The Nonlinear Effects of News through Uncertainty*

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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

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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.

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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. A partial list of major contributions in this body 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. A few important contributions in the latter stream of literature include Bloom, 2009, Rossi and Sekhposyan, 2015, Jurado, Ludvigson and Ng, 2015, Ludvigson, Ma and Ng, 2015 and Baker et al., 2016.

Somewhat surprisingly, uncertainty and news are usually regarded as distinct, if not completely independent, sources of business cycle fluctuations. But where does uncertainty stem from? The starting point of the present work is the idea that a part of *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. We will see below that the empirical evidence corroborates the idea that uncertainty and news are closely connected.

Out idea 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, 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.

We present a very stylized theoretical framework which is consistent with this idea. More precisely, uncertainty depends on the squared news shock, so that the news shock have both a linear effect, related to point expectations, and a quadratic effect, related to uncertainty.

We propose a new empirical procedure to estimate nonlinear effects using linear Structural Vector Autoregressions. The method involves two steps. First, a VAR is employed to estimate the news shock. We apply the identification scheme used in Forni, Gambetti ad Sala (2014) and Beaudry and Portier (2014). 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 below average reduce uncertainty, producing a temporary upturn of economic activity. 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. As discussed above, for small shocks, the uncertainty effect is positive; it therefore mitigates the negative first moment effect of bad negative news and reinforces the positive effect of good positive 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 covering the time span 1963:Q4-2015:Q2. We estimate a Bayesian VAR[1] with diffuse priors and 4 lags which includes the following variables: (log) TFP[2], (log) stock prices (the

[1] A frequentist VAR yields the same results.

[2] 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.

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), the Moody's Aaa interest rate (AAA) and the Survey's News variable[3]. 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).[4]

[3]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. The "No Mentions" variable takes on large values when most consumers report that they did not hear relevant news and small values when most people think that there is news worthy of mention. 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.

[4]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

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 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 shock.[5] 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. All in all, 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

information to identify the news shock.

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

worked, CPI inflation and new orders with this order and compute impulse responses.[6] 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.[7]

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

2.2 A simple and consistent informational framework

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

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

[7]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.

fundamental of the economy a_t follow

$$\Delta a_t = \epsilon_{t-1} \qquad (1)$$

where $\epsilon_t \sim N(0, \sigma_\epsilon^2)$ is shock with delayed effects.[8] Agents have imperfect information and cannot observe ϵ_t, but rather have access to news reporting the events underlying the shock, for instance natural disasters, scientific and technological advances, institutional changes and political events. 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 $E_t v_t = 1$, 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 $\epsilon_t = s_t + s_t(v_t - 1)$, 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.

A few examples can provide an intuition for this informational framework. Suppose that a diplomatic crisis takes place and is reported by media. The crisis can lead to a war ($\epsilon_t = 1$) or not ($\epsilon_t = 0$) 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 ($\epsilon_t = -3$),

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

but with probability 0.5 the government will intervene to rescue them ($\epsilon_t = -1$). 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

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

Notice that the conditional variance, i.e. uncertainty, depends on the news shock squared.[9] As long as s_t corresponds to the news shock estimated with the SVAR, 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.[10] It is easy to see that the news shock estimated from a VAR corresponds to s_t. Indeed, the representation of Δa_t and s_t is[11]:

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

Notice that the shock 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,

[9] 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.

[10] 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.

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

the news shock identified in the literature corresponds to s_t. The other shock, u_t, is what the VAR would identify as a surprise shock.

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 or negative news, 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.[12] Using the news shock obtained in section 2, we estimate a VAR which includes s_t, $s_t^2 - 1$[13] and Y_t and derive the Cholesky 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

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

[13]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.

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 on uncertainty. Notice that in our set-up the non-linear responses 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. It turns out that the ordering of s_t and s_t^2 is irrelevant: the impulse responses are similar.[14]

[14]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 $[v_t \;\; s_t]' \sim N(0, I)$.[15] 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 the 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

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

the vector Y_t) as[16]

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

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 the squared news shock has no effects on any of the variables in z_t and w_t is an exogenous shock which does not depend on s_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.

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

4.1 News and squared news

Let us discuss the features of the squared news shocks. The squared news has a correlation of 0.47 with the JLN3 indicator[17]. The news shocks, 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 (+) Unclear; 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

Here we discuss the effects of news shocks on the economy. The VAR we employ includes the estimated squared news shock, 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. Let us denote this model as VAR 2.

We first discuss the results relative to the estimated impulse response functions, i.e. the coefficients of the moving average representation (3), to shocks of magnitude $s_t = 1$ and $(s_t^2 - 1)/\sigma_{s^2} = 1$ separately, and then we focus on nonlinearities. Results are reported in Figure 3. The numbers on the vertical axis can be interpreted as yearly percentage

[17]Figure A.4 in the Appendix plots the news shock and the squared news shock along with the macroeconomic uncertainty measure JLN3.

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.[18] 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 becomes approximately zero around the 3-year horizon. 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 $\hat{A}_{i2}(L)\frac{(\bar{s}^2-1)}{\hat{\sigma}_{s^2}}$. A few observations are in order. First, the uncertainty effects of news shocks may be positive. This happens when the squared news shock is small, below its mean, that is, when $-1 < s_t < 1$. No news (or small news) produce a temporary upturn of economic activity. Uncertainty is below average and this stimulates the economy. Second, when the news shock is equal to 1 or -1, that is, when the news shock in absolute value is equal to its standard deviation (equivalently, when the uncertainty shock is equal to its mean), the innovation to uncertainty is zero and there are no uncertainty effects. Third, a news shock in absolute value larger than its standard deviation (equivalently, an uncertainty shock larger than its mean) produces

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

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).

We next 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.[19] 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, when s_t is big in absolute value and s_t^2 is larger than its mean, the asymmetry is reversed: the uncertainty effect is negative. Uncertainty exacerbates the negative first moment effect of bad news and mitigates the positive effect of good news. It is also interesting to notice that big and negative news shocks are faster to propagate on the real variables.

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.

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

[19] 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.

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 center 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. For stock prices and loans, a picture similar to that of real variables emerges. Large negative shocks have larger effects, enhanced by uncertainty, than positive shocks. For small shocks the opposite holds true.

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

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

[4] Baxter, B., L. Graham, and S. Wright (2011), "Invertible and non-invertible information sets in linear rational expectations models", Journal of Economic Dynamics and Control 35, pp. 295-311.

[5] Basu, S., L. Fernald and M. Kimball (2006), "Are Technology Improvements Contractionary?", American Economic Review, vol. 96(5), pp. 1418-48.

[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] 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,

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

[12] Chari, V.V., Kehoe, P.J. and E.R. McGrattan (2008), "Are structural VARs with long-run restrictions useful in developing business cycle theory?", Journal of Monetary Economics 55, pp. 1337-1352.

[13] Chen, B., Choi, J. and J.C. Escanciano (2015), "Testing for Fundamental Vector Moving Average Representations", CAEPR Working Paper No. 022-2015, forthcoming in Quantitative Economics.

[14] Christiano, L., C. Ilut, R. Motto and M. Rostagno (2007), Signals: Implications for Business Cycles and Monetary Policy, mimeo, Northwestern University.

[15] Cochrane, John H. (1994), "Shocks", Carnegie-Rochester Conference Series on Public Policy 41, 295-364.

[16] Coibion, O. and Y. Gorodnicenko (2012), "What can survey forecasts tell us about informational rigidities?", Journal of Political Economy 120, pp. 116-159.

[17] 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.

[18] Fernandez-Villaverde, J., J. F. Rubio, T. Sargent and M. Watson (2007), "A, B, C, (and D)'s for Understanding VARs", American Economic Review 97, pp. 1021-1026.

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

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

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

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

[23] 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.

[24] Giannone, D., and L. Reichlin (2006), "Does information help recovering structural shocks from past observations?", Journal of the European Economic Association 4, pp. 455-465.

[25] Gilchrist, S. and E. Zakrajsek (2012), "Credit spreads and business cycle fluctuations", American Economic Review, 102(4), pp. 1692-1720.

[26] Hansen, L.P., and T.J. Sargent (1991), "Two problems in interpreting vector autoregressions", in Rational Expectations Econometrics, L.P. Hansen and T.J. Sargent, eds. Boulder: Westview, pp.77-119.

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

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

[29] Keynes, J.M., (1936), *The general theory of employment, interest and money,* London: Macmillan.

[30] Kilian, L. (1998), "Small-sample confidence intervals for impulse response functions", Review of Economics and Statistics 80, 218-30.

[31] 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.

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

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

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

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

[36] Lorenzoni, G. (2010). "Optimal monetary policy with uncertain fundamentals and dispersed information", Review of Economic Studies 77, pp. 305-338.

[37] Lucas, R.E., Jr. (1972), “Expectations and the Neutrality of Money”, Journal of Economic Theory 4, 103-124.

[38] 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.

[39] Mankiw G. N. and R. Reis (2002), “Sticky information versus sticky prices: a proposal to replace the New Keynesian Phillips curve”, Quarterly Journal of Economics 117, 1295-1328.

[40] Mertens, K. and M. O. Ravn (2010), “Measuring the impact of fiscal policy in the face of anticipation: a structural VAR approach”, The Economic Journal, vol. 120(544), pp. 393-413.

[41] Pigou, A. C. (1927). “Industrial fluctuations”, London, Macmillan.

[42] Rozanov, Yu. (1967). *Stationary Random processes*, San Francisco: Holden Day.

[43] Schmitt-Grohé, S. and Uribe, M. (2012), “What’s News in Business Cycles”, Econometrica, 80: pp. 2733-2764.

[44] Sims, C. A. (2003), “Implications of Rational Inattention”, Journal of Monetary Economics 50, 665-690.

[45] Stock J. H and Watson, M. (2002), “Has the Business Cycle Changed and Why?”, NBER Macroeconomics Annual 2002, Mark Gertler and Ken Rogoff (eds), MIT Press.

[46] Woodford M. (2002), "Imperfect Common Knowledge and the Effects of Monetary Policy", in P. Aghion, R. Frydman, J. Stiglitz, and M. Woodford, eds., Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps, Princeton: Princeton University Press.

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.

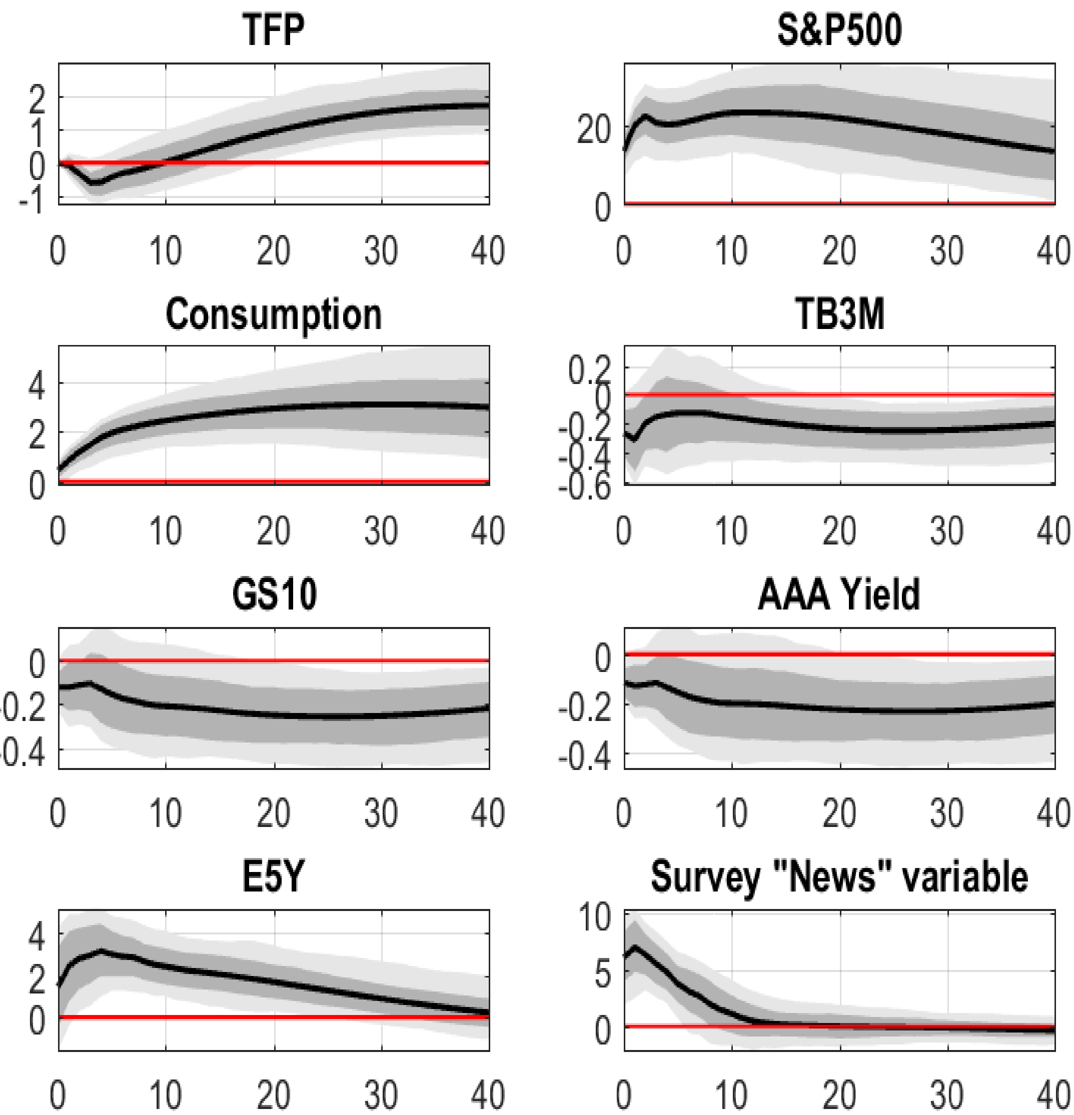

Figure 1: Impulse response functions to the news shock. Solid line: point estimate. Light grey area: 90% credible bands. Dark grey area: 68% credible bands.

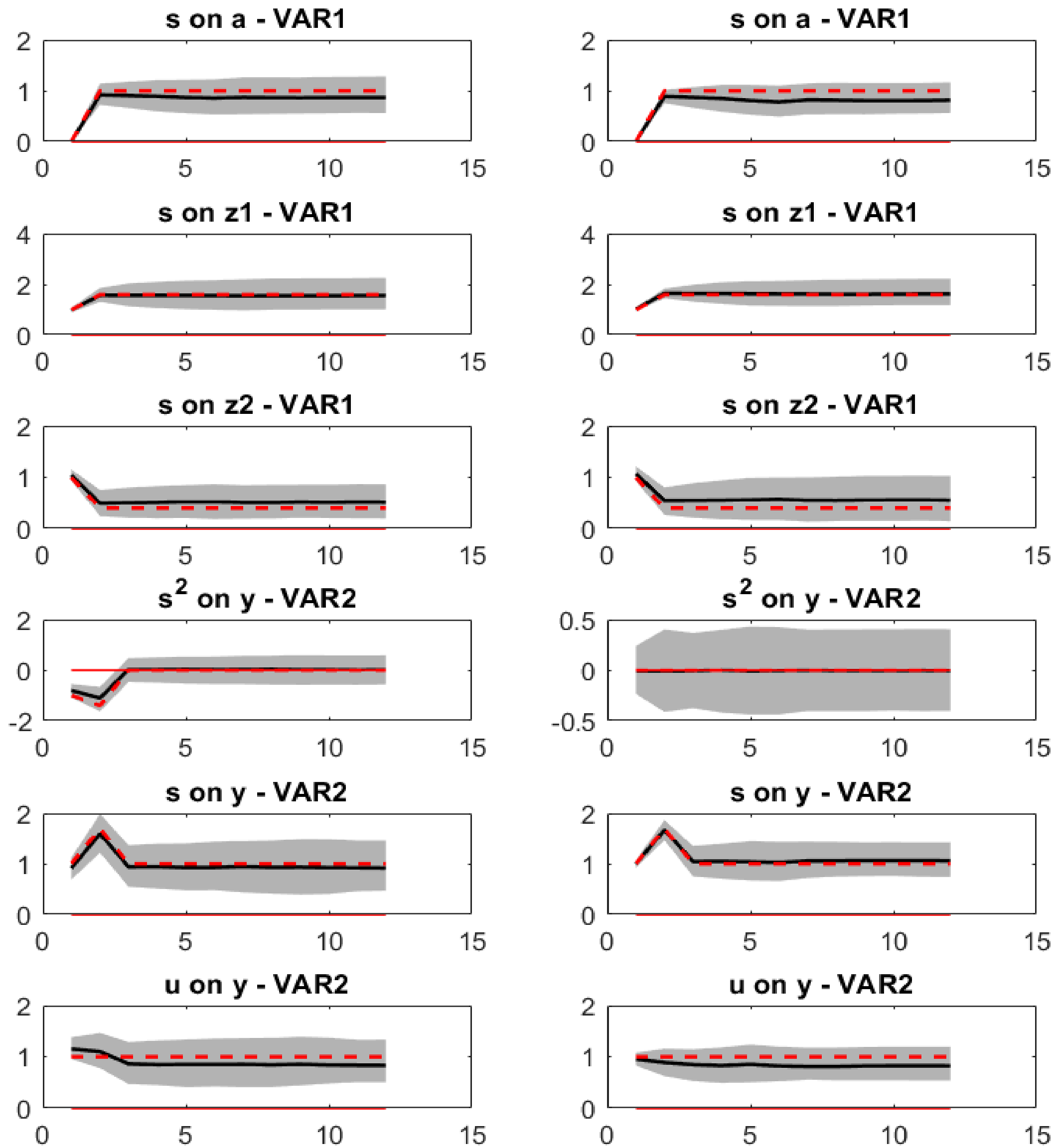

Figure 2: Impulse response functions functions of the two simulations. Left column: effects of news shocks. Right column: effects of uncertainty shocks. Solid line: point estimate. Grey area: 90% confidence bands. Red dashed line: true theoretical responses.

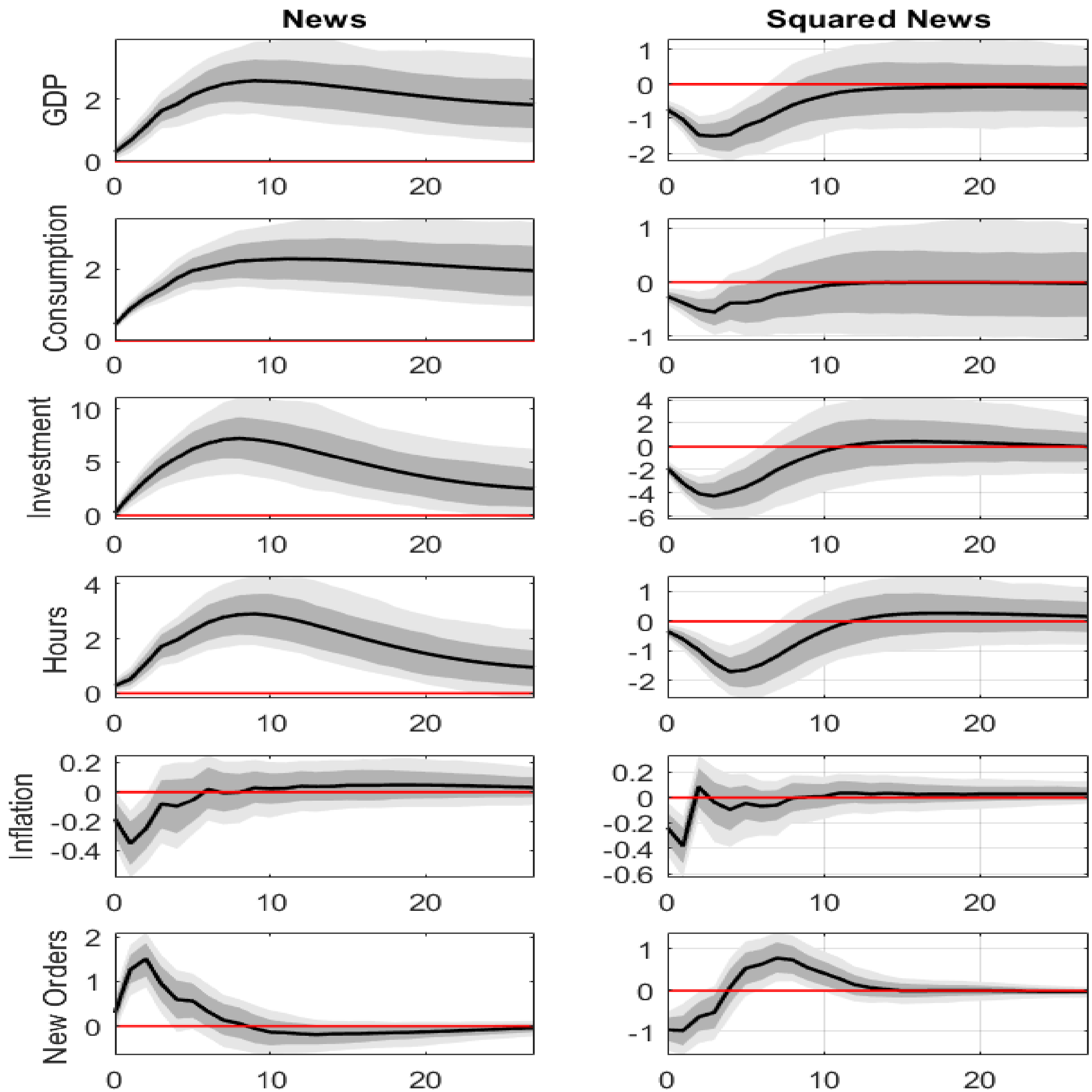

Figure 3: Impulse response functions to the news (left column) and the squared news (right column) shocks in VAR. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

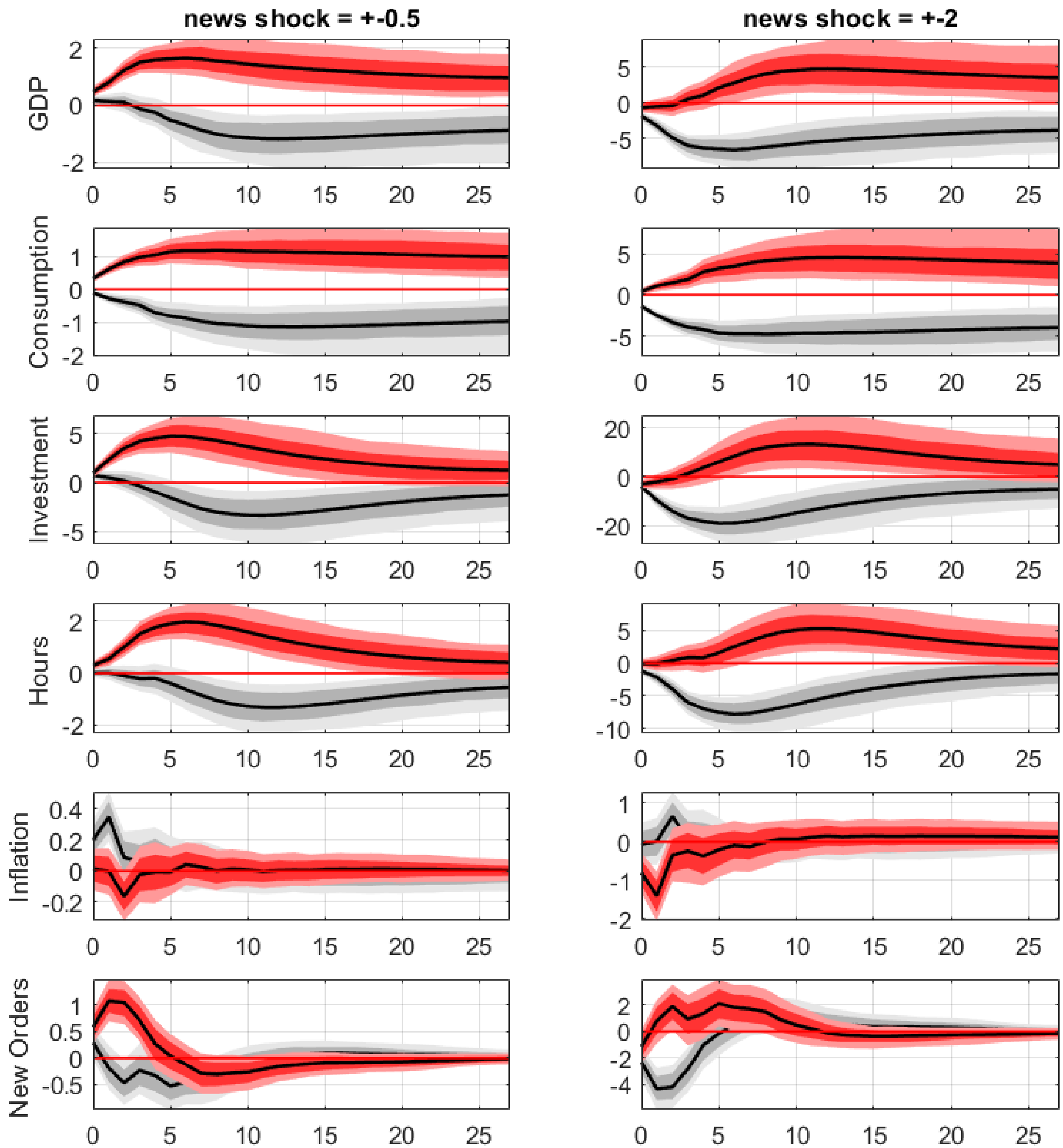

Figure 4: Total reaction of GDP to the news shock, including both the expectation and the uncertainty effect, for different values of the news shock. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

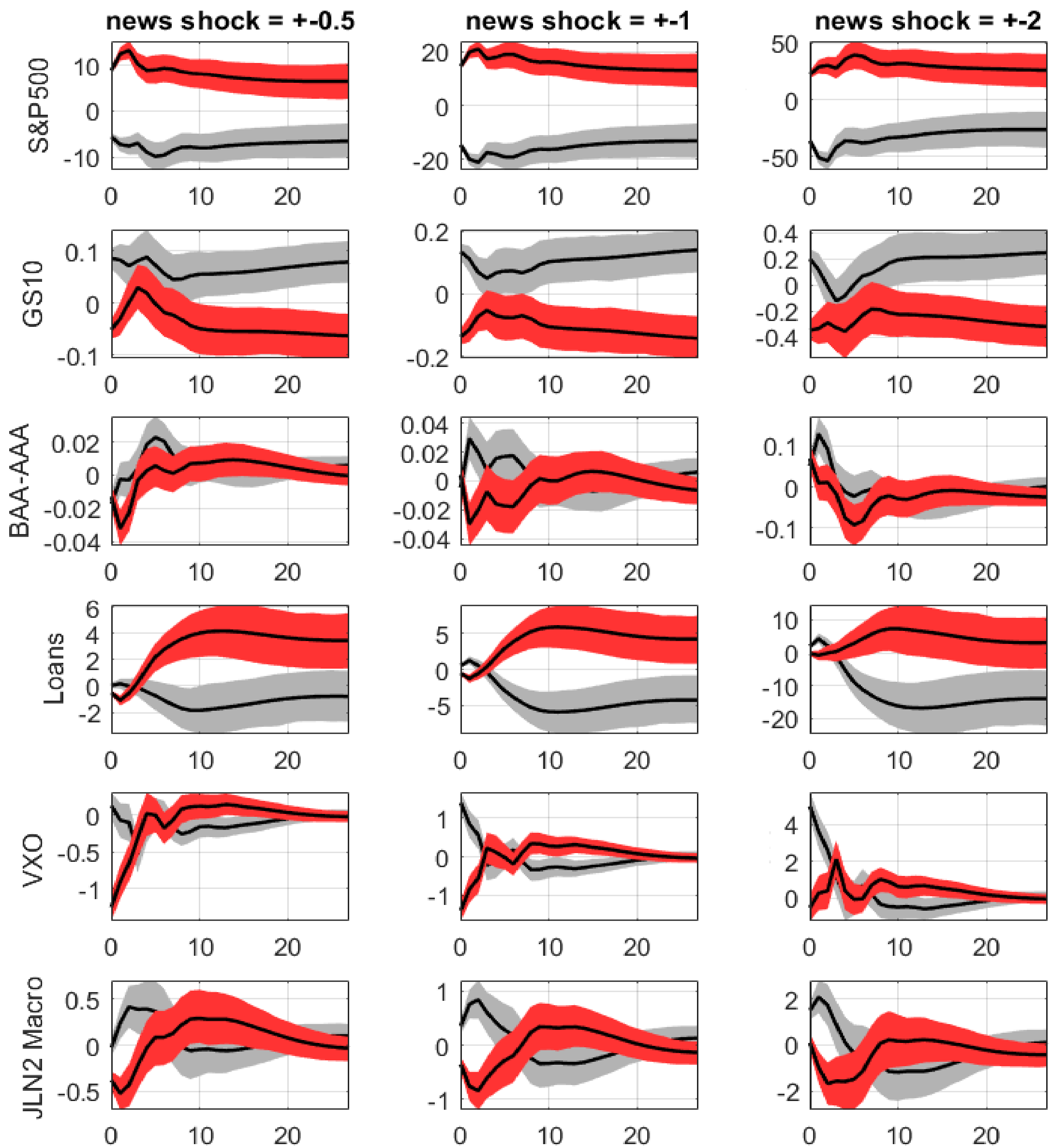

Figure 5: Impulse responses of the VAR with financial variables to the news shock, including both the expectation and the uncertainty effect, for different values of the news shock. Solid line: point estimate. Shaded area: 68% confidence band.

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.

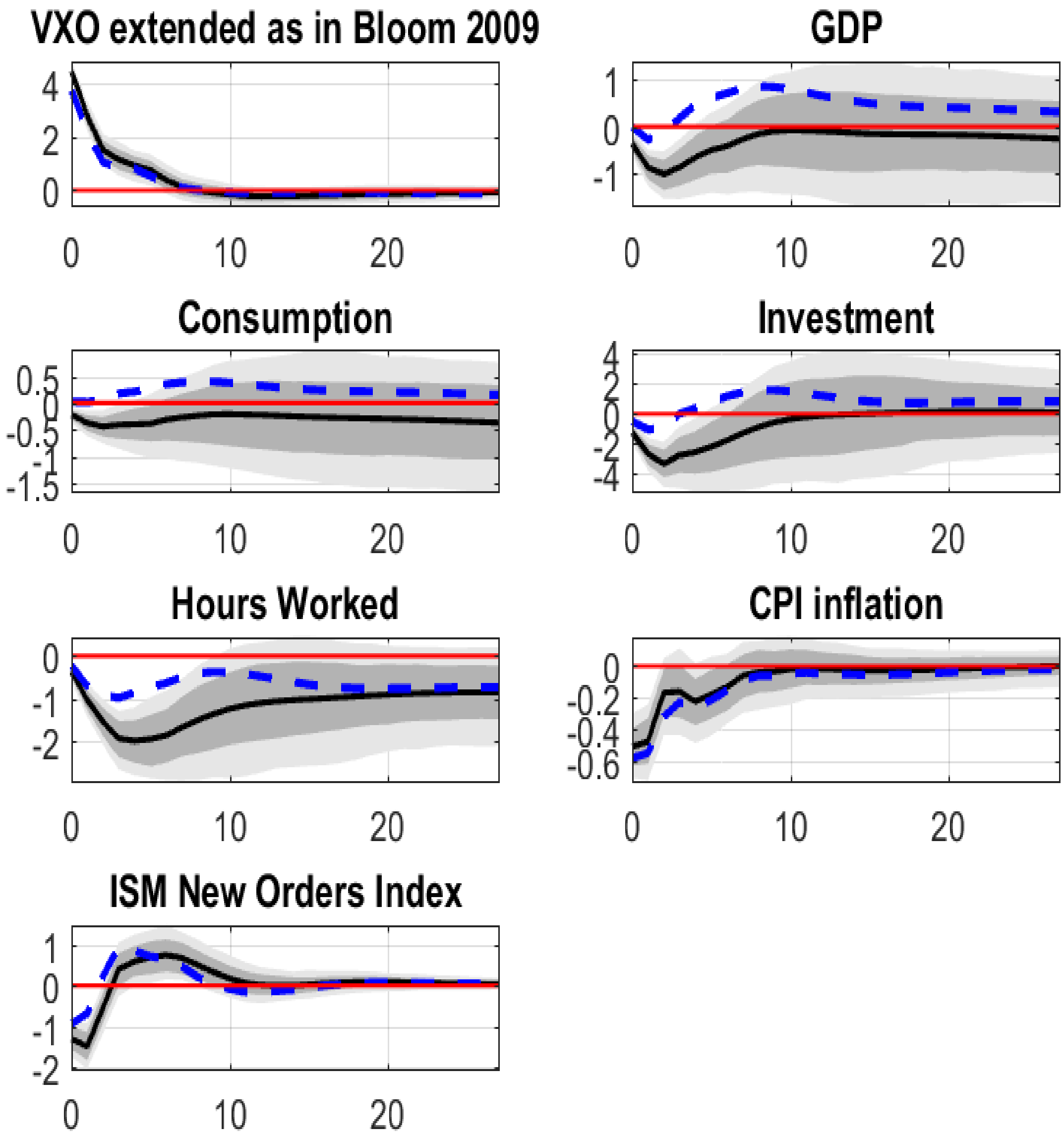

Figure A.1: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with the VXO ordered first. Black solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands. Blue dashed lines are the impulse response 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.

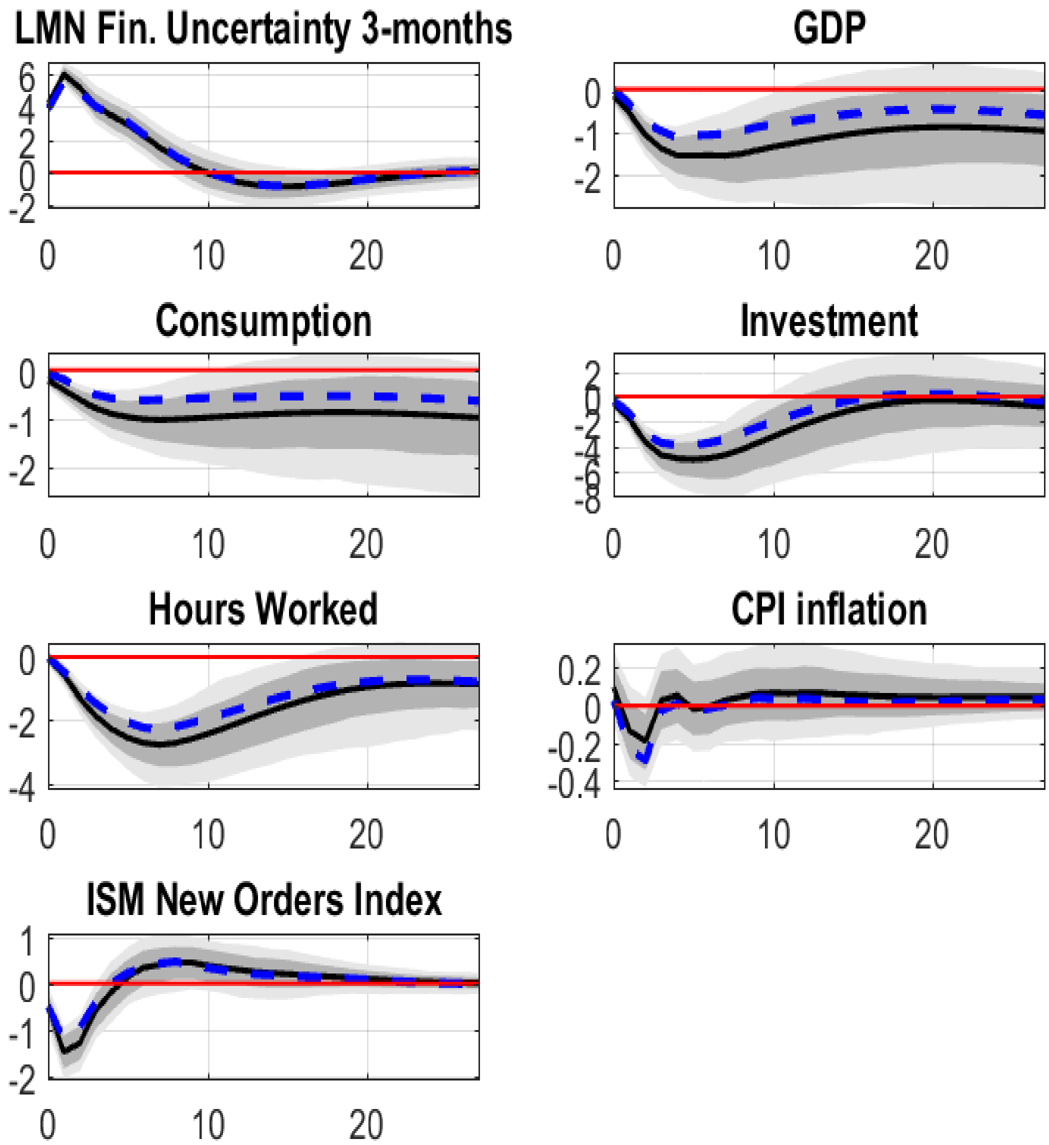

Figure A.2: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with LMN3 Fin. ordered first. Black solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands. Blue dashed lines are the impulse response 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.

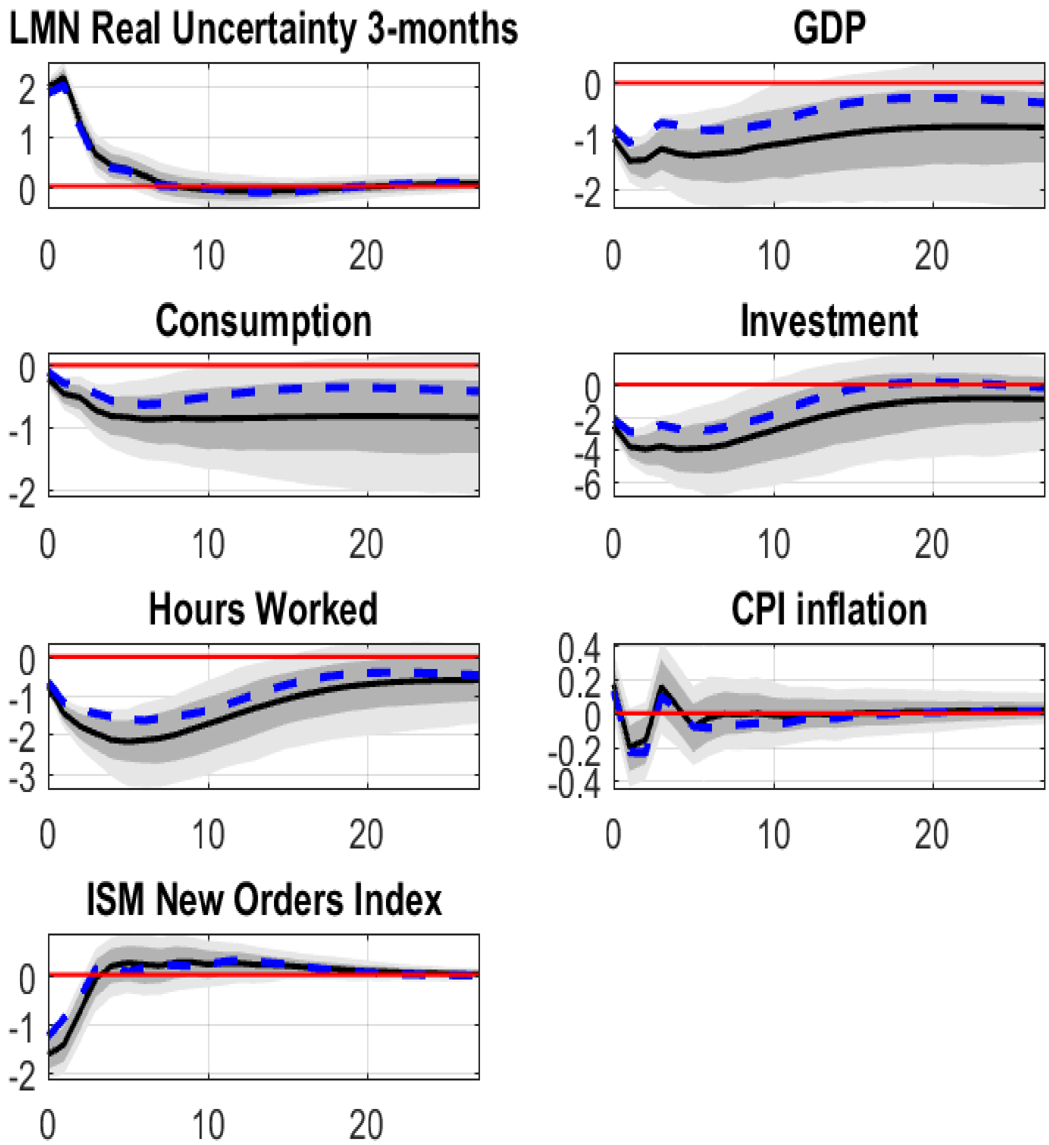

Figure A.3: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with LMN3 Real ordered first. Black solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands. Blue dashed lines are the impulse response 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.

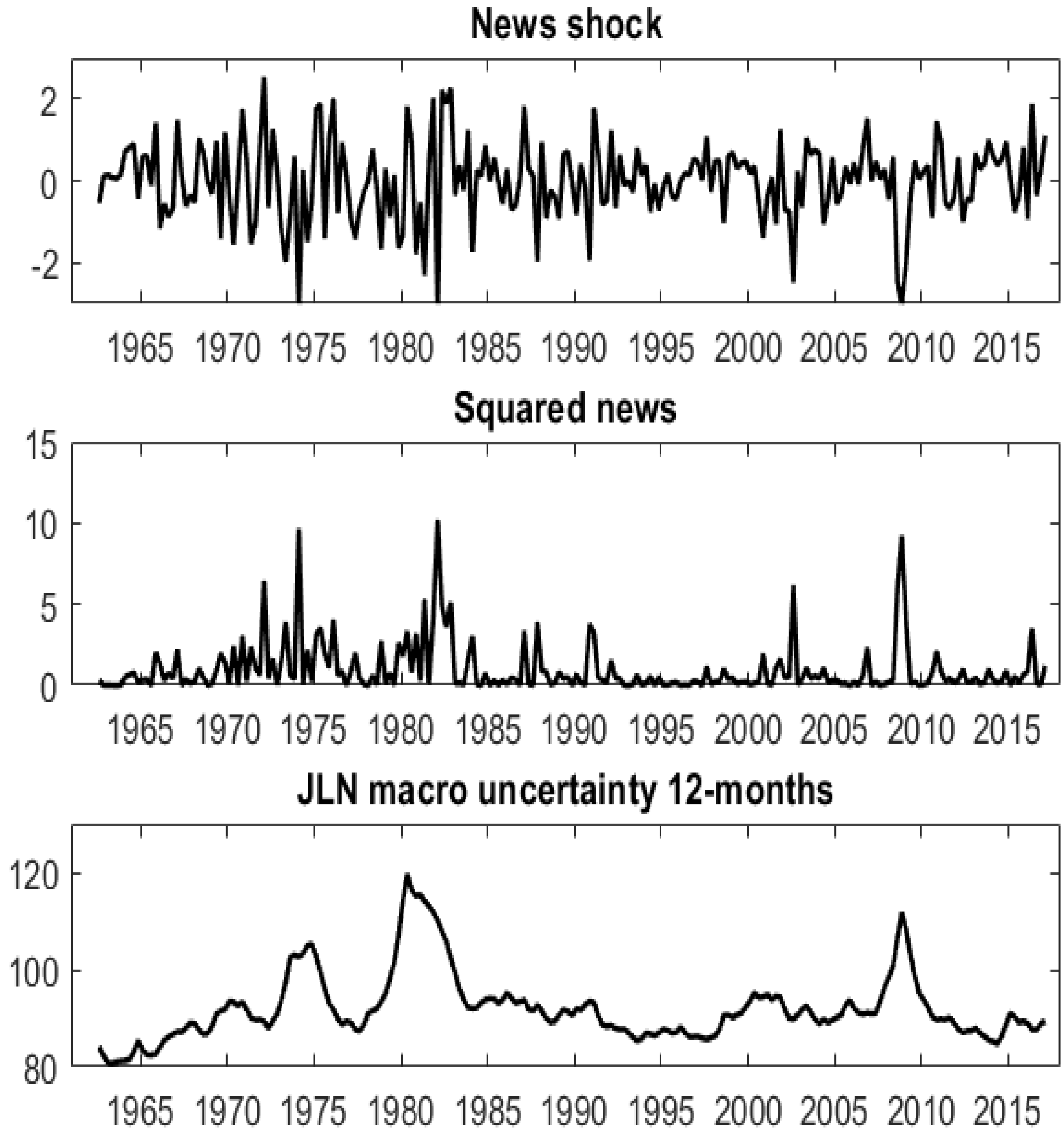

Figure A.4: News, news squared and JLN12

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.

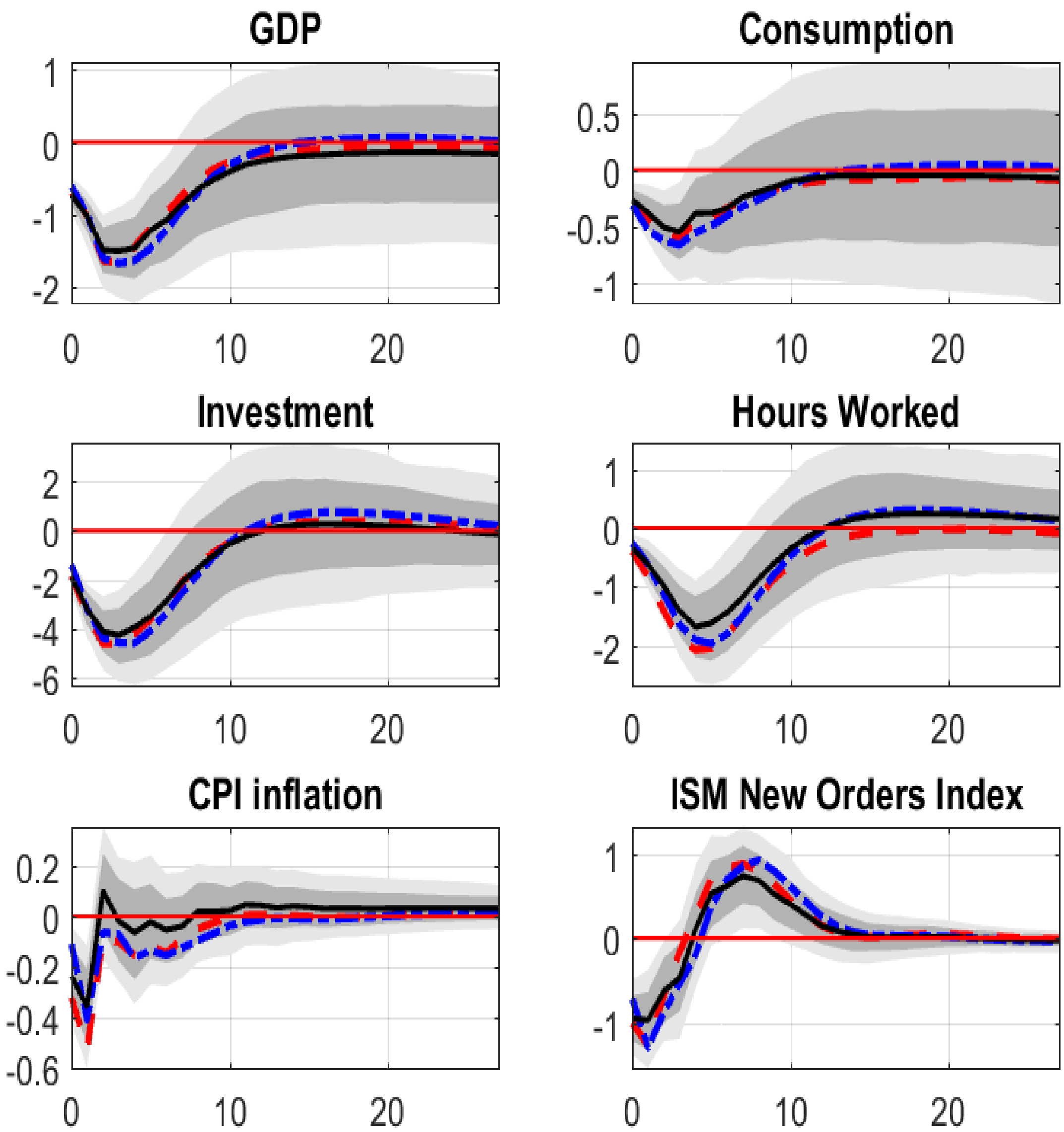

Figure A.5: Impulse response functions to the squared news shock for different specifications of VAR 1: (i) TFP, S&P500, Consumption and TB3M (red dashed line) and (ii) TFP, Investment and TB3M (blue dotted-dashed line). Identification of both VAR 1 and VAR 2 are unchanged. The black solid line and the confidence bands are the point estimate and the confidence bands of the benchmark case.

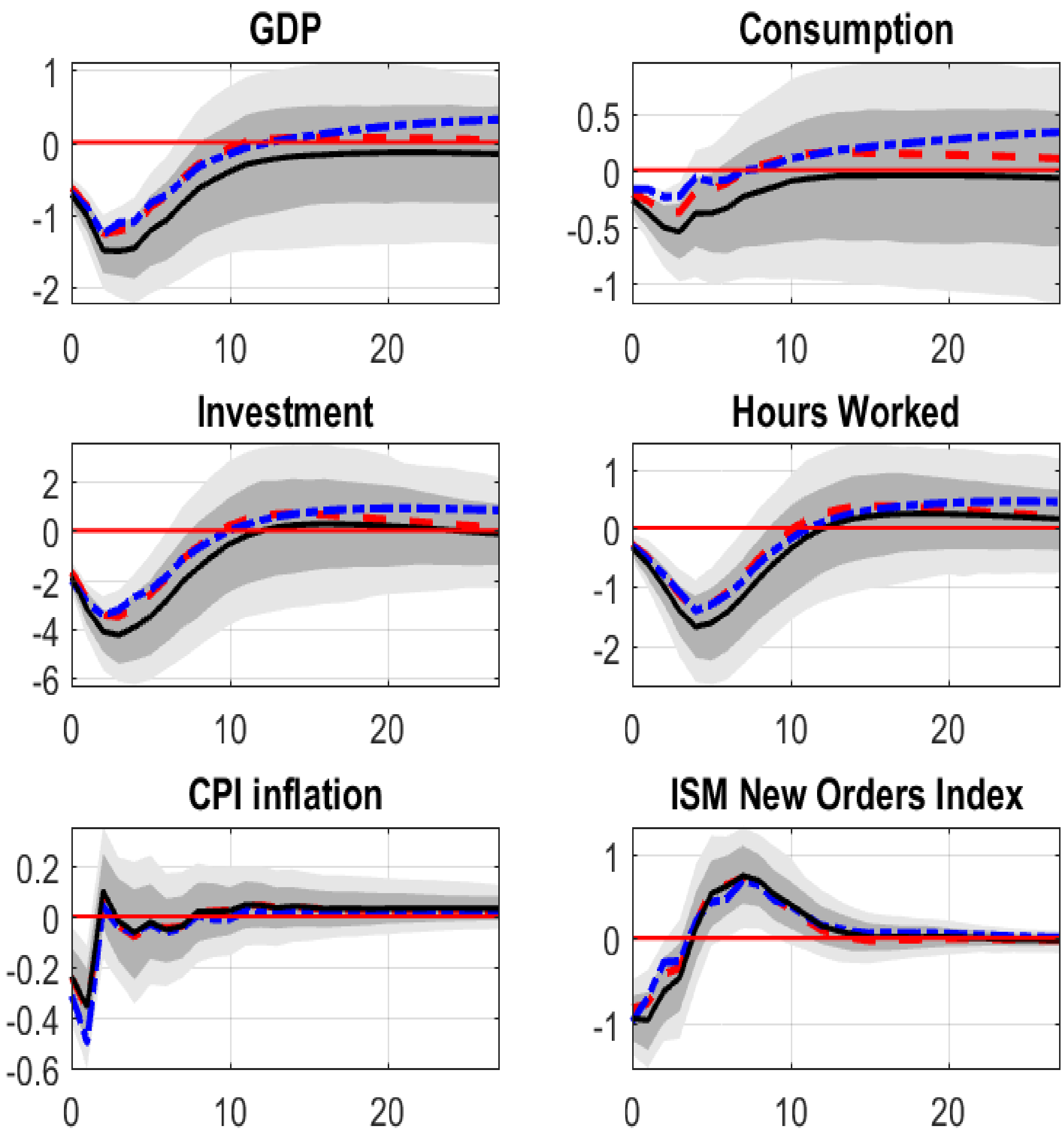

Figure A.6: Impulse response functions to the squared news shock for two alternative identification schemes of VAR 2: (i) a recursive scheme with the news shock ordered first (red dashed line) and a VARX model where s_t and s_t^2 are treated as exogenous variables (blue dotted-dashed line). The black solid line and the confidence bands are the point estimate and the confidence bands of the benchmark case.