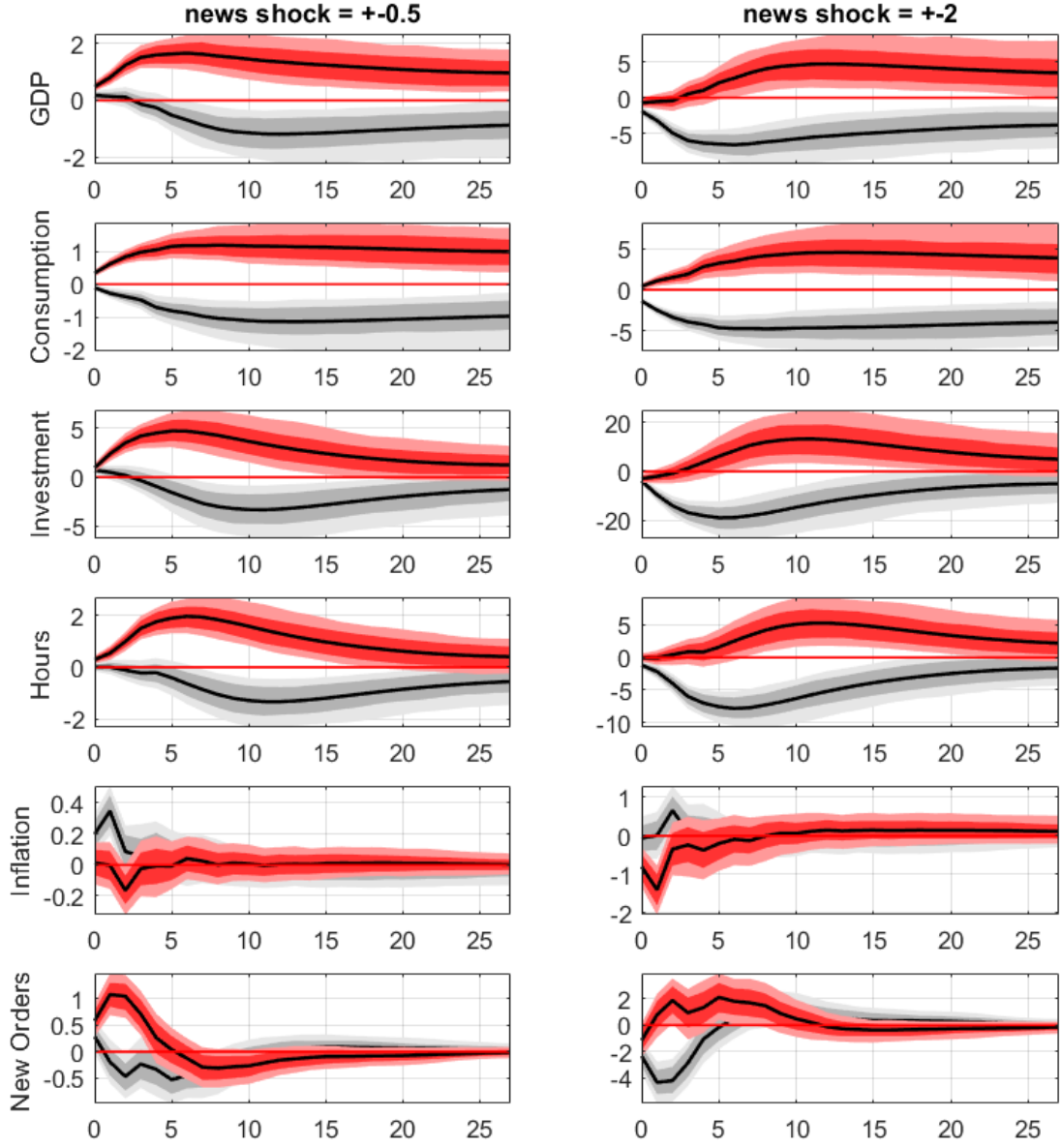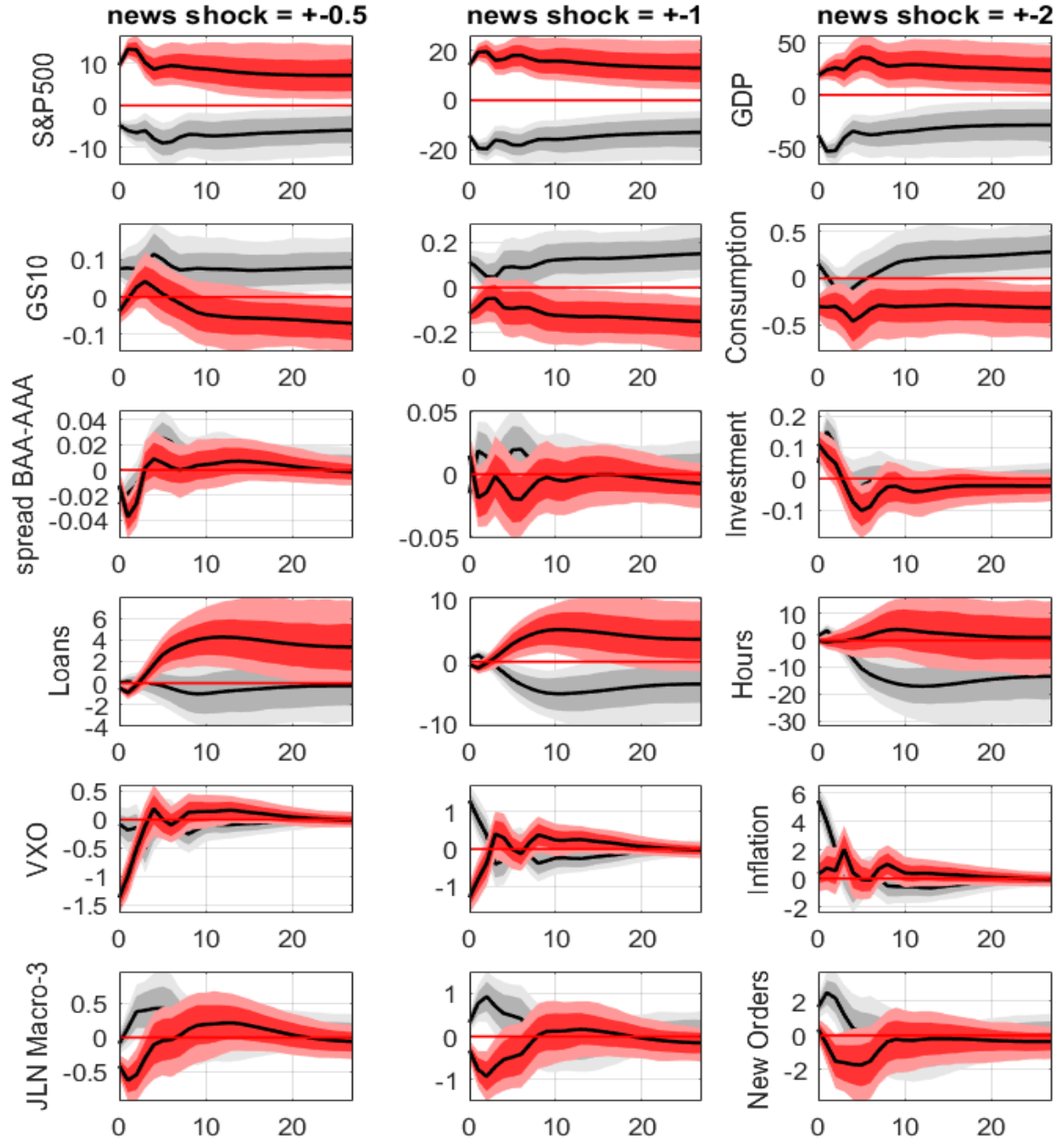
Figure 4: Nonlinear impulse response functions estimated with equation (4). Left column shock of size ±0.5. Right column shock of size ±2. Black solid lines: point estimates. Light grey area: 90% confidence bands, negative shock. Dark grey area: 68% confidence bands, negative shock. Light red area: 90% confidence bands, positive shock. Dark red area: 68% confidence bands, positive shock.

Figure 5: Nonlinear impulse response functions estimated with equation (4). Left column shock of size ±0.5. Mid column linear case ±1. Right column shock of size ±2. Black solid lines: point estimates. Light grey area: 90% confidence bands, negative shock. Dark grey area: 68% confidence bands, negative shock. Light red area: 90% confidence bands, positive shock. Dark red area: 68% confidence bands, positive shock.

Appendix (online publication)

	news shock		surprise shock	
	2 lags	4 lags	2 lags	4 lags
GDP	95.1	93.2	60.1	51.8
Investment	85.9	72.8	86.6	95.7
Hours Worked	91.3	98.6	35.0	47.4
Inflation	36.0	6.7	37.7	44.0
Federal Funds Rate	95.6	97.2	89.4	76.3
Consumers News variable	26.0	9.6	50.1	63.1
Consumers "No Mention" variable	81.0	85.9	60.8	84.7
Baa	96.9	99.8	97.0	99.6

Table A.1: Results of the informational sufficiency test for VAR 1. Each entry of the table reports the p-value of the F-test in a regression of the news shock (columns 2 and 3) and the surprise shock (columns 4 and 5) onto 2 and 4 lags of the variables on column 1.
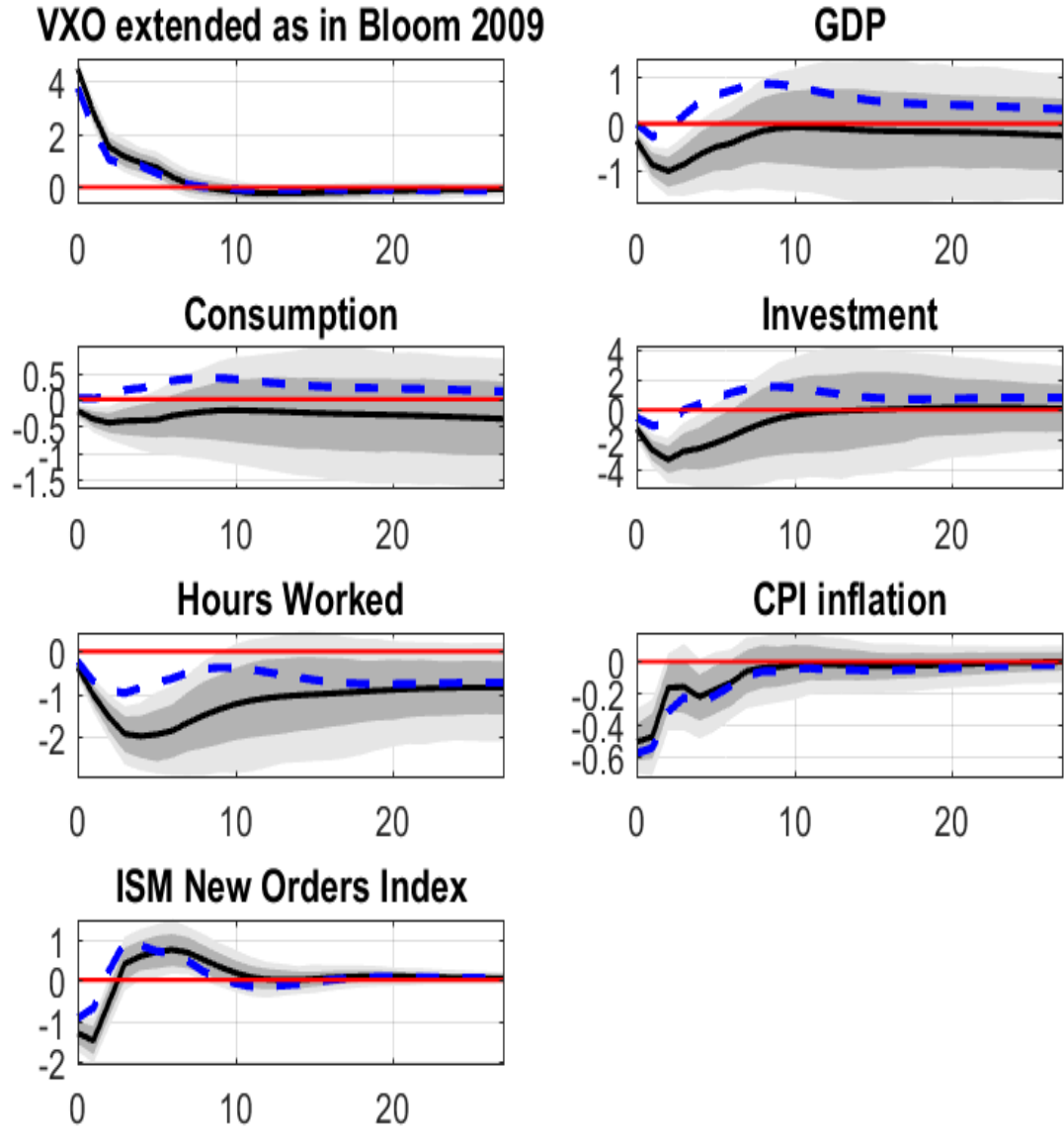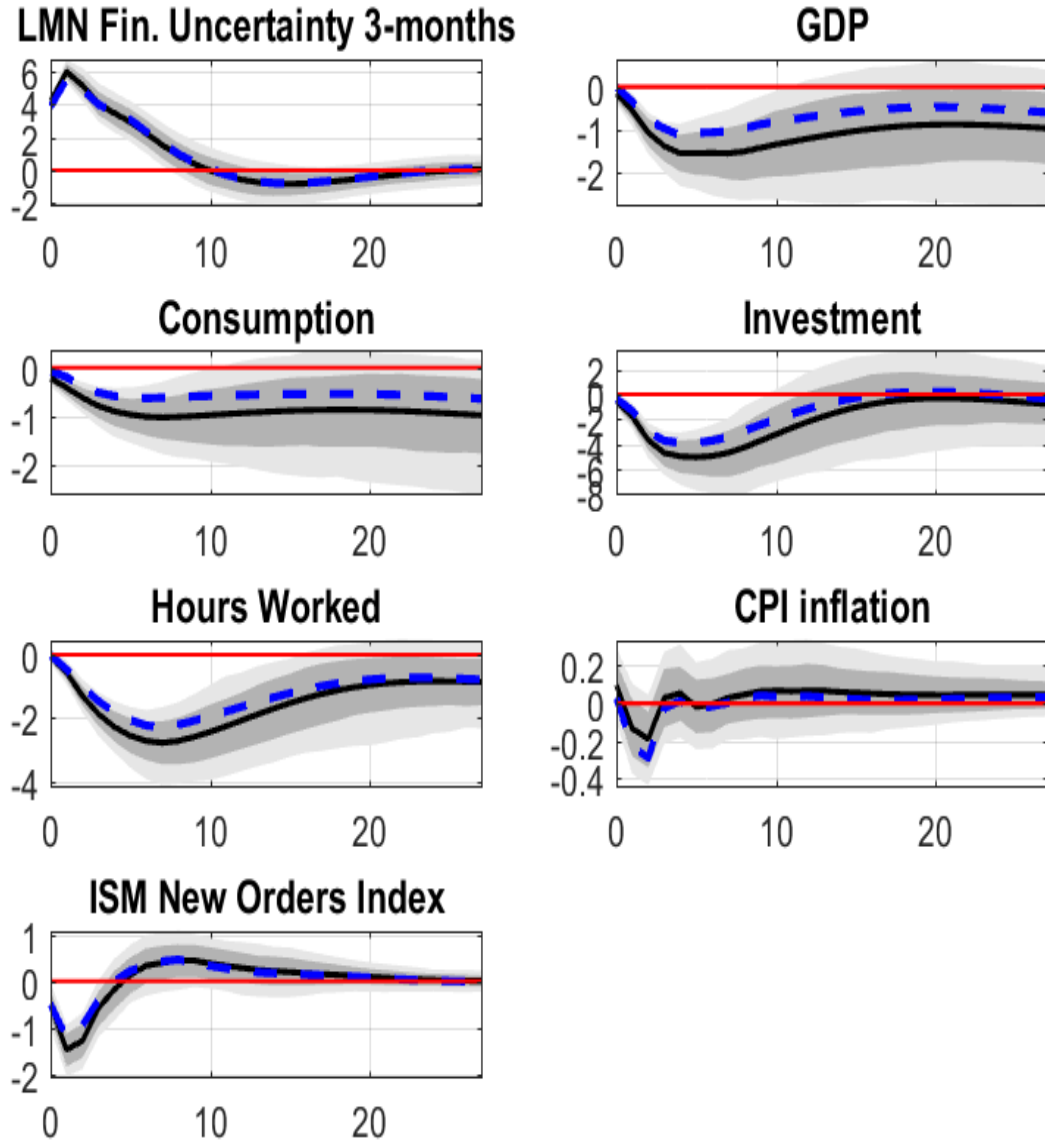
Figure A.1: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with the VXO ordered first. Black solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands. Blue dashed lines are the impulse response functions of the uncertainty shock identified as the third shock in a Cholesky decomposition with the VXO ordered third and news and squared news ordered first and second, respectively.
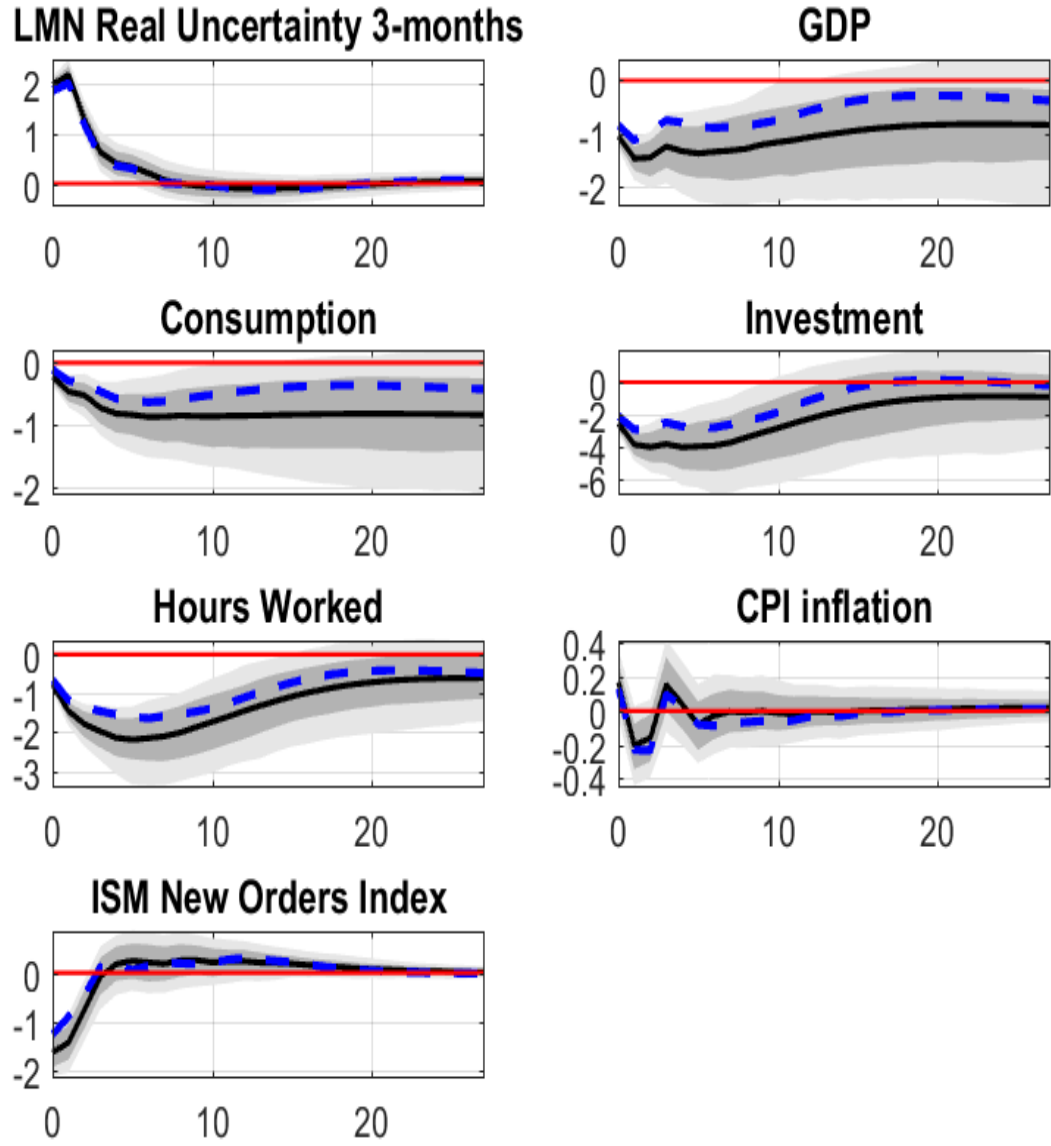
Figure A.2: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with LMN3 Fin. ordered first. Black solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands. Blue dashed lines are the impulse response functions of the uncertainty shock identified as the third shock in a Cholesky decomposition with LMN3 Fin. ordered third and news and squared news ordered first and second respectively.

Figure A.3: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with LMN3 Real ordered first. Black solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands. Blue dashed lines are the impulse response functions of the uncertainty shock identified as the third shock in a Cholesky decomposition with LMN3 Real ordered third and news and squared news ordered first and second respectively.
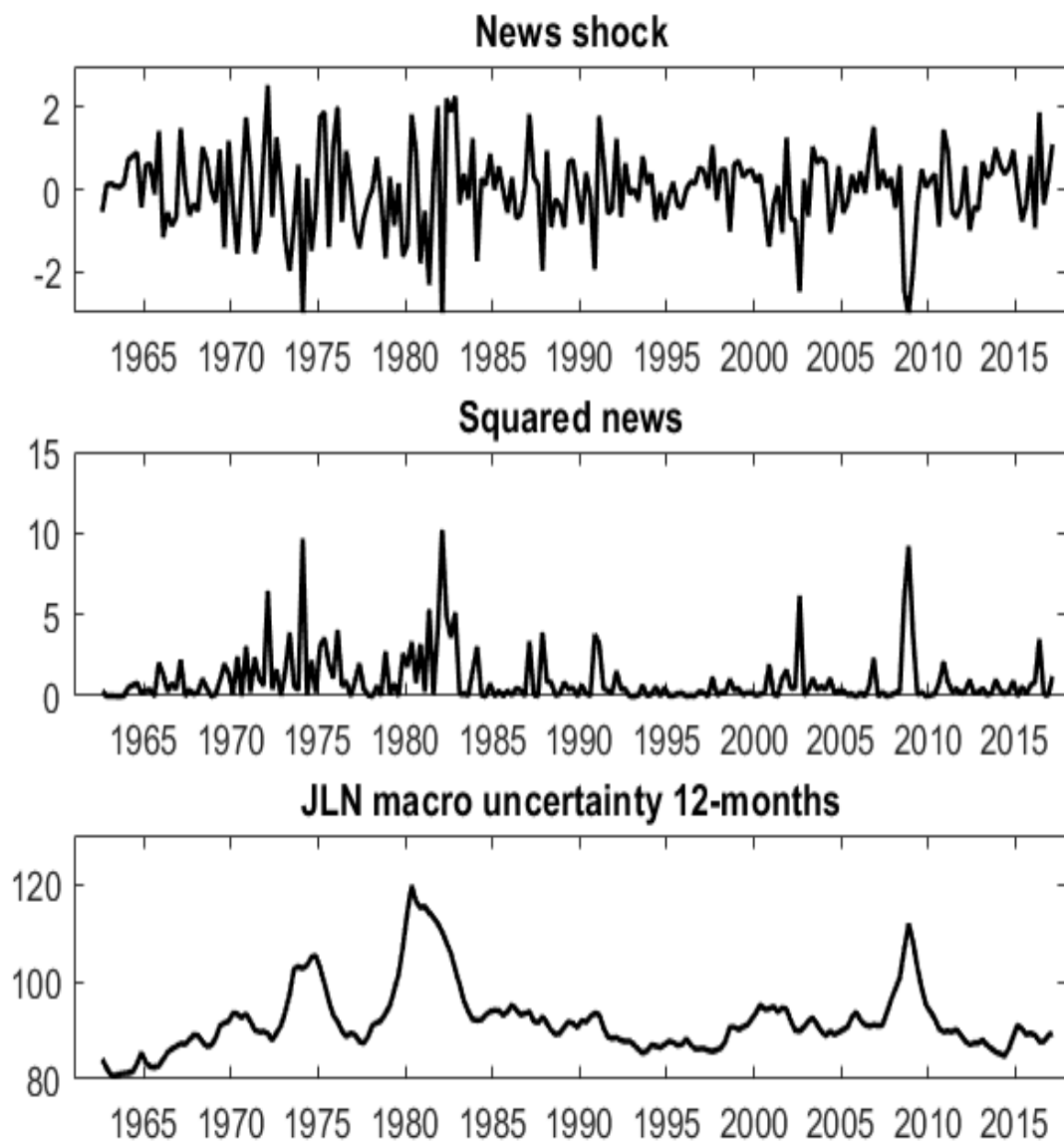
Figure A.4: News, news squared and JLN12

We show the results of two robustness exercises. In the first one, we try two different specifications for VAR 1, keeping the same identification. Specification (i) includes TFP, S&P500, Consumption, the TB3M, GS10 and the AAA yield. Specification (ii) includes TFP, S&P500, Consumption, the TB3M. Again, the impulse-response functions obtained with both specifications are very similar to those obtained with the baseline specification (see Figure A.5).

In the second exercise, we keep fixed the specification of VAR 1, the model used to identify the news shock, and try alternative identification schemes for VAR 2. In particular, we use a Cholesky scheme, where the news shock is ordered first and the squared news shock is ordered second. Second, we use a VARX where the news and the squared news shocks are treated as exogenous variables. Results are reported in Figure A.6. All in all, the two alternative identifications produce very similar results, with minor differences from a quantitative point of view, in that the short run effects of uncertainty are slightly smaller.
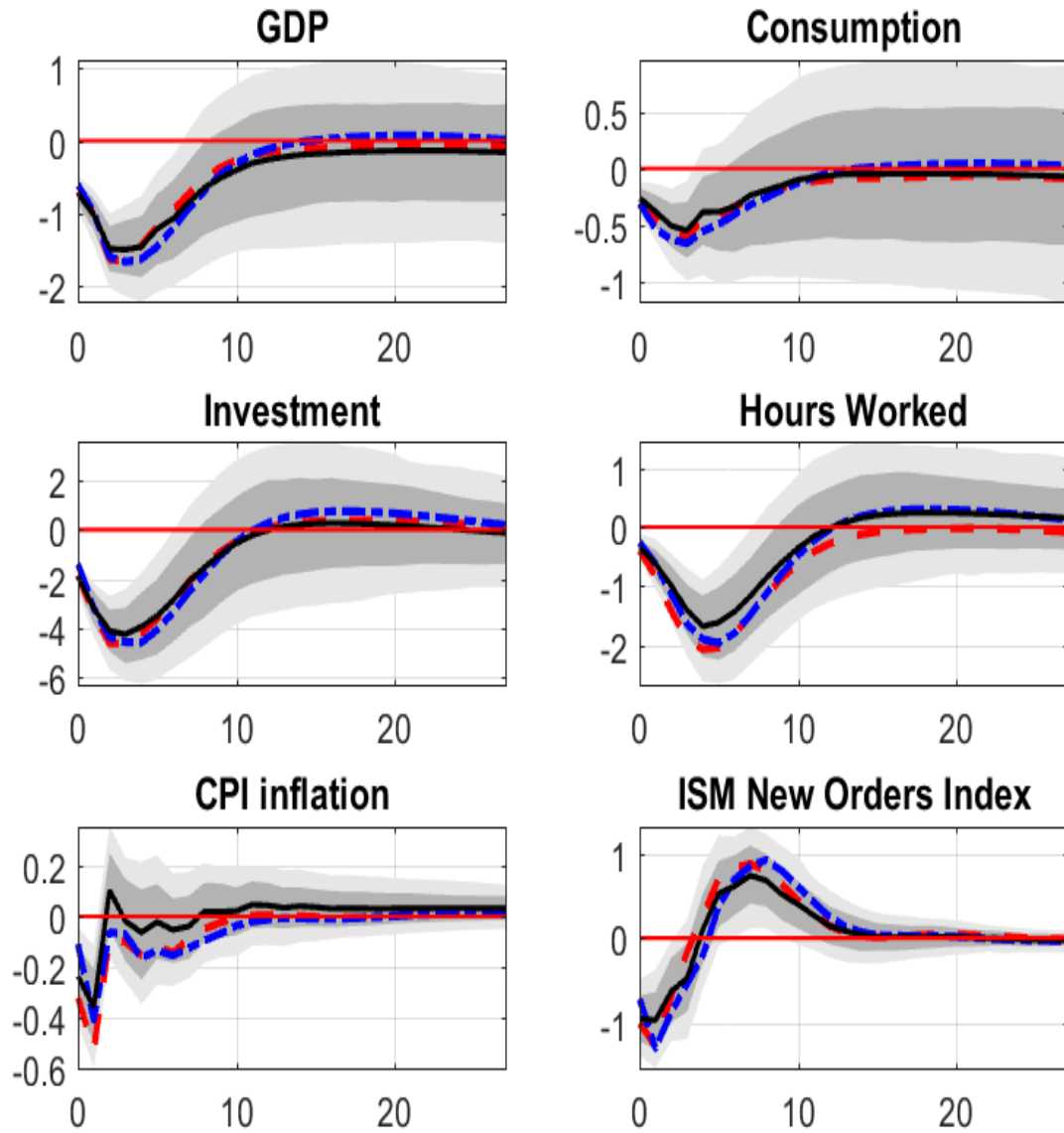
Figure A.5: Impulse response functions to the squared news shock for different specifications of VAR 1: (i) TFP, S&P500, Consumption and TB3M (red dashed line) and (ii) TFP, Investment and TB3M (blue dotted-dashed line). Identification of both VAR 1 and VAR 2 are unchanged. The black solid line and the confidence bands are the point estimate and the confidence bands of the benchmark case.
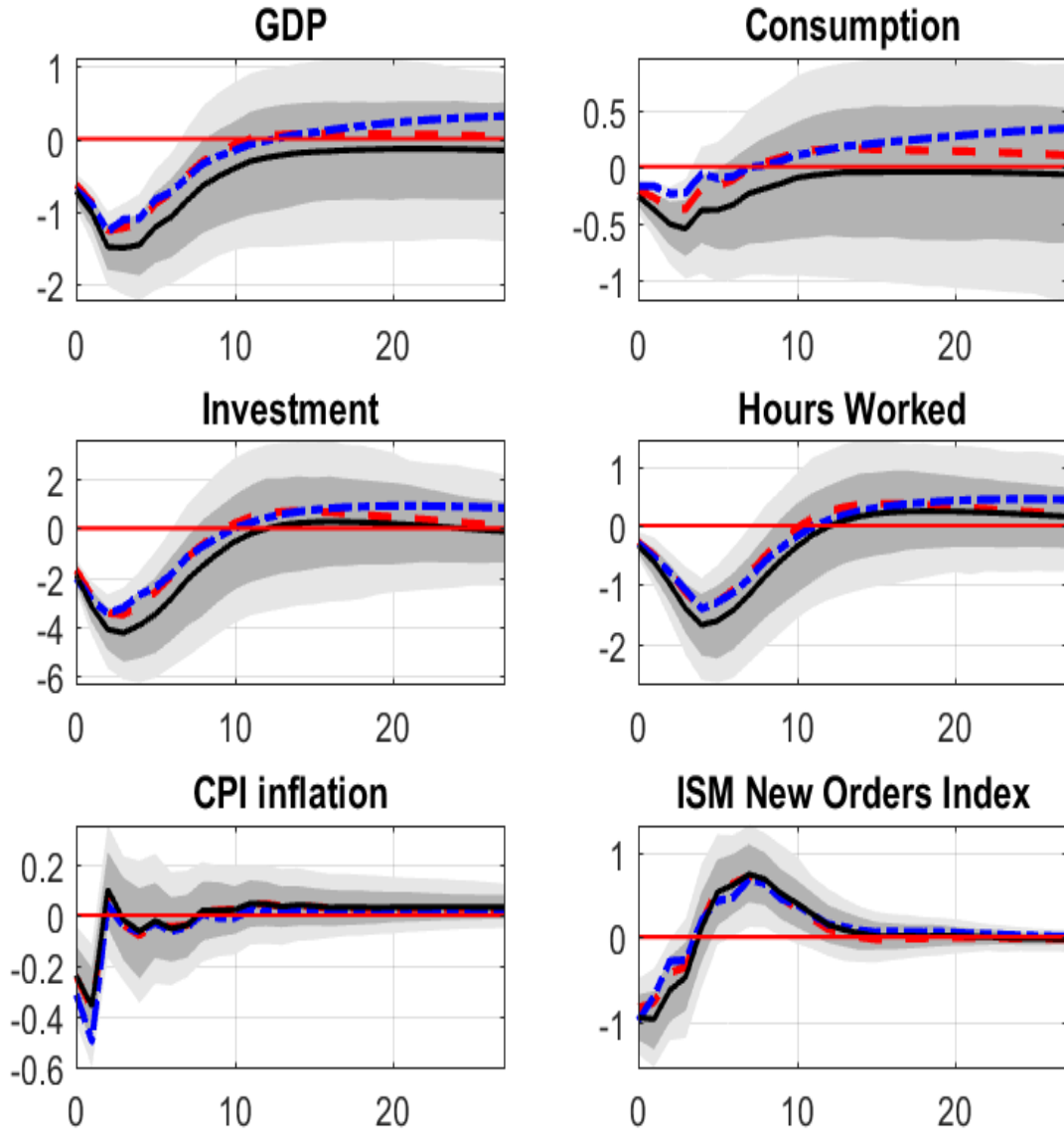
Figure A.6: Impulse response functions to the squared news shock for two alternative identification schemes of VAR 2: (i) a recursive scheme with the news shock ordered first (red dashed line) and a VARX model where s_t and s_t^2 are treated as exogenous variables (blue dotted-dashed line). The black solid line and the confidence bands are the point estimate and the confidence bands of the benchmark case.