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

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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 non-linear 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. This amplifies the effects of good news and mitigates the effects of bad news in the short run. The Volcker recession and the Great Recession were exacerbated by the uncertainty effects of news.

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1 Introduction

News shocks and uncertainty shocks have been in recent years at the heart of the business cycle debate. In the "news shock" literature, news about future fundamentals affect the current behavior of consumers and investors by changing their expectations. A partial list of major contributions in this body of literature includes Beaudry and Portier, 2004, 2006, and Barsky and Sims, 2011. By contrast, in the "uncertainty" shock literature, exogenous shocks change the "confidence" of economic agents about their expectations. An increase in uncertainty induces agents to defer private expenditure, thus producing a temporary downturn of economic activity. A few important contributions in the latter stream of literature include Bloom, 2009, Rossi and Sekhposyan, 2015, Jurado, Ludvigson and Ng, 2015, Ludvigson, Ma and Ng, 2015, 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 affect uncertainty without affecting expectations, or vice-versa. But it is quite reasonable to assume that first-moment and second-moment effects are most often closely related to each other. 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 positively 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 macroeconomic uncertainty estimated by Jurado, Ludvigson and Ng, 2015 (JLN3 henceforth), 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 macroeconomic 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 originating 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 JLN3 index (lower panel). 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 VXO index, the JLN3 index, the Jurado, Ludvigson and Ng, 2015 macroeconomic uncertainty index (12-month horizon, JLN12 henceforth), the Ludvigson, Ma and Ng, 2015, financial and real uncertainty indexes 3-months ahead (denoted respectively, LMN3 Fin. and LMN3 Real). 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]

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.

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 $(s_t^2 - \sigma_s^2)/\sigma_{s^2}$ and the standardized news shock s_t/σ_s[3]:

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

with $f(1) = g(1) = 0$. That is, we assume that uncertainty has temporary effects on output. Moreover note that, if s_t is serially independent, then $s_t^2 - \sigma_s^2$ is serially independent as well and independent of the past of s_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 $c(L) = L$.

The information structure of the agents remains as described in equations (2) and (3). In this model, ϵ_t is not completely revealed by observed productivity at time $t + 1$ and the

[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 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.

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

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

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

[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 $c(L) = L$.

innovations, with the difference that here the shock gets unveiled in the long run, rather than after one period.

Finally, we assume that output y_t is given by the sum of its trend a_t and a stationary component driven by by the news-uncertainty shock $(s_t^2 - \sigma_s^2)/\sigma_{s^2}$, the news shock s_t/σ_s as before, as well as other cyclical shocks w_t.

$$\Delta y_t \quad = \quad \Delta a_t + f(L)(s_t^2 - \sigma_s^2)/\sigma_{s^2} + g(L)s_t/\sigma_s + h(L)w_t \tag{12}$$

with $f(1) = g(1) = h(1) = 0$. That is, we assume that news, uncertainty, as well as the shocks w_t have temporary effects on output.

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 $s_t^2 - 1$ (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

$$\begin{aligned} a_{t+k} - P_t a_{t+k} &= D^k(L)u_{t+k} + C^k(L)s_{t+k} \\ &= R^k(L)s_{t+k}v_{t+k} + C^k(L)s_{t+k}, \end{aligned} \tag{13}$$

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,

$$U_t^k = \sigma_v^2 \sum_{h=0}^{\infty} (R_{k+h}^k)^2 (s_{t-h}^2 - 1) + \sigma_v^2 \sum_{h=0}^{k-1} (R_h^k)^2 + \sum_{h=0}^{k-1} C_h^2. \tag{14}$$

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 on the additional shocks $\tilde{w}_t$. $\tilde{w}_t$ is a $n_{\tilde{w}}$-dimensional vector of orthonormal economic shocks, orthogonal to u_t and s_t, which might potentially include $\frac{s_t^2-1}{\sigma_{s^2}}$. Therefore, we can write the joint representation of Δa_t and z_t as

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} d(L) & c(L) & \mathbf{0} \\ m(L)\sigma_u & n(L) & P(L) \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t \\ \tilde{w}_t \end{pmatrix} \tag{15}$$

where $m(L)$ and $n(L)$ are $n_z \times 1$ vectors of impulse-response functions, $\mathbf{0}$ is an $n_{\tilde{w}}$-dimensional row vector and $P(L)$ is an $n_z \times n_{\tilde{w}}$ matrix of impulse response functions. Note that, following the usual econometric convention, the shocks are normalized to have unit variance.

Assuming invertibility of (15), 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

The goal of the second step is to derive the effects of s_t and s_t^2 on a vector of m variables of interest Y_t, which includes Δy_t as one of the elements. Having an estimate of s_t, we compute s_t^2 and the related uncertainty U_t^k, according to formula (14). To evaluate the effects of news

— including uncertainty-related effects — on Y_t we simply estimate a VAR (VAR 2) which includes s_t, s_t^2 (or U_t^k) and Y_t and derive the impulse response function representation

$$\begin{pmatrix} s_t^2-1 \\ s_t \\ Y_t \end{pmatrix} = \begin{pmatrix} \sigma_{s^2} & 0 & 0 & \mathbf{0} \\ 0 & 1 & 0 & \mathbf{0} \\ & A(L) & & \end{pmatrix} \begin{pmatrix} \frac{s_t^2-1}{\sigma_{s^2}} \\ s_t \\ u_t/\sigma_u \\ w_t \end{pmatrix}, \tag{16}$$

where $A(L)$ is a $m \times m+2$ matrix of polynomials in the lag operator and $\mathbf{0}$ is a $1 \times m$ vector of zeros.[6]

A few remarks are in order. First, u_t and s_t^2 are jointly white noise.[7] 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 among 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 effects, on the one hand, and the "pure" second moment uncertainty effects, 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 (16). 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 directly use a VARX treating the news and the squares as exogenous variables; 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.

[6]Let, without loss of generality assume that Δy_t is ordered first in Y_t. The following restrictions between the coefficients of the fundamental and non-fundamental representation hold: $A_{11}(L) = f(L)$, $A_{12}(L) = c(L)+g(L)$, $A_{13}(L) = d(L)$. The reason is that (16) is the fundamental representation which can be obtained by replacing (8) and (10) in (12).

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

4.3 Impulse response functions

The dynamic effect of uncertainty is the main focus of the present paper. Here we discuss how to derive and measure the effects of news and uncertainty shocks in our econometric framework. The coefficients of the first and second column of $A(L)$ represent the effects of shock $s_t = 1$ and $(s_t^2 - 1)/\sigma_{s^2} = 1$ respectively. Although informative, one should not limit the attention to these quantities. The reason is that, while the effects of news will be proportional to the size of the shock, the effects of uncertainty will be not. Indeed, in order to study the effects of uncertainty on Y_{it+j} one should pay also attention to

$$A_{i2}(L)\frac{(\bar{s}^2 - 1)}{\sigma_{s^2}}$$

where $\bar{s}$ is a specific value of s_t, since shocks of different magnitudes might generate different responses. Finally, an interesting feature is to study the total effect of news on economic variables. To this aim, we can use a version of the Generalized Impulse Response Functions (GIRF, henceforth), see Koop, Pesaran and Potter (1996). More specifically, we define the GIRFs at the horizon j as

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

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

4.4 Simulations

We use two simulations to assess our econometric approach. The first simulation is designed as follows. We assume that $[v_t \quad s_t]' \sim N(0, I)$.[8] 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:

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

$$\begin{pmatrix} \Delta a_t \\ z_{1t} \\ z_{2t} \end{pmatrix} = \begin{pmatrix} 1 & L & 0 \\ 1+m_1L & 1+n_1L & 0 \\ 1+m_2L & 1+n_2L & 1+p_2L \end{pmatrix} \begin{pmatrix} u_t \\ s_t \\ w_t \end{pmatrix} \tag{17}$$

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 $[v_t \;\; s_t]$, we generate 2000 artificial series of length $T = 200$. For each set of series, we estimate a VAR for $[\Delta a_t \; z_{1t} \; z_{2t}]'$ and identify s_t as the second shock of the Cholesky representation. We define $\hat{s}_t$ as the estimate of s_t obtained from the VAR.

In the second step, using the same 2000 realizations of $[u_t \; s_t \; s_t^2]'$, we generate Δy_t as:[9]

$$\Delta y_t = u_t + [L + (1-L)(1+g_1L)]s_t - (1-L)(1+f_1L)\frac{s_t^2-1}{\sigma_{s^2}},$$

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 a_t, z_{1t} and z_{2t} of the news shock s_t. The right column reports the responses of y_t to the three shocks s_t, $\frac{s_t^2-1}{\sigma_{s^2}}$ and u_t. The solid line is the mean of the 2000 responses, the gray area represents the 68% confidence bands, while the dashed red lines are the true theoretical responses. In both simulations, and in all of the cases, our approach succeeds in correctly estimating the true effects of news and uncertainty shock, the theoretical responses essentially overlapping with the mean estimated effects.

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[10] as a proxy for the output trend.

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

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

In the first step of our econometric approach we use a VAR (VAR 1) which, besides TFP, includes seven additional variables: stock prices (the S&P500 index divided by the GDP deflator), which is the main variable used to identify news shocks in the literature; 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; real consumption of nondurables and services (Consumption), which according to economic theory should anticipate future income; the 3-month treasury bill secondary market rate (TB3M); the 10-year treasury constant maturity rate (GS10); the Moody's Aaa interest rate (AAA); the Survey's News variable used in Section (2). Interest rates are included to control for monetary policy, inflation expectations and the risk premium. This turns out to be very useful since absent the interest rate, the identified shocks would be predictable. In the robustness section we try other specification for VAR 1.

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).

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 a number of macroeconomic variables, taken one at a time and test for significance of the coefficients using a 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 incorporates 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, E5Y and the news variable jump on impact, as expected, while consumption increases more gradually. All interest rates reduce on impact, albeit the effect is barely significant. All in all, the effects of the news shock are qualitatively similar to those found in the literature. 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 7 quarters:

1974:Q1 (-) Stock Market Oil Embargo Crisis

1982:Q1 (-) Loan Crisis

1982:Q4 (+) End of early 80s recession.

1987:Q1 (+) Unclear

2002:Q3 (-) WorldCom Bankruptcy

2008:Q3 (-) Lehman Brothers Bankruptcy

2008:Q4 (-) Stock Market Crash

Most of these dates correspond to well identified historical events and/or cycle phases. The sign in brackets is the sign of the news shock. Most of large news is bad news (5 out of 7); this is the reason why the news shock and the squared news shock are negatively correlated.

Figure 5 plots three series: the square of the estimated news shock, the corresponding squared news uncertainty, computed according to formula (14) with $k = 2$, and the macroeconomic uncertainty measure JLN12. Clearly, the squared news shock and the related uncertainty measure are positively correlated with the JLN12.

Table 4 reports the contemporaneous correlation coefficient of the squared news shock and the related uncertainty U_t^2 and U_t^4 (see formula (14)), on the one hand, and a few existing measures of uncertainty: VXO, JLN3, JLN12, LMN3 Fin. and LMN3 Real. Such correlations are noticeable high. In particular, the correlation of U_t^2 with the reported measures ranges between 0.3 and 0.6.

5.3 The uncertainty effect of news

Here we discuss the results of VAR 2. The VAR includes 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, hours worked, CPI inflation and the ISM new orders index. Identification is obtained as explained in subsection 4.2.

We start off discussing the results relative to the estimated impulse response functions to shocks of magnitude $s_t = 1$ and $(s_t^2 - 1)/\sigma_{s^2} = 1$, i.e. the coefficients of the moving average representation implied by VAR 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 (Figure 6) has a significant negative effect on all variables on impact. The maximum effect on GDP is reached after 4 quarters and is about -1.5% in annual terms. Afterwards, the effect reduces and becomes approximately zero around the 3-year horizon. By using different identification schemes and different specifications for 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). Let us stress that the shock has essentially the nature of a demand shock: both new orders and prices jump down on impact (bottom panel).

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.[11]

Table 5 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 (19%, 16.8% and 10.4%, respectively). The effects on consumption are smaller, about 5%.

As discussed above, the effects of uncertainty are non-linear. To better understand the uncertainty effect of news, we derive the effect implied by different values of the shock:

$$\hat{A}_{i2}(L)\frac{(\bar{s}^2 - 1)}{\hat{\sigma}_{s^2}},$$

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

Figure 8 shows the results. A few observations are in order. First, the uncertainty effects of news may be positive (upper panels). This happens when the squared news shock is below its mean, that is, when $-1 < s_t < 1$. No news (or small news) produce a temporary upturn of economic activity. Agents perceive that uncertainty is below average and this stimulates the economy. Second, when the news shock is equal to 1 or -1, that is, when the news shock in absolute value is equal to its standard deviation (equivalently, when the uncertainty shock is equal to its mean), the innovation of uncertainty is zero and there are no uncertainty effects (lower-right panel). Third, a news shock in absolute value larger than its standard deviation (equivalently, an uncertainty shock larger than its mean) produces negative uncertainty effects. Such effects may be very large. For instance, a news shock equal to 2 times its standard deviation produces a reduction in GDP of around 7-8% on an yearly basis (lower-right panel)
.

We finally investigate the total effect of news, including both the expectation, first moment effect and the uncertainty effect, using the GIRF

$$\hat{A}_{j1}(L)\bar{s} + \hat{A}_{j2}(L)\frac{(\bar{s}^2 - 1)}{\hat{\sigma}_{s^2}}$$

for $\bar{s} = -2, -1, -0.5, 0.5, 1, 2$.

Results are reported in Figure 9. The basic finding here is that the effects of news are generally asymmetric, and the asymmetry is different for small shocks and large shocks. When

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

s_t is small in absolute value (equivalently, s_t^2 is smaller than its mean), the uncertainty effect is positive. In the short run, the effect of s_t^2 mitigates the negative first moment effect of bad news and reinforces the positive effect of good news (upper panels). When $|s_t| = 1$, the uncertainty effect is zero, so that the overall effects of news are symmetric (middle panels). For large shocks, when s_t is big in absolute value and s_t^2 is larger than its mean, the asymmetry is reversed: the uncertainty effect is negative. Uncertainty exacerbates the negative first moment effect of bad news and mitigates the positive effect of good news.

5.4 Historical decomposition

Figure 10 compares per-capita GDP (black solid line) with per-capita GDP cleaned from the uncertainty effect of news (red dashed line). The two lines are very far apart during two periods: the mid 80s 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 uncertainty effect of news substantially contributed to deepen the economic slowdown. 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 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 10-year government bond yield (GS10), the spread between Baa and Aaa corporate bonds, which may be regarded as a measure of the risk premium, the stock of commercial and industrial loans, the VXO, extended as in Bloom, 2009, and the macroeconomic uncertainty index JLN3.

Results are reported in Figures 12 and 13. The squared news shock (Figure 12) reduces stock prices and increases the risk premium significantly in the short run. As expected, the VXO increases significantly in the first year after the shock. The effect on JLN3 is somewhat more puzzling. The index increases significantly on impact but afterwards it reduces and the reduction is significant at the one-year horizon, albeit at the 68% level.[12]. Finally, loans are barely affected.

As for the first moment, expectation effects of the news shock (Figure 13), good news have a large, positive and persistent effect on stock prices. Moreover, good news reduce significantly the risk premium, the VXO index and the JLN3 index.

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 first 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 a 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 using a VARX where the news and the squared news shocks are treated as exogenous variables. The black solid line and the confidence bands are those of the benchmark identification.

All in all, the two alternative identifications produce very similar results, with minor differences from a quantitative point of view, in that the short run effects of uncertainty are slightly smaller. 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 second exercise, we keep fixed the 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, the TB3M, GS10 and the AAA yield. Specification (ii) includes TFP, S&P500, Consumption, the TB3M.

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 are very similar to those obtained with the baseline specification.

[12] By observing Figure 5, it is seen that the squared news shock is somewhat lagging with respect to the JLN3 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.

5.7 Standard uncertainty shocks

We study here the relation between the uncertainty generated by news and the standard uncertainty shocks (see Bloom, 2009). More specifically, we investigate to what extent standard uncertainty shocks are endogenous with respect to our shock. In other words, we want to examine if the standard uncertainty shock captures uncertainty which is actually driven by news. To this aim, we perform the following exercise. First, following Bloom (2009) we identify the standard uncertainty shock as the first shock in a Cholesky decomposition in a VAR, like VAR 1, which includes a measure of uncertainty, GDP, consumption, investment, hours worked, CPI inflation and new orders with this order and compute impulse responses. We consider three uncertainty measures: the VXO, LMN3 Fin. and LMN3 Real. Second, we study the effects of an uncertainty shock identified as the third shock in a Cholesky decomposition of a VAR which includes, in that order, the news shock, the squared news shock, a measure of uncertainty, GDP, consumption, investment, hours worked, CPI inflation and new orders and compute impulse responses.

If the standard uncertainty shock captures news uncertainty, then the impulse response functions of the two shocks should differ. Figures 17 and 18 plot the results for the three measures of uncertainty considered. The black lines are the point estimates of the first VAR (without news and squared news), the blue dotted lines are those of the second VAR (with news and squared news). For all of the three measures, when the standard uncertainty shock is imposed to be orthogonal to news and squared news, its effect becomes smaller. In the case of the VXO, the effects of the standard uncertainty shock basically vanish, meaning that a large part of the uncertainty identified by the shock is associated with news. For the other two measures the change in the responses is substantially milder, meaning that the type of uncertainty captured is not related to our concept of uncertainty.

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 and well recognized 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 on output. This mitigates the negative first-moment effect of bad news and reinforces 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.

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Appendix: Computing Uncertainty

In this Appendix we derive formula (14).

We have to project the square of the RHS of (13) 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 (13) 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

$$\sum_{h=0}^{k-1} C_h^2. \tag{18}$$

Coming to terms of the form (iv), we have $E(s_\tau^2 v_\tau^2) = \sigma_v^2$. Going back to (13) 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

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

and

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

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 (13) and the constant term, the projection of type-(iv) terms onto Ω_t is

$$\sigma_v^2 \sum_{h=0}^{\infty}(R_{k+h}^k)^2(s_{t-h}^2 - 1) + \sigma_v^2 \sum_{h=0}^{k-1}(R_h^k)^2. \tag{19}$$

Formula (14) is the sum of (19) and (18).

Tables

	VXO	JLN3	JLN12	LMN3 Fin.	LMN3 Real
No Mention variable	-0.4	-0.5	-0.5	-0.3	-0.1
Squared News variable	0.6	0.6	0.6	0.5	0.4
Squared centered News variable	0.5	0.5	0.4	0.4	0.4
Absolute News variable	0.6	0.7	0.6	0.5	0.4

Table 1: Contemporaneous correlation coefficients.

	news shock		surprise shock	
	2 lags	4 lags	2 lags	4 lags
GDP	0.9	0.9	0.6	0.5
GDPDEF inflation	0.1	0.1	0.4	0.6
Hours Worked	0.7	0.9	0.3	0.4
Federal Funds Rate	1.0	1.0	0.9	0.8
BAA Yield	1.0	1.0	0.9	1.0
spread BAA-AAA	0.8	0.9	0.6	0.8
spread BAA-GS10	1.0	1.0	0.8	1.0
Survey "No Mention" variable	1.0	1.0	0.7	0.9
VXO extended as in Bloom 2009	0.9	0.9	0.6	0.9
CPI deflated S&P 500	1.0	1.0	1.0	1.0
CPI inflation	0.4	0.3	0.3	0.4
Unemployment rate	0.5	0.4	0.5	0.5
JLN3 Macro Uncertainty	0.2	0.1	0.9	1.0
JLN12 Macro Uncertainty	0.1	0.1	0.9	1.0
LMN3 Fin. Uncertainty	0.1	0.1	0.6	0.7
LMN3 Real Uncertainty	0.9	0.1	0.6	0.3

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	3.3	3.3	3.4	39.5
S&P500	58.3	66.3	73.7	80.9	77.8
Consumption	15.1	45.3	57.3	71.8	80.4
TB3M	25.0	12.2	10.4	15.7	36.1
GS10	10.7	8.9	14.1	25.2	48.6
AAA Yield	15.7	13.9	17.8	26.0	47.0
E5Y	2.7	19.4	31.4	41.5	41.7
Survey "News" variable	21.9	39.6	38.4	34.2	33.0

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

	VXO	JLN3	JLN12	LMN3 Fin.	LMN3 Real
Squared News	0.3	0.5	0.4	0.3	0.4
Squared News uncertainty k=2	0.4	0.6	0.6	0.3	0.5
Squared News uncertainty k=4	0.3	0.5	0.5	0.3	0.5

Table 4: Contemporaneous correlation coefficients.

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

Table 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				
S&P500	3.5	2.7	1.4	0.8	0.4
GS10	0.9	3.5	2.6	1.7	1.2
spread BAA-AAA	4.3	4.5	4.8	4.6	4.8
Commercial and Industrial Loans	1.7	0.7	1.2	1.8	3.2
VXO extended as in Bloom 2009	9.1	12.6	11.0	9.8	9.6
JLN3 Macro Uncertainty	4.0	1.2	1.6	1.9	2.0
	News shock				
S&P500	50.2	43.0	39.9	35.0	31.1
GS10	10.7	4.0	4.2	6.6	14.0
spread BAA-AAA	0.0	1.9	1.9	1.5	1.8
Commercial and Industrial Loans	2.0	1.4	6.0	9.0	9.6
VXO extended as in Bloom 2009	11.3	9.0	8.0	8.4	8.4
JLN3 Macro Uncertainty	3.0	4.9	3.3	3.4	3.6

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

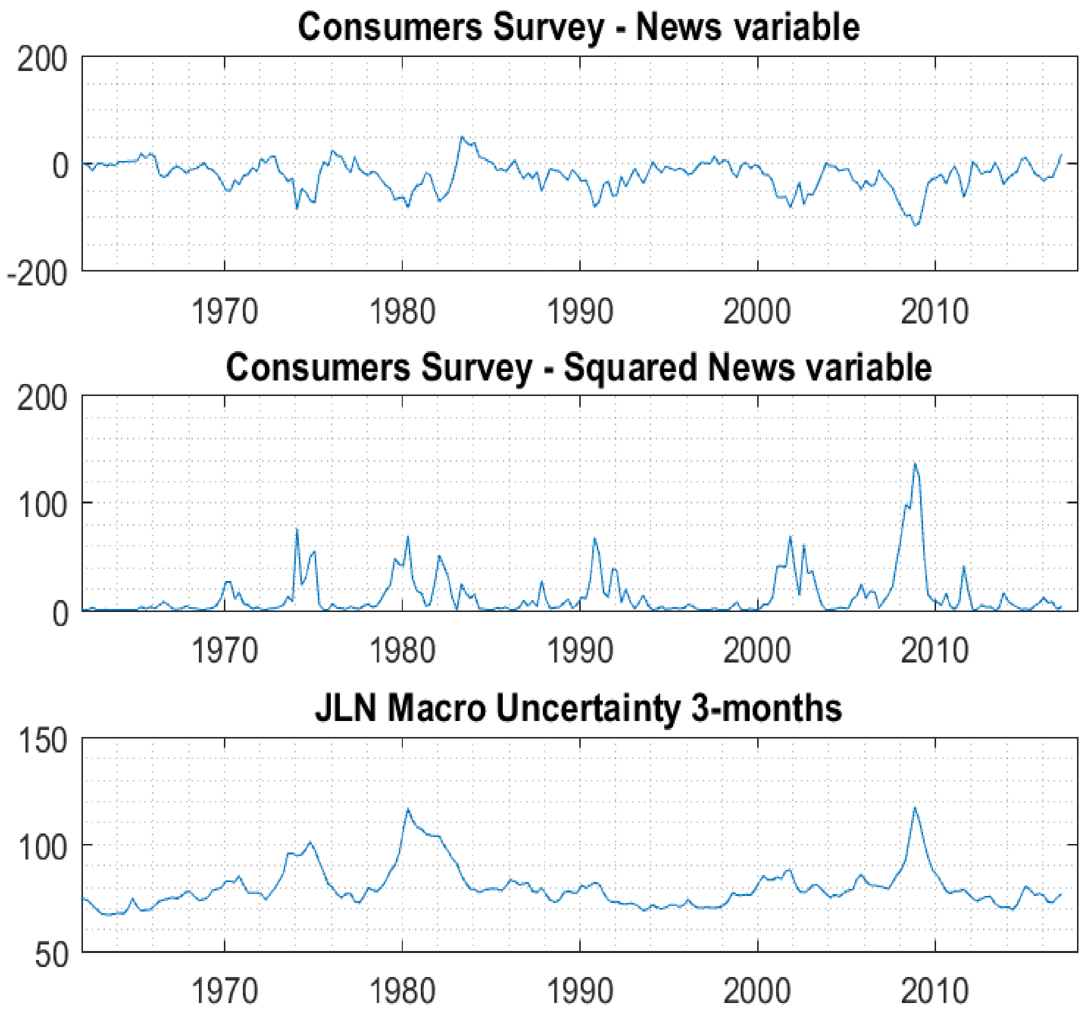

Figure 1: Plots of (a) the Consumers' survey news variable (upper panel); (b) the Consumers' survey squared news variable (middle panel), (c) Jurado, Ludvigson and Ng 3-month uncertainty (lower panel).

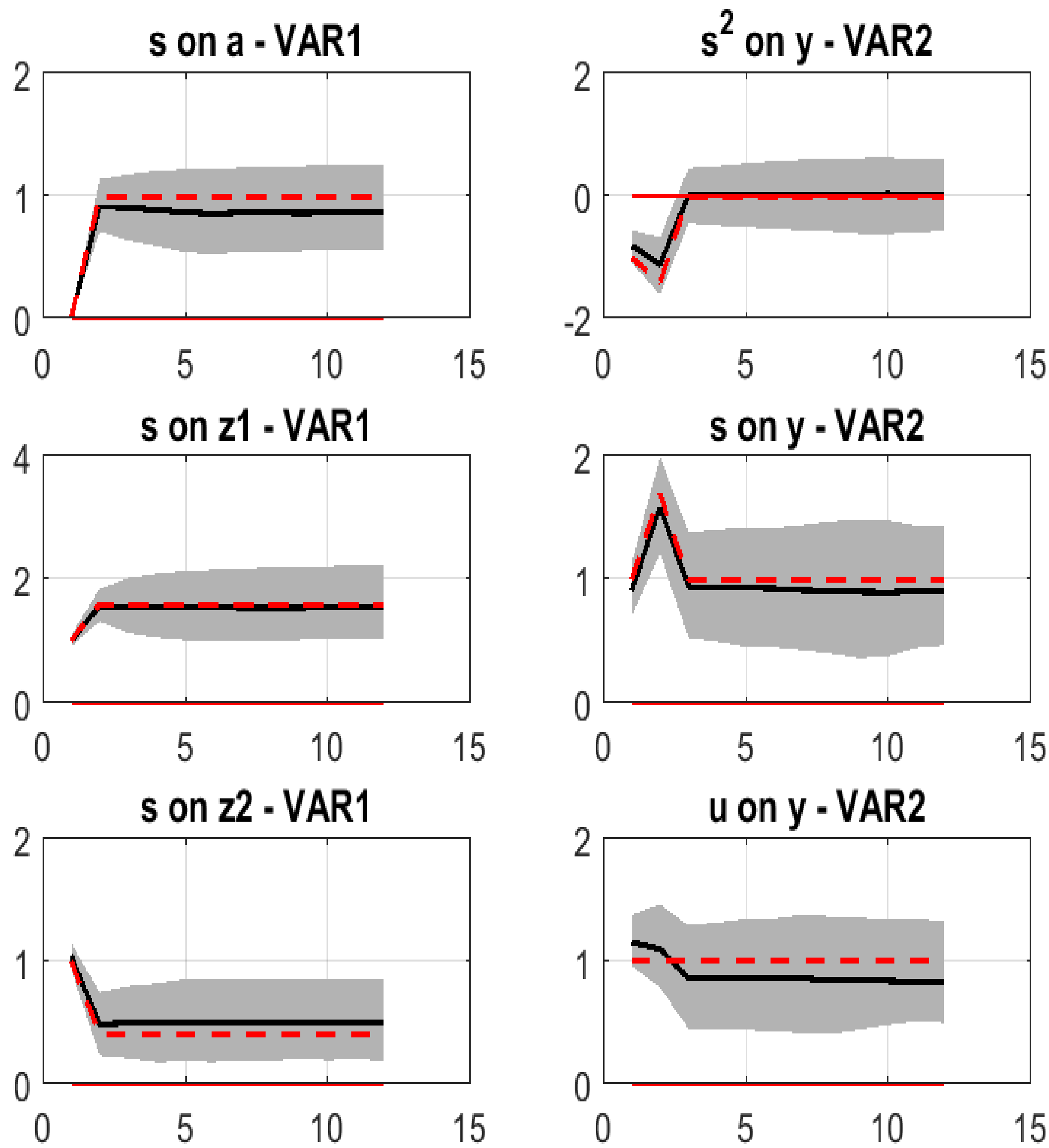

Figure 2: Impulse response functions functions of simulation 2. Effects of news are reported in the left column. The effects of the uncertainty shocks are reported in the right column. Solid line: point estimate. Grey area: 90% confidence bands. Red dashed line: true theoretical responses.

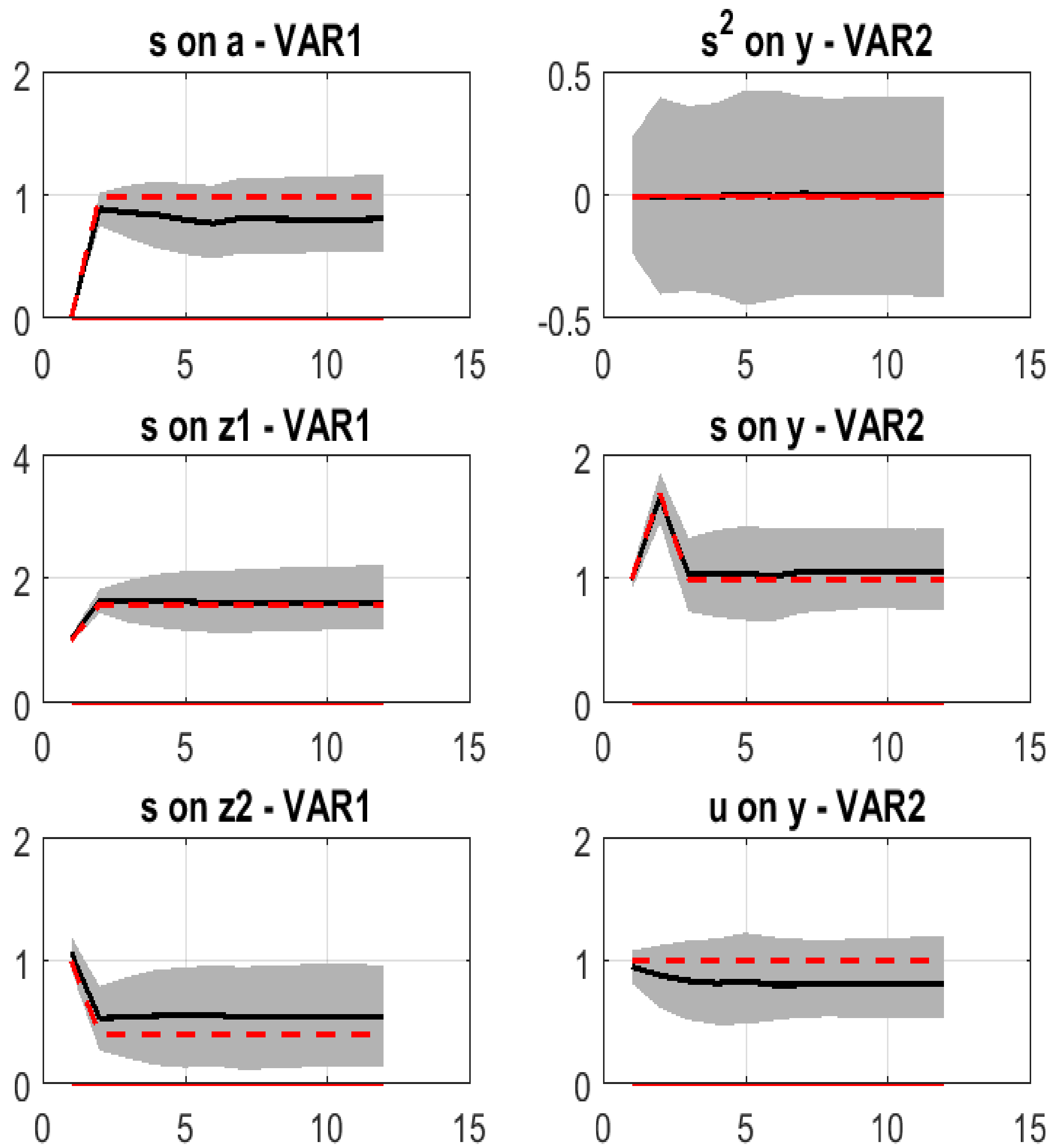

Figure 3: Impulse response functions functions of simulation 2. Effects of news are reported in the left column. The effects of the uncertainty shocks are reported in the right column. Solid line: point estimate. Grey area: 90% confidence bands. Red dashed line: true theoretical responses.

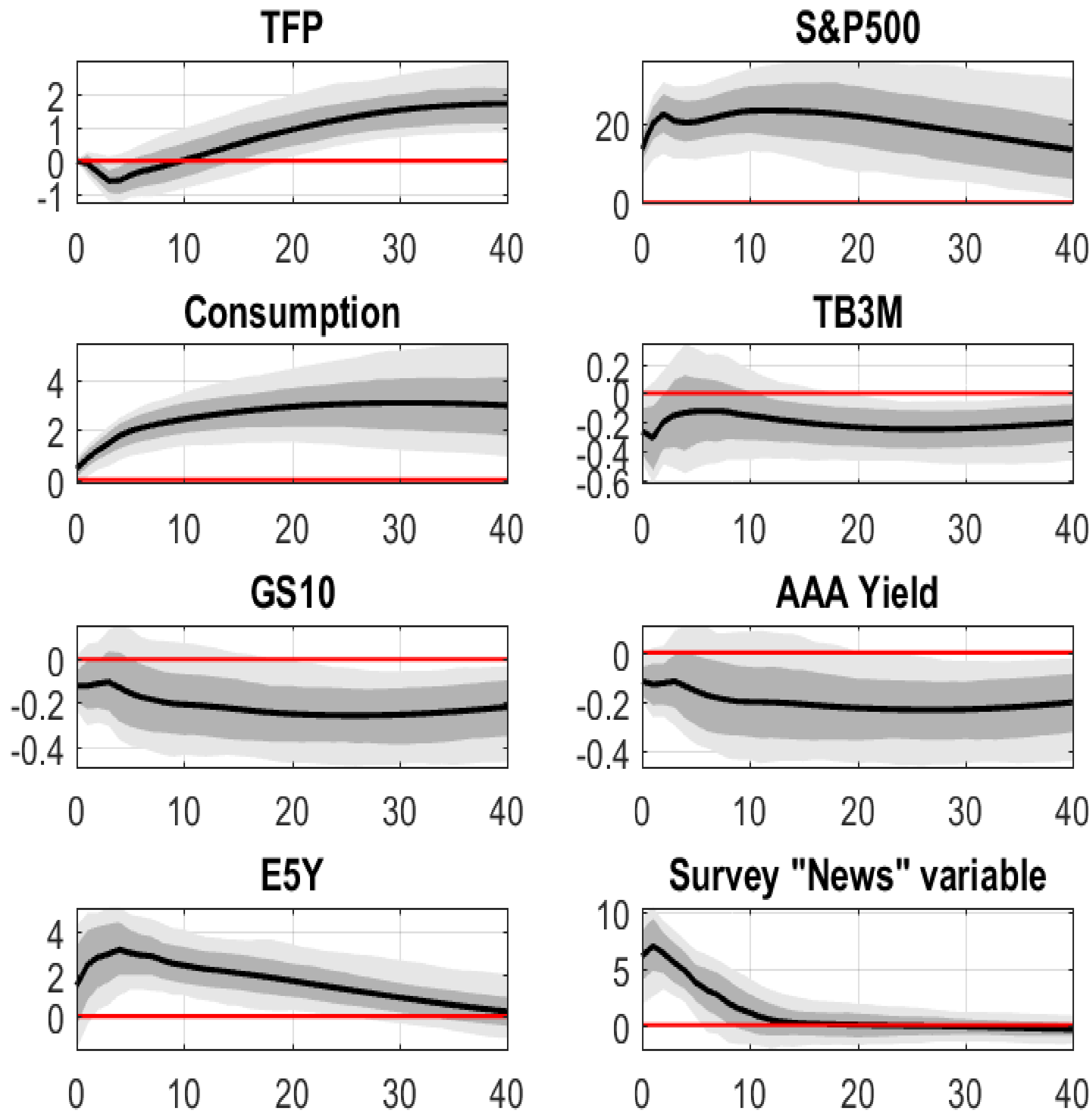

Figure 4: Impulse response functions to the news shock in VAR 1. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

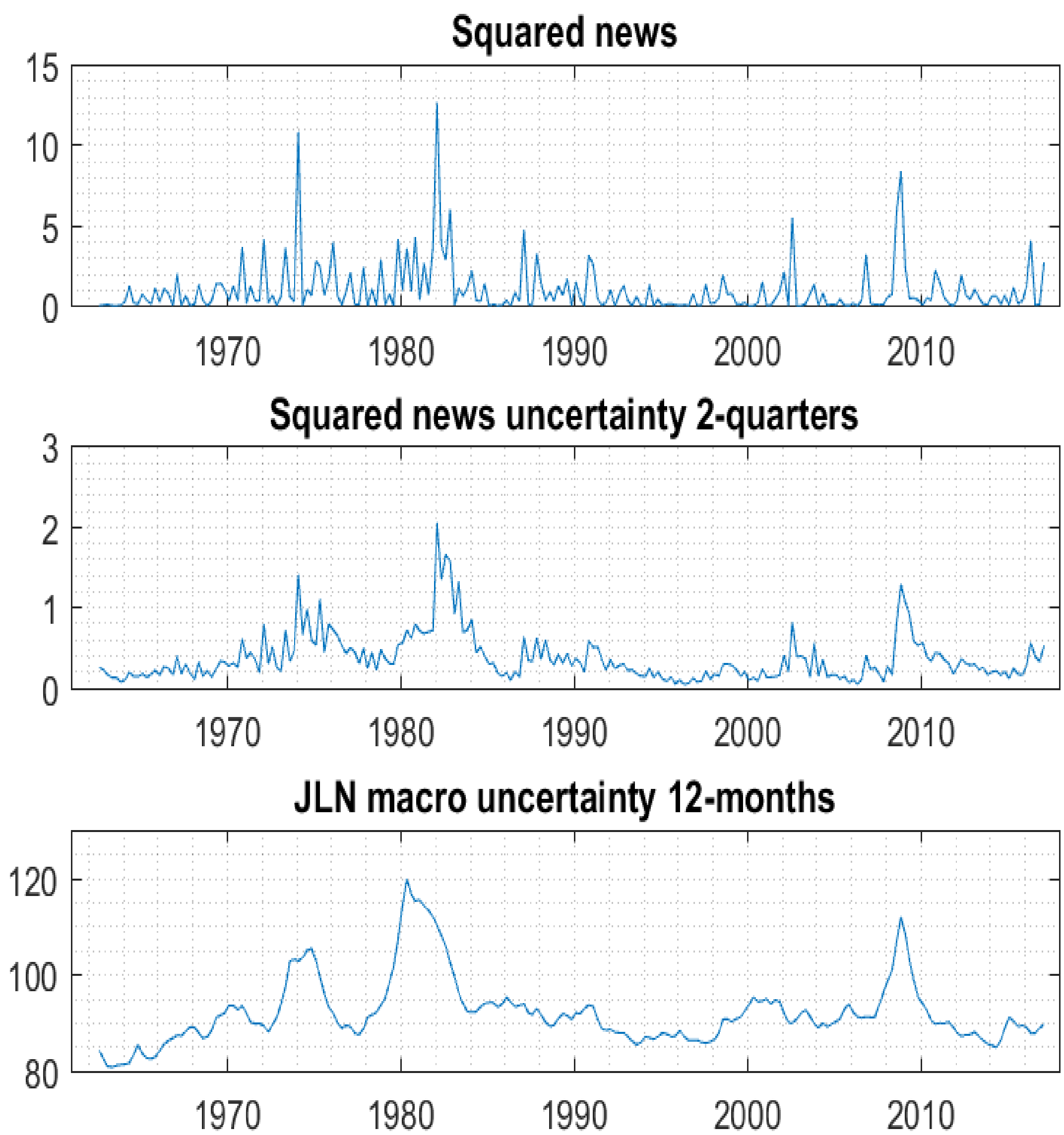

Figure 5: Plots of (a) the squared news shock (first panel), (b) squared-news uncertainty ($k = 2$), (c) Jurado, Ludvigson and Ng, 12-month uncertainty.

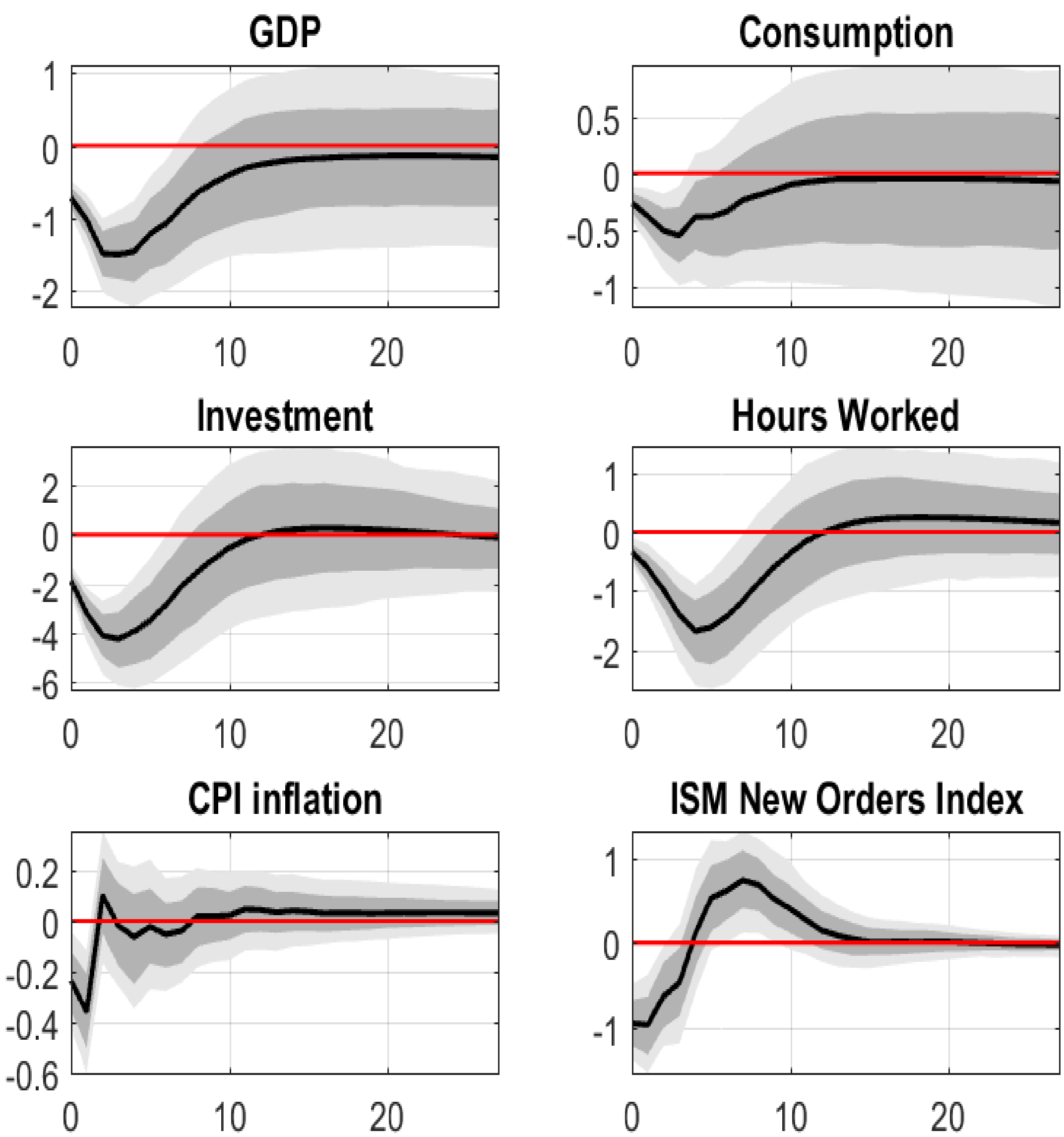

Figure 6: Impulse response functions to the squared news shock in VAR 2. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

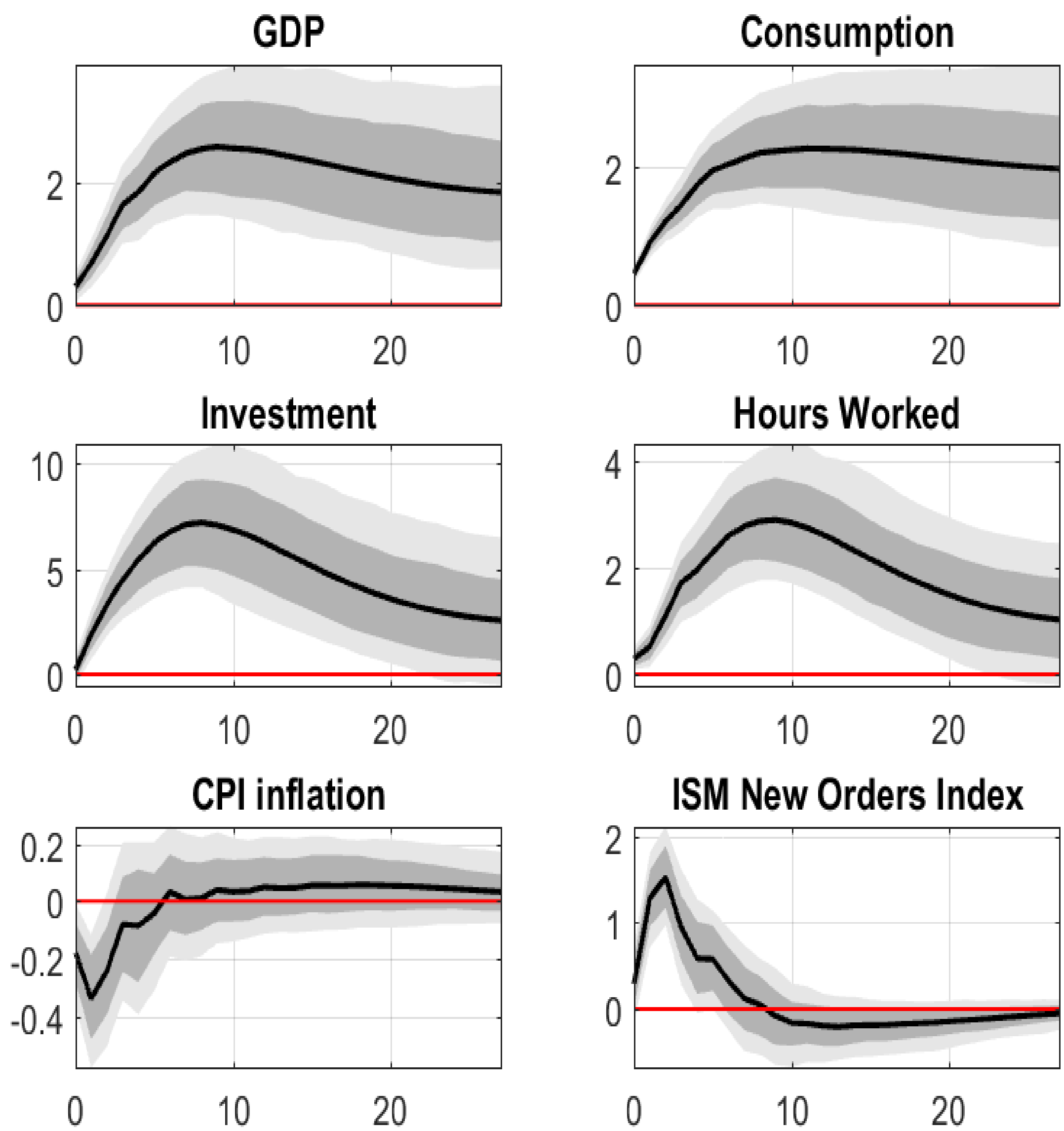

Figure 7: Impulse response functions to the news shock in VAR 2. Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

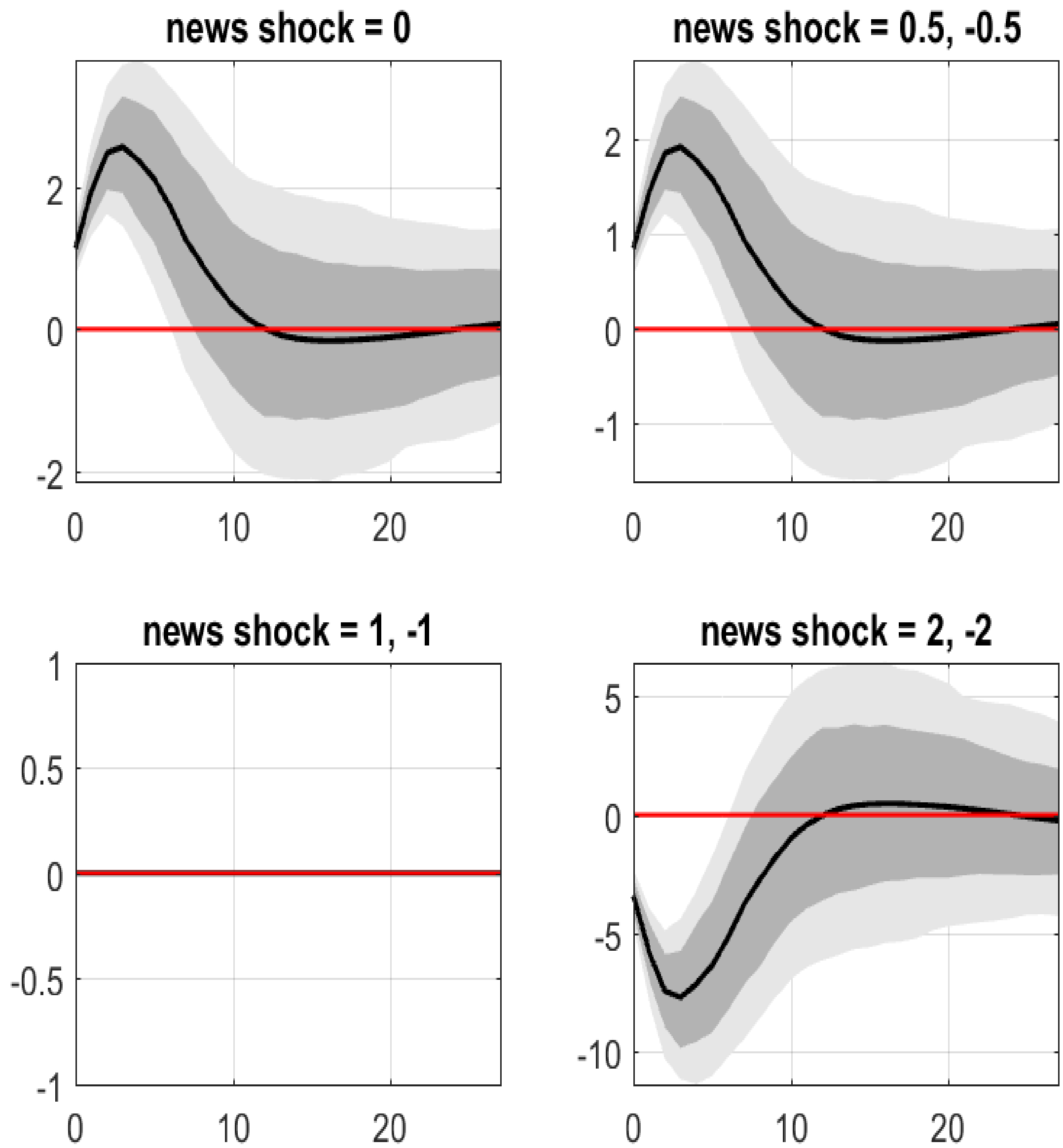

Figure 8: The uncertainty effect of the news shock on GDP, for different values of the news shock (VAR 2). Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

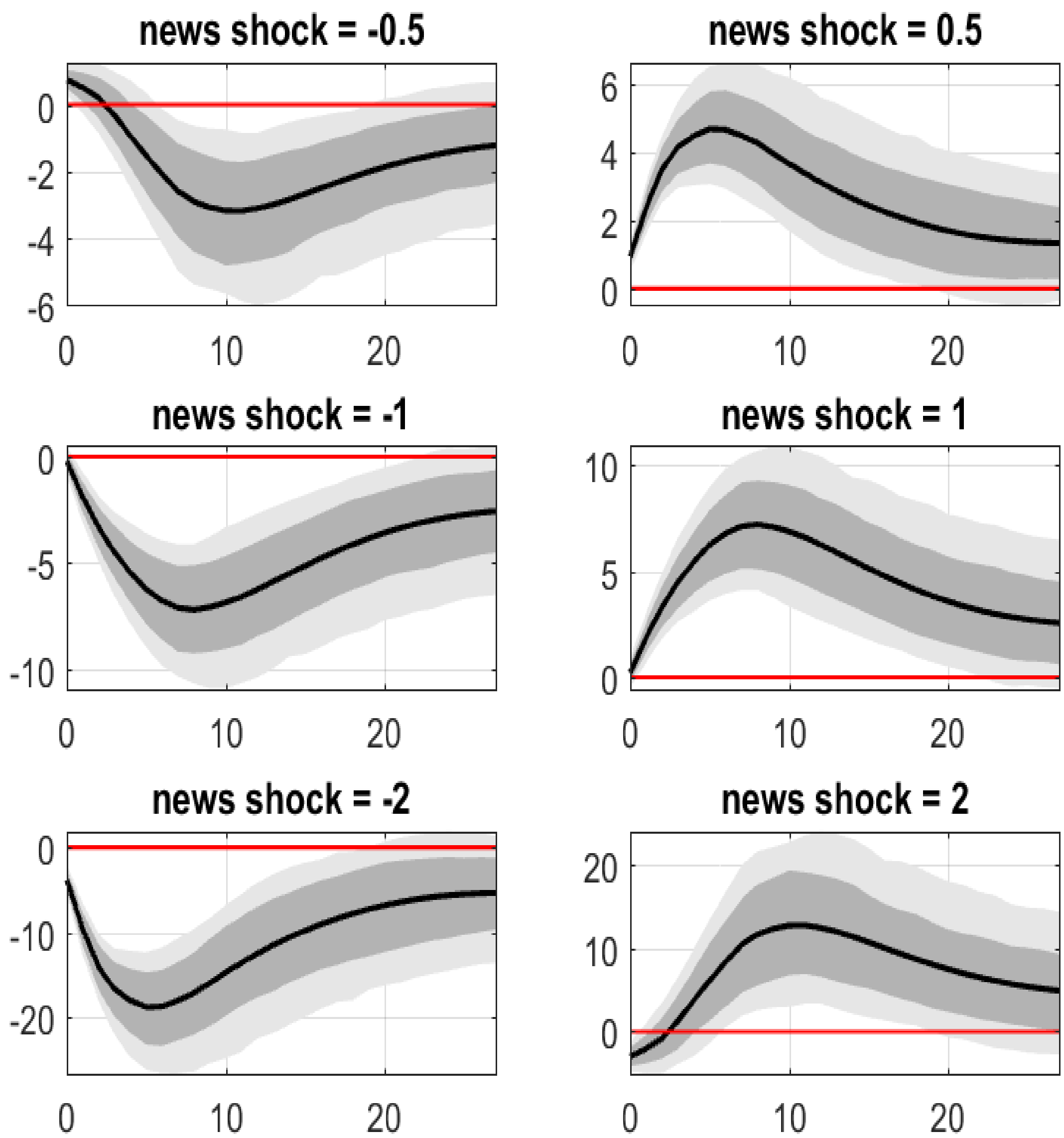

Figure 9: The total reaction of GDP to the news shock, including both the expectation effect and the uncertainty effect, for different values of the news shock (VAR 2). Solid line: point estimate. Light grey area: 90% confidence bands. Dark grey area: 68% confidence bands.

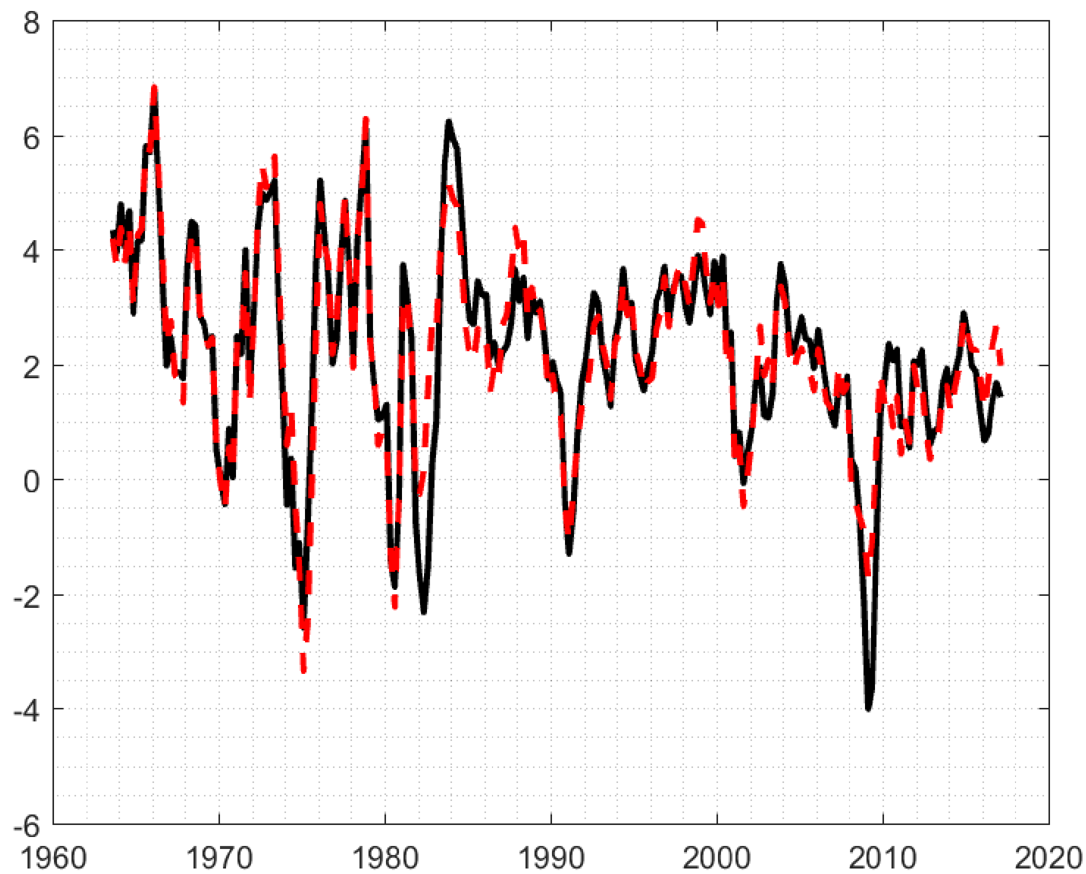

Figure 10: Historical decomposition of GDP (VAR 2). Black line: per-capita GDP. Red dashed line: per-capita GDP minus the uncertainty effects of news.

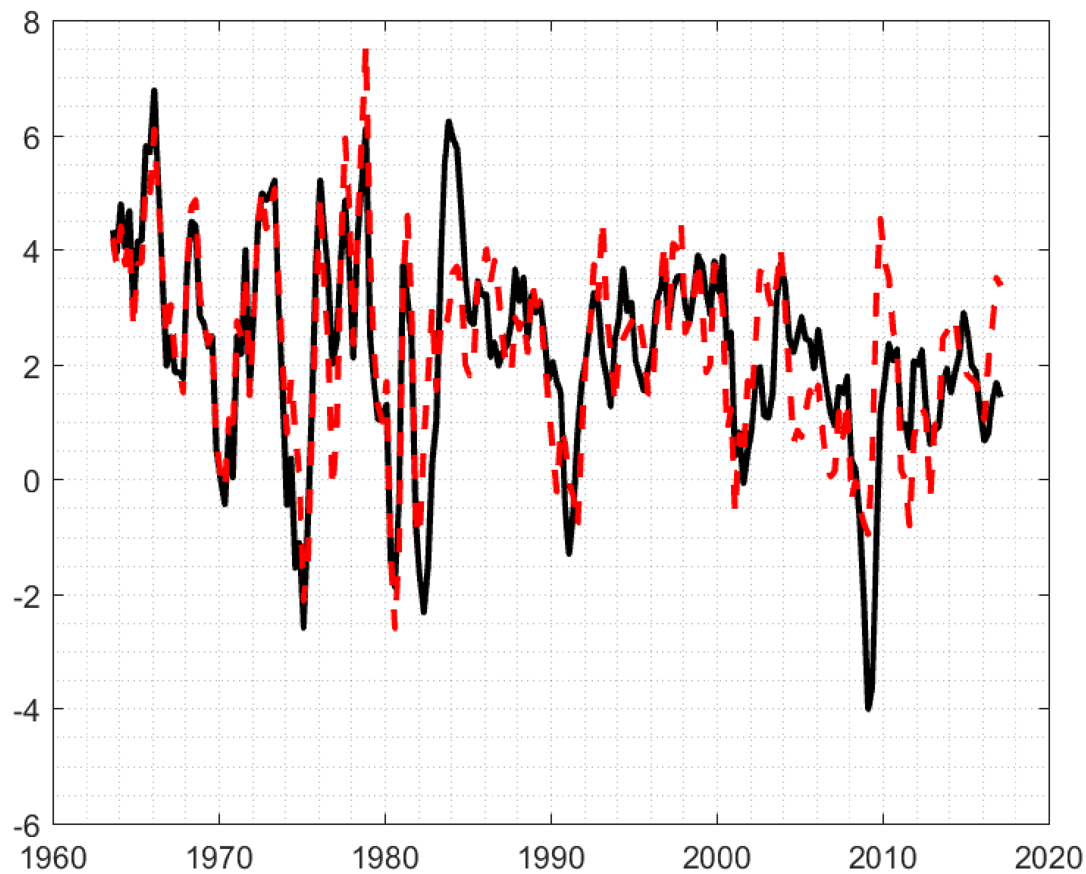

Figure 11: Historical decomposition of GDP (VAR 2). Black line: per-capita GDP. Red dashed line: per-capita GDP minus the total effects of news, including the uncertainty effects.

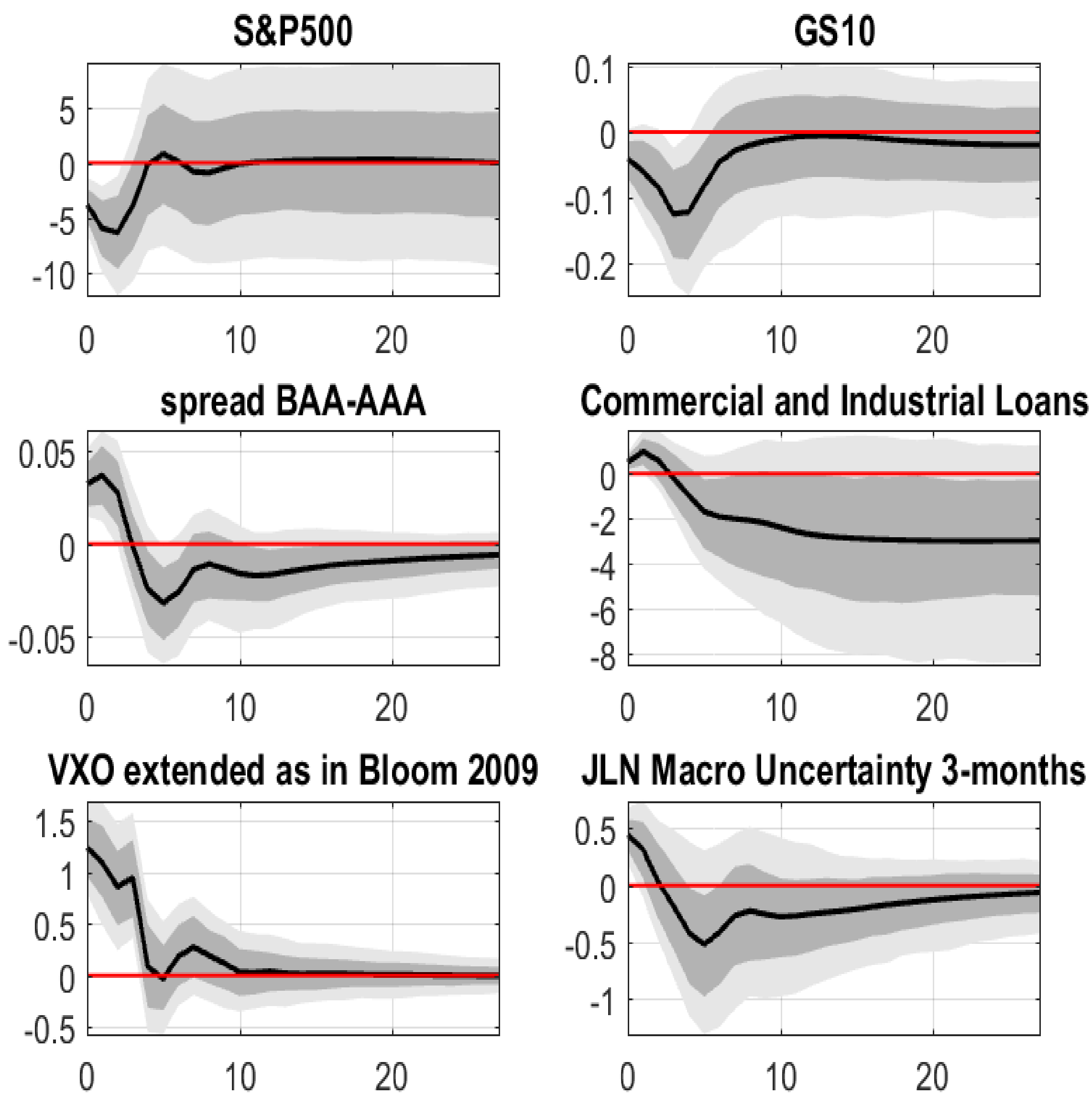

Figure 12: Impulse response functions to the squared news shock in VAR 3. Solid line: point estimate. Light gray area: 90% confidence bands. Dark gray area: 68% confidence bands.

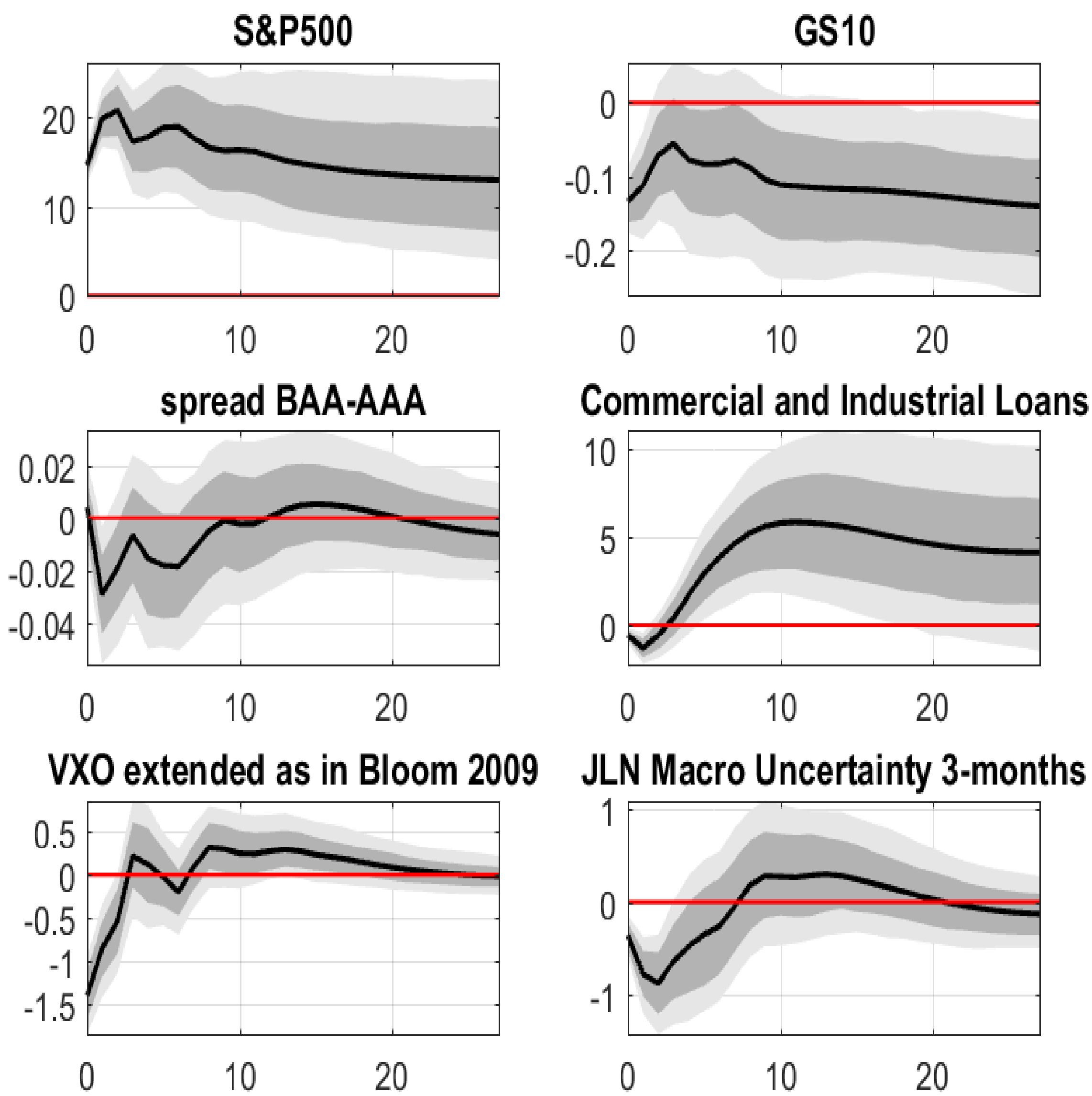

Figure 13: Impulse response functions to the news shock in VAR 3. Solid line: point estimate. Light gray area: 90% confidence bands. Dark gray area: 68% confidence bands.

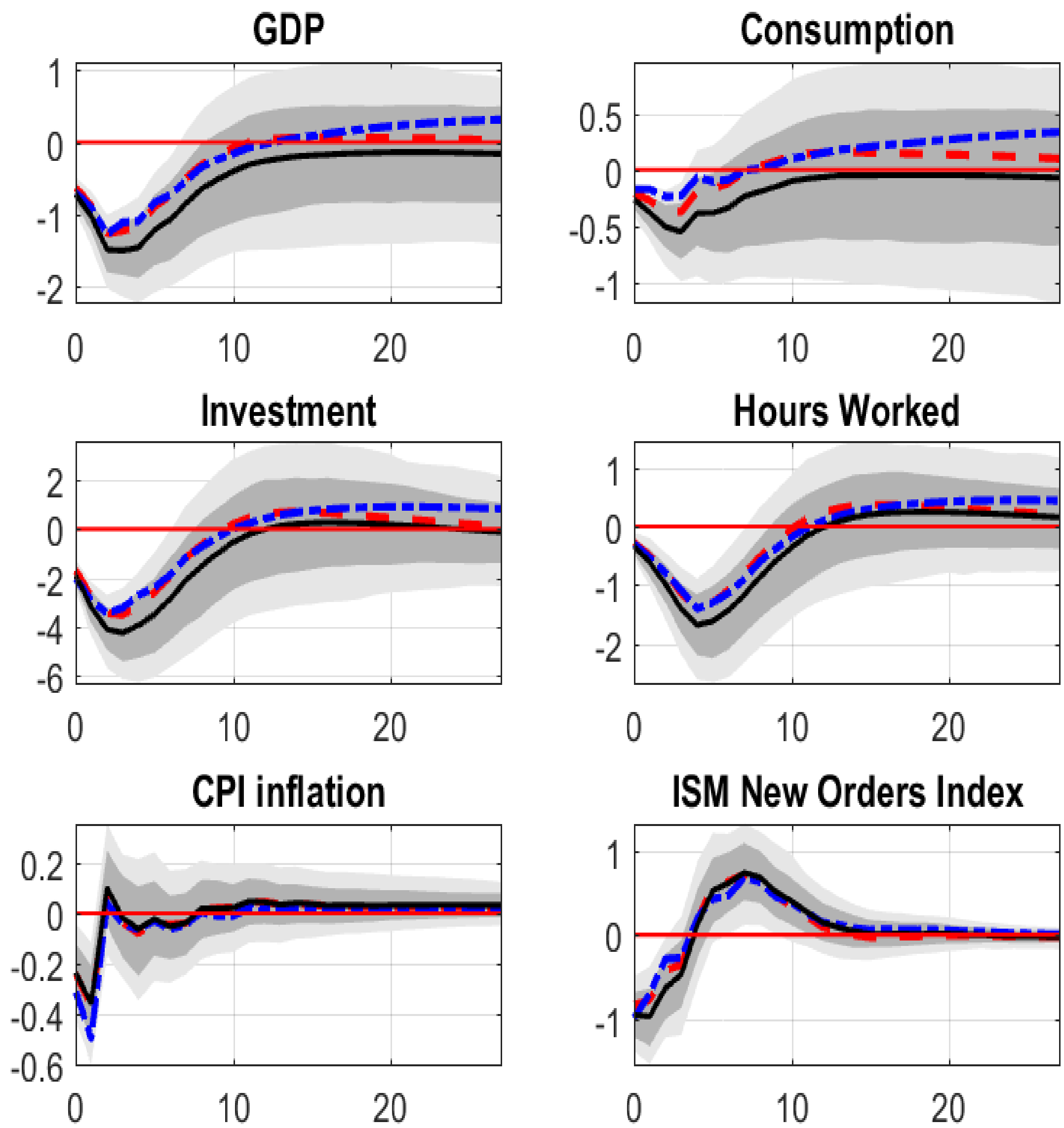

Figure 14: Robustness. Impulse response functions to the squared news shock with the specification of VAR 2 and two alternative identification schemes: the recursive scheme with the news shock ordered first (red dashed line) and a long-run restriction imposing zero effect of squared news on GDP at the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

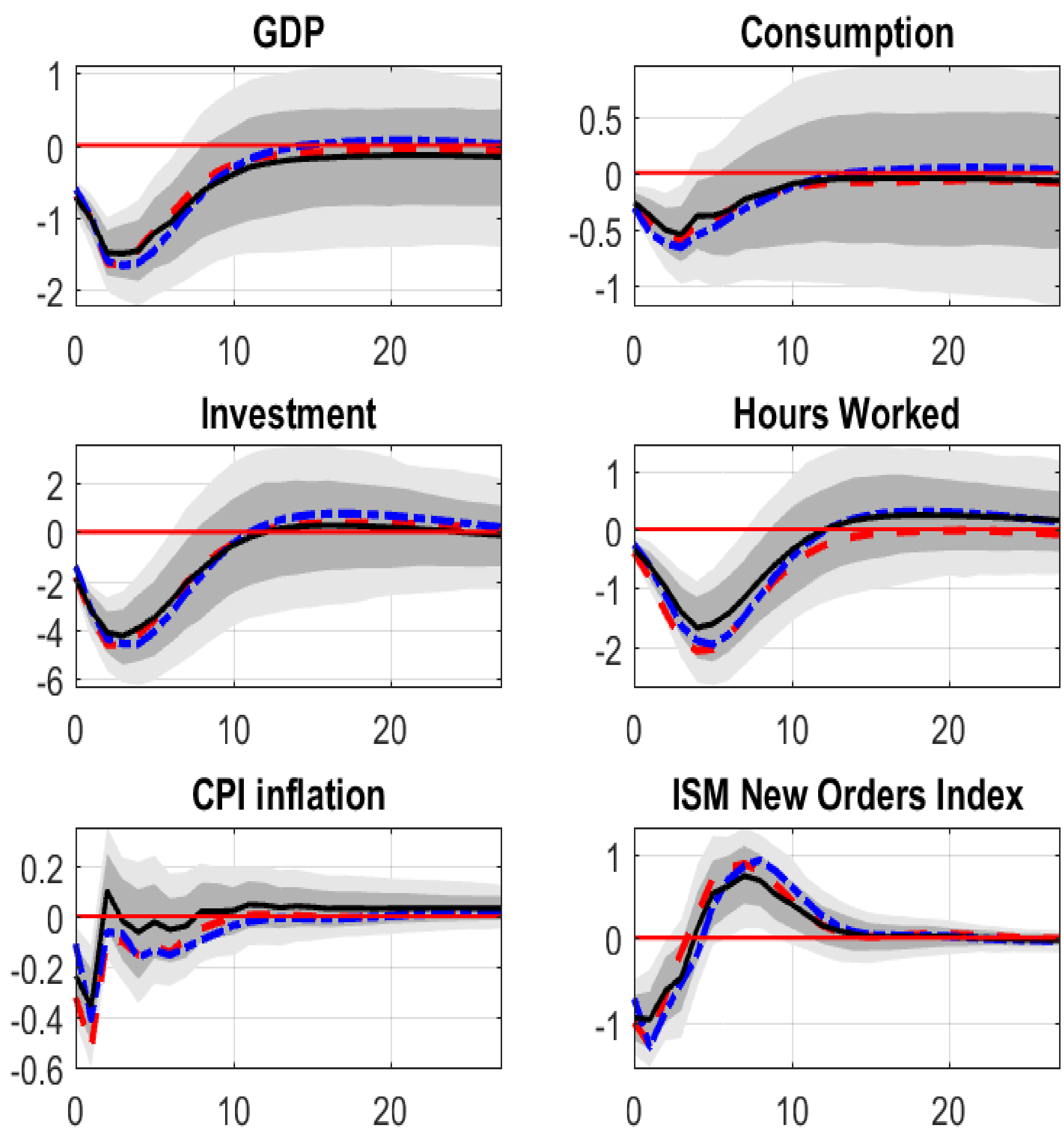

Figure 15: Robustness. Impulse response functions to the squared news shock for different specifications of VAR 1: (i) TFP, S&P500, Consumption and TB3M (red-dashed line) and (ii) TFP, Investment and TB3M (blue dotted-dashed line). Identification of both VAR 1 and VAR 2 are unchanged. The black solid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

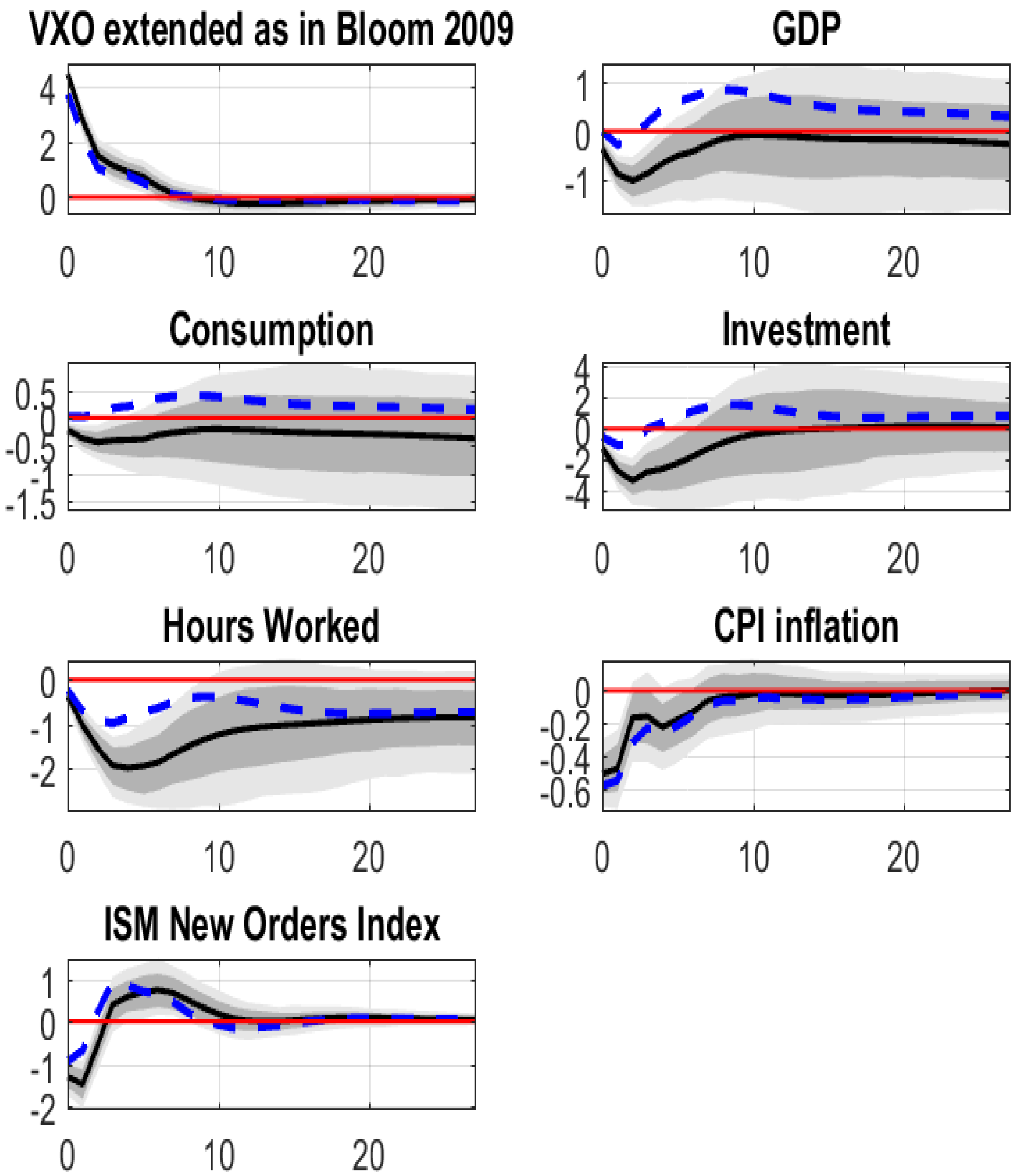

Figure 16: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with the VXO ordered first (same specification as in VAR 2 but omitting news and squared news). The black solid line and the confidence bands are the point estimate and the confidence 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.

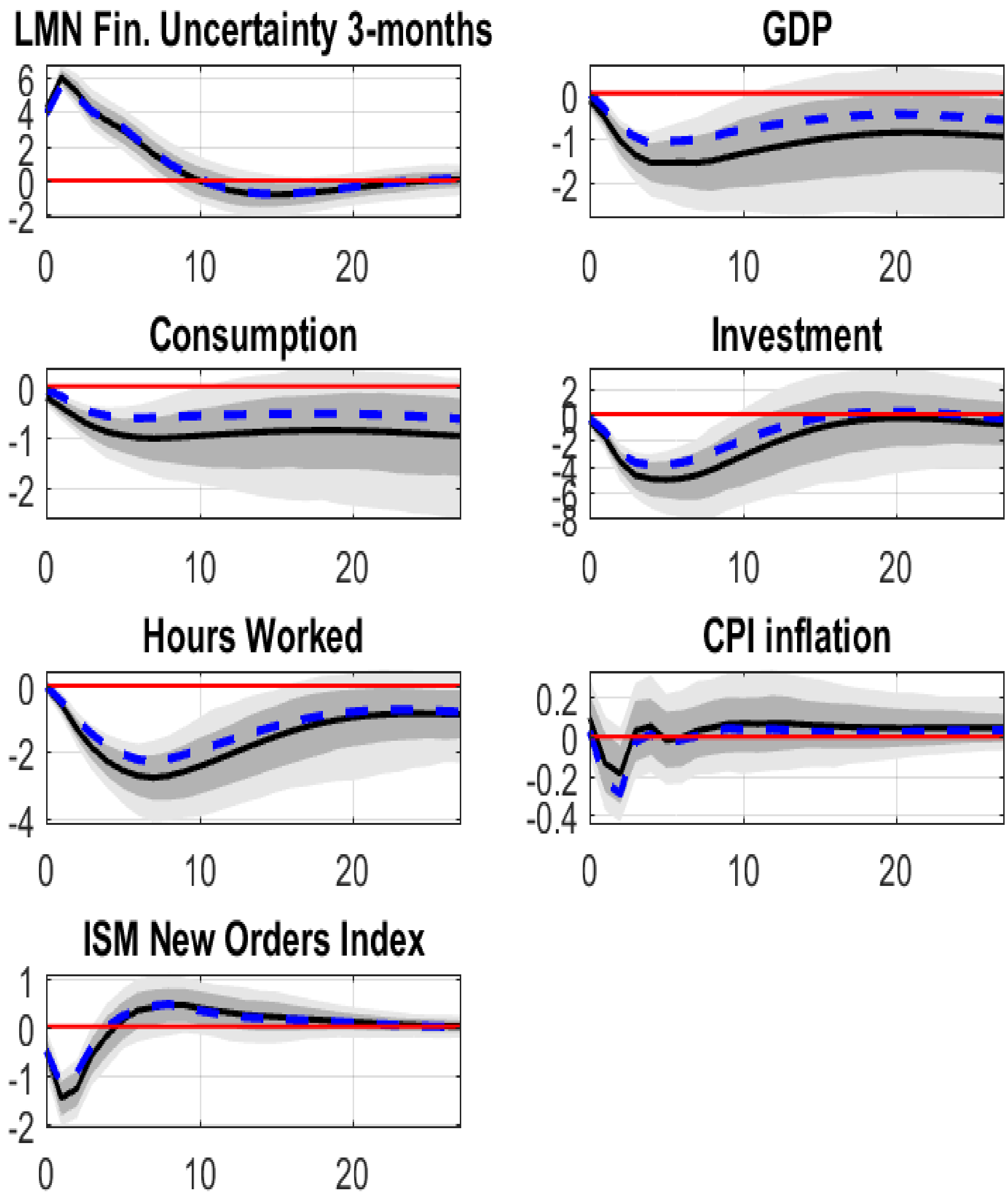

Figure 17: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with the VXO ordered first (same specification as in VAR 2 but omitting news and squared news). The black solid line and the confidence bands are the point estimate and the confidence 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.

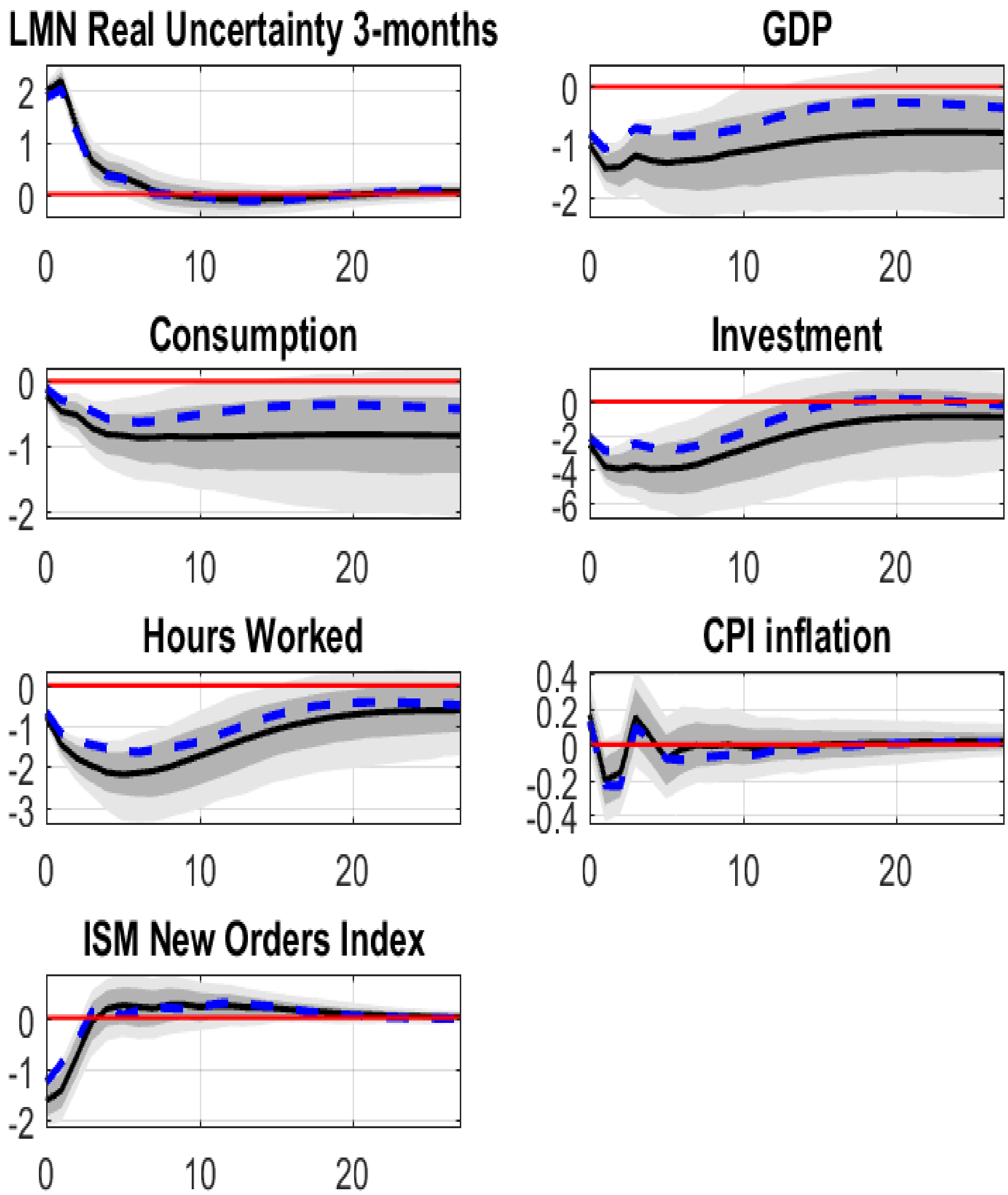

Figure 18: Impulse response functions to an uncertainty shock identified as the first shock in a Cholesky decomposition with the VXO ordered first(same specification as in VAR 2 but omitting news and squared news). The black solid line and the confidence bands are the point estimate and the confidence 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.