News, Uncertainty and Economic Fluctuations (No News is Good News)

Mario Forni*
Università di Modena e Reggio Emilia, CEPR and RECent

Luca Gambetti†
Universitat Autonoma de Barcelona and Barcelona GSE

Luca Sala‡
Università Bocconi, IGIER and Baffi CAREFIN

June 26, 2017

Abstract

We formalize the idea that uncertainty is generated by news about future developments in economic conditions which are not perfectly predictable by the agents. Using a simple model of limited information, we show that uncertainty shocks can be obtained as the square of news shocks. We develop a two-step econometric procedure to estimate the effects of news and we find highly nonlinear effects. Large news shocks increase uncertainty. This mitigates the effects of good news and amplifies the effects of bad news in the short run. By contrast, small news shocks reduce uncertainty and increase output in the short run. The Volcker recession and the Great Recession were exacerbated by the uncertainty effects of news.

JEL classification: C32, E32.

Keywords: news shocks, uncertainty shocks, imperfect information, structural VARs.

*The financial support from FAR 2014, Università di Modena e Reggio Emilia is gratefully acknowledged. Contact: Dipartimento di Economia Politica, via Berengario 51, 41100, Modena, Italy. Tel. +39 0592056851; e-mail: mario.forni@unimore.it.

†Luca Gambetti acknowledges the financial support of the Spanish Ministry of Economy and Competitiveness through grant ECO2015-67602-P and through the Severo Ochoa Programme for Centres of Excellence in R&D (SEV-2015-0563), and the Barcelona Graduate School Research Network. Contact: Office B3.1130 Departament d'Economia i Historia Economica, Edifici B, Universitat Autonoma de Barcelona, Bellaterra 08193, Barcelona, Spain. Tel. +34 935814569; e-mail: luca.gambetti@uab.cat.

‡Corresponding author. Contact: Department of Economics, Università Bocconi, via Roentgen 1, 20136, Milan, Italy. Tel. +39 0258363062; e-mail: luca.sala@unibocconi.it.

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 contribution 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 et al., 2015, Ludvigson et al., 2015, 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 *uncertainty arises from news*. The definition of uncertainty we focus on in this paper is the *forecast error variance*. Economic agents live in world with imperfect information, observe new important events, but cannot predict exactly their effects on economic activity. This increases the forecast error variance, i.e. uncertainty. Moreover, the more important the event, i.e. Brexit, the higher the uncertainty originating from news.

In other words, 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 affects uncertainty without affecting point forecasts, 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. If nothing new happens, expectations do not change and uncertainty is low. 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. To support this idea, we consider a variable measuring news from the Michigan Consumers Survey, square it and compute the correlation with respect to a number of uncertainty measures considered in the literature. It turns out that squared news and uncertainty are highly and negatively correlated.

We propose a simple model where a single, unobserved, structural shock drives the output trend. The "news" shock is nothing else than the expected value of the structural shock. The forecast error is the product of two independent factors: an observable one, the "news" shock itself, and an unobservable one, which generates uncertainty. The unobservable factor is the percentage deviation of the structural shock from the news shock. Owing to this multiplicative interaction, expectation errors have a time-varying conditional variance, proportional to the square of the news shock. Big news (either good or bad) are on average associated to large expectation errors, and therefore large uncertainty.

Output is modeled as the sum of the output trend and a cycle, possibly affected by uncertainty. Hence news shocks are allowed to have both a linear and a quadratic effect on output. The linear effect is the usual news shock effect, related to expectation changes. The quadratic effect is an additional effect, related to uncertainty, which has been neglected so far in the news shock literature.

It is important to stress that uncertainty in our model is not an "endogenous" variable, caused by business cycle fluctuations. Rather, it is quite the contrary: news-driven uncertainty is a genuine, independent source of business cycle fluctuations, which arises in combination with news shocks.

When the quadratic effect is taken into account, the business-cycle consequences of news appear more complex than usually believed. First, 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. 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 is positive; it therefore 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. Third, the density distribution of the squared news shock is of course highly skewed, with a fat tail on the right-hand side. As a consequence, positive uncertainty effects cannot be large, whereas negative effects can.

In the empirical part of the paper, we estimate the US news shock with standard VAR methods. We then compute the squared news shock, as well as the associated uncertainty implied by our model. The squared news shock peaks in quarters characterized by important recognizable economic, institutional and political events, such as the the Afghanistan war and the first oil shock, the monetary policy shocks of the Volcker era, the Lehman Brother bankruptcy and the subsequent stock market crash. Since large events are mainly negative, squared news is negatively correlated with news, though correlation is not large (about -0.20). Squared news uncertainty is highly correlated with existing measures of uncertainty: the correlation with VXO is about 0.65 and the correlation with the 3-month horizon uncertainty estimated by Jurado et al., 2015, is about 0.60.

In order to evaluate the business cycle effects of news uncertainty, we include both the news shock and the related uncertainty into a second VAR, together with the variables of interest. We find that (i) a positive news shock has effects similar to the ones found in the literature, with a gradual and persistent increase of GDP, consumption and investment; (ii) the squared news shock has a significant negative temporary effect on economic activity peaking after one quarter; (iii) the squared news shock affects positively and significantly on impact the VXO index and the risk premium.

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. As a consequence, most of the times the effect of square news is relatively small, but in a few episodes it is not. The historical decomposition of GDP reveals that news uncertainty explains a good deal of the early 1980s recession as well as the Great Recession.

The reminder of the paper is structured as follows: section 2 discuss some evidence about news and uncertainty; section 3 discuss the theoretical model; section 4 presents the econometric procedure; section 5 presents the empirical results; section 6 concludes.

2 News and uncertainty

News and uncertainty have been considered in the empirical literature as two separate factors driving economic fluctuations and the link between them has been largely neglected. However it is plausible to think of uncertainty as originated from news about future developments of the economy. Moreover, the intuition suggests that the more important is the event reported by the news, the higher should be the uncertainty generated by the news. For instance, the UK leaving Europe is expected to generate much more uncertainty that other minor events. In this first section we provide *prima facie* descriptive evidence in support of this idea using data from the Michigan University Surveys of Consumers.

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 responded 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. If our hypothesis is correct, no news should be associated with low uncertainty and relevant news with high uncertainty, so that No Mentions should be negatively correlated with existing measures of uncertainty.

A single “Consumers’ News” variable can be constructed simply by taking the difference between “Favorable News” and “Unfavorable News”. This variable (Figure 1, upper panel) takes on positive values when most consumers mention good news and negative values when most consumers mention bad news. The square of this variable, let us say "Consumers' Squared News" is large when there are more consumers that have heard the same type (positive or negative) of news. Of course this will happen when there are news (either negative or positive) which are widely perceived as important by consumers. The variable will take small values when either there are no news or the sign of news is ambiguous, so that negative and positive mentions compensate each other. If our idea is correct, Consumers' Squared News should be positively correlated with uncertainty.

The Consumers' Squared News variable is plotted in Figure 1, middle panel, together with the uncertainty measure proposed by Jurado, Ludvigson and Ng, 2015 (3-month horizon, JLN henceforth). The similarity between the two series is really impressive. Table 1 shows the correlation coefficients of the No Mention variable and the Consumers' Squared News variable with the VIX index, the VXO index, the JLN 3-month index and the JLN 1-month index. As expected, the No Mention variable is negatively correlated with all uncertainty indexes while the Squared News variable is positively correlated with all uncertainty indexes, with correlation coefficients ranging from 0.62 to 0.69. Large positive correlations are also obtained when using absolute values in place of squares or when centering the News variable before computing squares (last two lines).

In the empirical analysis below we replace the Consumers' News variable with a news shock identified by means of a standard structural VAR procedure (where the Consumers' News variable is not included in the VAR). Again, we find that big news is associated with large uncertainty.

Why the size of news shocks is so strongly correlated with uncertainty measures? In the next section we show a simple model producing this implication.

3 Theory

3.1 Toy model

We start off by assuming that Total Factor Productivity (TFP), a_t, is driven by a structural shock $\epsilon_t \sim iid(0, \sigma_\epsilon^2)$ with delayed effects. In the literature in which it is assumed that agents have perfect information, this kind of shock is known as "news" or "anticipated" shock. Here, we assume that ϵ_t is unobserved. To begin with, and for illustrative purposes, we assume only one period of delay

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

but we will generalize the process below. Agents have imperfect information and cannot observe ϵ_t, but rather can only observe the events underlying the shock, whose nature is qualitative in most cases: natural disasters, scientific and technological advances, institutional changes and political events. After observing such events, in order to take their decisions, agents form an "estimate" of the shock, which is assumed to simply be the expectation of ϵ_t, conditional on the available information set, $s_t = E_t\epsilon_t$. We do not explicitly model the agent's information set, but rather we model the error made in forecasting the value of the shock. More specifically, we assume that the percentage deviation of ϵ_t from s_t:

$$v_t = \frac{\epsilon_t - s_t}{s_t} \sim iid(0, \sigma_v^2) \tag{2}$$

is independent of s_t at all leads and lags, as well as other information available to the agents at time t. This simply means that agents tend to make the same error in percentage terms, irrespectively on the value of the expected economic shock and the available information set. The implication is that the forecast error

$$\epsilon_t - s_t = s_t v_t \tag{3}$$

is proportional to the expected shock, s_t.

From the above equation, one can see that the conditional covariance between ϵ_t and the forecast error $\epsilon_t - s_t$, is $\sigma_v^2 s_t^2$. This means that the larger is the shock ϵ_t, the larger will be the forecast error. This assumption captures the idea that when nothing happens, both ϵ_t and s_t are small and so is the error $\epsilon_t - s_t$. On the contrary, if important events take place, both ϵ_t and s_t will be large and the expectation error may be large as well.

We further assume that at time t agents perfectly observe a_t. In this simple version of the model this implies that even if ϵ_t is not known at time t, agents fully learn its realization one period later when a_{t+1} is observed. In this model, the innovation of Δa_t with respect to the agents' information set is

$$u_t = \Delta a_t - E_{t-1}\Delta a_t = \epsilon_{t-1} - E_{t-1}\epsilon_{t-1} = s_{t-1}v_{t-1}. \tag{4}$$

We define uncertainty as the variance of the prediction error. Since v_t and s_t are independent, $E_t s_t v_t = s_t E_t v_t = 0$, whereas the conditional variance is $E_t s_t^2 v_t^2 = s_t^2 \sigma_v^2$. When nothing happens, the conditional expectation of the shock will be small and so will be the conditional variance. This means that agents are more confident about their predictions. On the contrary, when facts perceived as important occur, s_t^2 will be generally large and uncertainty will increase. This prediction precisely matches the empirical fact presented in the previous section: news which are perceived as important are positively correlated with uncertainty.[1,2]

[1]Our model has some similarities with an ARMA-ARCH-in-Mean model. An ARMA-ARCH-M has indeed time-varying conditional mean and variance and both depend on past values of the innovation. In our model the conditional mean and variance both depend on the contemporaneous news shock.

[2]Our model is different from a model with news and noise shocks. In a news-noise model there is imperfect

The innovation representation of Δa_t and s_t is then

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} 1 & L \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix} \tag{5}$$

Notice that u_t and s_t are jointly white noise and orthogonal with unconditional variance $\sigma_u^2 = \sigma_v^2 \sigma_s^2$ and σ_s^2, respectively.

We allow for the presence of other shocks in the economy, collected in the vector w_t. Finally, we assume that output y_t is given by the sum of its trend a_t and a stationary component which may be affected by the standardized news-uncertainty shock $(s_t^2 - \sigma_s^2)/\sigma_{s^2}$, the standardized news shock s_t/σ_s, as well as other shocks w_t[3]:

$$\Delta y_t \quad = \quad \Delta a_t + f(L)(s_t^2 - \sigma_s^2)/\sigma_{s^2} + g(L) s_t/\sigma_s + h(L) w_t. \tag{6}$$

with $f(1) = g(1) = h(1) = 0$. That is, we assume that uncertainty has temporary effects on output, like the cyclical shocks w_t.

3.2 A more general model

Let us now consider a more general specification for productivity, i.e.

$$\Delta a_t = \mu + c(L)\epsilon_t = \sum_{k=1}^{\infty} c_k \epsilon_{t-k}, \tag{7}$$

where $c(L)$ is a rational impulse response function in the lag operator L. We assume that $c(0) = 0$, so that ϵ_t is still a news shock and the general model reduces to the special case of the previous subsection when $c(L) = L$.

In this model, ϵ_t is not completely revealed by observed productivity at time $t+1$ and the innovation of productivity with respect to agents' information set is no longer $s_{t-1}v_{t-1}$. The bivariate MA representation of Δa_t and s_t in the white noise vector $(s_t v_t \; s_t)'$ is

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} c(L) & c(L) \\ 0 & 1 \end{pmatrix} \begin{pmatrix} s_t v_t \\ s_t \end{pmatrix}. \tag{8}$$

information, agents observe a signal $q_t = \epsilon_t + \eta_t$, where η_t is a noise shock (Forni, Gambetti, Lippi and Sala, 2016, forthcoming) and use q_t to forecast ϵ_t. The main distinctions with respect to the model used here are that, first, differently from q_t which incorporates information on ϵ_t, v_t does not add anything on the information set of the agents and does not affect their conditional expectation; second, in a model with news and noise the forecast error is not time-varying. In this paper it is the time-varying forecast error that affects agents' choices.

[3]We are very loose in terms of economic modeling on purpose. We do not take a stand on what is the true model behind the data. Actually any stationary model, for instance models of precautionary saving, where consumers or investors react to uncertainty is compatible with our assumptions.

Without loss of generality, we now assume $\sigma_s^2 = 1$, the normalization being absorbed by $c(L)$.

The above representation is non-fundamental, since the determinant of the MA matrix, $c(L)$, vanishes by assumption for $L = 0$. This means that present and past values of the observed variables Δa_t and s_t contain strictly less information than present and past values of $s_t v_t$ and s_t.[4]

On the other hand, stationarity of Δa_t and s_t entails that the two variables have a fundamental representation with orthogonal innovations. Such a representation can be found as follows. Let r_j, $j = 1, \ldots, n$, be the roots of $c(L)$ which are smaller than one in modulus and

$$b(L) = \prod_{j=1}^{n} \frac{L - r_j}{1 - \bar{r}_j L} \tag{9}$$

where $\bar{r}_j$ is the complex conjugate of r_j. Let us consider the representation

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} d(L) & c(L) \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}, \tag{10}$$

where $d(L) = c(L)/b(L)$ and

$$u_t = b(L) s_t v_t = \sum_{k=1}^{\infty} b_k s_{t-k} v_{t-k}. \tag{11}$$

Since $b(L)$ is a so-called "Blasckhe factor" (see e.g. Lippi and Reichlin, 1993, Leeper et al., 2013), u_t has a flat spectral density function and therefore is a white noise process. Moreover, u_t and s_t are orthogonal at all leads and lags, since s_t and v_t are zero mean and independent at all leads and lags by assumption. Finally, the determinant of the matrix in (10), i.e. $c(L)/b(L)$, vanishes only for $|L| \geq 1$ because of the very definition of $b(L)$. Hence representation (10) is fundamental and u_t is the "surprise" shock, i.e. the new information conveyed by Δa_t with respect to available information, or, in other words, the residual of the projection of Δa_t onto its own past and the present and the past of s_t.[5]

By inverting equation (11), we get $s_t v_t = u_t / b(L) = b(F) u_t$, where F is the forward operator. As in the previous section, the structural shock $\epsilon_t = s_t + s_t v_t$ depends on future innovations, with the difference that here the shock gets unveiled in the long run, rather than after one period.

3.3 Prediction errors and uncertainty

We assume that the agents' information set, Ω_t is given by the linear space spanned by the constant and the present and past values of u_t, s_t and the centered, squared news shock $s_t^2 - 1$

[4] About fundamentalness see, among recent contributions, Forni, Gambetti and Sala, 2014.

[5] Notice that $b(L)$ reduces to L in the special case of the toy model where $c(L) = L$.

(recall that s_t is unit variance); the expected values are approximated by linear predictions onto Ω_t, denoted by P_t. Note that, while predictions are linear, the information set includes the squared news shock.

It is seen from equations (10) and (11) that the k-period ahead prediction error of a_t is given by

$$\begin{aligned} a_{t+k} - P_t a_{t+k} &= D^k(L) u_{t+k} + C^k(L) s_{t+k} \\ &= R^k(L) s_{t+k} v_{t+k} + C^k(L) s_{t+k}, \end{aligned} \tag{12}$$

where $R^k(L) = D^k(L)b(L)$, $D^k(L) = \sum_{h=0}^{k-1} D_h L^k$, $C^k(L) = \sum_{h=0}^{k-1} C_h L^k$, $D_h = \sum_{j=0}^{h} d_j$, $C_h = \sum_{j=0}^{h} c_j$, $d(L) = c(L)/b(L)$.

We define the k-period-ahead uncertainty U_t^k as $P_t(a_{t+k} - P_t a_{t+k})^2$, i.e. the linear projection of the squared error onto Ω_t. We show in the Appendix that, if the density distribution of v_t is symmetric,

$$U_t^k = \sigma_v^2 \sum_{h=0}^{\infty} (R_{k+h}^k)^2 (s_{t-h}^2 - 1) + \sigma_v^2 \sum_{h=0}^{k-1} (R_h^k)^2 + \sum_{h=0}^{k-1} C_h^2. \tag{13}$$

Uncertainty is the sum of three components. The first term in the right-hand side of the above equation is the component of uncertainty driven by the demeaned news-uncertainty shock. Again, the larger the perceived shock, the larger the effect on uncertainty. The intuition is the same as that discussed in the previous section.

4 The econometric approach

Our econometric approach to estimate the effects of uncertainty consists in a two-stage procedure. In the first stage the news shocks is estimated. In the second stage we feed the estimated news shock and its squared values in a new VAR and we identify the uncertainty shock. The procedure is relatively simple since it amounts at identifying two shocks in two separate VAR models. Here we apply our framework to news and uncertainty. The procedure however is very general and can be used to study potential non-linearities of any structural shock. Its advantage, relative to other non-linear approach, is that it is very easy to implement since it only requires the standard estimation of two linear VARs.

4.1 Step 1

In practice, the signal s_t is not observed by the econometrician. We therefore assume that there are observable variables, collected in the vector z_t, which reveal the signal. In principle, such variables may depend on both s_t and u_t, as well as the additional shocks w_t affecting the business cycle. Therefore, we can write the joint representation of Δa_t and z_t as

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} d(L) & c(L) & 0 \\ m(L)\sigma_u & n(L) & P(L) \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t \\ \tilde{w}_t \end{pmatrix}, \tag{14}$$

where $m(L)$ and $n(L)$ are $n_z \times 1$ vectors of impulse-response functions, 0 is an n_w-dimensional row vector and $P(L)$ is an $n_z \times n_w$ matrix of impulse response functions and $\tilde{w}_t$ is a vector of orthonormal economic shocks, orthogonal to u_t and s_t, which might potentially include $\frac{s_t^2-1}{\sigma_{s^2}}$. Note that, following the usual econometric convention, the shocks are normalized to have unit variance.

Assuming invertibility of (14), we can estimate it by means of a structural VAR (VAR 1). To identify the news shock s_t, we follow Forni, Gambetti and Sala (2014) and Beaudry et al. (2016) and we impose the following restrictions: (i) u_t is the only shock affecting a_t on impact; (ii) u_t and s_t are the only two shocks affecting a_t in the long-run. Condition (ii) is equivalent to maximizing the effect of s_t on a_t at the same horizon. This identification scheme is standard in the news shock literature and is very similar to the one used in Barsky and Sims (2011).

4.2 Step 2

Having an estimate of s_t, we compute s_t^2 and the related uncertainty U_t^k, according to formula (13). To evaluate the effects of news — including uncertainty-related effects — on economic activity, we include both s_t and s_t^2 (or U_t^k) into a new VAR (VAR 2), aimed at estimating the impulse response function representation

$$\begin{pmatrix} s_t^2 - 1 \\ s_t \\ \Delta y_t \end{pmatrix} = \begin{pmatrix} \sigma_{s^2} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ f(L) & [c(L)+g(L)] & d(L)\sigma_u & h(L) \end{pmatrix} \begin{pmatrix} \frac{s_t^2-1}{\sigma_{s^2}} \\ s_t \\ u_t/\sigma_u \\ w_t \end{pmatrix}, \tag{15}$$

where the last row is obtained from equations (6), (8) and (10).

A few remarks are in order. First, u_t and s_t^2 are jointly white noise.[6] 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, identification of s_t and s_t^2 can be carried out by means of a standard Cholesky scheme with s_t and s_t^2 ordered as the first two variables, the ordering

[6]This comes from the independence of s_t and v_t.

between them being irrelevant. However, in practice, it turns out that the distribution of s_t is not symmetric, since most of large news is bad news. The estimated contemporaneous correlation coefficient of s_t and s_t^2 is about -0.20. This produces an identification problem: what are the "pure" first moment expectation effect, on the one hand, and the "pure" second moment uncertainty effect, on the other hand? Below we orthogonalize the two shocks by imposing a Cholesky scheme with s_t^2 ordered first and s_t ordered second, as in (15). By using this scheme, the long-run effects of uncertainty on GDP, consumption and investment are close to zero, which is in line with our theoretical assumption. As an alternative, we might identify by directly imposing a zero effect on GDP in the long-run; we do this in the robustness section, where we also try the Cholesky scheme with s_t ordered first and s_t^2 ordered second. Fourth, inference of the impulse response functions of the second VAR should take into account the estimation uncertainty of s_t. So in principle for any realization of the shock obtained in the first VAR one should implement a bootstrap in the second VAR. However, in the empirical section we abstract from this complication and we treat s_t as an observed series.

4.3 Simulations

We use two simulations to assess our econometric approach. The first simulation is designed as follows. We assume that $[v_t \quad s_t]' \sim N(0, I)$.[7] Under the assumption $\Delta a_t = \epsilon_{t-1}$, the fundamental representation is $\Delta a_t = s_{t-1} + u_t$, where $u_t = s_{t-1}v_{t-1}$, see equation (4). We assume that there are two signals, $z_t = [z_{1t} \;\; z_{2t}]'$ following MA processes. 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:

$$\begin{pmatrix} \Delta a_t \\ z_{1t} \\ z_{2t} \end{pmatrix} = \begin{pmatrix} 1 & L & 0 \\ 1 + m_1 L & 1 + n_1 L & 0 \\ 1 + m_2 L & 1 + n_2 L & 1 + p_2 L \end{pmatrix} \begin{pmatrix} u_t \\ s_t \\ w_t \end{pmatrix} \tag{16}$$

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 from $[v_t \quad s_t]$, 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 $\hat{s}_t$ the estimates 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 Δy_t from the

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

counterpart of the last row of the VAR in equation (15):

$$\Delta y_t = u_t + \underbrace{[L + (1-L)(1+g_1 L)]}_{c(L)+g(L)} s_t - (1-L)(1+f_1 L)\frac{s_t^2 - 1}{\sigma_{s^2}},$$

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

The second simulation is similar to the first, the only difference being that w_t is exogenous and not a function of s_t. The values of the parameters are the same as before and $[v_t\ \ s_t\ \ w_t]' \sim N(0, I)$.

Results of simulation 1 are reported in Figure 2, while results of simulation 2 are reported in Figure 3. The left column plots the effects on Δa_t, z_{1t} and z_{2t} of the news shock s_t. The right column reports the responses of Δy_t to the three shocks s_t, $\frac{s_t^2-1}{\sigma_{s^2}}$ and Δa_t. The solid line is the mean of the 2000 responses, the grey 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.

5 Empirics

5.1 The news shock

Our empirical analysis focuses on quarterly US data covering the time span 1963:Q4-2015:Q2. Following Beaudry and Portier, 2006, we use total factor productivity (TFP) corrected for capacity utilization[8] as a proxy for the output trend. To reveal news, we use six variables: (a) stock prices (the S&P500 index divided by the GDP deflator), which is the main variable used to identify news shocks in the literature; (b) the Michigan University confidence index component concerning business conditions for the next five years (E5Y), whose anticipation properties are widely discussed in Barsky and Sims, 2011; (c) real consumption of nondurables and services (Consumption), which according to economic theory should anticipate future income; (d) the 3-month treasury bill secondary market rate (TB3M); (e) the 10-year treasury constant maturity rate (GS10) and (f) the Moody's Aaa interest rate. The interest rates react readily to news and therefore can in principle be able to reveal them. All data but TFP are taken from the FRED website.

We estimate a Bayesian VAR with diffuse priors and 4 lags. The series are taken in log-levels. The identification scheme is the one explained in subsection 4.1, where the long-run horizon is 48 quarters (12 years).

[8] The source is Fernald's website. TFP is cumulated to get level data.

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, as well as the "surprise" shock, u_t, onto the past values of seven additional variables, taken one at a time: real GDP (GDP), real investment plus durable consumption (Investment), hours worked, the GDP deflator inflation rate (Inflation), the federal funds rate, the Michigan University News variable described above, and Moody's Baa bond rate. We then computed the F-test. Table 2 reports the p-values. For all of the regressions, the null that all coefficients are zero cannot be rejected. We conclude that VAR 1 include enough information to identify the news shock.

Figure 4 shows the effects of the news shock on the variables in the VAR. The impulse-response function of TFP exhibits the typical S-shape which is usually found in the literature. Stock prices and E5Y 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.

In the robustness section we try alternative specifications for VAR 1 and show that results are robust.

5.2 Uncertainty: dating of large shocks and comparison with existing measures

The squared news shock exhibits very large values (larger than average by more than two standard deviations) in the following 8 quarters:

1972:Q1 (+) Tax Reduction Act, Smithsonian Agreement, Space Shuttle Program

1973:Q2 (-) Mid '70 Crisis

1974:Q1 (-) Stock Market Oil Embargo Crisis

1982:Q1 (-) Loan Crisis

1990:Q4 (-) Gulf War I (UN Resolution 678), Omnibus Budget Reconciliation Act

2002:Q3 (-) WorldCom Bankruptcy

2008:Q3 (-) Lehman Brothers Bankruptcy

2008:Q4 (-) Stock Market Crash

Most of these dates correspond to recognizable events and/or cycle phases. The sign in brackets is the sign of the news shock. Most of large news is bad news (7 out of 8); this is the reason why the news shock and the squared news shock are negatively correlated.

Figure 5 plots four series: the square of the estimated news shock, the corresponding squared news uncertainty, computed according to formula (13) with $k = 3$, the VXO and the uncertainty measure estimated by Jurado, Ludvigson and Ng, 2015, for the 3-month ahead horizon (JLN3 henceforth). Clearly, the squared news shock and the related uncertainty measure are positively correlated with both the VXO and the JLN measure.

Table 4 reports the contemporaneous correlation coefficient of the squared news shock and the related uncertainty U_t^2 and U_t^3 (see formula (13)), on the one hand, and a few existing measures of uncertainty: namely, the VXO and the VIX indexes, JLN3 and JLN12 (which is the 12-month ahead horizon JLN uncertainty index). Such correlations are noticeable high. In particular, the correlation of U_t^3 with the reported measures ranges between 0.51 and 0.68.

5.3 The uncertainty effect of news

Let us now come to the results of VAR 2, where we include the squared news shock and the news shock estimated with VAR 1, along with real GDP, real consumption of non-durables and services, real investment plus consumption of durables and hours worked. Identification is obtained as explained in subsection 4.2.

Results are reported in Figures 6 and 7. The numbers on the vertical axis can be interpreted as yearly percentage variations. The squared news shock has a significant negative effect on all variables on impact. The maximum effect on GDP is reached after 4 quarters and is about -2% in annual terms (-0.5% on a quarterly basis). Afterwards, the effects reduces and becomes approximately zero around the 3-year horizon. By using different identification schemes and different specifications for VAR 1 we find similar results, the maximal effect on GDP ranging between -1.5% and -2% at the 1-year horizon (see the robustness section).

As for the news shock, Figure 7 shows that it has a large, permanent, positive effect on real activity, reaching its maximum after about 2 years. This confirms results already found in the literature.[9]

Table 3 shows the variance decomposition. The most important finding is that the squared news shock explains a sizable fraction of output, investment and hours volatility at the 1-year horizon (22%, 20% and 22%, respectively). The effects on consumption are smaller (about 7%).

In Figure 8, we see the uncertainty effect of a standardized squared news shock equal to 1, i.e. our estimate of $f(L)$, say $\hat{f}(L)$. To better understand the uncertainty effects of news, it can be useful to see the uncertainty effects of the news shock itself, when it takes on different

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

values. To this end we compute

$$\hat{f}(L)\frac{(s_t^2-1)}{\hat{\sigma}_{s^2}},$$

for $|s_t| = 0, 0.5, 1, 2$ (of course, positive and negative news have the same uncertainty effects in our framework).

Figure 9 shows the result. A few observations are in order. First, the uncertainty effects of news may be positive (upper panels). This happens when the *centered* squared news shock is negative, that is, when $-1 < s_t < 1$. No news (or small news) produce a temporary upturn of economic activity. However, the largest positive effect is obtained when $s_t = 0$ (upper-right panel); such effect is small, the maximum being about 1.2% on a yearly basis.

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, the innovation of uncertainty is zero and there are no uncertainty effects (lower-right panel).

Third, a news shock larger than its standard deviation in absolute value produces negative uncertainty effects. Such effects may be very large – much larger than the largest possible positive effect. For instance, a news shock equal to 2 times its standard deviation (lower-right panel) produces a maximum GDP decrease around 4% on an yearly basis (1% on a quarter-on-quarter basis). In the 8 quarters reported in the previous subsection the uncertainty effects of news were larger or equal to the one depicted here.

To evaluate the total effect of news, including both the expectation, first moment effect and the uncertainty effect, we computed

$$\hat{f}(L)s_t + \hat{f}(L)\frac{(s_t^2-1)}{\hat{\sigma}_{s^2}}$$

for $s_t = -2, -1, -0.5, 0.5, 1, 2$.

Results are reported in Figure 9. The basic finding here is that the effects of news are generally asymmetric, but the asymmetry is different for small shocks and large shocks. When s_t is small (precisely, smaller than its standard deviation in absolute value), the uncertainty effect is positive, so that, in the short run, it mitigates the negative first moment effect of bad news and reinforces the positive effect of good news (upper panels). When $|s_t| = 1$, the uncertainty effect is zero, so that the overall effects of news are symmetric (middle panels). For large shocks, 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.

5.4 Historical decomposition

Figure 10 compares per-capita GDP (blue solid line) with per-capita GDP cleaned from the uncertainty effect of news (red dashed line). For a better reading, the sample is broken into three subperiods: 1965:Q4-1983:Q2 (upper panel), 1983:Q3-1998:Q2 (middle panel) and 1998:Q3-2015:Q2 (lower panel). The two lines are very far apart during two periods: the final part of the early 80's recession and the beginning of the subsequent recovery, on the one hand, and the second half of the Great Recession, on the other hand. In both cases the red line is above the blue line, meaning that the uncertainty effect of news was recessionary. The first period is characterized by the large negative news shock of 1982:Q1; the second period is characterized by the two large negative shocks of 2008:Q3 and 2008:Q4.

Figure 11 compares per-capita GDP (blue solid line) with per-capita GDP cleaned from the overall effect of news, including both the expectation effect and the uncertainty effect (red dashed line). The sample is broken into three subperiods as before. The main insight here is that the role of the news shock in driving GDP was large for most of the sample, with the noticeable exception of Reagan's recovery and the Great Moderation (middle panel), where the two lines are relatively close to each other. By looking at the dating of subsection 5.2 it is seen that there is no large news between 1990:Q4 and 2002:Q1, which seems to provide evidence in favor of Stock and Watson's (2002) "good luck" explanation of the Great Moderation.

5.5 News uncertainty and financial variables

In order to analyze the effects of news and squared news on financial variables and uncertainty variables we estimated an additional VAR (VAR 3), where we included again the squared news shock and the news shock estimated with VAR 1, along with stock prices, the spread between Baa bonds and ten-year treasury bonds (GS10), which may be regarded as a measure of the risk premium, the VXO, extended as in Bloom, 2009, and the 3-month JLN uncertainty index.

Results are reported in Figures 12 and 13. The squared news shock (Figure 12) reduces stock prices and increases the risk premium significantly on impact and at lags 1 and 2. As expected, the VXO increases significantly in the first year after the shock. The effect on the JLN index is somewhat more puzzling. The index increases significantly on impact but afterward it reduces and the reduction is significant at the one-year horizon, albeit at the 68% level.[10]

As for the first moment, expectation effects of the news shock (Figure 13), it is seen that good news have a large, positive and persistent effect on stock prices. Moreover, good news

[10]By observing Figure 5, it is seen that the squared news shock is somewhat lagging with respect to the JLN index in the first half of the 80's. This could be related to this result, even if of course it is not an explanation.

reduce significantly the risk premium, the VXO index and the JLN index.

Table 6 shows the variance decomposition. The squared news shock explains a sizable fraction of the forecast error variance of the VXO index at the 4-quarter horizon.

5.6 Robustness

In this subsection we show the results of two robustness exercises. In the former one, we keep fixed the specification of VAR 1 and try alternative identification schemes for VAR 2.

Figure 14 shows the results. The red dashed line is the response obtained with the Cholesky scheme, where the news shock is ordered first and the squared news shock is ordered second. The blue dotted-dashed line is the estimate obtained by imposing a zero effect of the squared news shock on GDP at the 10-year horizon. The black solid line and the confidence bands are those of the benchmark identification.

Both of the alternative schemes produce smaller short run uncertainty effects of news, even if the results are qualitatively similar to the benchmark. The positive long-run effect on consumption obtained with the alternative identification schemes are somewhat puzzling, particularly for the recursive ordering with the news shock ordered first (red-dashed line).

In the latter robustness exercise we keep fixed identification of VAR 1 as well as specification and identification of VAR 2, and try different specifications for VAR 1. Specification (i) includes TFP, S&P500, Consumption and TB3M. Specification (ii) includes TFP, Investment and TB3M (stock prices are excluded).

Figure 15 shows the results. The red-dashed line is the one obtained with specification (i); the blue dotted-dashed line the one obtained with specification (ii). The black solid line and the confidence bands are again the point estimate and the confidence bands of the benchmark case.

The impulse-response functions obtained with both specifications (i) and (ii) are similar to the benchmark. Notice that specification (ii) is very different from that of the benchmark case and specification (i), in that it excludes stock prices. Somewhat surprisingly, the correlation of news-driven uncertainty with VXO, VIX and the JLN uncertainty measure is still high. In particular, the correlation coefficient of U_t^4 and the above uncertainty variables ranges between 0.52 and 0.64.

6 Conclusions

In this paper we formalize the idea that: a) uncertainty is generated by news about future developments in economic conditions which are not perfectly predictable by the agents; b) when important events occur, expectations change substantially (either positively or negatively) and the associated uncertainty increases. News shocks have therefore a "first-moment" effect on the expected values of the structural shock and a "second-moment" effect on the variance of the agents' forecast error, our definition of uncertainty. Uncertainty has a time-varying conditional variance, proportional to the square of the news shock. Big news (either good or bad) are on average associated to large expectation errors, and therefore to large uncertainty.

When estimating the US news shock and the squared news shock, as well as the associated uncertainty, we see that the squared news shock peaks in quarters characterized by important recognizable economic, institutional and political events. Squared news turn out to be highly correlated with existing measures of uncertainty.

When the uncertainty effect is taken into account, the business-cycle consequences of news appear more complex than usually believed. First, news shocks below average reduce uncertainty, producing a temporary upturn of economic activity. A zero news shock implies a zero first-moment effect, but a reduction in uncertainty. 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 is positive, by mitigating the negative first-moment effect of bad news and reinforcing the positive effect of good news. For large shocks, the asymmetry is reversed: uncertainty 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 about 20% at the 1-year horizon. Given the right-skewed distribution of squared news shocks, most of the times the effect is relatively small, but in a few negative episodes it is not. The historical decomposition of GDP reveals that news uncertainty explains a good deal of the early 1980s recession as well as the Great Recession.

To put our research into a broader perspective, we believe that our approach will be useful in identifying potential non-linear effect of other shocks, such as monetary or fiscal policy shocks.

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. 141848.

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

[9] 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,

[10] 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.

[11] 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.

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

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

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

[15] 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.

[16] 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.

[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] 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.

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

[24] 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.

[25] Jaimovich, N. and S. Rebelo, (2009), "Can News about the Future Drive the Business Cycle?", American Economic Review, 99(4): 1097-1118

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

[27] Kilian, L. (1998), "Small-Sample Confidence Intervals for Impulse Response Functions", Review of Economics and Statistics 80, 21830.

[28] Leeper, E. M., Walker, T. B. and Yang, S.-C. S. (2013), "Fiscal Foresight and Information Flows", Econometrica, 81: 11151145

[29] Lippi, M. and L. Reichlin (1993), "The Dynamic Effects of Aggregate Demand and Supply Disturbances: Comment", American Economic Review 83, 644-652.

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

[31] Lorenzoni, G., (2009), "A Theory of Demand Shocks", American Economic Review, 99, 2050-84.

[32] Lorenzoni, G. (2010). "Optimal Monetary Policy with Uncertain Fundamentals and Dispersed Information", Review of Economic Studies 77, pp. 305-338.

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

[34] 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.

[35] 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.

[36] Pigou, A. C. (1927). "Industrial fluctuations", London, Macmillan.

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

[38] Schmitt-Grohé, S. and Uribe, M. (2012), "What's News in Business Cycles", Econometrica, 80: pp. 27332764.

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

[40] 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.

[41] 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.

Appendix: Computing Uncertainty

In this Appendix we derive formula (13).

We have to project the square of the RHS of (12) onto Ω_t. The letter involves four kinds of terms:

(i) $s_\tau v_\tau s_\phi v_\phi$, $\tau \neq \phi$;

(ii) $s_\tau v_\tau s_\phi$, $\phi > t$;

(iii) $s_\tau s_\phi$, $\tau > t$, $\phi > t$;

(iv) $s_\tau^2 v_\tau^2$.

Let us consider first the projections of terms of kind (i). Such terms are zero mean. Moreover, they are orthogonal to u_{t-k}, $k \geq 0$, being orthogonal to $s_\psi v_\psi$, for all ψ. For, $E(s_\tau v_\tau s_\phi v_\phi s_\psi v_\psi) = E(s_\tau s_\phi s_\psi)E(v_\tau v_\phi v_\psi)$ because of cross-independence of s_t and v_t at all leads and lags, and $E(v_\tau v_\phi v_\psi) = 0$ because of serial independence of v_t and the fact that $\phi \neq \tau$. The same terms are orthogonal to s_{t-k}, $k \geq 0$, since $E(s_\tau v_\tau s_\phi v_\phi s_\psi) = E(s_\tau s_\phi s_\psi)E(v_\tau v_\phi)$ and $E(v_\tau v_\phi) = 0$ for $\tau \neq \phi$. Finally, they are orthogonal to $s_{t-k}^2 - 1$, $k \geq 0$, since $E[s_\tau v_\tau s_\phi v_\phi (s_\psi^2 - 1)] = E[(s_\tau s_\phi (s_\psi^2 - 1)]E(v_\tau v_\phi)$ and $E(v_\tau v_\phi) = 0$. In conclusion, the projection of kind-(i) terms onto Ω_t is zero.

All terms of the form (ii) are zero-mean. Moreover, they are orthogonal to u_{t-k}, $k \geq 0$, since they are orthogonal to $s_\psi v_\psi$, for all $\psi \leq t$. This is because $E(s_\tau v_\tau s_\phi s_\psi v_\psi) = E(s_\tau s_\phi s_\psi)E(v_\tau v_\psi)$ and $E(s_\tau s_\phi s_\psi) = 0$ owing to serial independence of s_t and the fact that $\phi > t$ whereas $\psi \leq t$. In addition, such terms are orthogonal to s_ψ, $\psi \leq t$, since $E(s_\tau v_\tau s_\phi s_\psi) = E(s_\tau s_\phi s_\psi)E(v_\tau)$ and $E(v_\tau) = 0$. Finally, they are orthogonal to $s_\psi^2 - 1$, $\psi \leq t$, since $E[s_\tau v_\tau s_\phi (s_\psi^2 - 1) = E[(s_\tau s_\phi (s_\psi^2 - 1)]E(v_\tau)$ and $E(v_\tau) = 0$. Summing up, the projection of kind-(ii) terms onto Ω_t is zero.

Terms of form (iii) are zero-mean for $\tau \neq \phi$ and have mean equal to 1 for $\tau = \phi$. Considering (12) the projection of such terms onto the constant is $\sum_{h=0}^{k-1} C_h^2$. In addition, such terms are orthogonal to $s_\psi v_\psi$, for all $\psi \leq t$ and therefore to u_{t-k}, $k \geq 0$, since $E(s_\tau s_\phi s_\psi v_\psi) = E(s_\tau s_\phi s_\psi)E(v_\psi)$ and $E(v_\psi) = 0$. Moreover, type-(iii) terms are orthogonal to s_ψ, $\psi \leq t$, since $E(s_\tau s_\phi s_\psi) = E(s_\tau s_\phi)E(s_\psi)$, because of serial independence of s_t and the fact that both τ and ϕ are larger than $\psi \leq t$, and $E(s_\psi) = 0$. Finally, such terms are orthogonal to $s_\psi^2 - 1$, $\psi \leq t$, for the same reason. Hence the projection of kind-(iii) terms onto Ω_t is the constant

$$\sum_{h=0}^{k-1} C_h^2. \tag{17}$$

Coming to terms of the form (iv), we have $E(s_\tau^2 v_\tau^2) = \sigma_v^2$. Going back to (12) it is seen that their projection onto the constant is $\sigma_v^2 \sum_{h=0}^{k-1} (R_h^k)^2$. Moreover, such terms are orthogonal to $s_\psi v_\psi$, for all ψ. This is obvious for $\tau \neq \psi$, but is also true for $\tau = \psi$, since in this case $E(s_\tau^2 v_\tau^2 s_\psi v_\psi) = E(s_\tau^3 v_\tau^3) = E(s_\tau^3)E(v_\tau^3)$ which is zero since we are assuming that v_t has a symmetric density distribution. As a consequence these terms are orthogonal to u_{t-k}, $k \geq 0$. All such terms are also orthogonal to s_ψ and $s_\psi^2 - 1$ for $\tau \neq \psi$, because of independence of s_t and v_t at all leads and lags and serial independence of s_t. As for $\psi = \tau$, the projection of $s_\tau^2 v_\tau^2$ onto s_τ and $s_\tau^2 - 1$, $\tau \leq t$, is

$$\Gamma \Sigma^{-1} \begin{pmatrix} s_\tau \\ s_\tau^2 \end{pmatrix},$$

where

$$\Gamma = \sigma_v^2 \begin{pmatrix} E s_\tau^3 & E s_\tau^4 - 1 \end{pmatrix}$$

and

$$\Sigma = \begin{pmatrix} 1 & E s_\tau^3 \\ E s_\tau^3 & E s_\tau^4 - 1 \end{pmatrix}.$$

It is seen that $\Gamma \Sigma^{-1} = (0 \quad \sigma_v)$, so that the projection reduces to $\sigma_v^2 (s_{t-h}^2 - 1)$. Considering (12) and the constant term, the projection of type-(iv) terms onto Ω_t is

$$\sigma_v^2 \sum_{h=0}^{\infty} (R_{k+h}^k)^2 (s_{t-h}^2 - 1) + \sigma_v^2 \sum_{h=0}^{k-1} (R_h^k)^2. \tag{18}$$

Formula (13) is the sum of (18) and (17).

Tables

	VXO	VIX	JLN 3-month	JLN 1-month
No Mention	-0.30	-0.38	-0.53	-0.54
Consumers' squared News	0.62	0.67	0.67	0.69
Consumers' squared centered News	0.61	0.69	0.48	0.50
Consumers' absolute News	0.55	0.58	0.68	0.69

Table 1: Contemporaneous correlation coefficients.

	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 2: Results of the fundamentalness 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.

Variable	Horizon				
	Impact	1-Year	2-Years	4-Years	10-Years
TFP	0.0	3.4	3.4	3.6	36.9
S&P500	59.1	66.7	72.6	78.8	77.1
non durables and services	27.4	57.6	68.3	78.6	81.8
TB3M	22.9	8.9	6.6	10.1	28.2
GS10Q	6.3	4.2	8.1	16.9	40.4
Aaa	9.3	8.5	11.6	17.7	39.0

Table 3: Variance decomposition for VAR 1. The entries are the percentage of the forecast error variance explained by the news shock.

	VXO	VIX	JLN 3-month	JLN 12-month
Squared News Shock	0.58	0.59	0.46	0.43
squared news uncertainty k=2	0.62	0.64	0.52	0.48
squared news uncertainty k=3	0.65	0.68	0.56	0.51

Table 4: Contemporaneous correlation coefficients.

Variable	Horizon				
	Impact	1-Year	2-Years	4-Years	10-Years
	Squared news shock				
Squared News Shock	100.0	90.4	89.0	88.2	87.2
News Shock	7.5	9.0	9.0	9.0	9.0
GDP	9.6	22.4	14.8	9.0	6.0
non durables and services	4.9	7.3	4.2	2.3	1.8
Investment	9.2	19.9	12.2	7.7	6.4
Hours Worked	4.5	22.4	19.5	12.8	8.6
	News shock				
Squared News Shock	0.0	1.9	3.1	3.2	3.2
News Shock	92.5	87.5	87.2	86.9	86.7
GDP	1.6	19.3	32.5	44.1	51.9
non durables and services	20.9	42.7	52.0	58.6	61.5
Investment	0.2	17.4	28.9	37.2	42.0
Hours Worked	1.6	15.6	28.5	40.7	35.4

Table 5: Variance decomposition for VAR 2. The entries are the percentage of the forecast error variance explained by the shocks.

Variable	Horizon				
	Impact	1-Year	2-Years	4-Years	10-Years
	Squared news shock				
Squared News Shock	100.0	82.2	76.8	74.1	73.3
News Shock	6.9	7.9	7.9	7.9	7.9
S&P500	7.5	6.3	3.4	2.1	1.3
Spread Baa-GS10	6.0	6.5	6.8	7.0	6.5
VXO extended as in Bloom (2009)	15.7	16.1	13.8	12.8	12.7
JLN uncertainty	6.7	1.9	3.2	3.3	3.4
	News shock				
Squared News Shock	0.0	1.0	1.0	0.9	1.2
News Shock	93.1	86.0	85.4	85.1	85.1
S&P500	45.8	34.2	28.3	24.1	22.3
Spread Baa-GS10	0.4	1.7	1.5	2.7	4.3
VXO extended as in Bloom (2009)	9.2	7.5	7.3	7.8	7.8
JLN uncertainty	3.5	2.7	1.6	1.7	2.2

Table 6: Variance decomposition for VAR 3. The entries are the percentage of the forecast error variance explained by the shocks.

Figures

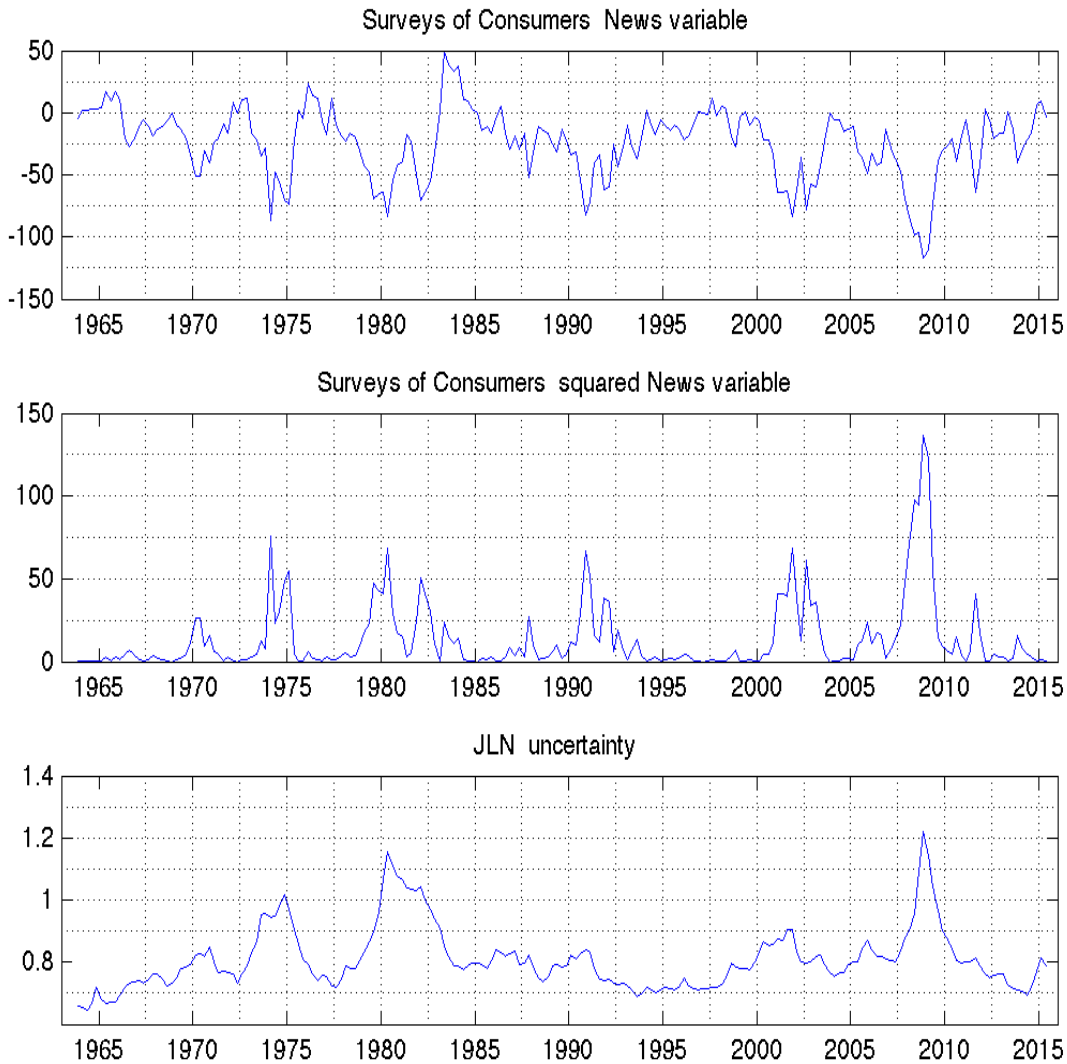

Figure 1: Plots of (a) the Consumers' news variable (upper panel); (b) the Consumers' squared news variable (middle panel), (c) Jurado, Ludvigson and Ng 3-month uncertainty (lower panel).

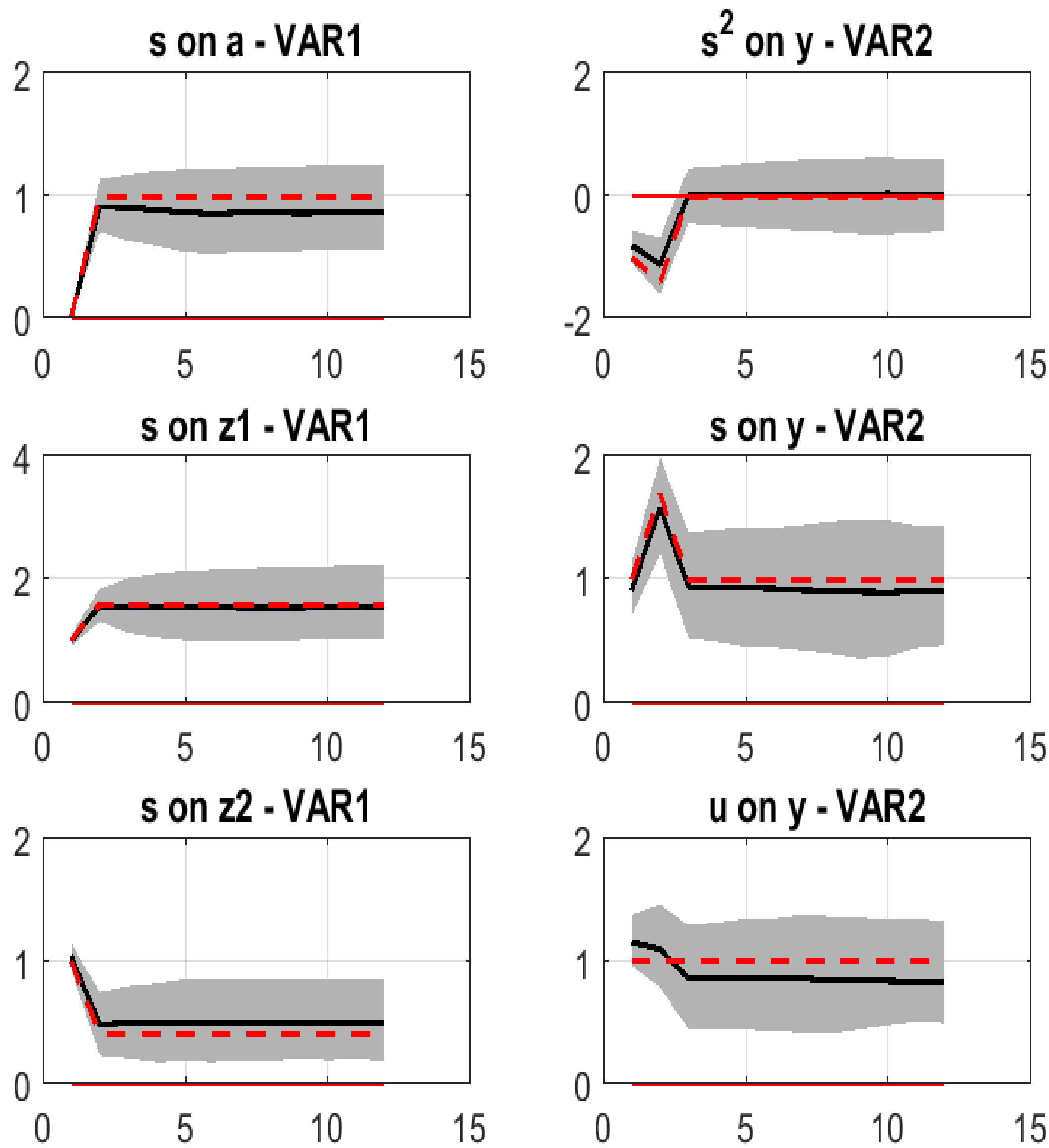

Figure 2: Impulse response functions functions of simulation 2. Effects of news are reported in the left column. The effects of the uncertainty shocks are reported in the right column. Solid line: point estimate. Grey area: 90% confidence bands. Red dashed line: true theoretical responses.

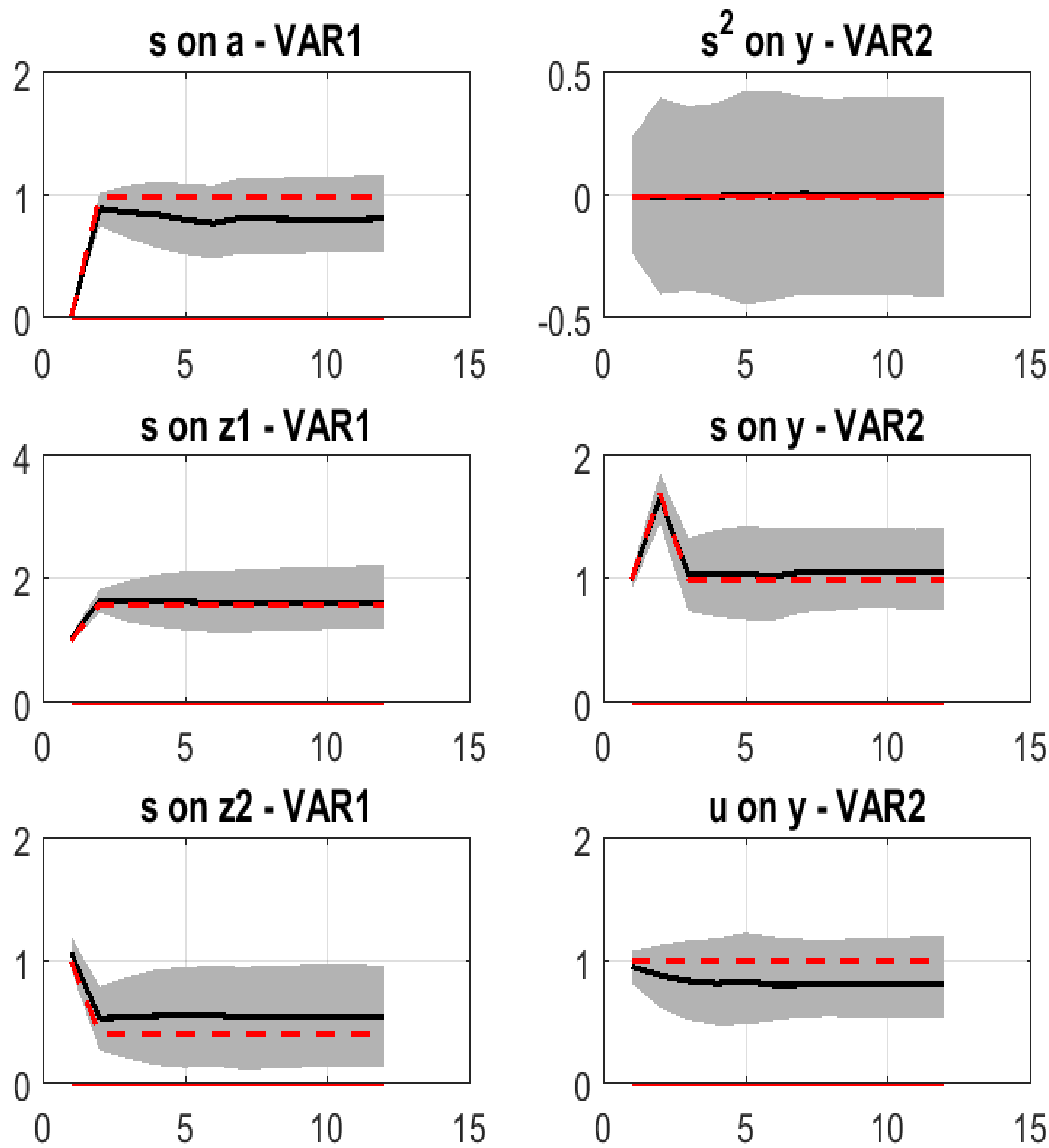

Figure 3: Impulse response functions functions of simulation 2. Effects of news are reported in the left column. The effects of the uncertainty shocks are reported in the right column. Solid line: point estimate. Grey area: 90% confidence bands. Red dashed line: true theoretical responses.

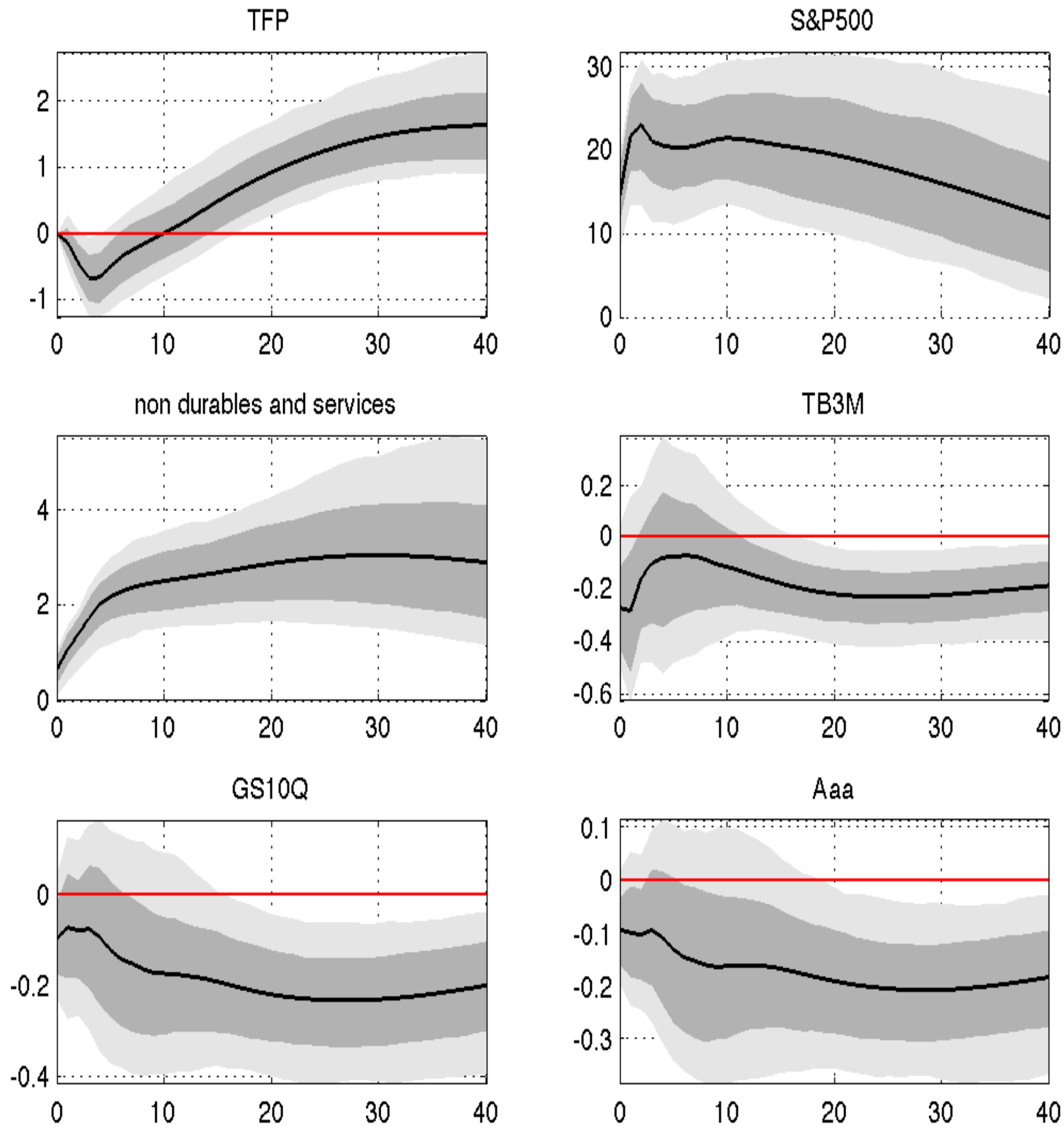

Figure 4: Impulse response functions to the news shock in VAR 1. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

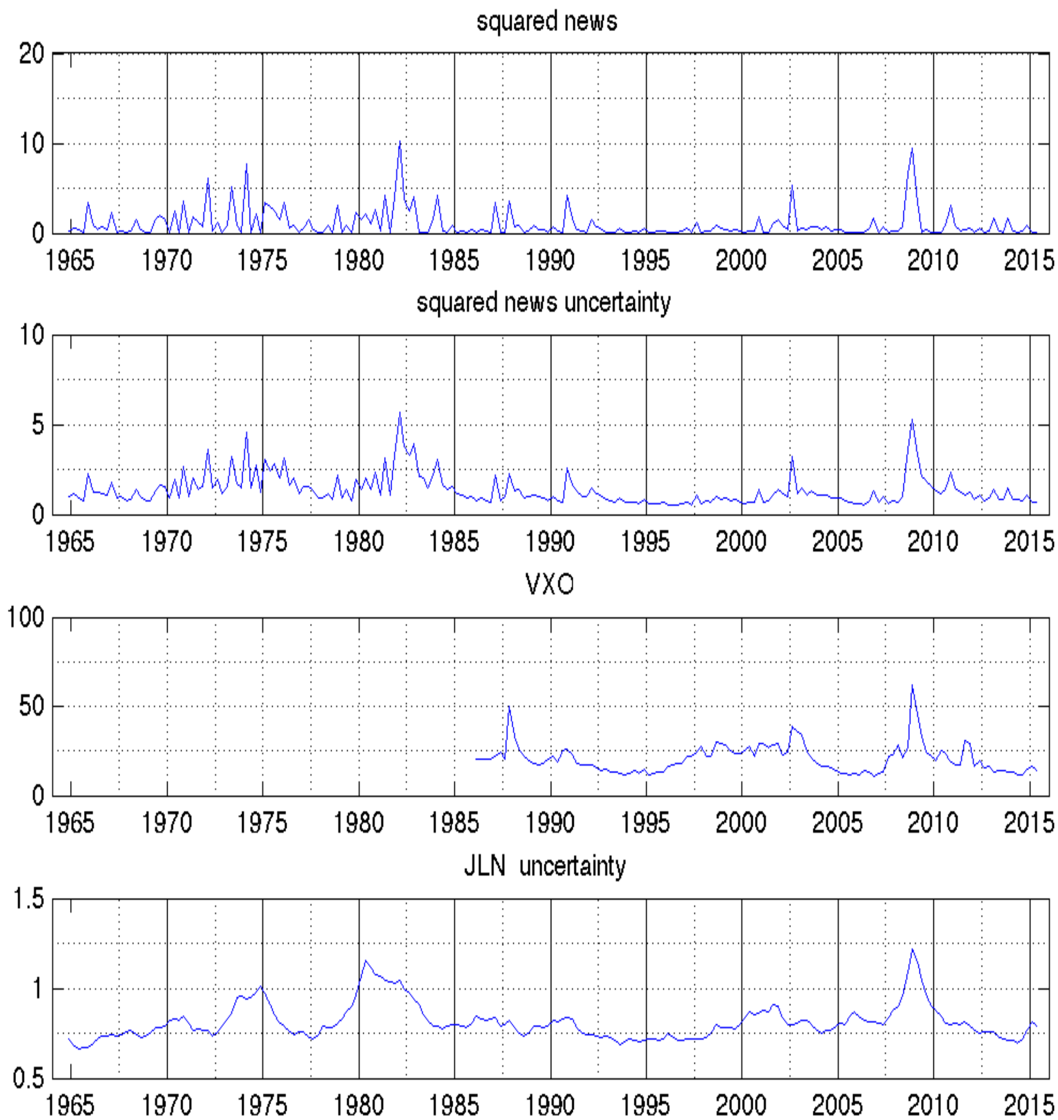

Figure 5: Plots of (a) the squared news shock (first panel), (b) squared-news uncertainty ($k = 3$), (c) VXO, (d) Jurado, Ludvigson and Ng 3-month uncertainty.

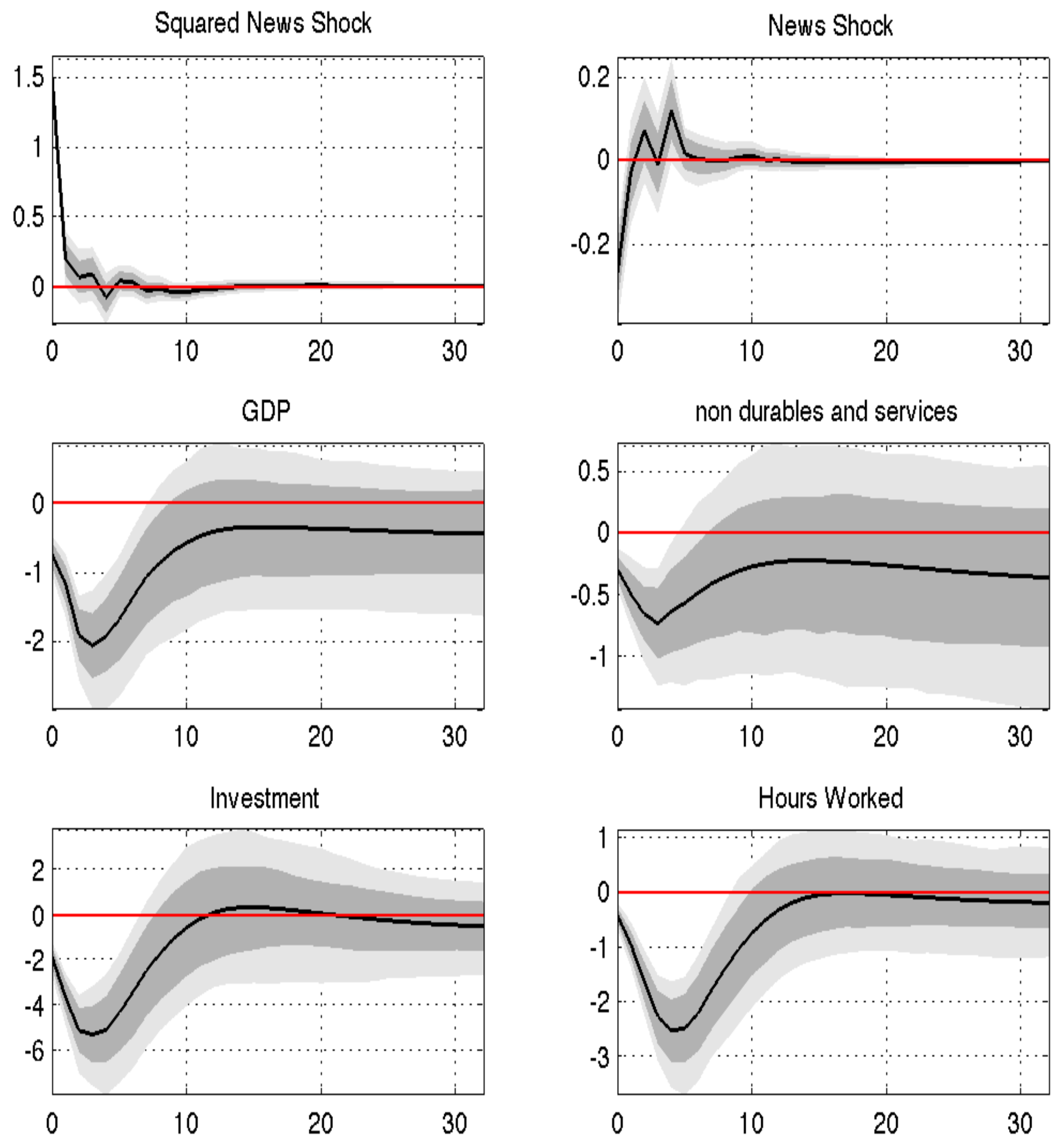

Figure 6: Impulse response functions to the squared news shock in VAR 2. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

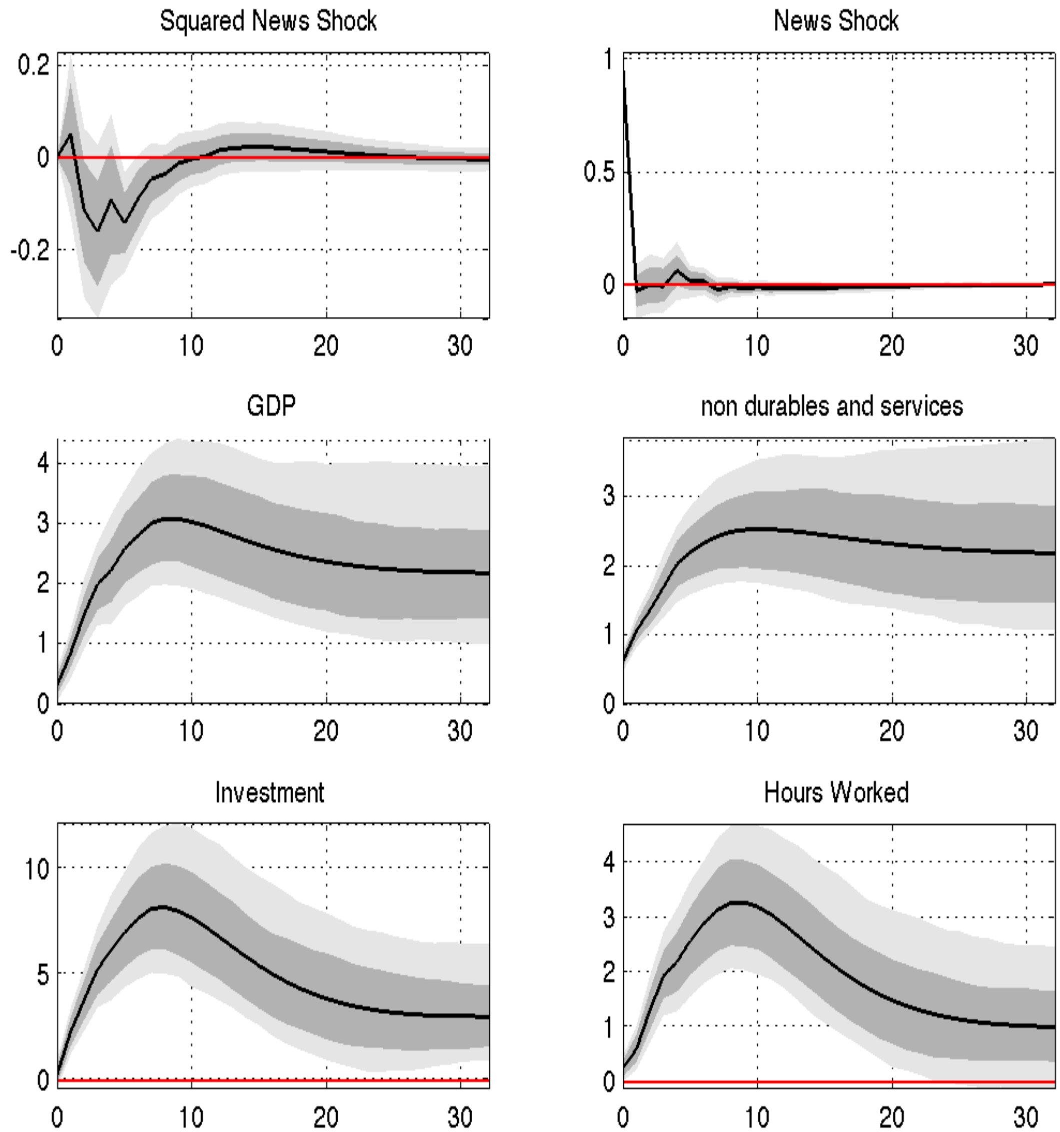

Figure 7: Impulse response functions to the news shock in VAR 2. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

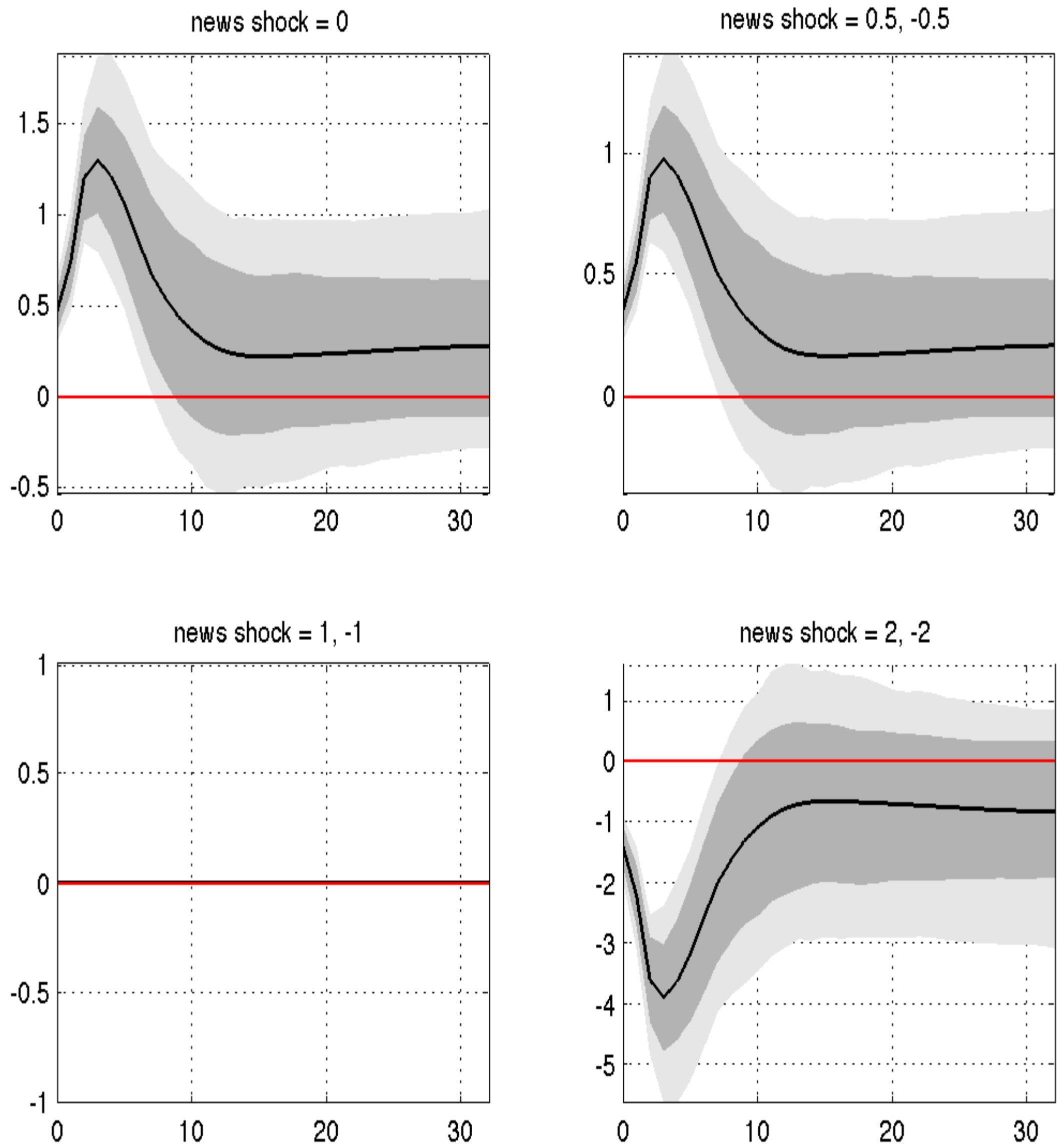

Figure 8: The uncertainty effect of the news shock on GDP, for different values of the news shock (VAR 2). Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

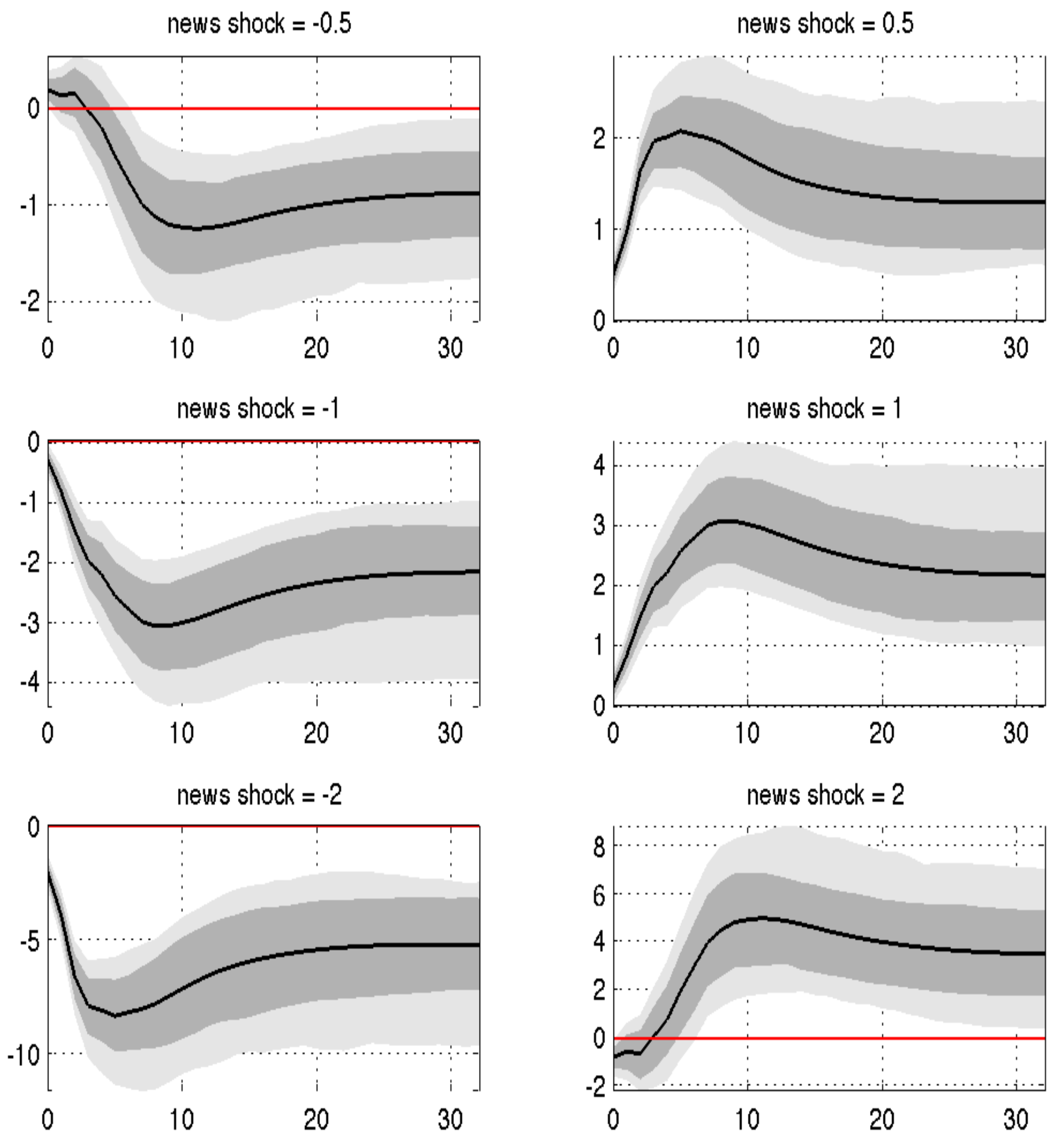

Figure 9: The total reaction of GDP to the news shock, including both the expectation effect and the uncertainty effect, for different values of the news shock (VAR 2). Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

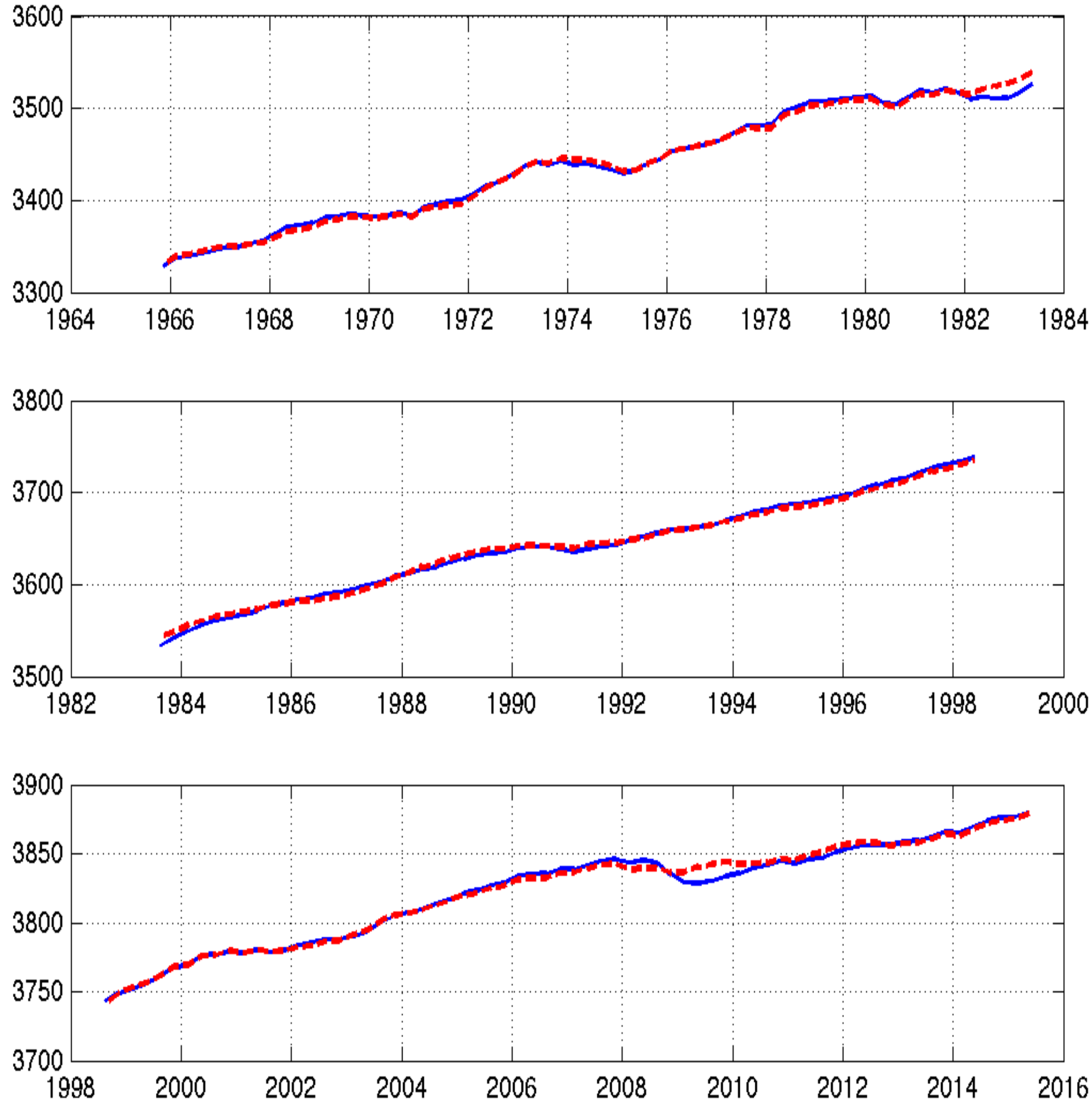

Figure 10: Historical decomposition of GDP (VAR 2). Blue line: per-capita GDP. Red line: per-capita GDP minus the uncertainty effects of news.

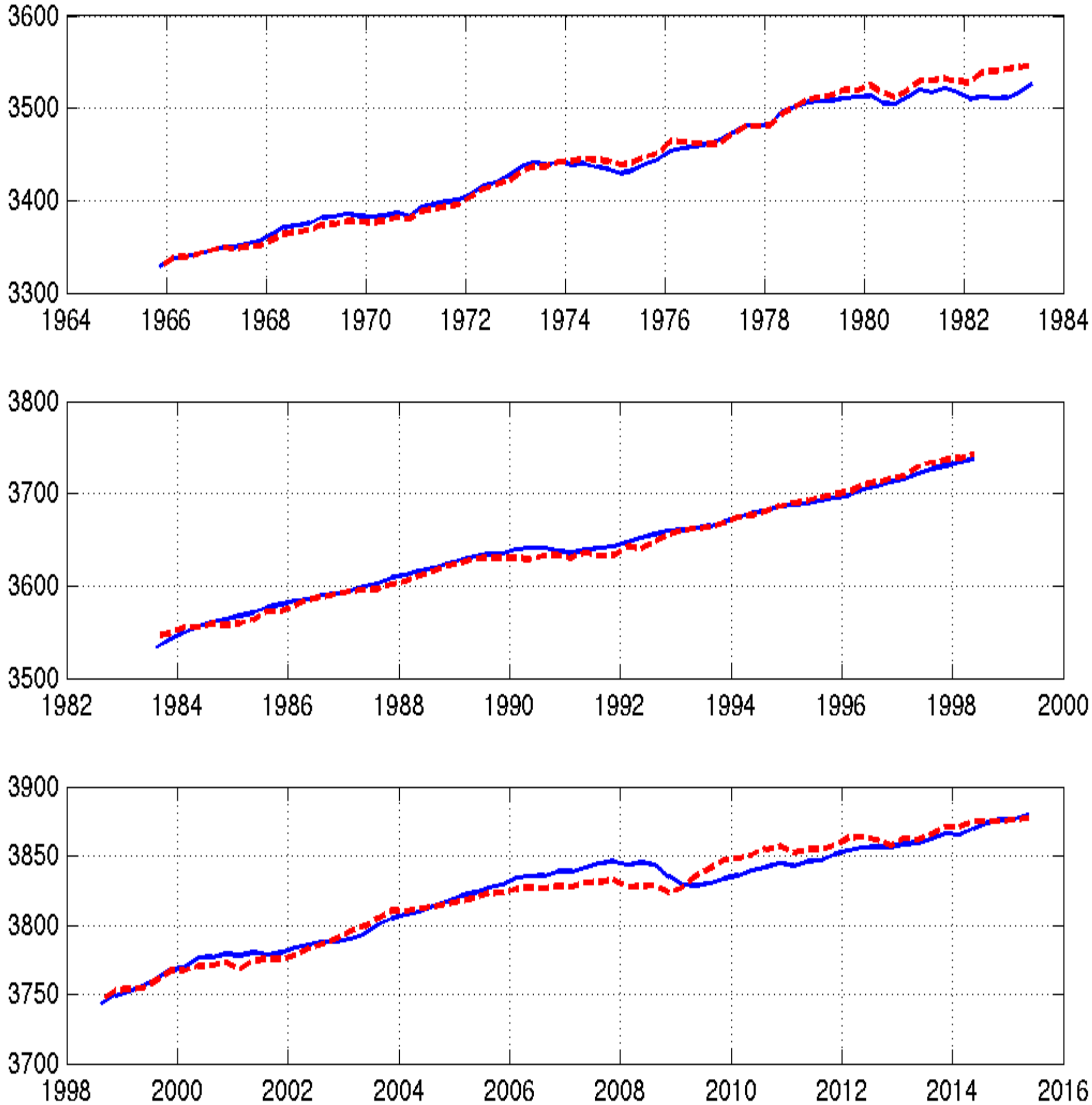

Figure 11: Historical decomposition of GDP (VAR 2). Blue line: per-capita GDP. Red line: per-capita GDP minus the total effects of news, including the uncertainty effects.

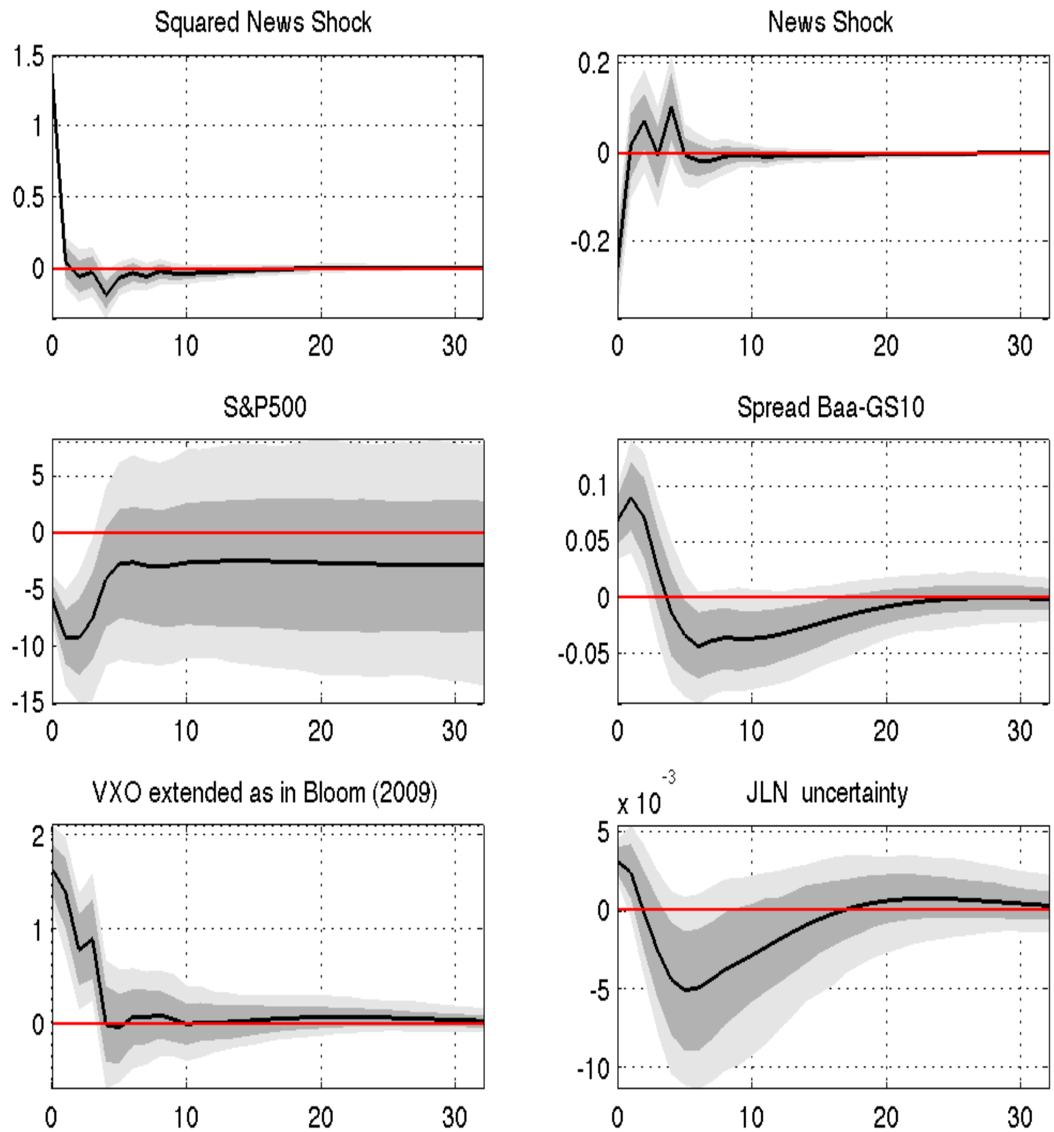

Figure 12: Impulse response functions to the squared news shock in VAR 3. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

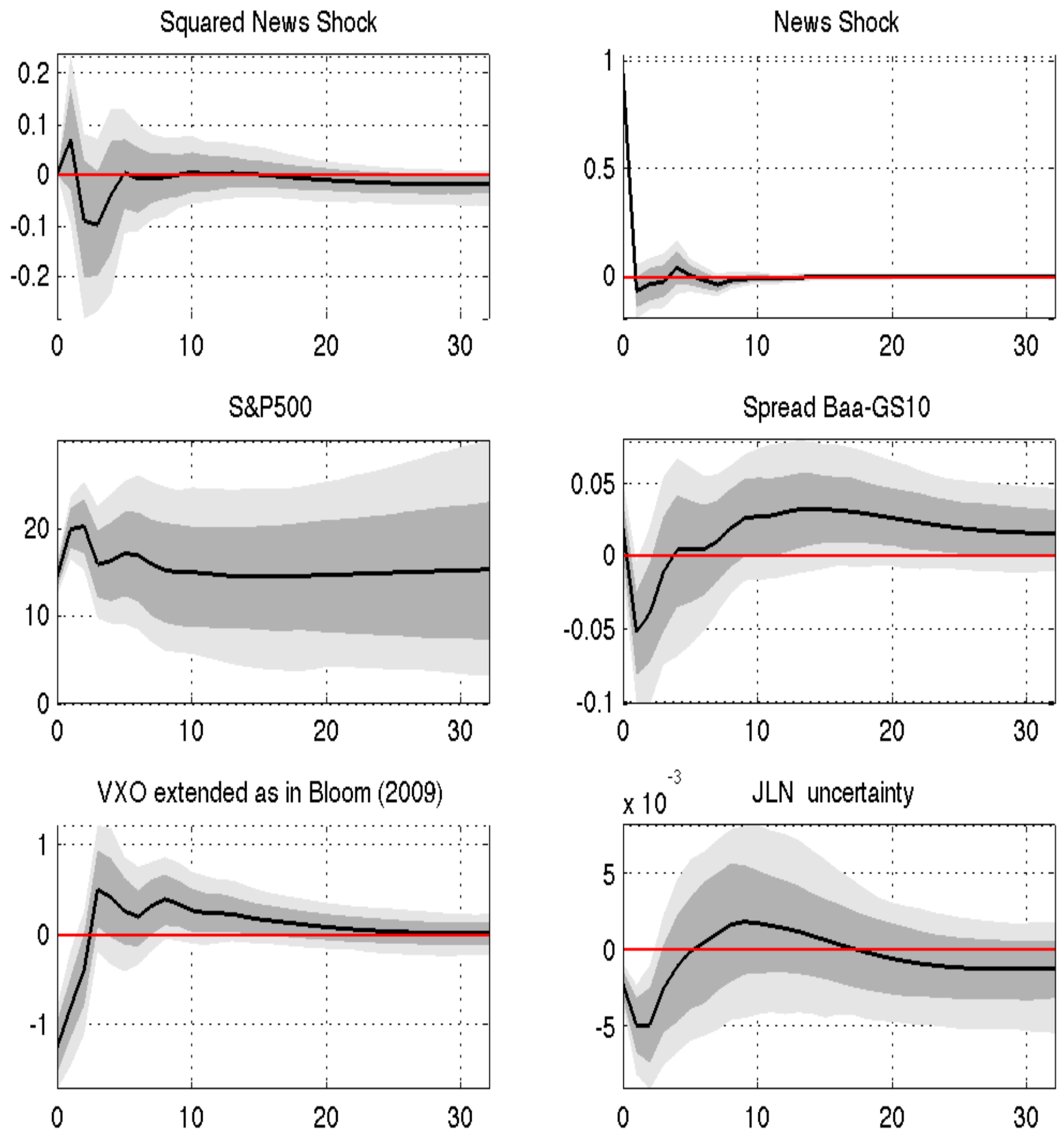

Figure 13: Impulse response functions to the news shock in VAR 3. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

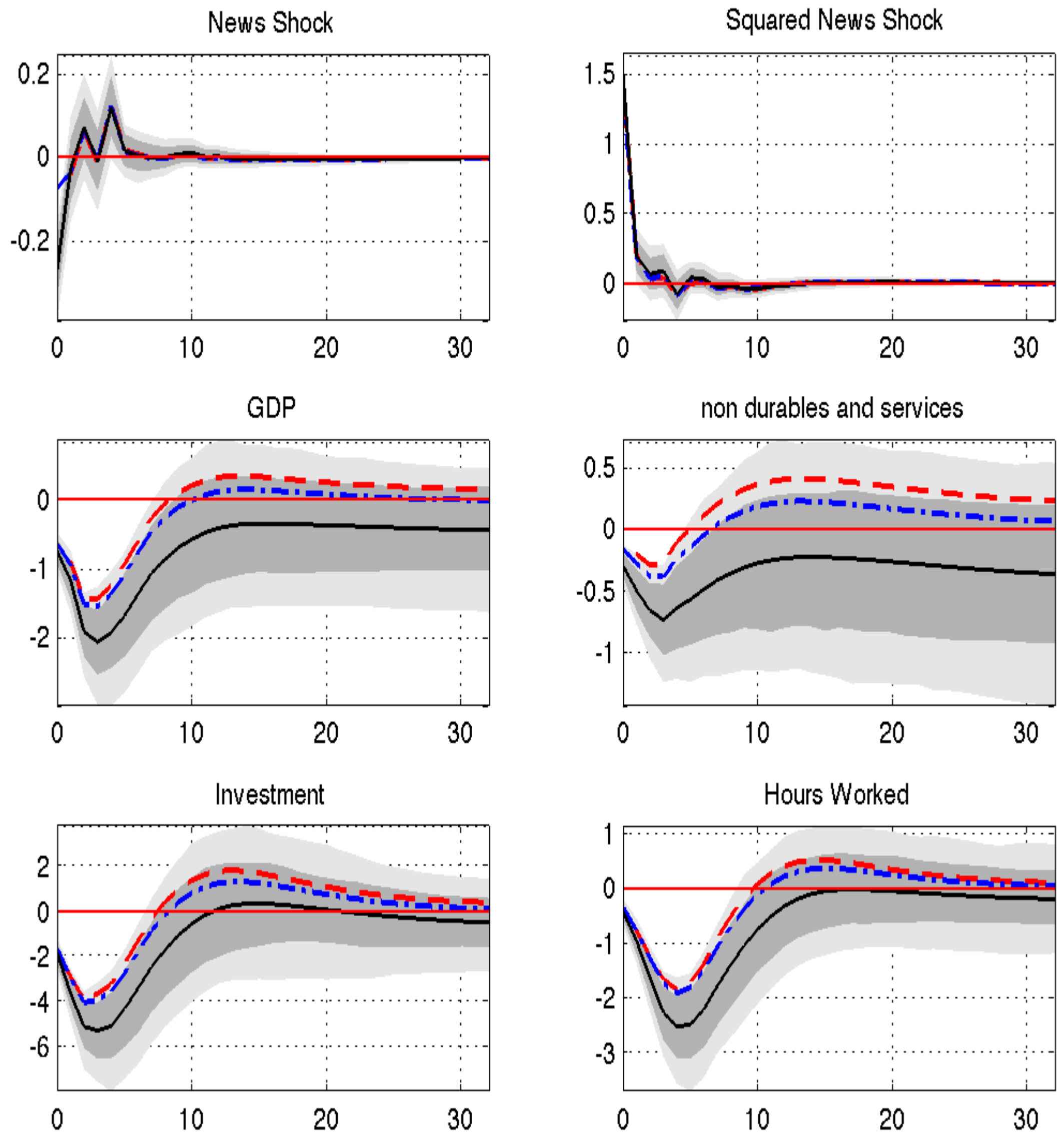

Figure 14: Robustness. Impulse response functions to the squared news shock with the specification of VAR 2 and two alternative identification schemes: the recursive scheme with the news shock ordered first (red dashed line) and a long-run restriction imposing zero effect of squared news on GDP at the ten-year horizon. The black solid line and the confidence bands are the point estimate and the confidence bands of the benchmark case.

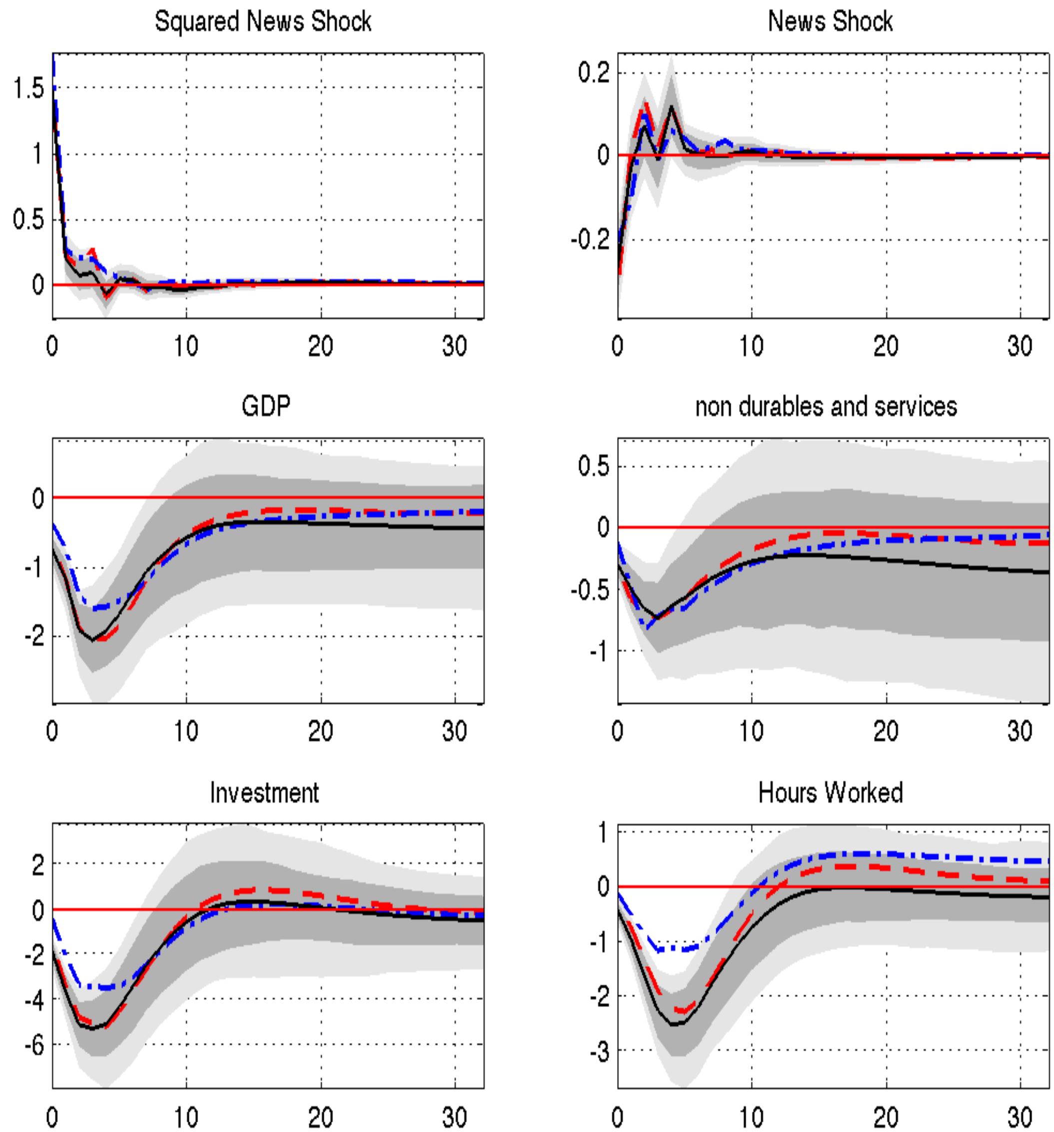

Figure 15: Robustness. Impulse response functions to the squared news shock for different specifications of VAR 1: (i) TFP, S&P500, Consumption and TB3M (red-dashed line) and (ii) TFP, Investment and TB3M (blue dotted-dashed line). Identification of both VAR 1 and VAR 2 are unchanged. The black solid line and the confidence bands are the point estimate and the confidence bands of the benchmark case.