The Asymmetric Effects of News through Uncertainty *

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Abstract

Bad news about future economic developments have larger effects than good news. The result is obtained by means of a simple nonlinear approach based on SVAR and SVARX models. We interpret the asymmetry as arising from the uncertainty surrounding economic events whose effects are not perfectly predictable. Uncertainty generates adverse effects on the economy, amplifying the effects of bad news and mitigating the effects of good news.

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1 Introduction

Recently, many contributions have investigated the role of news shocks for business cycle fluctuations. News shocks are typically defined as exogenous anticipated changes in future economic fundamentals, mainly Total Factor Productivity (TFP). Several works have provided the theoretical grounds of the old idea (Pigou, 1927) that changes in expectations about the future can affect the current behavior of consumers and investors, and therefore can generate cyclical fluctuations, see Jaimovic and Rebelo (2009), Den Haan and Kaltenbrunner (2009) and Schmitt-Grohé and Uribe (2012). On the empirical side, a number of works have assessed the role of news shocks. A partial list of empirical contributions in this stream of literature includes Beaudry and Portier (2004, 2006, 2014), Barsky and Sims (2011, 2012), Kurmann and Otrok (2013) and Forni et al. (2014). News shocks are typically found to play a role in generating macroeconomic fluctuations, although their relative importance varies across investigations.

Common to all of those empirical works is the hypothesis that bad and good news have symmetric effects. Such an hypothesis is translated into the model through the assumption of linearity. In this paper we relax such an assumption and study whether there are any asymmetries in the transmission of news shocks. More specifically, we study whether bad and good news about future changes in TFP have different effects on the economy, and whether the size of the shock matters. There are several reasons which could explain an asymmetric transmission. We will discuss these below in detail.

We contribute to the literature by using a modified version of the method recently proposed by Debortoli et al. (2020). The approach, in essence, consists of a two step procedure where (i) the news shock is identified in an informationally sufficient VAR (see Forni and Gambetti, 2014)) and (ii) the estimated shock is used, together with some nonlinear function of it, as exogenous variable in a VARX including a set of endogenous variables whose response are of interest to us. By combining the (linear) impulse response functions of the VARX, asymmetries and nonlinearities of the transmission of news shocks can be estimated. The news shock is identified along the lines of Forni et al. (2014) and Beaudry and Portier (2014). The nonlinear function we use in the VARX is the square of the news shock, since it can account for both sign and size nonlinearities. We also check whether the validity conditions of the econometric procedure hold, and they do.

When the quadratic effect of news is taken into account, the business-cycle dynamics generated by news shocks appear more complex than usually believed. First, good (negative) news shocks have positive (negative) permanent effects on real economic activity variables, as already found in the literature. Second, squared news shocks produce a temporary downturn in economic activity. These two results imply that the response of output to positive and negative news is generally asymmetric: bad news shocks have larger effects in absolute value than good news shocks. The reason is that the effect of bad news shocks is exacerbated by the negative effect of the square term. On the contrary, the negative effect of the square dampens the expansionary effect of good news. Finally, a higher sensitivity to bad news is also found for financial variables, like stock prices and credit spreads.

As mentioned above, there can be several reasons that explain asymmetries in the effects of news. The political science literature has stressed that agents pay more attention to bad news than good news (Soroka, 2006). The reason can be the existence of a loss aversion effect, agents are more concerned about losses than gains (see Kahneman, 1997). But it could also simply be that negative economic events have a higher media coverage than positive events (Soroka, 2012).

In recent years, an important stream of literature focused on the role of uncertainty as driver of economic fluctuations. After Bloom (2009), a huge empirical literature studying the link between uncertainty and economic fluctuations emerged. A non-exhaustive list of empirical contributions includes Bachmann, Elstner and Sims (2013), Rossi and Sekhposyan (2015), Jurado et al. (2015), Ludvigson et al. (2020), Baker et al. (2016), Caldara et al. (2016) and Carriero et al. (2017). Fernàndez-Villaverde and Guerròn-Quintana (2020) review both empirical and theoretical works on uncertainty.

The literature on news and uncertainty have developed independently from each other until the recent contribution of Berger, Dew-Becker and Giglio (2020). The authors show that there exists a link between news shocks and uncertainty and between squared news shocks and uncertainty. Our analysis supports this idea. Indeed, we find that the squared news shock and a smoothed version of it have a high positive correlation with existing measures of uncertainty.[1] Here we embrace the view that the square term can be interpreted as a proxy for uncertainty endogenously arising from news, and its effects as uncertainty effects. Uncertainty acts as an amplifier mechanism, creating asymmetries and nonlinearities in the transmission of news shocks. At the end of the paper we use a very simple model of limited information to show how uncertainty can arise from news. Our story unfolds as follows. Agents receive news about economic events and act on the basis of the value of the expected shock (first-moment effect). News, due to limited information, generate uncertainty. The larger is the event, the larger uncertainty. Uncertainty generates a contractionary demand-type effect, possibly induced by a more cautionary behavior of the agents (second-moment effect). The two effects combined yield an asymmetry in the effects of news shocks since uncertainty enhances the effects of bad news and mitigates the effects of good news.

The remainder of the paper is structured as follows: Section 2 discusses the empirical model; Section 3 presents the results; Section 4 discusses the uncertainty channel; Section 5 concludes.

2 Econometric approach

Here we discuss the empirical model we employ to study asymmetries in the transmission of news shocks.

2.1 The model

We use a modified version of the method recently proposed by Debortoli et al. (2020). The method aims at estimating a nonlinear moving average representation of the economy where a shock of interest and a nonlinear function of it drive economic variables. The model can be estimated using a two step procedure where (i) the shock of interest is

[1] Cascaldi-Garcia and Galvao (2020) in a parallel and independent investigation, also find evidence of a link between news and uncertainty.

identified in an informationally sufficient VAR[2], and (ii) the estimated shock is used, together with some nonlinear function of it, as an exogenous variable in a VARX which includes a set of variable of interest. By combining the (linear) impulse response functions of the VARX nonlinearities and asymmetries of the shock of interest can be estimated.

Let Y_t be a vector of m variables of interest and s_t the shock of interest. They postulate that Y_t has the following representation:

$$Y_t = \mu + \alpha(L)s_t + \beta(L)s_t^2 + B(L)\varepsilon_t \tag{1}$$

where s_t is the news shock in our case, $B(L)$ is a $m \times m$ matrix of polynomials in the lag operator L, $\alpha(L)$ and $\beta(L)$ are $m \times 1$ vectors of polynomial in L. The terms $\alpha(L)$ and $\beta(L)$ represent the impulse response functions of the linear and the nonlinear term on Y_t. The vector ε_t is a vector of shocks orthogonal to s_t and s_t^2. The impulse response functions to a news shock of size $\bar{s}$ are given by $\alpha(L)\bar{s} + \beta(L)\bar{s}^2$ in case of a positive shock and $-\alpha(L)\bar{s} + \beta(L)\bar{s}^2$ in case of a negative shock.

Obviously, in order to estimate equation (1) an estimate of s_t is required. The first step of the procedure aims at estimating the shock of interest, the news shock in our case.

To do so, we assume that X_t is a vector of variables which is informationally sufficient for s_t. We include the following variables: (log) TFP[3], (log) stock prices, the Michigan Survey confidence index component concerning business conditions for the next five years, (log) real consumption of nondurables and services, the 10-year government bond, the spread between the 3-month Treasury Bill and the 10-year bond, the Moody's Aaa interest rate (AAA), the spread Aaa-Baa and the CPI inflation. We then estimate a VAR on X_t and we call it VAR 1.[4]

[2]See Forni and Gambetti (2014).

[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.

[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

To identify the news shock, we follow Forni, Gambetti and Sala (2014) and Beaudry et al. (2011) 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).

The second step aims at estimating asymmetries and nonlinearities in the transmission of news. As shown in Debortoli et al., (2020), equation (1) can be estimated using a VARX for Y_t

$$A(L)Y_t = c + \tilde{\alpha}(L)s_t + \tilde{\beta}(L)s_t^2 + \varepsilon_t \tag{2}$$

where $A(L)$ is a $m \times m$ matrix of p-th order polynomials in the lag operator, and $\tilde{\alpha}(L)$ and $\tilde{\beta}(L)$ are $m \times 1$ vectors of polynomial in L. The impulse response functions to a news shock of size $\bar{s}$ can be obtained as $A(L)^{-1}(\tilde{\alpha}(L)\bar{s} + \tilde{\beta}(L)\bar{s}^2)$ for a positive shock and $A(L)^{-1}(-\tilde{\alpha}(L)\bar{s} + \tilde{\beta}(L)\bar{s}^2)$ for a negative shock.

A few remarks about our econometric procedure are in order. First, s_t is well estimated as long as the VAR used to estimate s_t is informationally sufficient, and it is (see Table 1). Second, as discussed in Debortoli et al. (2020), this procedure is valid if one of these two sets of conditions hold: (i) the variables included in VAR 1 are unaffected by the nonlinear term; (ii) s_t ad s_t^2 are uncorrelated and s_t^2 has zero autocorrelation. The rationale for condition (ii) is that the (demeaned) term s_t^2 can be considered as one of the remaining shocks of VAR 1 and parameters estimation and the identification of s_t are unaffected by the presence of s_t^2. In our case, condition (i) does not hold while condition (ii) does hold. Indeed the correlation between s_t and s_t^2 is -0.09 with a p-value of 0.17 for the test of zero correlation and the first five autocorrelations of s_t^2 are low, below 0.2, and insignificant.

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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 1). We conclude that the model incorporates enough information to identify the news shock.

3 Results

In this Section we report and discuss the empirical results. 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[5] with diffuse priors and 4 lags.

3.1 The news shock

The news shock and its square exhibit very large values (more than two standard deviations larger than average) in seven quarters. In Figure 1 we focus on the squared news shock. Five of the seven quarters correspond to periods associated to negative shocks and two are periods associated to positive shocks. The squared news shock is therefore left skewed, with skewness of -0.36. The seven quarters are the following (in parenthesis the sign of the shock and the corresponding event): 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.

Figure 2 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.

3.2 The effect on macroeconomic variables

The VARX we employ to study the effects of news on the economy includes: (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. The estimated news shock and the squared news shock are used as exogenous variables.

[5] A frequentist VAR yields the same results.

We organize the discussion as follows. First we present the VARX results relative to the estimated impulse response functions to s_t and s_t^2 for $\bar{s} = 1$. Then, we focus on nonlinearities. Results are reported in Figure 3. The numbers on the vertical axis are 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 the findings of the literature.[6] 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 around -1%. Afterwards, the effect reduces and vanishes after about 2-3 years. The effects of the square term are also sizable and significant for investment and hours, while the effects on consumption are somewhat milder and not significant. By inspecting the response of inflation, it is clear that square effects are demand-type effects, since GDP increases and inflation significantly falls.

Figure 4 plots the total response of economic variables to the news shock. Recall that the total responses are $A(L)^{-1}(\tilde{\alpha}(L)\bar{s}+\tilde{\beta}(L)\bar{s}^2)$ for a positive shock and $A(L)^{-1}(-\tilde{\alpha}(L)\bar{s}+\tilde{\beta}(L)\bar{s}^2)$ for negative shocks. We plot the responses to shocks of size $\bar{s} = 1$, i.e. one standard deviation (first column), $\bar{s} = 0.5$ (second column) and $\bar{s} = 2$ (third column). The solid line represents the mean response to a positive news shocks, the gray area are the 68% probability intervals. The dashed red line represents the effects of a negative news shock with reversed sign (multiplied by -1), in order to ease the comparison in terms of magnitude between good and bad news.

A positive news shock permanently increase real economic activity variables: GDP, Consumption, Investment and Hours worked. The responses however are quite sluggish. Indeed, except for consumption, the impact effects are zero. Inflation significantly falls and new orders increase. By inspecting the two lines, a clear asymmetry emerges. A bad news shocks has higher short run effects than a good news shocks on real economic activity variables. Summing up, the impact effects are higher for bad news than for good news. Indeed, for negative shocks the effects of the square term enhance those of news. The contrary holds for positive shocks: the square term mitigates the expansionary effects of news. Interestingly, the result is different for inflation since good news have larger effects

[6]Barsky and Sims (2011), Forni, Gambetti and Sala (2014).

than bad news.

The asymmetry is amplified in the case of a large shock $\bar{s} = 2$ (third column) and dampened in the case of a small shock $\bar{s} = 0.5$ (second column). The larger is the shock, the larger is the asymmetry since the square term becomes more important.

Table 2 reports the variance decomposition. In particular, it reports the proportion of variance of the variables attributable to news shocks. This includes both the linear and the quadratic term. The shock has important effects in the medium and long run for GDP, consumption, investment and hours. For these variables the shock explains between 40% and 60& of the variance at horizons longer than one year.

3.3 The effects on financial variables

In order to analyze the effects of news on financial variables and uncertainty, we estimated an additional VARX including stock prices, the 3M T-Bill bond yield, 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, and three indices of uncertainty, the extended VXO index of implied volatility in option prices, see Bloom (2009), the macroeconomic uncertainty index 12-month ahead (denoted as JLN12), developed by Jurado, Ludvigson and Ng (2015) and the Ludvigson, Ma and Ng (2020) real uncertainty index 12-months ahead (denoted as LMN R12).

Results are reported in Figure 5 and 6. In Figure 5, the left column reports the effects of s_t and the right column the effects of s_t^2. Figure 6 reports the total effects for different magnitudes of the shock.

We start by analyzing the effects of the linear and quadratic components in Figure 5. The linear news shock increases permanently stock prices and reduces uncertainty, the risk premium and the T-bill. The squared term is, as for macroeconomic variables, contractionary. It is interesting to notice that a positive shock to the squared term has a significant positive effects on the three uncertainty indices, VXO, JLN12 and LMN R12. There is a close link between squared news shock and uncertainty measures. We will come back to this result later on.

Moving to the total effect reported in Figure 6, good news have a large, positive and persistent effect on stock prices and significantly reduce the risk premium, and the uncertainty indices. Bad news have the opposite effects (notice again that we report the response to a negative shock multiplied by -1): persistent and significant reduction of stock prices and increase in the risk premium and uncertainty. Again, a substantial asymmetry arises. Stock prices and the VXO react much more to bad news than to good news and the risk premium reacts faster. The response of the T-Bill is different. Indeed this variable displays smaller effects for bad news than good news.

From the variance decomposition, Table 3, it can be seen that the shock is very important for stock price fluctuations, explaining around 40% to 50% of the variance of the variable. On the contrary, the shock plays a smaller role for the other variables. It is interesting to notice that more than 30% of the variance of the VXO is accounted for by the shock while the percentage is a bit less for the JLN12 measure (around 10%) and LMNR12 (around 15%). A sizable part of the existing measure of uncertainty are explained by news. Of course, this leaves the door open for the existence of an exogenous component of uncertainty that has nothing to do with news.

4 The uncertainty channel

In this section we provide an interpretation of the square term by connecting news and uncertainty. Cascaldi-Garcia and Galvao (2020) and Berger et al. (2020), in two independent investigations, have suggested that there is a close link between news and uncertainty. We believe that the idea is very appealing and reasonable. Indeed, news about economic events, whose effects are not perfectly predictable, can create uncertainty.

In what follows, we will show that the squared news shock and various measures of uncertainty are closely related and report some *prima facie* evidence on the link between news and uncertainty. We also present a simple framework of limited information where time-varying uncertainty arises from news.

4.1 Evidence

To explore the relation between squared news and uncertainty we compute the correlation of the squared shock and its smoothed version with 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 1-, 3- and 12-month ahead (denoted respectively JLN1 JLN3 and JLN12 henceforth); (iii) the Ludvigson, Ma and Ng, 2020, financial and real uncertainty indexes 1-, 3- and 12-months ahead (denoted respectively, LMN F and LMN R and the number referring to the month).

Table 4 reports the correlations. The first column refers to the squared shock while the second column to a centered 5-quarter moving average of the squared shock. For the squared shocks, correlations range from 0.24 (VXO) to 0.40 (JLN3 and JLN12) while for the moving average correlations range from 0.36 (VXO) to 0.67 (JLN3 and JLN12). The squared news shock is positively correlated with all recent measures of uncertainty, the correlation being particularly high for the JLN measures. Figure 7 plots the (standardized) 5-quarter moving average of the news shock (red solid line) together with the (standardized) JLN12 measure (blue dotted line). The result is striking, the two variables closely track each other and display several coincident peaks. Notice that the estimation of the news shock is completely independent of uncertainty since no uncertainty measure is included in the first estimation step.

This is in line with the results of the VARX for financial variables, Figure 5. There, we saw that a positive squared news shock generates a positive conditional comovement among uncertainty measures. Here, we see that the positive comovement between squared news and uncertainty also arises unconditionally.

As a second check to understand the link between uncertainty and news, we identify an uncertainty shock as the first shock in a Cholesky decomposition in a VAR which includes, in that order, the VXO, GDP, Consumption, Investment, Hours worked, CPI inflation and new orders with this order and compute impulse responses.[7] We then repeat

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

the estimation with the same specification but adding the news shock and the squared news shock as first and second variable in the VAR. The uncertainty shock becomes now the third shock in the Cholesky decomposition. If the standard uncertainty shock has nothing to do with news and squared news, the impulse response functions in the two model 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 8). 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. We repeat the same exercise replacing the VXO with LMNR12. Results, see Figure 9, point to the same conclusion. When news and squared news are included, the effects of the uncertainty shocks are substantially mitigated, meaning that to some extent, uncertainty endogenously depends on news.

4.2 A simple informational framework

Why could uncertainty, defined as the conditional forecast error variance, arise from news? Here we discuss a simple illustrative case where this can happen.

Let us assume that the TFP, a_t, follows

$$\Delta a_t = \varepsilon_{t-1} \tag{3}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$ is an economic shock with delayed effects.[8] At time t, 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.[9] At each point in time, agents form an expectation, $s_t = E_t\varepsilon_t$ of the true shock.[10] The shock and the expectation however, because information is imperfect, do not coincide. We assume that there is a random

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

[9]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.

[10]We will show below that s_t coincides with the news shocks identified in Section 2.

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 $E_t(v_t - 1)^2 = \sigma_v^2$, i.e. constant. 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, while common in engineering and control system, to our knowledge has not been employed before in the literature of limited information. Typically, an additive structure is used mainly for the purpose of analytical tractability. However, we find it particularly attractive since it can describe several relevant economic situations. A few examples can provide a better intuition. Suppose that a diplomatic crisis takes place 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 depending on the president's decision. The decision is taken in t but, for national security reasons, made public only in $t+1$. So the expected shock is $s_t = -0.5$. The noise, which captures the uncertainty surrounding the president's decision, will be $v_t = 2$ in case of war and $v_t = 0$ otherwise, with equal probabilities. 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 ($\varepsilon_t = -1$). The government's decision is taken in t but agents do not know it, so the expected shock is $s_t = -2$ and v_t can be either 1.5 or 0.5 with equal probabilities.

In this simple informational framework, the TFP forecast error is

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

We follow Ludvigson, Jurado and Ng (2015) and define uncertainty as the conditional variance of the forecast error, which is

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

The conditional variance, or uncertainty, depends on the squared expected shock.[11] Going back to the previous examples, the bigger the war in case of going to war, or the larger the consequences of the domino effect if government does not intervene, i.e. in both cases the larger the value of ε_t in absolute value, the larger is uncertainty since the larger is s_t.

Through the lens of this interpretative framework therefore, the effects of s_t^2 on the economy, not modeled here, can be interpreted as attributable to uncertainty. Can the interpretation be extended to our empirical findings? Can we interpret the asymmetries as arising from the uncertainty generated by news? The answer, essentially, depends on whether the news shock identified in Section 2 can be interpreted as s_t. It is easy to see that this is the case. The model representation of Δa_t and s_t is

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} 1 & L \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}. \tag{4}$$

Notice that (i) the shock s_t satisfies the identifying restrictions used in the empirical model: positive long run effect and zero impact effect on a_t; and (ii) the representation above is invertible, i.e. can be estimated with a SVAR. This means that under this informational assumption s_t is exactly the news shock identified in the SVAR of Section 2. As a result, the effects of the squared term in our empirical findings can be interpreted as effects attributable to uncertainty arising from news.

Summing up, our story unfolds as follows. Agents receive news about economic events and act on the basis of the value of the expected shock (first-order moment effect). However events, due to the fact that they are not seen with certainty, generate uncertainty. The larger is the event, the larger is the uncertainty. Uncertainty generates a contractionary demand-type effect possibly induced by a more cautionary behavior of the agents (second-order moment effect). The two effects combined yield an asymmetry in the effects

[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.

of news shocks since uncertainty enhances the effects of bad news and mitigate the effects of good news.

Our results has important implications for DSGE models. Second moment effects, related to changes in conditional volatility, appear in higher order terms of the approximation of DSGE models, see Fernández-Villaverde et al. (2015a, 2015b). Here we show that, at least for the case of the news shock, these terms are important from an empirical point of view, stressing the importance of going beyond linearization to correctly describe fluctuations in macroeconomic variables.

4.3 Simulations

Now that we have a simple model in which uncertainty is generated by the squared news shocks, we come back to our econometric methodology. In this Section we ask the following question: is our method able to detect the first- and second-order effects of the news shock, as generated by the model? We use two simulations to assess our econometric approach. The first simulation is designed as follows. Consider the simple model of Section 4.2. Assume that $[v_t \;\; s_t]' \sim N(0, I)$.[12] 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

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

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 one of the variables of interest in the vector Y_t) as[13]

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

where $g_1 = 0.7$ and $f_1 = 1.4$. We estimate a VARX for Δy_t using $\hat{s}_t^2$ and $\hat{s}_t$ as exogenous variables. 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 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 then estimate a VARX for Δy_t using $\hat{s}_t^2$ and $\hat{s}_t$ as exogenous variables.

The results of simulation 1 are reported in the left column of Figure 10, 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 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.

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. 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 good news. The literature on nonlinearities of news is still in its infancy. This paper represents one of the few con-

[13]This is the corresponding row of the VAR in equation (2).

tributions. Of course there might be other types of nonlinearities and channels which propagate news in a nonlinear way which will be investigated in future research.

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Tables

Variables	Lags	
	2	4
GDP	0.94	0.96
Inflation	0.68	0.40
Hours Worked	0.98	1.00
Federal Funds Rate	0.82	0.94
BAA Yield	1.00	1.00
BAA-AAA	1.00	1.00
BAA-GS10	1.00	1.00
E5Y	1.00	1.00
VXO	0.55	0.80
S&P 500	1.00	1.00
Inflation	1.00	1.00
Unemployment	0.73	0.95
LMN F3	0.13	0.11
LMN R3	0.58	0.12
JLN12	0.46	0.11
JLN3	0.50	0.27

Table 1: Orthogonality test. P-values of the F-test of the null that the coefficients of the lags of the variables are zero in a regression of the estimated shock onto the lagged variables.

Variables	Horizon				
	$k = 0$	$k = 4$	$k = 12$	$k = 20$	$k = 40$
			News shock		
GDP	3.18	31.91	55.21	58.74	61.16
Consumption	23.56	56.41	66.24	65.82	65.21
Investment	0.43	23.75	40.10	42.62	46.33
Hours Worked	1.33	23.91	50.63	53.90	50.00
Inflation	22.72	21.12	17.58	16.79	16.26
New Orders	0.05	25.65	19.43	19.30	19.29
			Squared shock		
GDP	12.25	22.99	8.64	7.03	7.90
Consumption	5.16	1.62	2.98	5.12	7.31
Investment	16.16	20.69	8.82	8.65	9.38
Hours Worked	9.74	15.26	9.35	9.01	9.50
Inflation	4.74	11.65	10.39	9.81	9.33
New Orders	10.62	9.12	17.83	17.98	17.95
			News shock + Squared shock		
GDP	15.43	54.90	63.84	65.77	69.06
Consumption	28.72	58.04	69.23	70.94	72.51
Investment	16.59	44.44	48.92	51.26	55.70
Hours Worked	11.07	39.17	59.99	62.91	59.50
Inflation	27.47	32.76	27.97	26.60	25.59
New Orders	10.67	34.78	37.26	37.28	37.24

Table 2: Variance decomposition for macroeconomic variables. Percentage of variance attributable to the news shock, the squared shock and the sum of the two.

Variables	Horizon				
	$k = 0$	$k = 4$	$k = 12$	$k = 20$	$k = 40$
			News shock		
S&P500	37.01	46.19	51.25	51.29	48.88
TB3M	13.19	3.05	3.10	7.51	18.84
BAA-AAA	5.32	4.41	6.51	5.51	5.91
VXO	6.41	10.77	10.79	11.41	11.57
JLN12	3.96	10.88	7.24	6.95	8.01
LMNR12	1.94	9.83	9.56	10.15	12.87
			Squared shock		
S&P500	4.08	10.85	5.29	3.98	3.03
TB3M	0.47	9.21	6.92	6.51	5.48
BAA-AAA	1.27	10.78	8.12	7.64	7.42
VXO	9.71	25.45	23.16	21.66	20.49
JLN12	8.85	2.51	1.54	1.62	1.59
LMNR12	5.03	6.32	4.46	4.43	4.12
			News shock + Squared shock		
S&P500	41.08	57.04	56.54	55.28	51.91
TB3M	13.66	12.25	10.02	14.01	24.32
BAA-AAA	6.60	15.19	14.63	13.14	13.33
VXO	16.11	36.22	33.94	33.07	32.06
JLN12	12.81	13.40	8.78	8.57	9.60
LMNR12	6.97	16.14	14.02	14.58	16.98

Table 3: Variance decomposition for financial variables. Percentage of variance attributable to the news shock, the squared shock and the sum of the two.

	Shock	5-quarter MA
VXO	0.24	0.36
JLN1	0.40	0.67
JLN3	0.40	0.67
JLN12	0.38	0.65
LMN F1	0.28	0.44
LMN F3	0.28	0.44
LMN F12	0.27	0.44
LMN R1	0.33	0.53
LMN R3	0.36	0.58
LMN R12	0.38	0.62

Table 4: Correlation with JLN and LMN uncertainty. First column: square of the raw shock. Second column: 5-quarter moving average of the shocks.

Figures

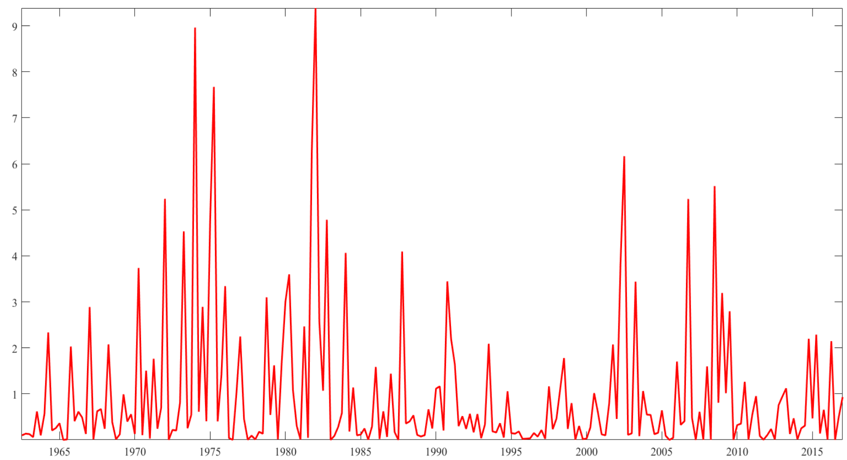

Figure 1: Squared news shock. There are seven quarters with peaks corresponding to the following events (in parenthesis the sign of the shock): 1974:Q (−, Stock Market Oil Embargo Crisis); 1982:Q1 (−, loan crisis); 1982:Q4 (+, end of early 80s recession); 1987:Q1 (+, oil price collapse); 2002:Q3 (−, WorldCom bankruptcy); 2008:Q3 (−, Lehman Brothers bankruptcy); 2008:Q4 (−, stock market crash).

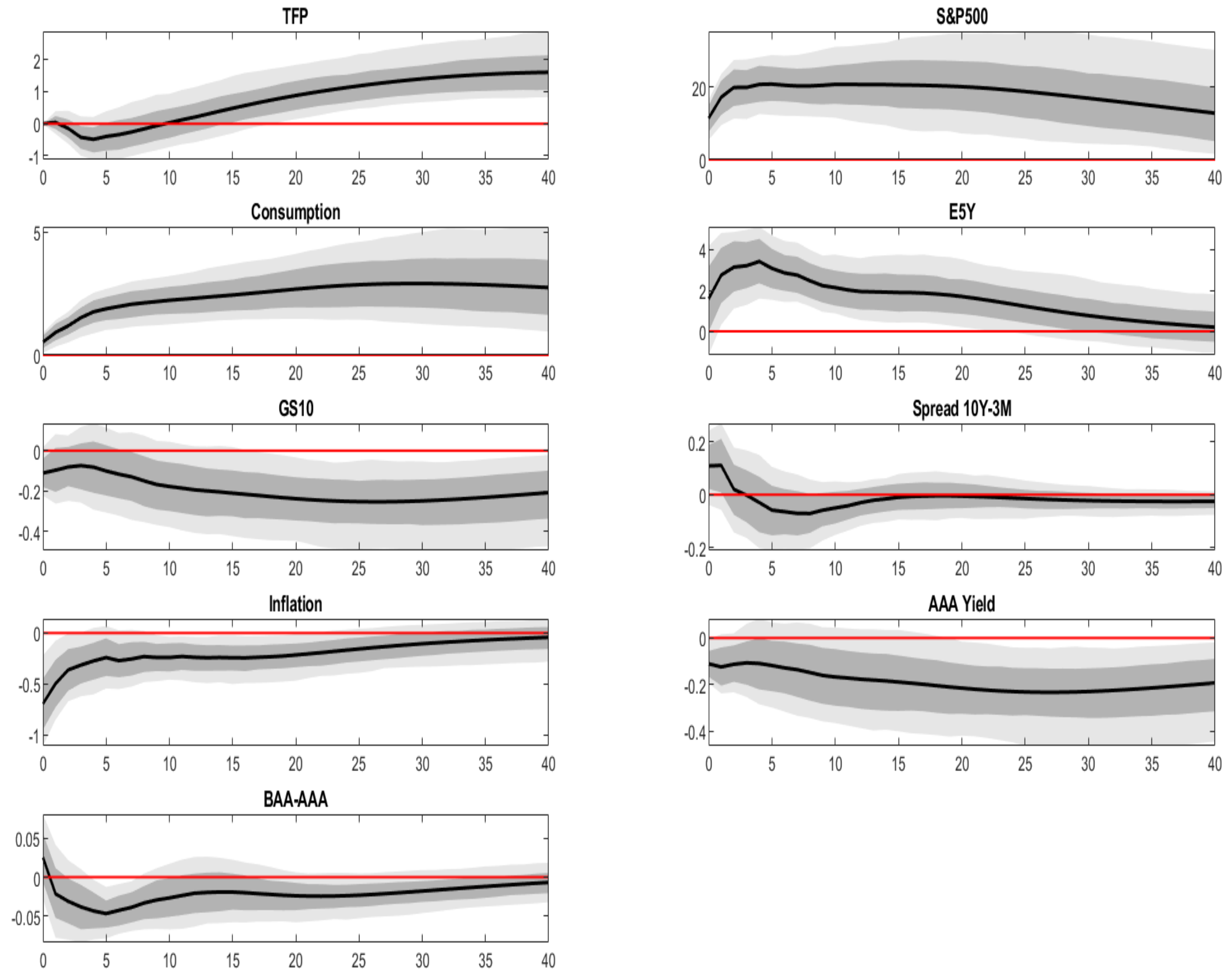

Figure 2: Impulse response functions to the news shock (VAR 1). Solid line: point estimate. Light grey area: 90% credible bands. Dark grey area: 68% credible bands.

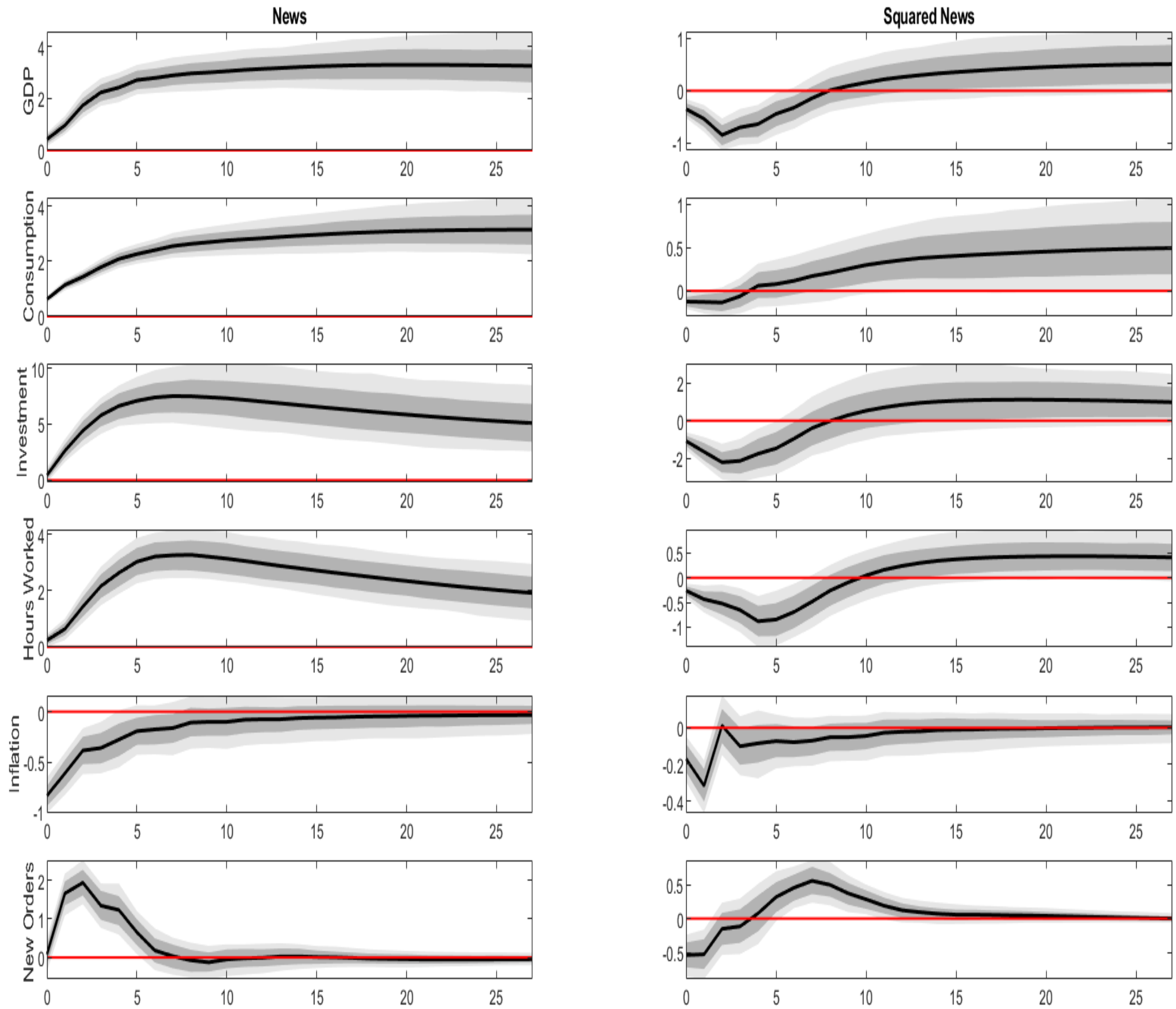

Figure 3: Impulse response functions to the news shock (left column) and the squared news shock (right column) obtained with the VARX. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

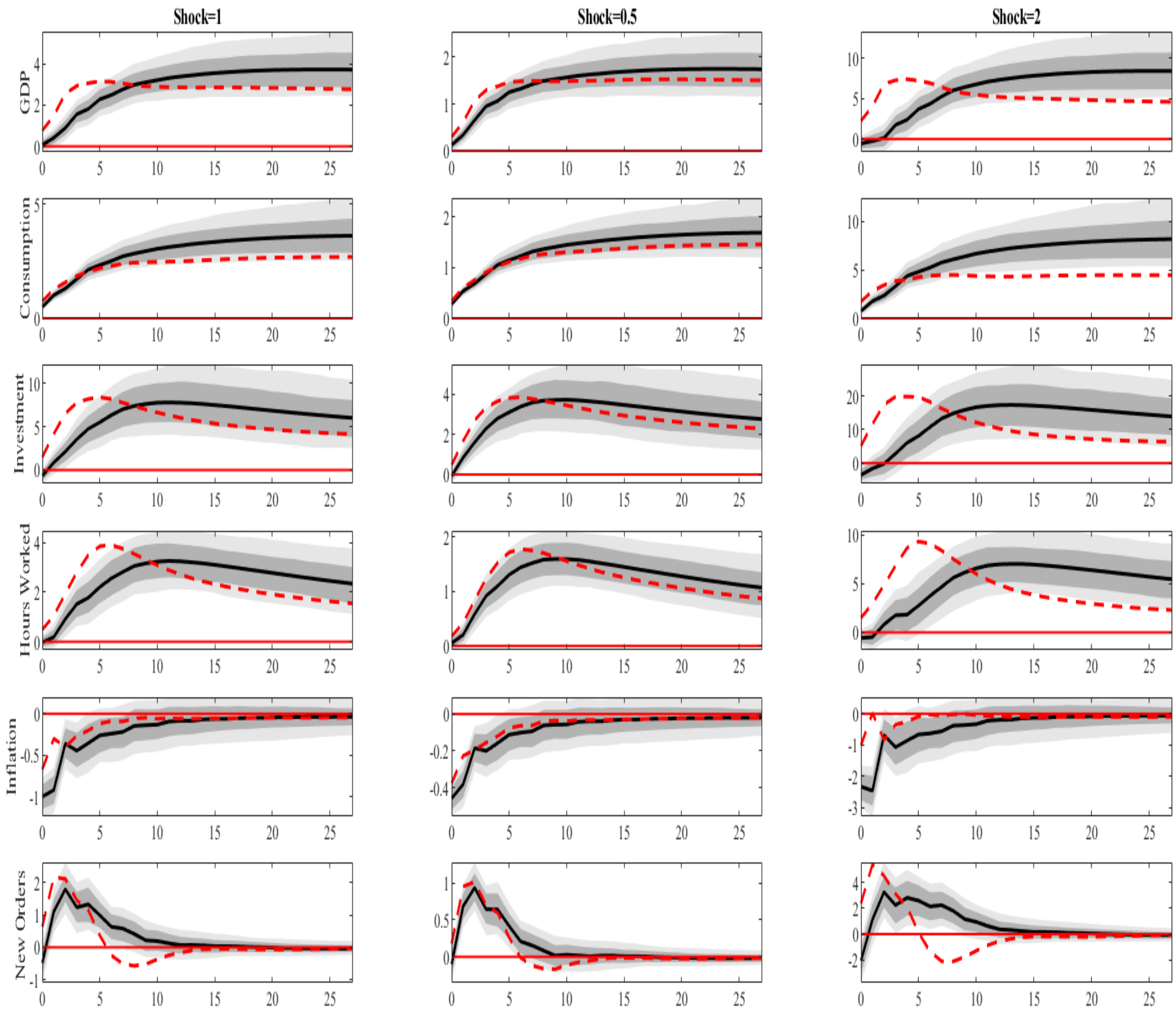

Figure 4: Nonlinear impulse response functions estimated from the VARX with equation (2). Left column: shock of size 1; middle column: shock of size 0.5; right column: shock of size 2. Black solid lines: point estimates. Light grey area: 90% confidence bands of a positive news shock. Dashed red lines are the responses to a negative shock with reversed sign.

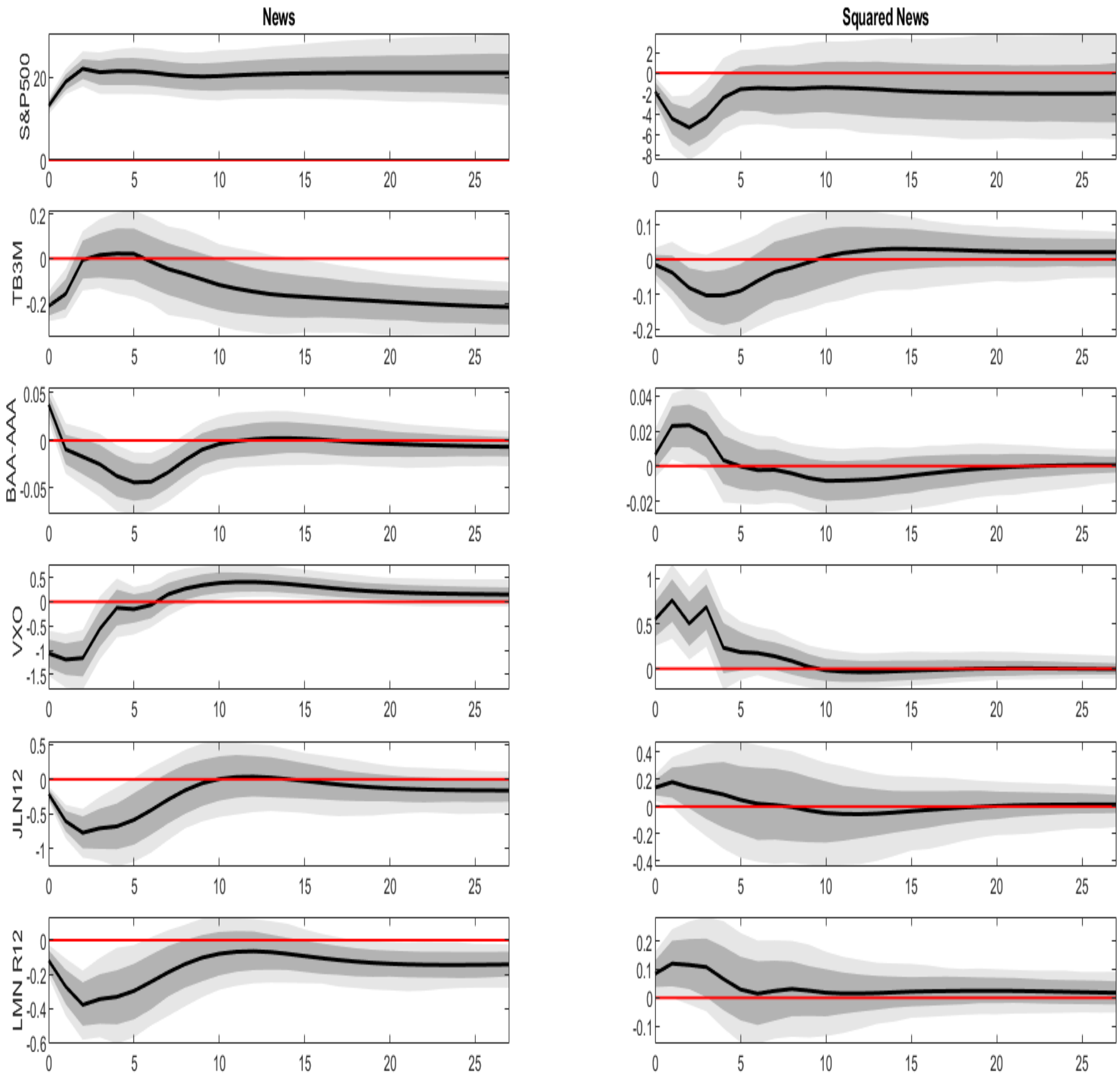

Figure 5: Impulse response functions to the news shock (left column) and the squared news shock (right column) obtained with the VARX. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

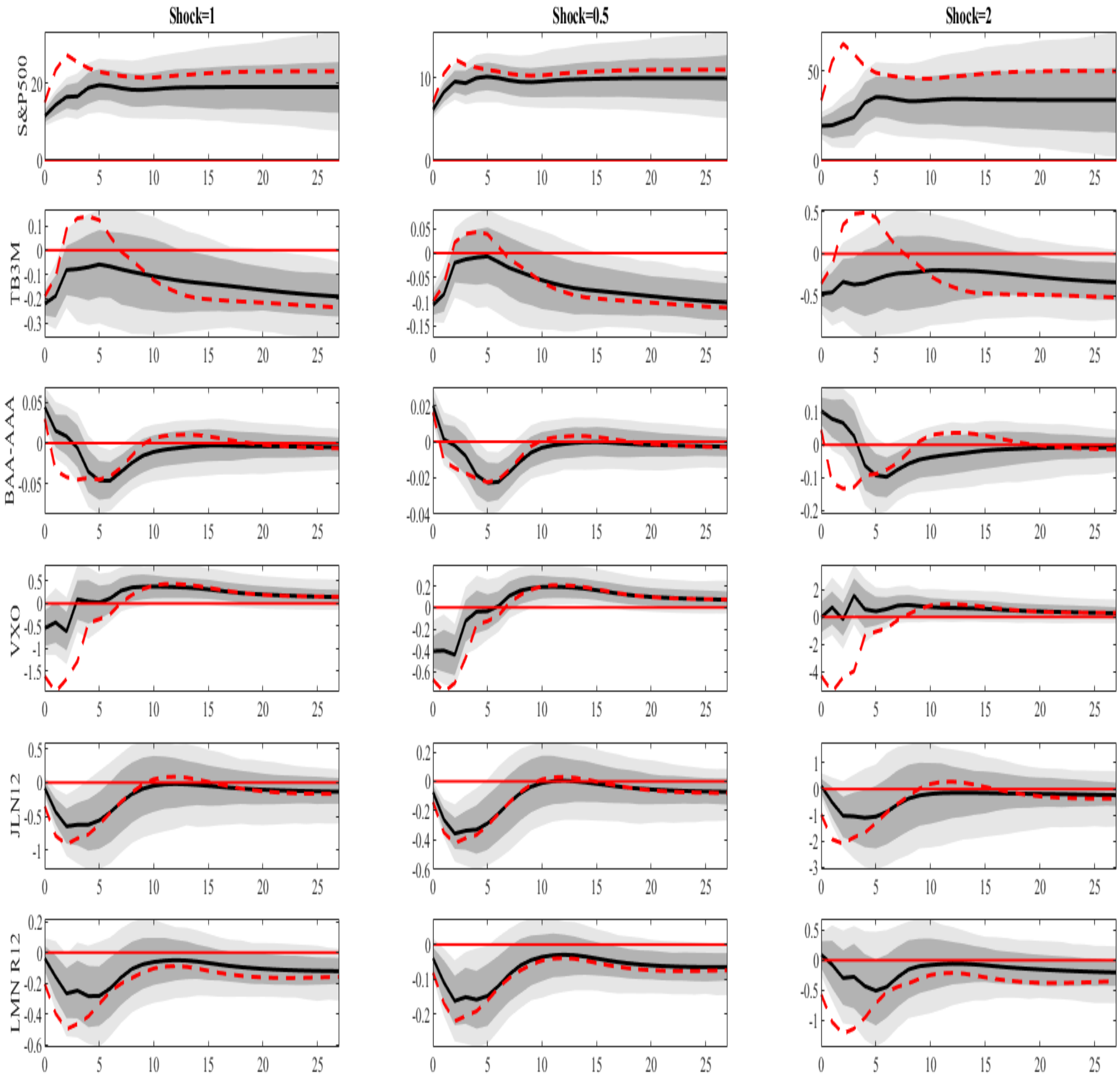

Figure 6: Nonlinear impulse response functions of financial variables estimated from the VARX with equation (2). Left column: shock of size 1; middle column: shock of size 0.5; right column: shock of size 2. Black solid lines: point estimates. Light grey area: 90% confidence bands of a positive news shock. Dashed red lines are the responses to a negative shock with reversed sign.

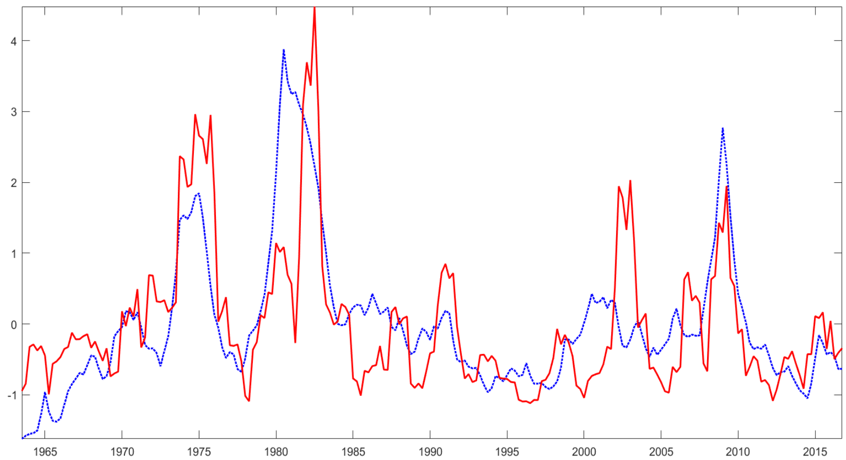

Figure 7: 5-quarter moving average of the news shock (red solid) and the LMN3 uncertainty measure (blue dotted).

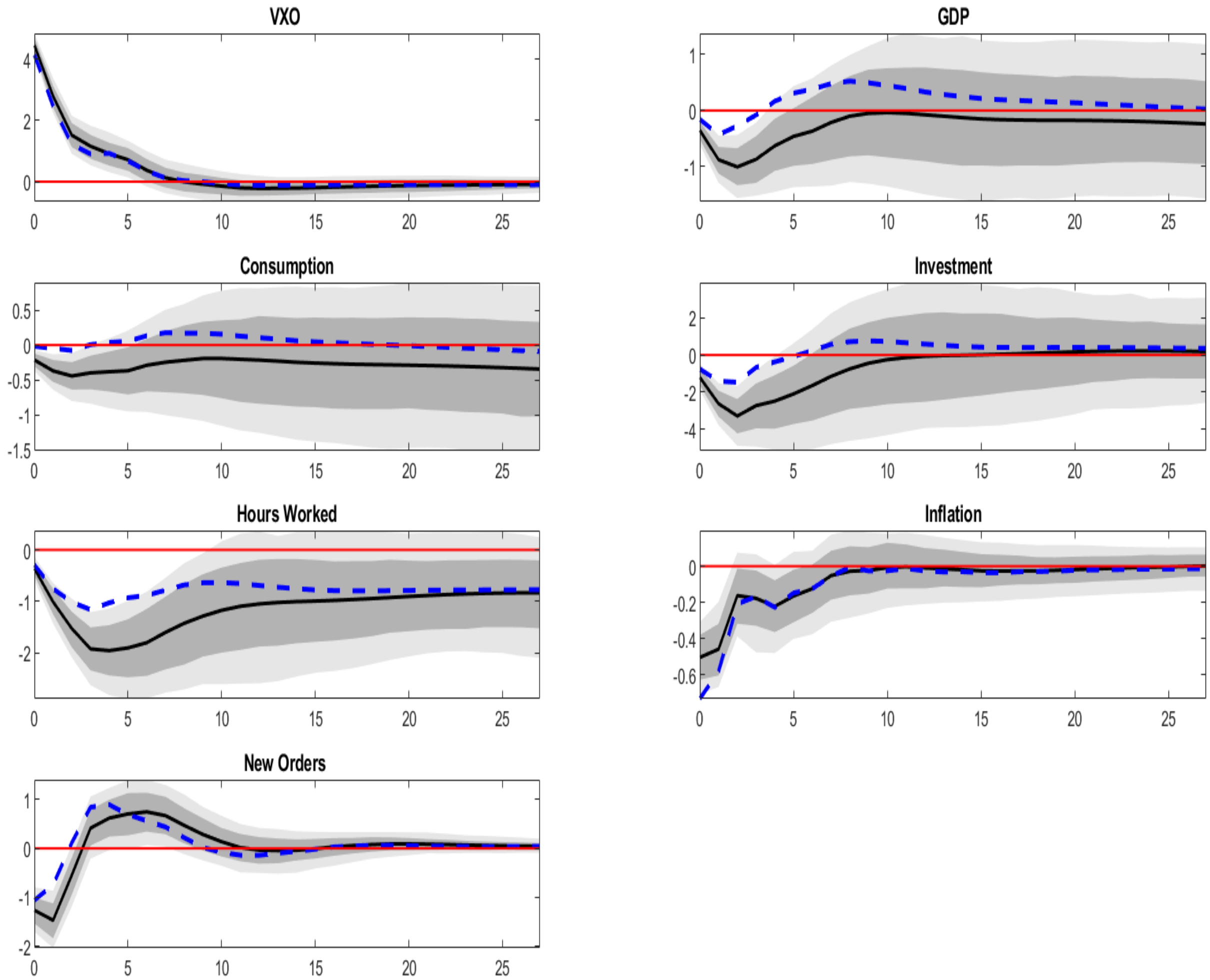

Figure 8: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with the VXO ordered first. Black solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands. Blue dashed lines are the impulse response 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.

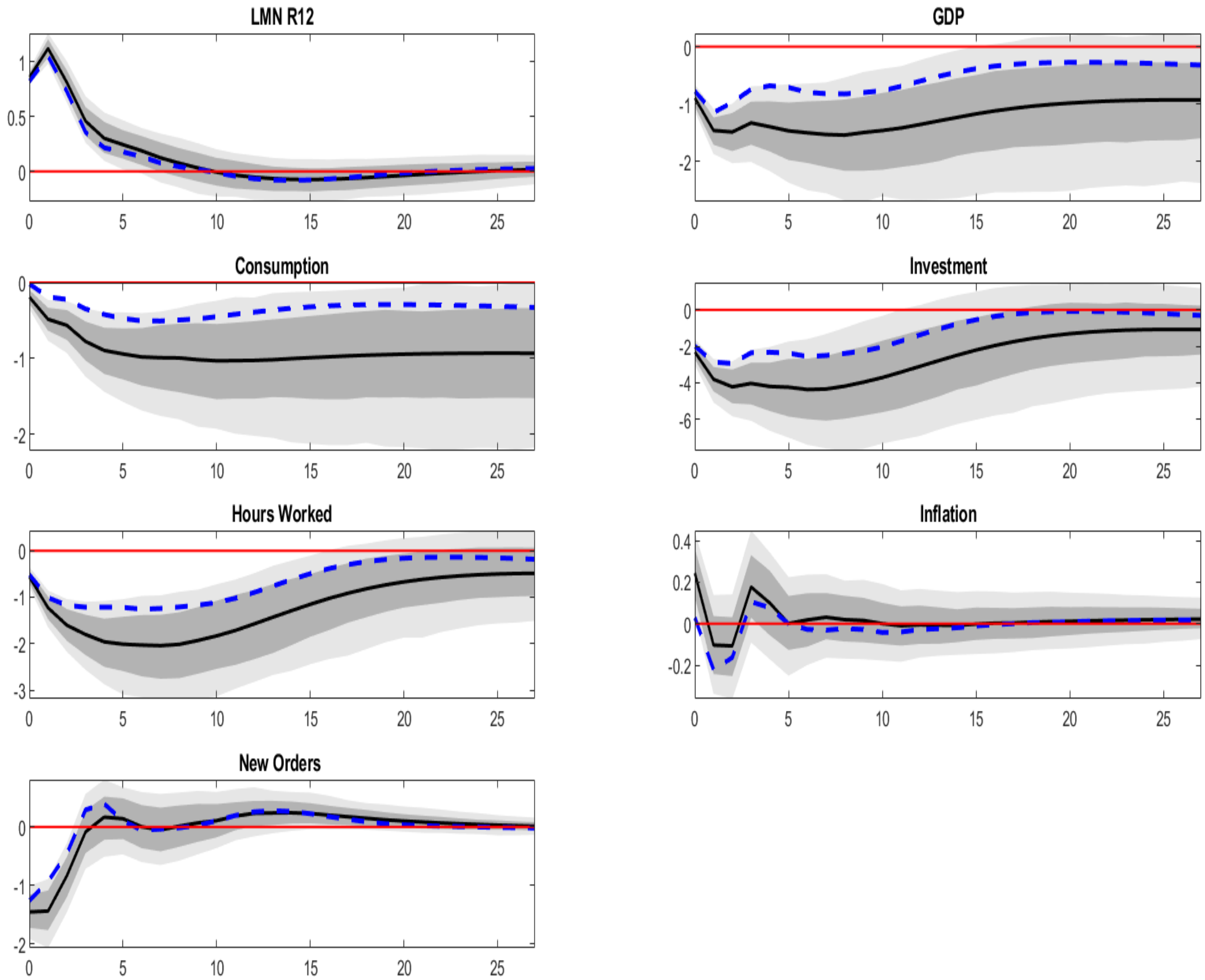

Figure 9: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with the LMN12 ordered first. Black solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands. Blue dashed lines are the impulse response 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.

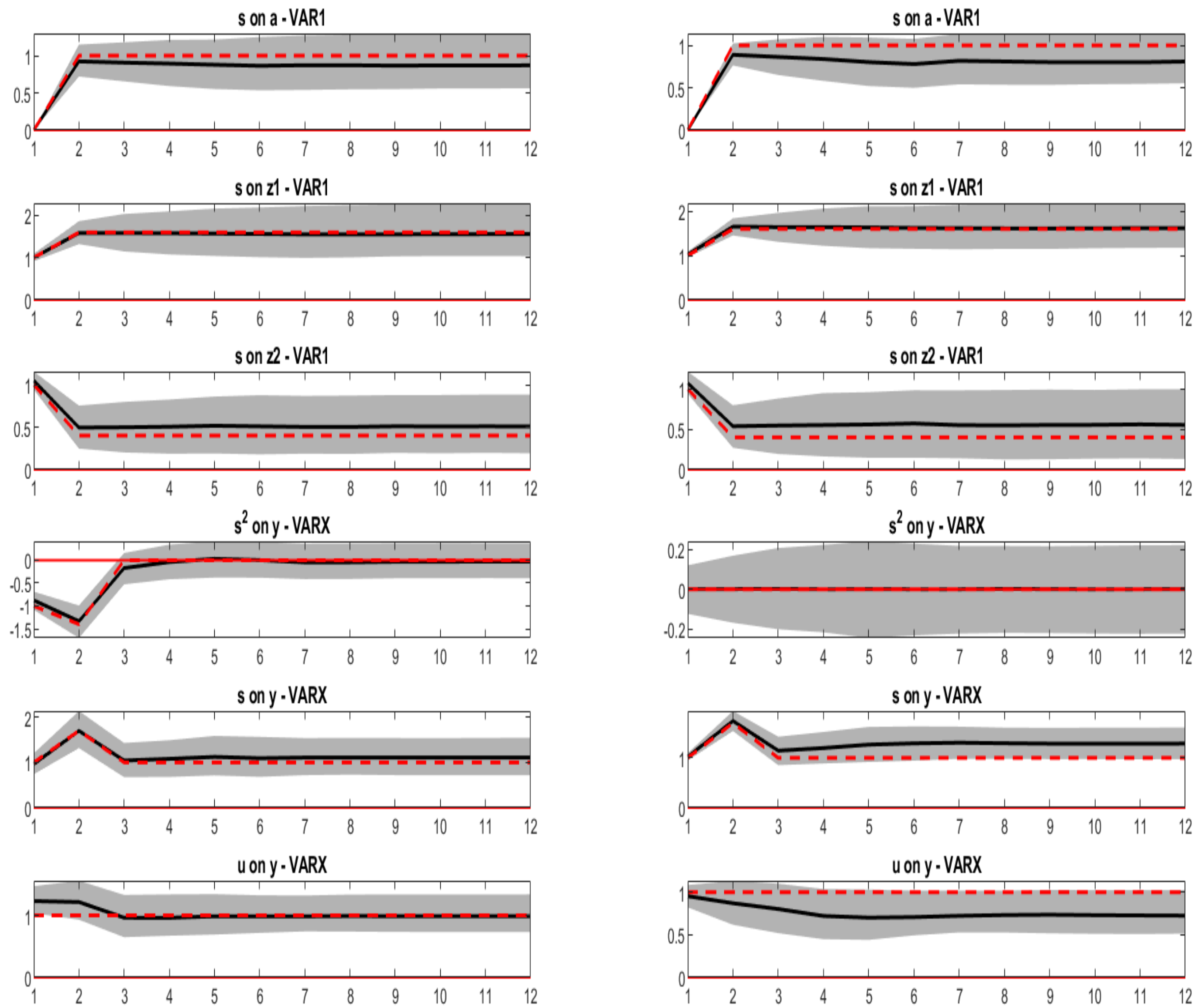

Figure 10: Impulse response functions functions of the two simulations. Left column: simulation 1. Right column: simulation 2. Solid line: point estimate. Grey area: 90% confidence bands. Red dashed line: true theoretical responses.