Noisy News in Business Cycles

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Abstract

The contribution of the present paper is twofold. First, we show that in a situation where agents can only observe a noisy signal of the shock to future economic fundamentals, the "noisy news", SVAR models can still be successfully employed to estimate the shock and the associated impulse response functions. Identification is reached by means of *dynamic* rotations of the reduced form residuals. Second, we use our identification approach to investigate the role of noise and news as sources of business cycle fluctuations. We find that noise shocks, the component of the signal unrelated to economic fundamentals, generate hump-shaped responses of GDP, consumption and investment and account for a third of their variance. Moreover, news and noise together account for more than half of the fluctuations in GDP, consumption and investment.

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1 Introduction

In recent years there has been a renewed interest in the old idea that business cycles could be driven by changes in the expectations about future economic conditions (see Pigou, 1927, and Keynes, 1936). The focus has been mainly on anticipated changes in productivity, the so-called "news shocks" (Cochrane, 1994). The seminal paper by Beaudry and Portier, 2006, (BP henceforth) finds that news shocks account for the bulk of fluctuations in GDP and generate the pattern of comovements among macroeconomic aggregates typically observed over the cycle.[1] Several papers have provided theoretical foundations for these results, by proposing models where news shocks can drive the business cycle (see e.g. Jaimovich and Rebelo, 2009, Den Haan and Kaltenbrunner, 2009, Schmitt-Grohe and Uribe, 2008). In these models news shocks are assumed to be observable for the agents. The implication is that only anticipated change in future economic conditions which eventually materialize can generate economic fluctuations.

A few works, however, have challenged this assumption, arguing that in many situations economic agents receive imperfect signals about present and future economic conditions (see Woodford, 2002, Mankiw and Reis, 2002, Sims, 2003, Beaudry and Portier, 2004, Lorenzoni, 2009, Angeletos and La'O, 2010, among others). Lorenzoni, 2009, presents a simple New-Keynesian model where agents can only observe a noisy signal about future productivity. The main implication is that, in a framework with limited information economic fluctuations can also be driven by noise, the component of the signal unrelated to the economic fundamentals. In other words, under imperfect information, business cycles can be driven by anticipated change in future economic condition which never actually materialize.

The empirical analysis in Blanchard, Lorenzoni and L'Huillier, 2012 (BLLH henceforth), overturns the result in BP and concludes that noise shocks – let us say "animal spirits" – account for the bulk of cyclical fluctuations in output and consumption, while news shocks have a limited role.[2] This evidence has fueled a new debate, which can be cast in terms of noise vs news driven business cycles. A major contribution is Barsky and Sims, 2012 (BS from now on) which, unlike BLLH, finds a negligible role of noise shocks as a source of cyclical fluctuations.

Relaxing the assumption of agents' perfect information has dramatic implications for the empirical analyses conducted with standard structural VAR methods. If agents observe the structural shocks, then economic data, by reflecting agents' behavior, can be used by the econometrician to estimate the shocks and the related impulse response functions. But if the shocks cannot be observed, then current (and past) values the

[1] Beaudry and Lucke, 2009, and Dupaigne and Portier, 2006, find similar results.

[2] On the effects of news shocks see also Forni, Gambetti and Sala, 2010, Barsky and Sims, 2011.

economic variables cannot convey the relevant information. This implies that it is not possible to recover the shocks as linear combinations of the VAR residuals. After all, if this is be possible for the econometrician, it would be possible for the agents as well, contrary to the starting assumption.

To put it another way, under imperfect information the structural shocks are *non-fundamental* with respect to agents' information set (Hansen and Sargent, 1991, Lippi and Reichlin, 1993, 1994). This kind of non-fundamentalness is different from the one that arises when the econometrician's information set is narrower than that of the agents. In the latter case, the problem can be solved in principle by enlarging the data set (Forni, Giannone, Lippi and Reichlin, 2009, Forni and Gambetti, 2011). By contrast, in the case studied here, a VAR cannot be amended by adding variables. Hence, it seems that VAR models cannot be useful empirical tools under imperfect information. This is also the conclusion reached in both BLLH and BS.

The contribution of the present paper is twofold. First, we present a theoretical model where agents observe a noisy signal about the shock affecting future economic fundamentals; the signal is the sum of the structural shock and a noise shock. We show that in this framework VAR models can still be successfully employed to estimate the shocks and the associated impulse response functions. This is because, unlike the papers discussed above, here *future* data reveal completely the shock occurred in the past. That is, as time goes by, agents learn whether the signal was noise or the true economic shock. While a contemporaneous linear combination of the VAR residuals cannot deliver the correct shock, a *dynamic* combination, i.e. a combination of present and future residuals, can. More precisely, we show that, once the reduced form VAR has been estimated, the structural shocks and the corresponding impulse response functions can be obtained by applying Blaschke transformations to the residuals and the reduced-form impulse response functions.

The second contribution of the paper is to study the role of noise and news as sources of business cycle fluctuations. We find that noise and news together, the "noisy news", explain more than half of the fluctuations of GDP, consumption and investment. Expectations of future changes in economic fundamentals, which in part do not eventually materialize, in part do, should be considered a major source of business cycle fluctuations. A large fraction of such fluctuations is due to noise shocks which generate hump-shaped responses of GDP, consumption and investment and account for about one third of their variance at short- and medium-run horizons. The role of noise is much larger than in BS, where "animal spirits" have negligible effects, and qualitatively different from BLLH, where it is found to explain a very large fraction of consumption fluctuations on impact, but a relatively small fraction of consumption variance at the 3-year horizon and almost nothing of investment fluctuations.

The remainder of the paper is organized as follows. Section 2 discusses the economic model and the econometric implications; Section 3 presents the econometric model; Section 4 presents the empirical evidence; Section 5 concludes.

2 Some theory

In this section we present a simple model where agents decide the current level of consumption on the basis of expected future economic fundamentals, which are driven by a news shock. Expectations however are based on a limited information set, since agents receive noisy news. The implication is that consumption reacts to both news and noise.

2.1 A simple model

We assume that potential output, a_t, follows the exogenous relation

$$a_t = a_{t-1} + \varepsilon_{t-1}, \tag{1}$$

where ε_t, the news shock, is a Gaussian, serially uncorrelated process affecting a_t with a one-period delay. Consumers observe a noisy signal of ε_t, the "noisy news", given by

$$s_t = \varepsilon_t + v_t, \tag{2}$$

where v_t, the noise shock, is a Gaussian white noise, uncorrelated with ε_t at all leads and lags. The variance of the signal is the sum of the variances of the two shocks, $\sigma_s^2 = \sigma_\varepsilon^2 + \sigma_v^2$. In addition, agents observe potential output a_t, so that the consumers' information set is given by present and past values of a_t and s_t, i.e. $\mathcal{I}_t = \text{span}(a_{t-k}, s_{t-k}, k \geq 0)$. Given the delayed effects of the news shock, this information is not enough to distinguish current news from noise. At time $t+1$, however, consumers learn about the past realization of the two shocks since they observe $\varepsilon_t = \Delta a_{t+1}$ and therefore $v_t = s_t - \varepsilon_t$.

Following BLLH, we assume that agents set consumption, c_t, on the basis of expected long-run fundamentals; precisely,

$$c_t = \lim_{j \to \infty} E(a_{t+j} | \mathcal{I}_t). \tag{3}$$

Realized output, y_t, is fully demand-determined, i.e. $y_t = c_t$; employment adjusts to clear the labor market.

2.2 Solution and economic implications

Given the process for a_t, we have $E(a_{t+j}|\mathcal{I}_t) = E(a_{t+1}|\mathcal{I}_t)$ for any $j > 1$, so that

$$c_t = E(a_{t+1}|\mathcal{I}_t) = a_t + E(\varepsilon_t|\mathcal{I}_t). \tag{4}$$

Since a_{t-k}, $k \geq 0$, and s_{t-k}, $k > 0$, are uninformative about ε_t, $E(\varepsilon_t|\mathcal{I}_t)$ is simply the projection of ε_t on s_t, that is γs_t, where $\gamma = \sigma_\varepsilon^2/\sigma_s^2$. Therefore $c_t = a_t + \gamma(\varepsilon_t + v_t)$ and the change in consumption is

$$\Delta c_t \quad = \quad \Delta a_t + \gamma\Delta(\varepsilon_t + v_t) = \gamma\varepsilon_t + (1-\gamma)\varepsilon_{t-1} + \gamma v_t - \gamma v_{t-1}. \tag{5}$$

Following a news shock consumption immediately jumps by $\gamma\varepsilon_t$ and in the second period reaches its new long run level $c_{t-1} + \varepsilon_t$. Consumption reacts also to the noise shock: following a positive noise shock, consumption increases by γv_t on impact and then reverts back to its initial level c_{t-1} after one period. Notice that the impact responses are identical, since agents cannot distinguish between the two shocks immediately. However, after one period, observed potential output unveils the nature of the shock and agents, recognizing it was noise, undo the initial increase by reducing consumption by γv_t. While the news shock has a permanent effect, the noise shock has only a temporary effect.

It is instructive to compare these results with the case in which agents can observe the news shock without error. In this case, equation (4) implies $c_t = a_t + \varepsilon_t$ and

$$\Delta c_t = \varepsilon_t,$$

so that after a news shock consumption jumps immediately to its new long run level.[3] Imperfect information has two implications. First, agents are more cautious in changing their consumption pattern. More precisely, for a given variance of the news shock, the higher is the variance of noise, the smaller is the contemporaneous change in consumption (recall that $\gamma = \sigma_\varepsilon^2/\sigma_s^2$). Second, the noise shock can generate cyclical fluctuations in consumption and output completely unrelated to economic fundamentals.

Let us see how quantitatively important these fluctuations can be. The total variance of consumption change is σ_ε^2.[4] The contribution of the noise component is then

$$\frac{2\gamma^2\sigma_v^2}{\sigma_\varepsilon^2} = 2\frac{\sigma_\varepsilon^2}{\sigma_s^4}\sigma_v^2 = \frac{2\sigma_\varepsilon^2\sigma_v^2}{(\sigma_v^2 + \sigma_\varepsilon^2)^2},$$

which depends on the variance of the noise component. Let us consider the two limiting cases $\sigma_v^2 = 0$ and $\sigma_v^2 \to \infty$. In the former case there is no noise, so that its contribution to total variance is obviously zero. In the latter case the signal is dominated by noise, so that it is not informative at all. Interestingly, the variance of the noise component approaches zero also in this case. The reason is that agents recognize that the signal is uninformative and do not react to it. Finally, it is easily seen that the above expression

[3] Notice that consumption is a random walk in both cases of complete and incomplete information. To see this, consider that the first order autocovariance of Δc_t in equation (5) is $\sigma_\varepsilon^2\gamma(1-\gamma) - \sigma_v^2\gamma^2 = \sigma_\varepsilon^2\gamma - \gamma^2(\sigma_\varepsilon^2 + \sigma_v^2) = \sigma_\varepsilon^2\frac{\sigma_\varepsilon^2}{\sigma_s^2} - \frac{\sigma_\varepsilon^4}{\sigma_s^4}\sigma_s^2 = 0$.

[4] From (5) we have $\mathrm{var}(\Delta c_t) = [\gamma^2 + (1-\gamma)^2]\sigma_\varepsilon^2 + 2\gamma^2\sigma_v^2 = 2\gamma^2\sigma_s^2 + (1-2\gamma)\sigma_\varepsilon^2 = 2\sigma_\varepsilon^4/\sigma_s^2 - 2\sigma_\varepsilon^4/\sigma_s^2 + \sigma_\varepsilon^2 = \sigma_\varepsilon^2$.

reaches its maximum when $\sigma_v^2 = \sigma_\varepsilon^2$. In this case 50% of the fluctuations of consumption change are due to noise.

2.3 The failure of standard structural VAR methods

Imperfect observability of structural shocks has important econometric implications. To see this, let us rewrite the solution of the model as

$$\begin{pmatrix} \Delta a_t \\ \Delta c_t \\ s_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ \gamma + (1-\gamma)L & \gamma - \gamma L \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}, \tag{6}$$

where L is the lag operator. To simplify things, let us further assume for the moment that the econometrician can observe s_t.

First, the econometrician (just like the agents) would not be able to recover news and noise shocks from the present and past values of a_t and s_t. It is easily seen from (6) that the polynomial matrix of the subsystem associated to Δa_t and s_t has determinant vanishing in zero, which implies that the corresponding bivariate MA representation is non-invertible and *non-fundamental* and a VAR representation in the structural shocks does not exist.

The econometrician could also use consumption, in addition to potential output and the signal, but still he would fail to recover the shock. For, the rank of the polynomial matrix in (6) is one for $L = 0$, which means that even this "tall" representation is non-invertible and non-fundamental. In other words, the two shocks cannot be obtained from present and past values of the three variables.

Non-fundamentalness is a debated issue in the structural VAR literature. Early references are Hansen and Sargent, 1991, and Lippi and Reichlin, 1993, 1994; more recent contributions include Giannone and Reichlin, 2006, Fernandez-Villaverde *et al.*, 2007, Chari *et al.*, 2008, Forni and Gambetti, 2011. In essence, the problem is that standard SVAR methods assume that the structural shocks are linear combinations of the residuals obtained by estimating a VAR. If the structural MA representation of the variables included in the VAR is non-fundamental, the structural shocks are not linear combinations of such residuals, so that the method fails.[5]

[5] An MA representation is fundamental if and only if the associated matrix is full column rank (i.e. the rank is equal to the number of shocks) for all L with modulus less than one (see Rozanov, 1967, Ch. 2). This condition is slightly different from invertibility, since invertibility requires full column rank also for L with unit modulus. Hence non-fundamentalness implies non-invertibility, whereas the converse is not true. When the variables are cointegrated, for instance, the MA representation of the first differences is not invertible, but nonetheless can be fundamental. In such a case, non-invertibility can be easily circumvented by resorting to structural ECM or level VAR estimation. Non-fundamentalness is a kind of non-invertibility which cannot be solved in this way.

In most of the economic literature, the structural shocks are elements of agents' information set and non-fundamentalness may arise if the econometrician uses less information than the agents. In this case, non-fundamentalness can in principle be solved by enlarging the information set used by the econometrician (Forni, Giannone, Lippi and Reichlin, 2009, Forni and Gambetti, 2011). But in the present setting non-fundamentalness stems from agents' ignorance and cannot be solved by adding variables to the VAR. The economic intuition is that agents' behavior cannot reveal information that agents do not have. Consumption or other variables which are the outcome of agents' decisions do not add anything to the information already contained in a_t and s_t. More generally, in models assuming that agents cannot see the structural shocks, the structural representation is non fundamental for whatever set of observable variables. For, if it were, agents could infer the shocks from the variables themselves, contrary to the assumption.

2.4 Agents' innovations and structural shocks

As discussed above, the relevant shocks cannot be found by using standard VAR methods. Hence a question arises: what shocks would the econometrician recover by running a VAR for potential output and the signal? To answer to this question we need to find shocks which are fundamental for Δa_t and s_t. Consider the representation

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}. \tag{7}$$

Representation (7) can be rewritten as the Wold decomposition:

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} 1 & L\sigma_\varepsilon^2/\sigma_s^2 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix} \tag{8}$$

where

$$\begin{pmatrix} u_t \\ s_t \end{pmatrix} = \begin{pmatrix} L\frac{\sigma_v^2}{\sigma_s^2} & -L\frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}, \tag{9}$$

since (8) and (9) imply (7). Notice that u_t and s_t are jointly white noise and orthogonal with variance $\sigma_u^2 = \sigma_v^2\sigma_\varepsilon^2/\sigma_s^2$ and σ_s^2 respectively.[6] Moreover, the determinant of the matrix in (8) is 1, so that the corresponding representation is fundamental, implying that u_t and s_t are innovations of agents' information set. The shock u_t can be interpreted as the "learning" shock, as it represents the new information about past structural shocks, resulting from observing present and past Δa_t and s_t.

In conclusion, by running a VAR for Δa_t and s_t, the econometrician would not recover the structural shocks ε_t and v_t, but rather two shocks – learning and signal – which are

[6] To see that u_t and v_t are jointly white noise, observe that the covariance of u_t and s_{t-1} is $\sigma_v^2\sigma_\varepsilon^2/\sigma_s^2 - \sigma_\varepsilon^2\sigma_v^2/\sigma_s^2 = 0$.

combinations of present *and past* values of the structural shocks. Of course, standard identification schemes would fail, since no linear combination of the two innovations at time t can deliver the structural shocks.

The next question is: can the true structural shocks be recovered and how? The answer is yes, using the future values of the fundamental shocks. As already observed, after one period the observation of potential output unveils the news or noise nature of the signal. Indeed, representation (9) can be inverted toward the future:

$$\begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix} = \begin{pmatrix} L^{-1} & \frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ -L^{-1} & \frac{\sigma_v^2}{\sigma_s^2} \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}. \tag{10}$$

The above equation shows that the structural shocks, though not recoverable as static linear combinations of the VAR residuals, can be obtained as *dynamic* linear combinations, involving future values. This is the key result we will use in the econometric section to identify news and noise.

2.5 Agents' "learning": a comparison with BLLH and BS

A crucial novelty of our model with respect to existing literature is agents' learning process. For the sake of comparison, let us recast the BLLH model, with minor modifications, in our notation. BLLH assumes that a_t is the sum of two components: a permanent one (which may affect a_t on impact), driven by the shock ε_t, and a temporary one, driven by the shock η_t. More specifically,

$$a_t = a_{t-1} + (1 - \rho L)^{-1}\varepsilon_t + (1 - L)(1 - \rho L)^{-1}\eta_t. \tag{11}$$

The signal is the same as in our model and is given by equation (2). As in our model, agents can observe a_t and the signal s_t.

The key difference between this model and ours is the reason why observing a_t and s_t does not reveal the structural shocks. In our model, agents cannot see the structural shocks because the shock affecting potential output has delayed effects; in other words, because it is a news shock. On the other hand, in BLLH, non-observability is due to the fact that there is also a temporary shock; that is, there are three shocks and only two dynamically independent observable variables. Similarly, the model proposed in BS for productivity and the signal has three shocks and just two variables.

This has a crucial implication. In our model, as time goes by, agents can recover past shocks exactly: in the simple version of the model described above, they learn everything after one period; in a more general setting (see section 3) agents learn gradually, but in the long run they can see past shocks without error. By contrast, in both BLLH and BS, agents never learn completely the news or noise nature of past shocks. In both models, the MA equilibrium representation for the observable variables is rectangular, with more columns than rows. For instance, in BLLH we have

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} (1-\rho L)^{-1} & 0 & (1-L)(1-\rho L)^{-1} \\ 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \\ \eta_t \end{pmatrix}. \tag{12}$$

Obviously, (12) cannot be inverted, not even in the future: past shocks cannot be written as dynamic linear combinations of the observables.

Similarly, the implications of our model for VAR analysis are different from what found in the previous literature. In the frameworks of BLLH and BS, VAR methods fail because it is impossible to estimate the impulse response functions of three independent shocks —as well as the shocks themselves— with a bivariate VAR. In our framework instead, as we will show below, SVAR models can be employed successfully, as long as dynamic identifications are used.

3 The econometric model

In this section we generalize the simple model of section 2.4 and propose our dynamic identification procedure.

Dynamic structural VAR identification is discussed in detail in Lippi and Reichlin, 1994. In their more general framework, the conditions required to reach identification are very demanding. The econometrician should know the relevant unitary dynamic transformation (the so called "Blaschke matrix"), which is characterized by the roots of the determinant of the structural representation that are smaller than one in modulus. Economic theory can hardly provide such information.

In the present setting, however, a restriction arises quite naturally from the theory: the conceptual distinction between news and noise shocks requires that Δa_t, the variable representing economic fundamentals, *is not affected by noise at any lag.* As a consequence, the reaction of Δa_t to past signals s_{t-1}, and "true" news ε_{t-1}, are equal, up to a multiplicative constant which is given by the signal-to-noise variance ratio. This in turn implies that the "wrong" roots of the structural representation are revealed by the impulse response function of Δa_t to the signal s_t, which can be estimated.

3.1 Structural and fundamental representations

Let us consider a more general specification for potential output,

$$\Delta a_t = c(L)\varepsilon_t, \tag{13}$$

where $c(L)$ is a rational function in L with $c(0) = 0$. The structural representation becomes

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} c(L) & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}, \tag{14}$$

This 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 ε_t and v_t.

As seen before, 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

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

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

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s^2} \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}, \tag{15}$$

where

$$\begin{pmatrix} u_t \\ s_t \end{pmatrix} = \begin{pmatrix} b(L)\frac{\sigma_v^2}{\sigma_s^2} & -b(L)\frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix} \tag{16}$$

As before, u_t and s_t are orthogonal innovations for agents' information set, so that $\mathcal{I}_t = \text{span}(u_{t-k}, s_{t-k}, k \geq 0)$.[7]

The relation between the fundamental shocks and the structural shock is given by

$$\begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix} = \begin{pmatrix} b(F) & \frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ -b(F) & \frac{\sigma_v^2}{\sigma_s^2} \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}. \tag{17}$$

where F is the forward operator, i.e. $F = L^{-1}$.[8] As in the previous section, the structural shocks depend on future fundamental innovations, with the difference that here the news or noise nature of the signal unveils in the long run, rather than after one period.

We further assume that the signal is not observable to the econometrician but there is one observable variable, z_t, which reveals the signal. In principle such a variable may

[7] To see this, observe that the determinant of the matrix in (15), i.e. $c(L)/b(L)$, vanishes only for $|L| \geq 1$ because of the very definition of $b(L)$.

[8] Observe that $1/b(L) = b(F)$.

depend on both s_t and u_t. Therefore we can write the representation of Δa_t and z_t as

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} a_{11}(L) & a_{12}(L) \\ a_{21}(L) & a_L(L) \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix} \tag{18}$$

where, following the usual econometric convention, the shocks are normalized to have unit variance. Observe however that the above representation is not necessarily fundamental, since the determinant of the MA matrix depends on $d(L)$ and $f(L)$. In order to have fundamentalness, z_t has to be sufficiently informative to reveal the signal. In the reminder of this section we assume fundamentalness of (18); in the empirical section we will test for this property.

Moreover,

$$\begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix} = \begin{pmatrix} \frac{b(L)\sigma_v^2\sigma_\varepsilon}{\sigma_u\sigma_s^2} & -\frac{b(L)\sigma_\varepsilon^2\sigma_v}{\sigma_s^2\sigma_u} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix} \tag{19}$$

so that the structural representation is

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} c(L)\sigma_\varepsilon & 0 \\ f(L)\sigma_\varepsilon + b(L)d(L)\frac{\sigma_\varepsilon\sigma_v^2}{\sigma_s^2} & f(L)\sigma_v - b(L)d(L)\frac{\sigma_v\sigma_\varepsilon^2}{\sigma_s^2} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix} \tag{20}$$

3.2 Dynamic identification

Dynamic identification of the structural shocks is done in two parts. First we estimate and identify the fundamental representation (18); second we identify (19). Given the estimates of the two representations, an estimate of representation (20) immediately follows.

More specifically, the steps are the following.

1. Estimate an unrestricted VAR for Δa_t and z_t and compute the MA representation.

2. Impose that $a_{12}(0) = 0$. This condition implies that s_t does not affect Δa_t and comes from the theoretical restriction $c(0) = 0$. In the bivariate case, this is sufficient to identify the two fundamental shocks u_t and s_t and estimate all the elements of the matrix of the impulse response functions of representation (18).

3. Let us call $\hat{a}_{12}(L)$ the estimate of $c(L)\sigma_\varepsilon^2/\sigma_s$ (see equation (18)). An estimate $\hat{b}(L)$ of $b(L)$ can be obtained as follows. Compute the roots of $\hat{a}_{12}(L)$ and select the roots which are smaller than one in modulus (of course, one out of these roots will be zero by construction, because of the identifying assumption $c(0) = 0$ of step 1). Using the roots which are smaller than one in modulus, estimate the polynomial $b(L)$ in equation (3.1).

4. Let $\hat{a}_{11}(L)$ be the estimate of $a_{11}(L)$, i.e. our estimate of $c(L)\sigma_u/b(L)$, and observe that $b(1) = 1$. Estimate $\sigma_\varepsilon/\sigma_v$ as the ratio[9]

$$\frac{\hat{a}_{12}(1)}{\hat{a}_{11}(1)}.$$

5. Using the property that: $\sigma_v^2/\sigma_s^2 + \sigma_\varepsilon^2/\sigma_s^2 = 1$, $\widehat{\sigma_\varepsilon/\sigma_s}$ and $\widehat{\sigma_v/\sigma_s}$ are obtained as $\sin(\arctan(\widehat{\sigma_\varepsilon/\sigma_v}))$ and $\cos(\arctan(\widehat{\sigma_\varepsilon/\sigma_v}))$, respectively.

These five steps give the estimates of all the elements of representations (18) and (19) and consequently of all the elements in (20).

The (normalized) structural shocks $\varepsilon_t/\sigma_\varepsilon$ and v_t/σ_v can be estimated by inverting equation (19). Since the determinant of the matrix in (19) $1/b(L) = b(F)$ involves future values of u_t and s_t, the structural shocks cannot be estimated consistently at the end of the sample. This is in line with the assumption that neither the agents, nor the econometrician can see the current values of the structural shocks. However, in the middle of the sample the future is known and (17) can in principle provide reliable estimates of $\varepsilon_t/\sigma_\varepsilon$ and v_t/σ_v. Such estimates can be used in combination with the corresponding response functions to decompose the series into the news and noise components and assess their importance in terms of explained variance.

Let us remark that the theoretical restrictions appearing in the first line of representation (18) are only partially exploited for identification and therefore can be used for testing. Such restrictions entail that in the structural representation (20) the impulse response function of Δa_t to a noise shock be identically zero, an hypothesis that can be easily verified by looking at the confidence bands.[10]

3.3 Multivariate specifications

Let us now consider a multivariate extension of the bivariate model described so far. This model will be used in the empirical section to investigate the role of noisy news in generating cyclical fluctuations.

Let Δw_t be an $n-2$-dimensional vector of additional variables. In order to have a square system, it is convenient to assume that there are also $n-2$ additional shocks, potentially affecting a_t. Equation (1) becomes

$$\Delta a_t = c(L)\varepsilon_t + g(L)e_t, \tag{21}$$

[9]In practice we compute the cumulated long-run effects as the effects at forty quarters.

[10]The identification restrictions 1-5 impose a zero impact effect and a zero long-run cumulated effect; but between lag 0 and the maximal lag the impulse response function can be significantly different from zero.

where e_t is an $n-2$-dimensional white noise vector with identity variance covariance matrix, orthogonal to ε_t at all leads and lags, and $g(L)$ is an $n-2$-dimensional row vector of rational functions in L. Moreover, we assume for simplicity that agents can observe e_t.

Under these assumptions, the "innovation" representation can be written as

$$\begin{pmatrix} \Delta a_t \\ z_t \\ \Delta w_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} & g(L) \\ d(L)\sigma_u & f(L)\sigma_s & p(L) \\ q(L) & h(L) & m(L) \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \\ e_t \end{pmatrix} \tag{22}$$

where $p(L)$, $q(L)$, $h(L)$ and $m(L)$ are conformable vectors and matrices of rational functions in L. Again, we assume fundamentalness of such representation. The corresponding structural representation is obtained by postmultiplying the above matrix by

$$\begin{pmatrix} \frac{b(L)\sigma_v^2\sigma_\varepsilon}{\sigma_u\sigma_s^2} & -\frac{b(L)\sigma_\varepsilon^2\sigma_v}{\sigma_s^2\sigma_u} & 0' \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} & 0' \\ 0 & 0 & I_{n-2} \end{pmatrix} \tag{23}$$

where 0 denotes the $n-2$-dimensional column vector of zeros.

Within the multivariate framework, the condition that the news shock does not affect a_t on impact is no longer sufficient, alone, to identify the model. To identify the learning shock u_t and the signal s_t, we impose a Cholesky triangularization with the ordering Δa_t, z_t and Δw_t. The learning and signal shocks will be the first two Cholesky shocks. The reason for this identification is that we want to allow for a contemporaneous effect of u_t and s_t on Δw_t. The drawback of this identification scheme is that Δa_t is not allowed to react contemporaneously to s_t and e_t, while z_t is not allowed to react contemporaneously to e_t. For this reason we will also try a different scheme where Δw_t is ordered first, Δa_t and z_t second and third, respectively. The shocks u_t and s_t will be the last two Cholesky shocks.

4 Evidence

In this section, we apply the methods described above to study the role of news and noise as sources of business cycle fluctuations. The main conclusion is that both news and noise shocks explain a sizable fraction of the forecast error variance of GDP, consumption and investment at business cycle horizons.

4.1 Data

The first step of our empirical analysis is to choose two series for a_t and z_t. Remind that the former is the variable representing economic fundamentals, which is unaffected by noise, while the latter is a variable revealing the signal.

To represent a_t we take the log of US potential GDP from the CBO (GDPPOT), divided by population aged 16 years or more (civilian noninstitutional population). We choose per-capita potential output rather than total factor productivity (TFP), which is widely used in the news shock literature, because TFP does not pass the test described at the end of Section 3.2., that is we find that it is significantly affected by noise, contrary to a basic assumption of our model.

We use expected business conditions within the next 12 months (E12M), which is a component of the consumer confidence index from the Michigan University Consumer Survey, to represent z_t.[11] In the robustness exercise below we try two alternative series for z_t, i.e. the Conference Board leading economic indicators index and the Standard & Poor's index of 500 common stocks. The latter variable is obtained from the monthly S&P500 index provided by Datastream. We converted the series in quarterly figures by taking simple averages and divided the resulting series by the GDP implicit price deflator in order to express it in real terms. The resulting series is taken in logs.

Since we are interested in evaluating the business cycle effects of news and noise, we take in addition from the NIPA tables real GDP, real consumption, obtained as the sum of nondurables and services, and real investment, obtained as the sum of private investment and durable consumption. All variables are divided by civilian noninstitutional population and taken in logs.

Finally, in order to test for fundamentalness of the VAR, expressed in representation (22), we use the principal components form a large data set of macroeconomic variables. Such variables, along with the corresponding transformations, are reported in the Appendix. The time span of all data is 1960 I — 2010 IV.

4.2 VAR specification and the fundamentalness test

Our benchmark VAR specification includes potential GDP, E12M, real GDP (GDP), real consumption of nondurables and services (CONS) and real private investment plus consumption of durables (INV). To avoid potential cointegration problems we estimate the VAR in levels. According to the AIC criterion we include four lags.

As explained in Section 3, identification is obtained by assuming that potential GDP reacts on impact only to the learning shock and that expected business conditions react on impact to the learning and signal shocks. This implies that the two shocks can be found as the first two Cholesky shocks of the model with potential GDP ordered first and expected business conditions ordered second. Such a scheme has the feature that GDP, consumption and investment can react on impact to both learning and signal shocks. The

[11]Similar results, not shown here, are obtained with the expected confidence index and expected business condition over the next 5 years, which is another component of the consumer sentiment index, extensively discussed in BS.

structural representation is obtained by following the procedure explained in Section 3. Before identifying shocks, impulse response functions from the VAR in levels have been differenced.

As a first step, we test for fundamentalness of representation (22) as suggested in Forni and Gambetti, 2011. The idea underlying their method is simple: if representation (22) is fundamental, i.e. if the variables used in the VAR span the information set of the agents, then the estimated shocks (learning and signal) must be orthogonal to all available past information. The same orthogonality necessary condition holds *a fortiori* for the structural shocks, news and noise, which are linear combination of present and future values of learning and signal shocks.

To represent available macroeconomic information we take the principal components of the US macroeconomic data set reported in the Appendix. Table 1 reports the p-values of the F-test of the regression of the estimated shocks on 2 and 4 lags of the first j principal components, with $j = 1, ..., 6$. The null of orthogonality is never rejected.

For comparison, we report the corresponding results for the VAR including only GDPPOT and E12M (Table 2). For the bivariate specification, orthogonality of signal, news and noise shocks is rejected, indicating that potential income and the confidence index do not convey enough information to recover the signal and the structural shocks.

4.3 Impulse response functions

Figures 1 and 2 depict the impulse response functions of the five variables to learning and signal shocks. Shaded areas are confidence bands at the 68% and 90% level. As expected, the signal shock has a large and significant impact effect on consumers' confidence and anticipates significantly future potential GDP. Moreover, it has a positive and significant impact effect on consumption, investment and realized GDP, reaching its maximum at the 2-year horizon. Afterwards, the effect declines, while, at the same time, the effect of learning increases and becomes significant. As agents learn about the past news and noise shocks by looking at potential GDP, they partially correct their previous response to the signal.

Figure 3 reports the impulse response functions of potential GDP and E12M to news and noise shocks. The noise, as predicted by the model, has no effects on potential output at all horizons. On the contrary, the response of potential output to the news shock increases steadily, after a zero initial effect, reaching its new long run level after about five years.

As for the consumer confidence indicator, both news and noise have a significant impact effect, but the effect of noise is larger, reflecting the estimate of $\sigma_\varepsilon/\sigma_s$ which is only 0.40, as against an implied estimate of σ_v/σ_s of 0.91.

Next we turn our attention to GDP, consumption and investment (Figure 4). The responses of the three variables to all shock have similar shapes. In the case of the noise shock, the responses are hump-shaped with a relatively small, although significant, impact effect; they reach a maximum after about two years, then decline approaching zero after about five years. On the contrary, the responses to genuine news shocks are permanent. As predicted by the model, noise shocks spur a wave of private consumption and investment which vanishes once economic agents realize that the signal was just noise.

4.4 Variance decomposition

Variance decompositions are reported in Table 3. The signal shock explains a relatively small fraction of potential output volatility (about 23% at the four-year horizon), but a very large fraction of realized GDP, consumption and investment (about 50-60% at the 2-year and the 4-year horizons). This seems consistent with the general idea that signals, while providing a rather imperfect anticipation of future changes of economic fundamentals, are an important source of business cycle fluctuations.

Turning to the analysis of noise and news shocks, business cycle fluctuations are largely driven by noise, which accounts for 30-40% of the forecast error variance of the three variables at the two-year horizon. The news shock has a sizable, but more limited role in the short run, accounting for about 20-25% of the variance of GDP and consumption at the 2-year horizon. Investment, in particular, is largely dominated by noise, which explains 45% of fluctuations at the 2-year horizon, as against only 5% for "genuine" news.

News shocks explain most of the variance of potential output at all horizons. By contrast, consistently with the impulse response functions of Figure 3, the variance of the consumer confidence indicator E12M is largely dominated by noise shocks, that is, shocks unrelated to economic fundamentals. This finding supports the "animal spirit" interpretation of consumer sentiment and is in sharp contrast with what obtained in BS, where fluctuations of confidence indicators are almost entirely attributable to news.

Noise and news shock together explain more than half of the fluctuations GDP, consumption and investment at horizons ranging from 2 to 4 years. This finding and the fact that the two shocks generate positive co-movements between GDP, consumption and investment in the short and medium run, drives us to the main conclusion that noisy expectations of future changes in economic fundamentals, which in large part do not eventually materialize, should be considered a major source of business cycles.

Let us discuss the case of an econometrician that assumes that noise shocks do not exist. He/she therefore mistakenly identifies the signal shock as the news shock (when news shocks are absent, a shock that does not move on impact potential output is a news shock) and will conclude that news shocks explain approximately 50-60% of real variables. The econometrician will therefore attribute a higher role to news shocks, while a significant part of business cycle fluctuations is driven by noise shocks.

The results on the relative role of news and noise shocks differ substantially with what found in previous literature. First, the role of noise is much larger than in BS, where "animal spirits" have negligible effects. Second, they are qualitatively different from what found in BLLH, where noise explain a very large fraction of consumption fluctuations on impact, a small fraction of consumption variance at the 3-year horizon, and almost nothing of investment fluctuations at all horizons. Such large differences call for some explanations. For the reasons explained in Section 2, the results of BLLH and BS are not obtained by estimating a structural VAR. They specify a theoretical model and estimate the parameters of the model. A shortcoming of such procedure is that it requires strong *a priori* restrictions on the dynamic responses of the variables to the structural shocks. For instance, BLLH assumes that the impulse response function of Δa_t to the news shock is $1/(1-\rho L)$, whereas BS assumes $L/(1-\alpha L)$. Both models assume that there is a second shock affecting productivity; BS assumes a permanent shock with no dynamic at all, whereas BLLH assumes a transitory shock with response function $(1-L)/(1-\rho L)$, the parameter ρ being the same as before. Clearly such restrictions are arbitrary to a large extent and may in principle have important effects on the final results. From this point of view, structural VAR methods have the advantage that the dynamic shape of the impulse response functions is quite general. Here, impulse response functions are obtained by imposing standard Choleski identification restrictions, along with the condition that Δa_t does not react contemporaneously to noise.

4.5 Historical decomposition

Figure 5 reports the yearly growth rates of GDP (top panel) and the cyclical component of real GDP (bottom panel), as well as the component of the two series due to the noise shock over the last two decades.[12]

Several interesting results emerge. First, during the boom of the late 90s the noise is responsible for about half of the growth rate of GDP. Second, the shock substantially contributes to the 2001 recession and the slow recovery of the following two years. The low pace consumption and investment growth of the 2002 and 2003, according to the picture, was largely attributable to bad signals about future potential output outcomes which ex-post turned out to be just noise. Between 2004 and 2006 the shock again substantially contributed to the economic expansion. It is interesting to notice that the periods 1995-2000 and 2003-2006 were associated to asset prices bubbles.

[12]The cyclical component of GDP is obtained by filtering the log of per-capita GDP with a band-pass filter retaining waves of periodicity between 6 and 32 quarters.

In a companion paper, we show that noise in stock prices fully explains the information technology boom of the stock market at the end of the nineties and the subsequent burst (Forni, Gambetti, Lippi and Sala, 2013).

4.6 An alternative identification

The drawback of our identification procedure is that, presumably, also other shocks in addition to learning and the signal, could affect expected economic conditions contemporaneously. For this reason we implement an alternative Cholesky identification, where potential GDP and expected business conditions are ordered fourth and fifth, respectively. With this identification, both potential output and consumer sentiment are allowed to react contemporaneously to all other shocks.

Figure 6 and 7 reports the impulse response functions for the alternative identification (dashed lines) as well as the point estimates and the confidence bands obtained in the benchmark specification (solid line and gray areas). The results of the two identification schemes are qualitatively and quantitatively similar.

Table 4 reports the variance decomposition for the alternative identification. The fraction of forecast error variance attributable to both noise and news shocks is slightly reduced as compared with Table 3, but the two shocks taken together still account for about 50-60% of the variance of the three variables at the 4-year horizon.

4.7 Alternative proxies for the signal

In this subsection we repeat the analysis done in the previous section for the benchmark specification using different proxies for the signal. In particular we replace expected business conditions with real stock prices (S&P500) and the Conference Board Leading Economic Indicators Index. The two variables are ordered second after the potential GDP. Figure 8 plots the impulse response obtained in the two new specifications (dashed and dashed-dotted lines) as well as the point estimate and the confidence bands obtained in the benchmark specification (solid line and gray areas).

The results for the new specifications are again qualitatively similar to those obtained in the benchmark case with a few differences. In particular, with stock prices the responses of GDP, consumption and investment to the noise shock tend to be larger than those obtained with the two other specifications, and, consequently noise shocks even more important for cyclical fluctuations.

Figures 9 and 10 report the historical decomposition of GDP for the two new specifications. The results are similar to those obtained in the benchmark specification. The ups and downs in the noise component are well synchronized with fluctuations in GDP. The noise shock substantially contributes to the two booms and the 2001 recession.

5 Conclusions

In this paper we have presented a business cycle model where agents receive imperfect signals about future economic fundamentals. We have shown that in this model the structural MA representation of economic variables is non-fundamental, so that standard structural VAR methods fail. We have argued that this is a general feature of models where economic agents cannot see the structural shocks.

As times goes by, both the agents and the econometrician learn about past structural shocks. A distinguishing feature of our model is that the structural shocks can be recovered exactly from future information. This is is because, unlike existing models with imperfect information, the number of structural shocks is equal to the number of independent sources of informations observed by the agents. We have shown that in this case structural VARs can still be successfully used to estimate the structural shocks and the related impulse response functions, provided that identification is generalized to include dynamic transformations of VAR residuals.

In the empirical section, we have estimated a VAR and imposed a dynamic scheme to identify news and noise shocks and the related impulse response functions. We have found that noise and news together explain more than half of the fluctuations of GDP, consumption and investment. A large fraction of such fluctuations is due to noise shocks which generate hump-shaped responses of GDP, consumption and investment and account for about one third of their variance at short- and medium-run horizons. The role of noise shocks is much larger than in BS, where “animal spirits” have negligible effects, and qualitatively different from BLLH, where it explains a very large fraction of consumption fluctuations on impact, but a relatively small fraction of consumption variance at the 3-year horizon and almost nothing of investment fluctuations.

Appendix: Data

Transformations: 1 = levels, 2 = logs, 3 = first differences of logs. Most series are taken from the FRED database. TFP data are taken from the Federal Reserve Bank of San Francisco database. A few stock market and leading indicators are taken from Datastream. Monthly data have been temporally aggregated to get quarterly figures. CNP = Civilian Noninstitutional Population (Fred mnemonic: CNP16OV).

no.series	Transf.	Mnemonic	Long Label
1	2	GDPC1/CNP	Real Gross Domestic Product/CNP
2	2	GNPC96/CNP	Real Gross National Product/CNP
3	2	(NICUR/GDPDEF)/CNP	(National Income/GDP Deflator)/CNP
4	2	DPIC96/CNP	Real Disposable Personal Income/CNP
5	2	OUTNFB/CNP	Nonfarm Business Sector: Output/CNP
6	2	FINSLC1/CNP	Real Final Sales of Domestic Product/CNP
7	2	(FPIC1+PCNDGC96)/CNP	(Real Private Fixed Inv. + Real Durables Cons.)/CNP
8	2	PRFIC1/CNP	Real Private Residential Fixed Investment/CNP
9	2	PNFIC1/CNP	Real Private Nonresidential Fixed Investment/CNP
10	2	GPDIC1/CNP	Real Gross Private Domestic Investment/CNP
11	2	(PCNDGC96+PCESVC96)/CNP	(Real Pers. Cons. Exp.: Non Durables + Services)/CNP
12	2	PCNDGC96/CNP	Real Pers. Cons. Exp.: Nondurable Goods /CNP
13	2	PCDGCC96/CNP	Real Pers. Cons. Exp.: Durable Goods/CNP
14	2	PCESVC96/CNP	Real Pers. Cons. Exp.: Services/CNP
15	2	(GSAVE/GDPDEF)/CNP	(Gross Saving/GDP Deflator)/CNP
16	2	FGCEC1/CNP	Real Federal Cons. Exp. & Gross Investment/CNP
17	2	(FGEXPND/GDPDEF)/CNP	(Federal Gov.: Current Exp./ GDP Deflator)/CNP
18	2	(FGRECPT/GDPDEF)/CNP	(Federal Gov. Current Receipts/ GDP Deflator)/CNP
19	1	CBIC1	Real Change in Private Inventories
20	2	EXPGSC1/CNP	Real Exports of Goods & Services /CNP
21	2	IMPGSC1/CNP	Real Imports of Goods & Services /CNP
22	2	CP/GDPDEF	Corporate Profits After Tax/GDP Deflator
23	2	NFCPATAX/GDPDEF	Nonfin. Corp. Bus.: Profits After Tax/GDP Deflator
24	2	CNCF/GDPDEF	Corporate Net Cash Flow/GDP Deflator
25	2	DIVIDEND/GDPDEF	Net Corporate Dividends/GDP Deflator
26	2	HOANBS/CNP	Nonfarm Business Sector: Hours of All Persons/CNP
27	2	OPHNFB	Nonfarm Business Sector: Output Per Hour of All Persons
28	2	UNLPNBS	Nonfarm Business Sector: Unit Nonlabor Payments
29	2	ULCNFB	Nonfarm Business Sector: Unit Labor Cost
30	2	WASCUR/CPI	Compensation of Employees: Wages & Salary Accruals/CPI
31	3	COMPNFB	Nonfarm Business Sector: Compensation Per Hour
32	2	COMPRNFB	Nonfarm Business Sector: Real Compensation Per Hour
33	3	GDPCTPI	Gross Domestic Product: Chain-type Price Index
34	3	GNPCTPI	Gross National Product: Chain-type Price Index
35	3	GDPDEF	Gross Domestic Product: Implicit Price Deflator
36	3	GNPDEF	Gross National Product: Implicit Price Deflator
37	2	INDPRO	Industrial Production Index
38	2	IPBUSEQ	Industrial Production: Business Equipment
39	2	IPCONGD	Industrial Production: Consumer Goods

no.series	Transf.	Mnemonic	Long Label
40	2	IPDCONGD	Industrial Production: Durable Consumer Goods
41	2	IPFINAL	Industrial Production: Final Products (Market Group)
42	2	IPMAT	Industrial Production: Materials
43	2	IPNCONGD	Industrial Production: Nondurable Consumer Goods
44	1	AWHMAN	Average Weekly Hours: Manufacturing
45	1	AWOTMAN	Average Weekly Hours: Overtime: Manufacturing
46	1	CIVPART	Civilian Participation Rate
47	2	CLF16OV	Civilian Labor Force
48	2	CE16OV	Civilian Employment
49	2	USPRIV	All Employees: Total Private Industries
50	2	USGOOD	All Employees: Goods-Producing Industries
51	2	SRVPRD	All Employees: Service-Providing Industries
52	2	UNEMPLOY	Unemployed
53	2	UEMPMEAN	Average (Mean) Duration of Unemployment
54	1	UNRATE	Civilian Unemployment Rate
55	2	HOUST	Housing Starts: Total: New Privately Owned Housing Units Started
56	1	FEDFUNDS	Effective Federal Funds Rate
57	1	TB3MS	3-Month Treasury Bill: Secondary Market Rate
58	1	GS1	1- Year Treasury Constant Maturity Rate
59	1	GS10	10-Year Treasury Constant Maturity Rate
60	1	AAA	Moody's Seasoned Aaa Corporate Bond Yield
61	1	BAA	Moody's Seasoned Baa Corporate Bond Yield
62	1	MPRIME	Bank Prime Loan Rate
63	3	M1SL	M1 Money Stock
64	3	M2MSL	M2 Minus
65	3	M2SL	M2 Money Stock
66	3	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks
67	3	CONSUMER	Consumer (Individual) Loans at All Commercial Banks
68	3	LOANINV	Total Loans and Investments at All Commercial Banks
69	3	REALLN	Real Estate Loans at All Commercial Banks
70	3	TOTALSL	Total Consumer Credit Outstanding
71	3	CPIAUCSL	Consumer Price Index For All Urban Consumers: All Items
72	3	CPIULFSL	Consumer Price Index for All Urban Consumers: All Items Less Food
73	3	CPILEGSL	Consumer Price Index for All Urban Consumers: All Items Less Energy
74	3	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy
75	3	CPIENGSL	Consumer Price Index for All Urban Consumers: Energy
76	3	CPIUFDSL	Consumer Price Index for All Urban Consumers: Food
77	3	PPICPE	Producer Price Index Finished Goods: Capital Equipment
78	3	PPICRM	Producer Price Index: Crude Materials for Further Processing
79	3	PPIFCG	Producer Price Index: Finished Consumer Goods
80	3	PPIFGS	Producer Price Index: Finished Goods
81	3	OILPRICE	Spot Oil Price: West Texas Intermediate
82	3	USSHRPRCF	US Dow Jones Industrials Share Price Index (EP) NADJ
83	2	US500STK	US Standard & Poor's Index if 500 Common Stocks
84	2	USI62...F	US Share Price Index NADJ
85	2	USNOIDN.D	US Manufacturers New Orders for Non Defense Capital Goods (B CI 27)
86	2	USCNORCGD	US New Orders of Consumer Goods & Materials (BCI 8) CONA
87	1	USNAPMNO	US ISM Manufacturers Survey: New Orders Index SADJ

no.series	Transf.	Mnemonic	Long Label
88	2	USCYLEAD	US The Conference Board Leading Economic Indicators Index S ADJ
89	2	USECRIWLH	US Economic Cycle Research Institute Weekly Leading Index
90	2	GEXPND/GDPDEF/CNP	(Government Current Expenditures/ GDP Deflator)/CNP
91	2	GRECPT/GDPDEF/CNP	(Government Current Receipts/ GDP Deflator)/CNP
92	2	GCEC1/CNP	Real Government Consumption Expenditures & Gross Investment/CNP
93	2		Fernald's TFP growth CU adjusted
94	2		Fernald's TFP growth
95	2		(DOW JONES/GDP Deflator)/Civilian Noninstitutional Population
96	2		(S&P500/GDP Deflator)/Civilian Noninstitutional Population
97	2		Fernald's TFP growth - Investment
98	2		Fernald's TFP growth - Consumption
99	2		Fernald's TFP growth CU - Investment
100	2		Fernald's TFP growth CU - Consumption
101	1		Michigan Consumer Sentiment: Personal Finance Current
102	1		Michigan Consumer Sentiment: Personal Finance Expected
103	1		Michigan Consumer Sentiment: Business Condition 12 Months
104	1		Michigan Consumer Sentiment: Business Condition 5 Years
105	1		Michigan Consumer Sentiment: Buying Conditions
106	1		Michigan Consumer Sentiment: Current Index
107	1		Michigan Consumer Sentiment: Expected Index

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Shock	Lags	Principal Components					
		1	2	3	4	5	6
Learning	2	0.730	0.908	0.892	0.945	0.980	0.962
	4	0.577	0.691	0.773	0.842	0.850	0.699
Signal	2	0.975	0.860	0.594	0.769	0.673	0.718
	4	0.999	0.990	0.909	0.982	0.964	0.938
News	2	0.483	0.355	0.600	0.734	0.812	0.792
	4	0.627	0.575	0.488	0.627	0.702	0.777
Noise	2	0.717	0.883	0.970	0.994	0.995	0.993
	4	0.664	0.616	0.855	0.879	0.934	0.828

Table 1: Results of the fundamentalness test in the 5-variable VAR. Each entry of the table reports the p-value of the F-test in a regression of the shock on 2 and 4 lags of the first differences of the first j principal components, $j = 1, \ldots, 6$.

Shock	Lags	Principal Components					
		1	2	3	4	5	6
Learning	2	0.619	0.861	0.897	0.948	0.983	0.927
	4	0.439	0.492	0.656	0.771	0.845	0.531
Signal	2	0.160	0.066	0.003	0.010	0.007	0.012
	4	0.412	0.141	0.022	0.084	0.108	0.128
News	2	0.042	0.040	0.032	0.072	0.100	0.128
	4	0.122	0.070	0.044	0.094	0.146	0.209
Noise	2	0.338	0.263	0.005	0.012	0.038	0.031
	4	0.397	0.534	0.063	0.135	0.275	0.230

Table 2: Results of the fundamentalness test in the bivariate VAR. Each entry of the table reports the p-value of the F-test in a regression of the shock on 2 and 4 lags of the first differences of the first j principal components, $j = 1, \dots, 6$.

Variable	Horizon				
	Impact	1-Year	2-Years	4-Years	10-Years
	Learning				
GDPPOT	100.0	91.5	78.8	62.6	49.6
E12M	0.1	1.5	5.0	8.1	8.8
GDP	6.4	3.4	4.7	16.3	29.0
CONS	15.3	6.5	7.0	17.7	32.3
INV	0.5	0.9	0.7	4.0	12.3
	Signal				
GDPPOT	0.0	2.9	12.5	23.0	15.2
E12M	99.9	88.9	79.4	65.6	59.4
GDP	8.2	37.2	58.1	57.2	31.7
CONS	5.5	32.3	50.2	54.3	30.0
INV	7.7	36.1	49.0	47.5	35.3
	News				
GDPPOT	0.0	87.4	87.6	81.4	63.1
E12M	16.3	15.1	21.2	23.3	21.2
GDP	1.4	15.7	22.2	39.3	44.3
CONS	1.0	18.7	23.9	41.6	48.9
INV	1.3	3.3	4.6	11.8	18.5
	Noise				
GDPPOT	0.0	4.6	2.1	3.1	1.1
E12M	83.7	75.1	63.0	51.1	47.1
GDP	7.3	24.6	40.0	33.5	16.2
CONS	5.5	19.3	32.4	29.6	13.1
INV	6.5	33.5	45.0	39.3	29.0
	News+Noise				
GDPPOT	0.0	92.0	89.7	84.5	64.1
E12M	100.0	90.2	84.2	74.4	68.3
GDP	8.7	40.2	62.2	72.8	60.4
CONS	6.5	38.0	56.3	71.2	62.0
INV	7.8	36.8	49.7	51.1	47.5

Table 3: Variance decomposition in the 5-variable VAR, E12M ordered second. The entries are the percentage of variance explained by the shocks.

Variable	Horizon				
	Impact	1-Year	2-Years	4-Years	10-Years
	Learning				
GDPPOT	74.9	70.3	58.8	49.1	45.2
E12M	1.2	2.6	6.5	12.3	12.5
GDP	0.0	0.9	1.0	11.5	26.8
CONS	0.0	1.1	1.0	10.2	28.3
INV	0.0	1.9	1.3	7.9	20.7
	Signal				
GDPPOT	0.0	3.2	13.1	26.3	21.0
E12M	88.2	83.6	81.2	69.5	62.6
GDP	0.0	13.0	36.1	48.9	31.1
CONS	0.0	14.1	33.2	48.1	31.5
INV	0.0	15.2	33.1	42.8	34.0
	News				
GDPPOT	0.0	61.6	66.7	71.4	64.7
E12M	21.9	16.8	27.0	32.7	30.1
GDP	0.0	1.3	7.4	31.4	43.9
CONS	0.0	1.2	6.9	30.0	47.1
INV	0.0	1.2	4.5	20.9	32.9
	Noise				
GDPPOT	0.0	5.8	2.2	2.8	1.0
E12M	67.4	69.3	60.5	49.0	45.0
GDP	0.0	12.4	29.4	28.2	13.7
CONS	0.0	13.8	27.1	27.5	12.3
INV	0.0	15.3	29.9	29.1	21.6
	News+Noise				
GDPPOT	0.0	67.4	72.9	76.4	65.1
E12M	89.3	86.1	87.1	80.3	73.3
GDP	0.0	13.7	36.8	59.6	57.6
CONS	0.0	15.0	34.0	57.5	59.4
INV	0.0	16.5	34.4	50.0	54.5

Table 4: Variance decomposition in the 5-variable VAR, E12M ordered last. The entries are the percentage of variance explained by the shocks.

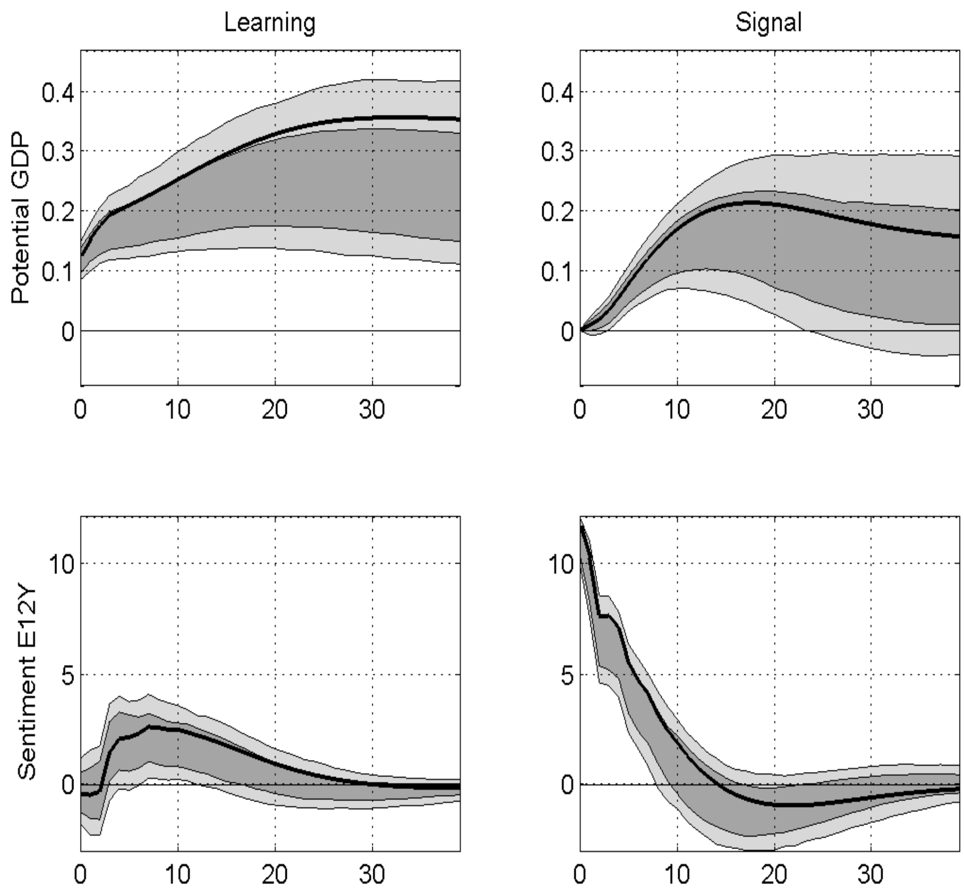

Figure 1: Impulse response functions to learning and signal in the 5-variable VAR. Solid line: point estimate. Dark gray area: 68% confidence bands. Light grey area: 90% confidence bands.

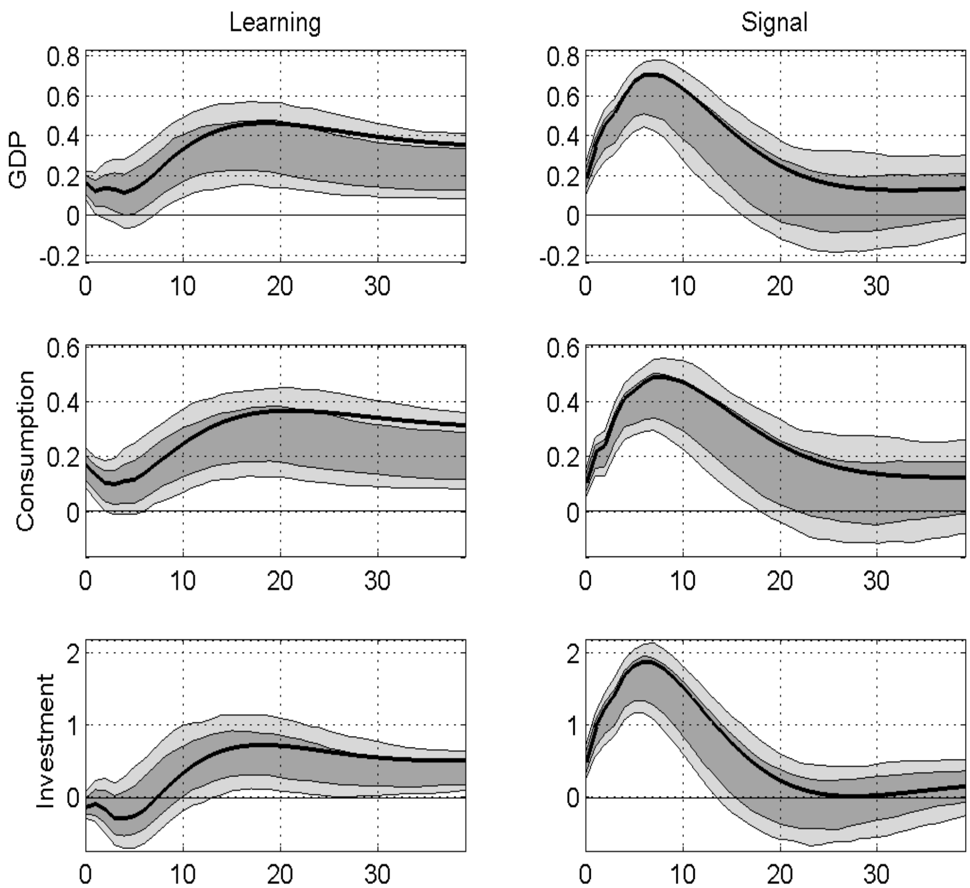

Figure 2: Impulse response functions to learning and signal in the 5-variable VAR. Solid line: point estimate. Dark gray area: 68% confidence bands. Light grey area: 90% confidence bands.

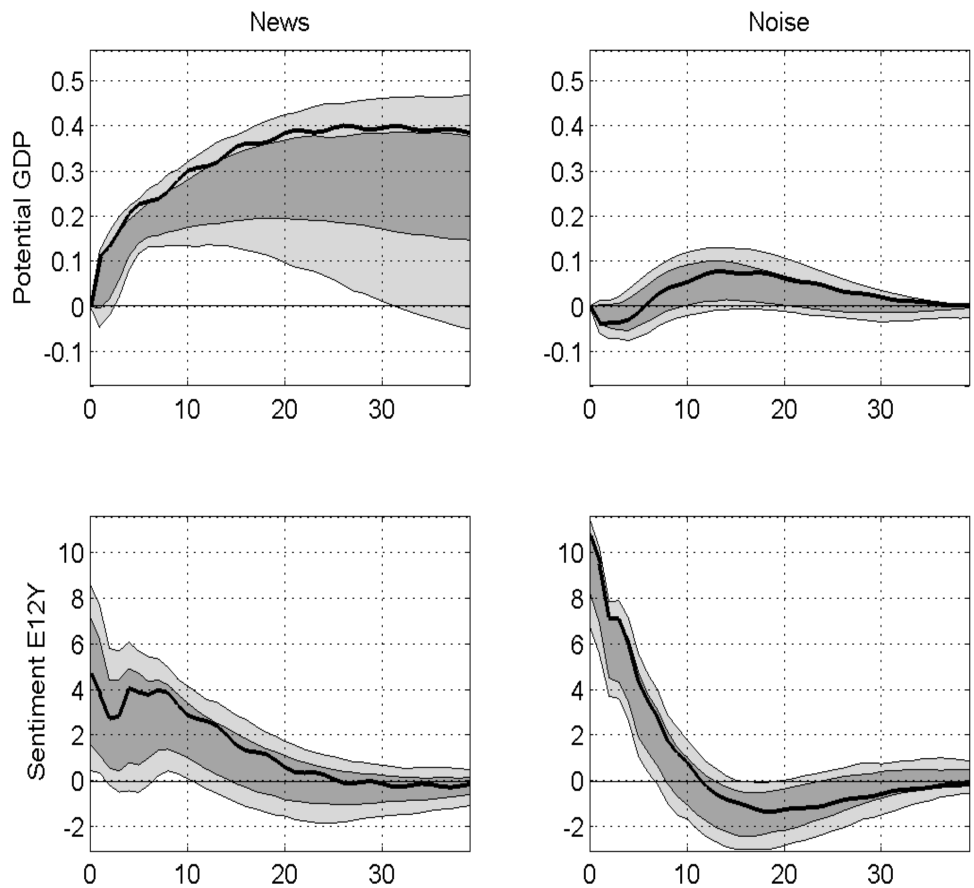

Figure 3: Impulse response functions to news and noise in the 5-variable VAR. Solid line: point estimate. Dark gray area: 68% confidence bands. Light grey area: 90% confidence bands.

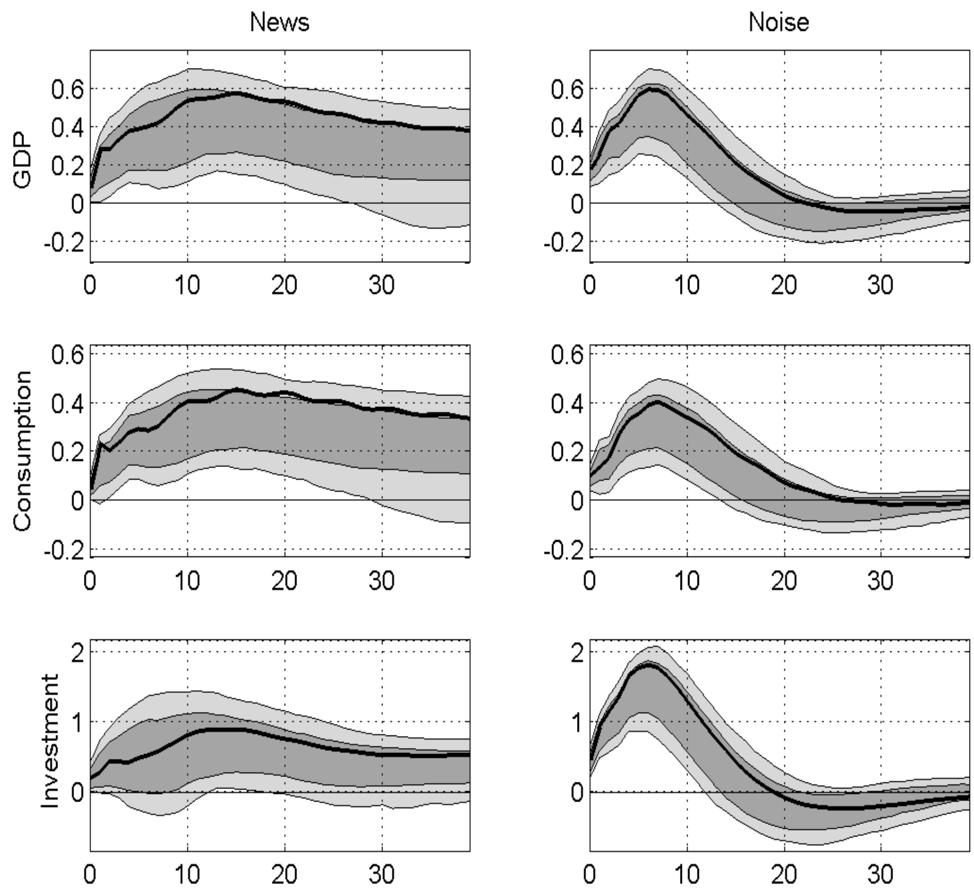

Figure 4: Impulse response functions to news and noise in the 5-variable VAR. Solid line: point estimate. Dark gray area: 68% confidence bands. Light grey area: 90% confidence bands.

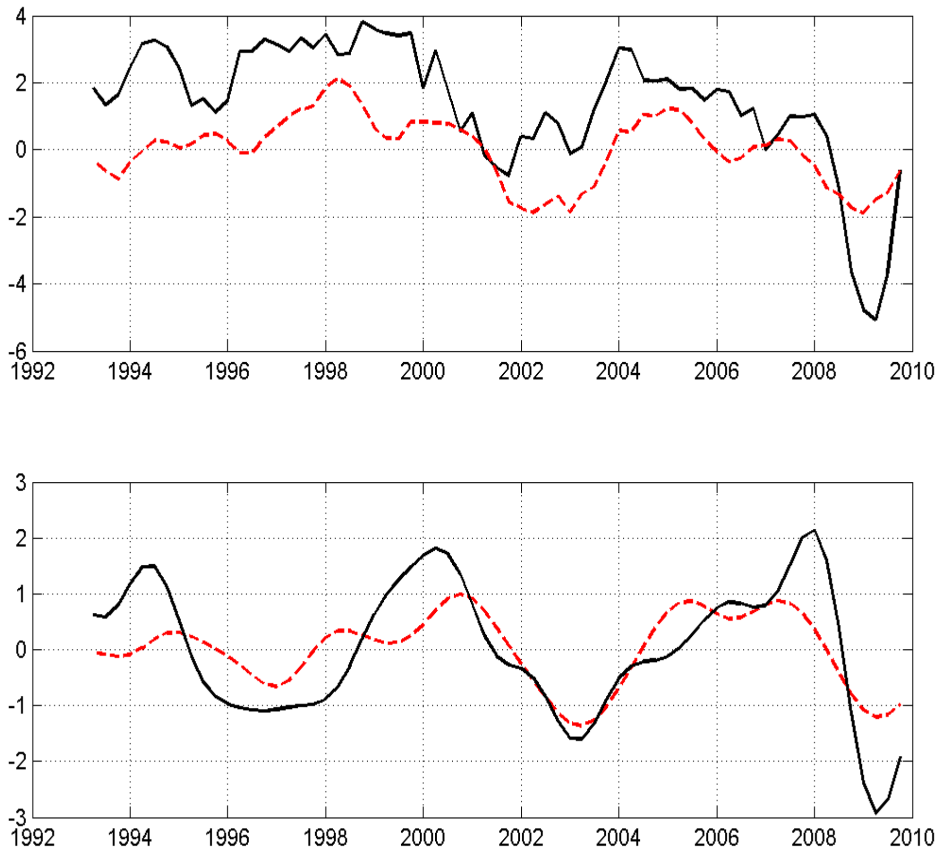

Figure 5: Historical decomposition in the benchmark 5-variable VAR. Top panel: solid line: yearly growth rates of GDP; dotted line: the noise component of the yearly growth rate of GDP. Bottom panel: solid line: business cycle component of real GDP (frequencies between 6 to 32 quarters); dotted line: noise component of the business cycle component of real GDP.

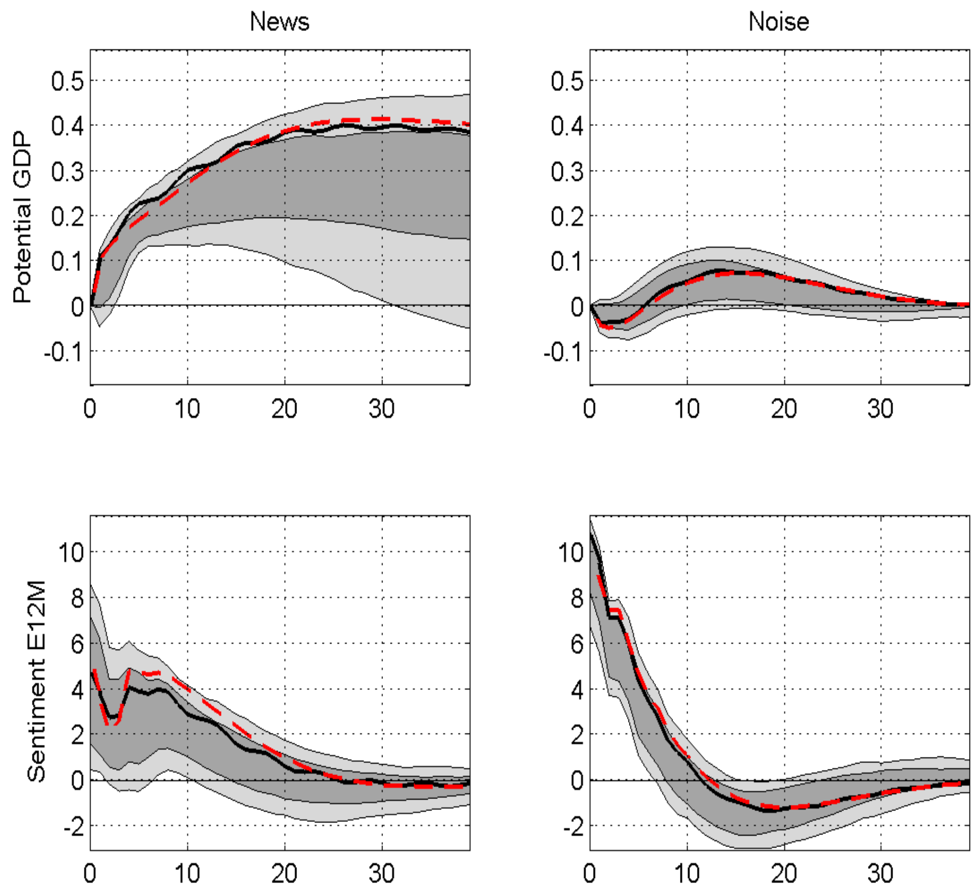

Figure 6: Impulse response functions to news and noise in the 5-variable VAR. Solid line: point estimate of the VAR with E12M ordered second. Dark gray area: 68% confidence bands. Light grey area: 90% confidence bands. Dotted line: point estimate of the VAR with E12M ordered last.

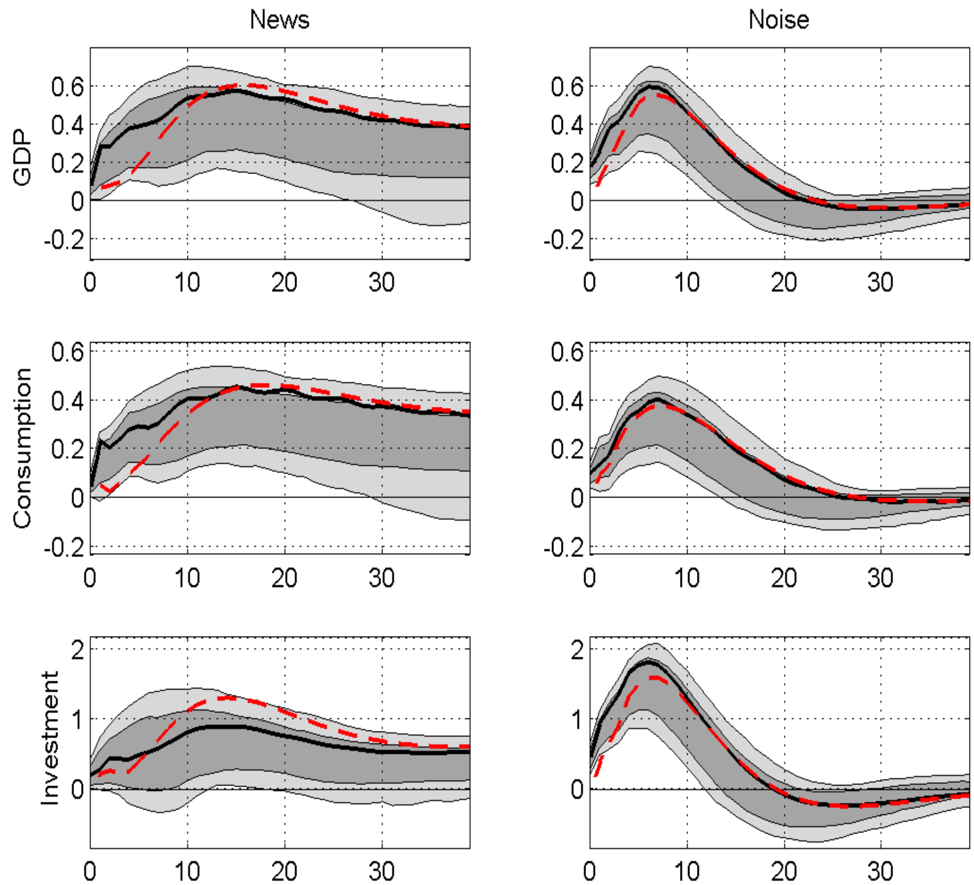

Figure 7: Impulse response functions to news and noise in the 5-variable VAR. Solid line: point estimate of the VAR with E12M ordered second. Dark gray area: 68% confidence bands. Light grey area: 90% confidence bands. Dotted line: point estimate of the VAR with E12M ordered last.

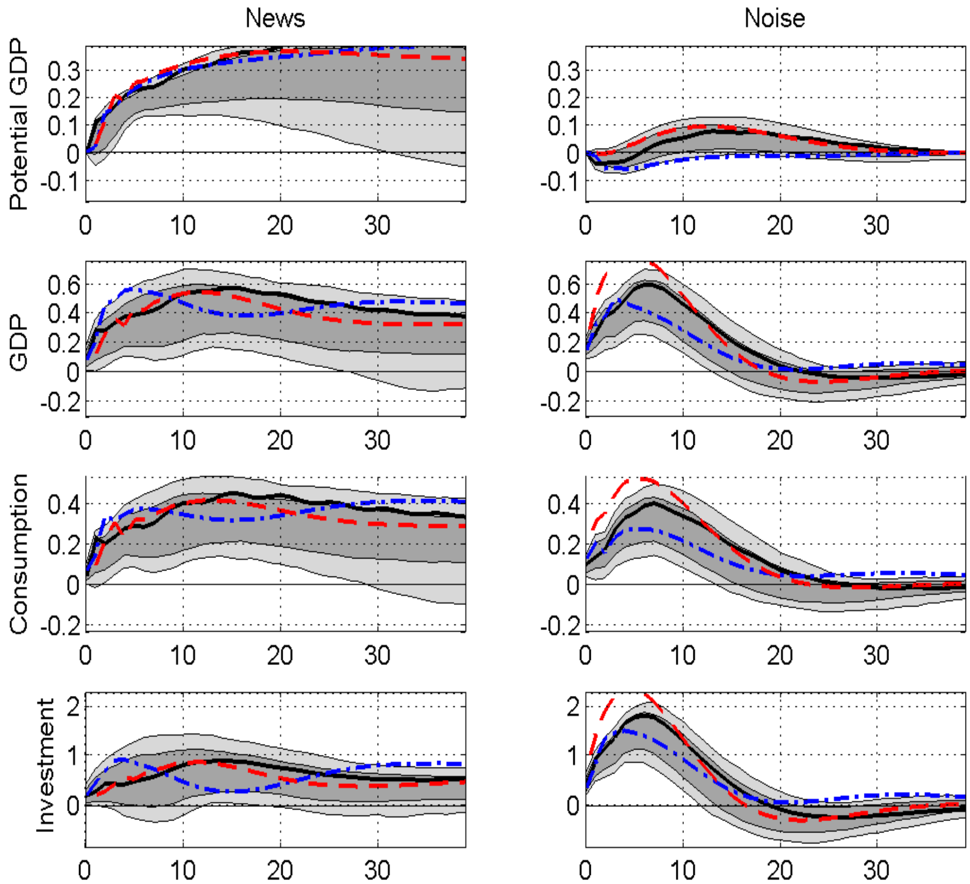

Figure 8: Impulse response functions to news and noise in the 5-variable VAR. Solid line: point estimate. Dark gray area: 68% confidence bands. Light grey area: 90% confidence bands. Dashed-dotted line: point estimate of the VAR using stock prices (S&P500) as expectation variable. Dashed line: point estimate of the VAR using stock prices (S&P500) as expectation variable.

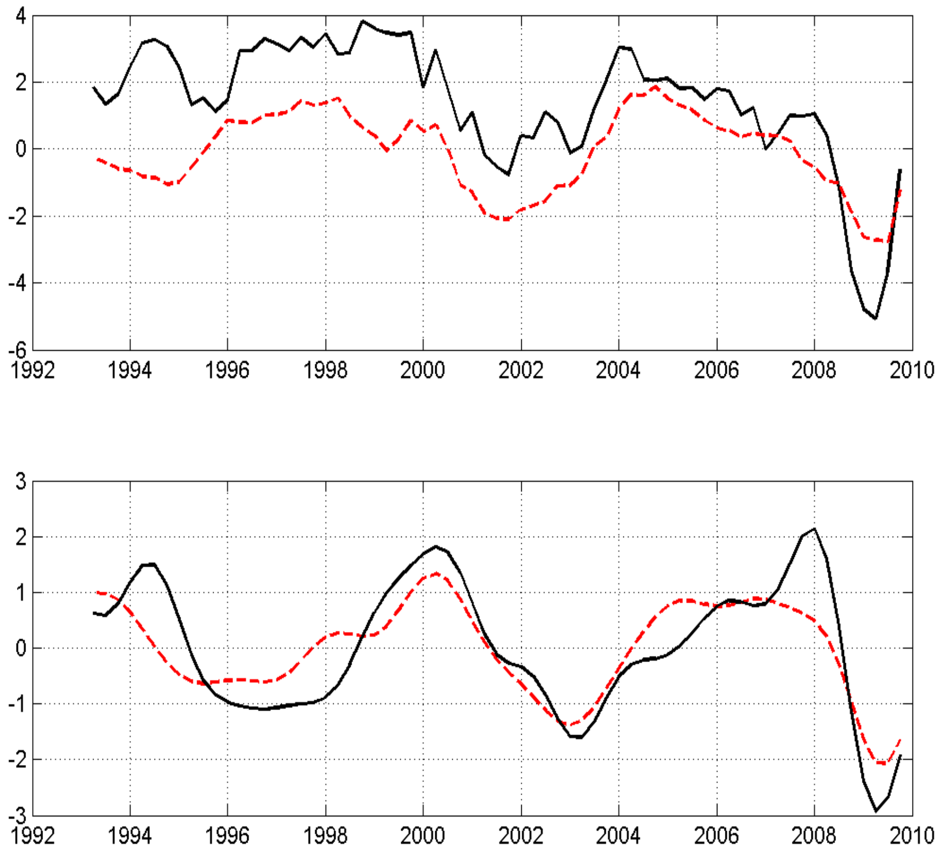

Figure 9: Historical decomposition in the 5-variable VAR using stock prices (S&P500) as expectation variable. Top panel. Solid line: yearly growth rates of GDP; dotted line: noise component of the yearly growth rate of GDP. Bottom panel. Solid line: business cycle component of real GDP (frequencies between 6 to 32 quarters); dotted line: the noise component of the business cycle component of real GDP.

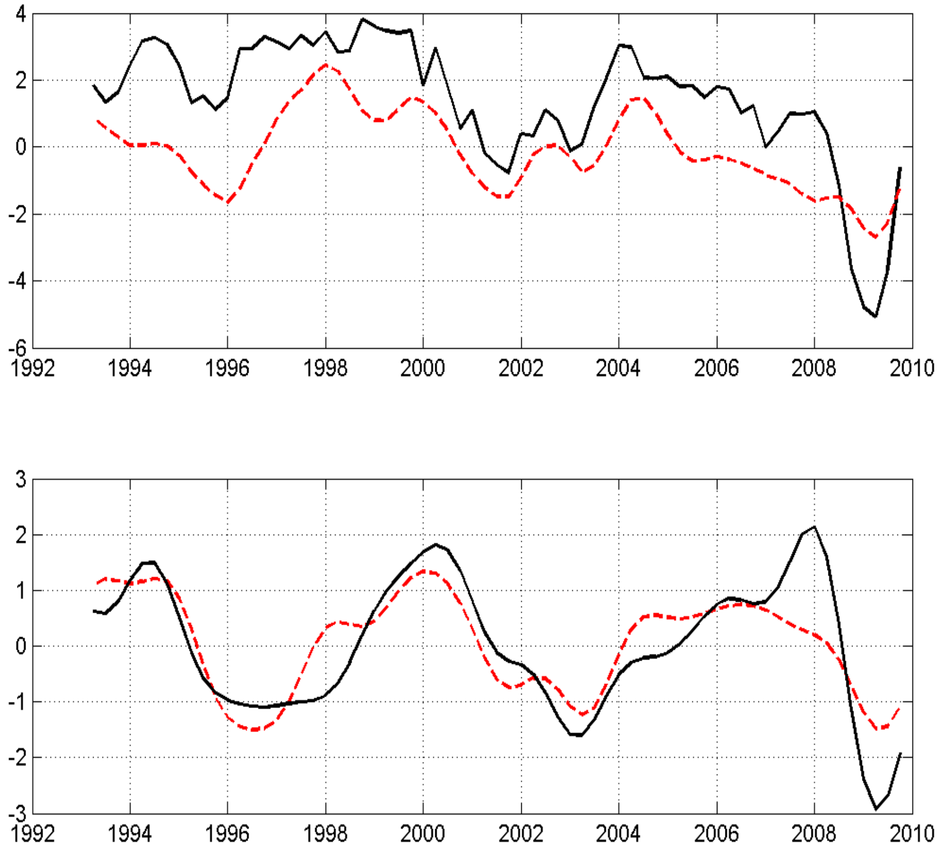

Figure 10: Historical decomposition in the 5-variable VAR using the Conference Board Leading Economic Indicators Index as expectation variable. Top panel. Solid line: yearly growth rates of GDP; dotted line: noise component of the yearly growth rate of GDP. Bottom panel. Solid line: business cycle component of real GDP (frequencies between 6 to 32 quarters); dotted line: noise component of the business cycle component of real GDP.