Identifying Noise Shocks: a VAR with Data Revisions*

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February 16, 2016

Abstract

We propose a new VAR identification strategy to study the impact of noise shocks on aggregate activity. We do so exploiting the informational advantage the econometrician has, relative to the economic agent. The latter, who is uncertain about the underlying state of the economy, responds to the noisy early data releases. The former, with the benefit of hindsight, has access to data revisions as well, which can be used to identify noise shocks.

By using a VAR we can avoid making very specific assumptions on the process driving data revisions. We rather remain agnostic about it but make our identification strategy robust to whether data revisions are driven by noise or news.

Our analysis shows that a surprising report of output growth numbers delivers a persistent and hump-shaped response of real output and unemployment. The responses are qualitatively similar but an order of magnitude smaller than those to a demand shock. Finally, our counterfactual analysis supports the view that it would not be possible to identify noise shocks unless different vintages of data are used.

JEL CODES: E3, C10, D8

KEYWORDS: Noise Shocks, Data Revisions, VAR, Impulse-Response Functions

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*We are particularly grateful to Larry Christiano, Giorgio Primiceri, Roberto Motto and Efrem Castelnuovo. We also thank Abi Haddow, Lena Köerber, Francesca Monti, Michele Piffer, Kate Reinold, Kostas Theodoridis and Matt Waldron for their comments on early versions of the manuscript and Rhys Mendes for allowing us to cite his work. We would also like to thank participants at the XXI International Conference on Money, Banking and Finance, the 2013 SNDE Symposium, the 2013 Congress of the European Economic Association, the 2013 Money Macro and Finance Conference, the 6th London Macroeconomic Workshop at LSE and seminar participants at Univesitat Pompeu Fabra. Part of this research was carried out while Riccardo M. Masolo was a student at Northwestern University and a trainee at the European Central Bank, whose support is gratefully acknowledged. The views and opinions expressed in this work are solely those of the authors and so cannot be taken to represent those of the Bank of England or the European Central Bank.

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1 Introduction

Contrary to what is assumed in most macroeconomic models (e.g. Christiano, Eichenbaum, Evans 2005 and Smets and Wouters 2003) the state of the economy in not known for certain when economic decisions are made.

The constant stream of revisions in many macroeconomic series confirms this view[1] and a small but growing number of DSGE models try to account for the effects implied by imperfect knowledge of the state of the economy, e.g. Lorenzoni (2009), Mendes (2007), Masolo (2011).

These models are typically characterized by imperfect and heterogeneous information regarding the state of the economy. As a result, agents attach weight even to noisy indicators of aggregate economic activity, which would be completely disregarded in a full-information environment.

The precision of aggregate economic indicators plays a key role for at least two reasons. Firstly, it can reduce the overall uncertainty about the state of the economy. Secondly, it correlates the information available to different agents thus reducing the need for them to guess what the other agents' assessment of the state of the economy might be.

In such a setting, even noisy signals about the *past* are useful to economic agents, which makes the mapping to the data much more straightforward, because early data releases are the real-world counterpart of noise-ridden signals of past output growth in dispersed information models. As a result, a noise shock will have an impact on future decision-making, as is the case in Barsky and Sims (2012) and Blanchard, L'Huillier and Lorenzoni (2013), but *not because it reveals something about the future* but rather because it is genuinely informative about the current state of the economy.

[1] Which has been explored in the context of policy analysis by Orphanides (2003) and Altavilla and Ciccarelli (2011).

Dispersed-information models tend to be cumbersome to solve, hence Bayesian estimation is impractical. Melosi (2013) represents an attempt in this direction but restricts information dispersion to firms.

The difficulty to bring dispersed information models to the data induced a dychotomy in the literature. On the one hand is a long series of works, dating back to Mankiw and Shapiro (1986) and including Arouba (2008)[2], which try to analyze the statistical properties of data revisions, thus assessing the quality of early data vintages.

On the other hand, modelers (e.g. Mendes (2007)) have produced impulse-responses of aggregate variables to noise shocks based on calibrated models.

In our opinion, the best attempt to quantify the impact of noise shocks in a VAR for the sake of comparison to a dispersed information model is in Lorenzoni (2009) who estimates a VAR in the tradition of Galí (1999) and Blanchard and Quah (1989). This class of VARs identifies a demand shock and a supply or productivity shock by assuming that only the latter has a permanent effect on the level of output. Lorenzoni (2009) attributes all the effects of the demand shocks he identifies in his VAR to noise. As he himself acknowledges, this is an extreme assumption because it attributes the effects of all shocks which do not have a permanent effect on the level of output, e.g. monetary and fiscal shocks, to noise. This strong assumption serves him well in his exercise because it works against his model but leaves open the possibility of finding a more accurate quantification of the effects of noise shocks on the macro aggregates, which is what we set out to do.

Clearly related to our work is the work by Blanchard, L'Huillier and Lorenzoni (2013)[3] which estimates responses to noise shocks and shows that a VAR cannot separate out the impact of noise shocks in the context of a model in which information is imperfect. It is important to note that Blanchard, L'Huillier and Lorenzoni (2013) *impossibility result*[4], i.e. their

[2]See Croushore and Stark (2001) for a summary.

[3]Although their definition of noise is somewhat different, as described above.

[4]Blanchard, L'Huillier and Lorenzoni (2013) section 2.2

statement that a noise shock cannot be identified in the context of a VAR, crucially relies on the assumption that the econometrician has access to the same information as the agents or less. In our analysis, however, the econometrician has more information (at least along this dimension) than the agents because of the *benefit of hindsight*, i.e. the econometrician knows the state of the economy which was not known to the agent at the time the decision was made[5]. While one might argue that the true underlying state is never fully revealed, it seems reasonable to work under the assumption that successive revisions are more accurate than those available when decisions are made. As a consequence, the information set of the econometrician who carries out an ex-post analysis is richer[6] than that of the economic agents.

Note that information dispersion (not only information imperfection) is critical here. If all agents shared the same information, no matter how imprecise, then they would get to know aggregate endogenous variables (such as output) by a simple symmetry argument, which would negate the econometrician's informational advantage or, at best, reduce it to one period[7]. When information is not the same across agents, though, agents will correctly not presume that other agents' decisions will be the same as theirs, hence they will remain uncertain about the aggregate level of the endogenous variables. As a result, they will find a noisy signal, such as the early data release, useful.

Related and complementary to the work by Blanchard, L'Huillier and Lorenzoni is a recent work by Forni, Gambetti, Lippi and Sala (2013). The latter proposes a way to identify the effect of noise shocks in the context of a model similar to that in Blanchard L'Huillier and

[5]And this is not limited to having a longer sample as Blanchard, L'Hullier and Lorenzoni (2013) consider in Section 2.5. By observing the early and the latest vintages of data the econometrician observes what in Blanchard, L'Hullier and Lorenzoni (2013) is the signal and what would correspond to true underlying permanent productivity in their setup.

[6]When we say richer we mean that the information set of the econometrician is not a subset of that of the agent. We do not necessarily imply that the agent's information set is contained in that of the econometrician.

[7]Knowledge of exogenous process can be imperfect for a long time but when all agents are the same, they get to know endogenous variables simply by setting them.

Lorenzoni but both papers assume the noise shock to affect a signal concerning some future exogenous process (i.e. technology) while we maintain the assumption that the noise shock "corrupts" early releases of *past* output growth, which is clearly endogenous. As a result we allow the noise shock to affect future (but not present) realizations of the variable it affects while this is not the case in Forni, Gambetti, Lippi and Sala (2013). In Forni, Gambetti, Lippi and Sala (2013) it is the agents' learning that allows to uncover the impact of what they call "noisy news", while we take advantage of the econometrician's richer information set (which we refer to as *benefit of hindsight*) to identify noise shocks to the early data releases. In a way, the two approaches are complementary because they focus on two different but non-exclusive definitions of noise. Also note that our procedure does not run into the issue of non-fundamentalness because, from the econometrician's perspective, the noise shock can be recovered by the difference between two observables[8].

Our approach is also related to Enders, Kleeman and Müller (2015)

So far we have described, why using data revisions might help overcome Blanchard, L'Huillier and Lorenzoni (2013) impossibility result. That comes at a cost, however. Data revisions are not nearly as well behaved as noise shocks are assumed to be in the context of theoretical models, as a vast literature shows (e.g. Arouba (2008)). To assume that the revision corresponds to the noise shock would not only imply that the model correctly captures the private sector agents' behavior but also that the specific functional form of the noisy signal is an accurate representation of early data releases. In most theoretical models (e.g. Mendes 2007 and Masolo 2011) the noise shock and the model-implied data revision correspond exactly. In reality we know things are more complicated, Clements and Galvão (2010) try to model the statistical properties of data revisions.

[8]Section 3.2 discusses how our procedure is robust to the case in which the noise shock does not correspond exactly to the revision in the data.

Our VAR is much more flexible in this respect, in the original spirit of Sims (1980), in that it captures the essential transmission mechanism of a noise shock while not getting specific about the details of the data revision process. Indeed, we take advantage of the timing restriction arising from the noise shock impacting the early data release directly and true fundamentals only with a lag, through the decision-making process of the agents, while remaining agnostic on the process for data revisions. We know from empirical studies, e.g. Arouba (2008), that characterizing the revision process as purely news-driven or noise-driven is problematic. The benefit of using a VAR is that we can try to make our identification robust to this.

As the discussion in Section 3 clarifies, the use of a VAR is critical in this respect because it ensures the orthogonality of the noise shock to the final release of data even when the revision would not be (the *news* case).

In sum, our analysis shows how a simple timing identification assumption can deliver sensible results. For one thing, the qualitative responses of output and unemployment to a noise shock are in line with those of a demand shock, i.e. the responses of output and unemployment are inversely related in response to a noise shock. In this sense, our analysis confirms the maintained assumption in Lorenzoni (2009). However, from a quantitative standpoint, the responses to noise shocks, while statistically significant, are much smaller than responses to demand shocks. This confirms the impression that considering the identified demand shocks as being exclusively driven by noise greatly over estimates their impact, which we quantify to be around 5-8 percent of the business cycle (as measured by the shares of the variances of output growth and unemployment explained by the noise shock).

Following the suggestion in Rodriguez-Mora and Schulstadt (2007), we also introduce a measure of investment in our VAR and find that the responses of output and unemplyment to noise shocks are still signficant and that, consistent with accepted business cycle evidence (e.g. see King and Rebelo (1999)) investment seems to be more volatile than output.

We complete our analysis with a simple counterfactual exercise, aimed at illustrating how our identification crucially depends on what we deemed above the *benefit of hindsight*. If the econometrician did not have more information than the economic agent then our evidence confirms that the noise shock could not be recovered.

In this sense we see our analysis as making better use of all the available information to assess the impact the uncertainty about the state of the economy might have on agents' decisions.

The rest of paper comprises and overview of noise shocks in models with dispsersed information in Section 2, followed by the description of our general setup in Section 3. A discussion of our estiamted VAR is in Section 4 while Section 5 illustrates our counterfactual experiment and Section 6 concludes the paper.

2 Noise Shocks in Dispersed Information Models

A recent series of dispersed information general equilibrium models, e.g. Lorenzoni (2009), Mendes (2007) and Masolo (2011), provide the ideal theoretical foundation to study noise shocks.

In standard full information economic models (e.g. Christiano, Eichenbaum and Evans 2005 or Smets and Wouters 2003), information about the past is irrelevant: the agents know the current state of the economy, hence they will not respond to any noisy information about the past.

In reality, however, people are uncertain the state of the economy so they take advantage of published data about, say, GDP growth in recent quarters to increase the accuracy of their expectations of the current state of the economy. The very fact that such series get revised shows that those numbers are not fully accurate (especially for the most recent periods), yet they contain useful information for the economic agents.

Dispersed information models capture exactly this. Because agents are uncertain about the state of the economy, they will respond to an informative, albeit noisy, signal about the state of the economy as it improves the accuracy of their predictions.

Note that heterogeneous information is important in this process. If the state was imperfectly known but information was the same across agents, once each of them made a decision, because of symmetry, he or she would know for certain that everyone else will have made the same decision, while when information differs across agents, the noisy early release increases the agents' knowledge and also affects the correlation of the agents' information set.

Moreover, the precision of the signal will impact the quantitative response but will not prevent agents from responding to noise. The impact of the noise embedded in the signal will only die out as agents learn about the true fundamentals, i.e. they become able to separate the genuine movement in economic variables from the noise embedded in the preliminary release[9].

Models such as those mentioned above can typically be readily cast in a state-space[10] form in which at least the observation equation is household specific (as denoted by the h subscript):

$$\mathbf{Z}_t = \Psi_1 \mathbf{Z}_{t-1} + \Psi_0 \underline{u}_t \quad (1)$$

$$\underline{\mathbf{s}}_{ht} = \Gamma_1 \mathbf{Z}_t + \Gamma_0 \underline{\zeta}_{ht} \quad (2)$$

Equation (**??**) is the transition equation, which controls the evolution of the state of the economy $\mathbf{Z}_t$ while, $\underline{\mathbf{s}}_{ht}$ characterizes the information set of the economic agents which com-

[9]The speed of learning is obviously a matter of one's preferred calibration in a model. One of the benefits of our analysis is to cast light on the time span over which these effects are statistically significant.

[10]It is usually the case that more lags of the state variables are needed to solve a dispersed information model. Typically they are stacked to form a first-order system.

prises a sequence of signals defined as linear combinations of (aggregate) state variables plus idiosyncratic components (ζ_{ht}). We allow for each agent to observe different bits of information but, in a linear setting, all the idiosyincratic components integrate out in the aggregate. On the contrary, the noise shock does not net out in the aggregate because it is observed by all agents, hence usually the noise shock will be a component of the vector $\underline{u}_t$[11].

Typically the noise shock corrupts information regarding output growth or productivity in a way that is meant to mimic early releases of output growth figures which are available to everyone and yet are never fully precise.

Because all the agents have access to this type of signal, aggregate variables will respond to some degree to the unexpected inaccuracies in the reports of, say, output growth. As a result we can investigate the impact of noise shocks with no need for individual-level data or survey expectations.

2.1 Timeline

While forecasts of macroeconomic variables are certainly available, it is realistic to assume that agents will only receive signals about aggregate variables (which we can consider imperfect measures rather than pure forecasts) not before the end of period of interest[12], i.e. once the aggregate variable of interest has materialized.

As a result the following timing pattern (depicted in Figure 1) arises naturally:

1. The noise shock, which we will denote by v_t, hits the economy.

2. At the end of the period the economy-wide signal, denoted by (x_t^0, e.g. early release of

[11]In principle the noise component might be itself autocorrelated, in which case it will enter the state vector $\mathbf{Z}_t$, while $\underline{u}_t$ will include the innovation to that same process. Moreover, because the variable impacted by the noise shocks (e.g. an early release of output growht) is observed symmetrically by all agents in the economy the row of Γ_0 corresponding to the noisy variable will comprise all zeros.

[12]Or equivalently at the beginning of the following period

output growth), which is affected by the noise shock, is released

3. At the beginning of the following period the noise will be reflected in the agents' information sets and, as a consequence, in their economic decisions (x^f_{t+1}).

When one thinks of x^f_t, x^0_t and v_t as elements of the state-space system illustrated in equations (**??**) and (1), the timeline above translates in a set of zero-restrictions in the matrix Ψ_0. In particular if the economy-wide signal we are concerned with (early data release, x^0_t) is the $j-th$ entry in $\mathbf{Z}_t$ and the noise shock is the $m-th$ entry in $\underline{u}_t$, then the $m-th$ column of Ψ_0 will comprise all zeros except on row j.

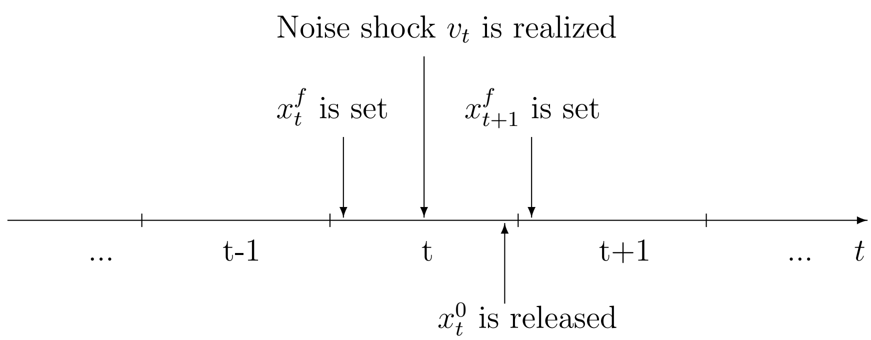

Figure 1: Timeline of decision making and data releases

3 Setup

We have illustrated the timing assumption underlying our identification strategy. Now we turn to showing how it applies in our VAR setting. Before doing so it is important to note a key benefit of estimating a VAR. In the context of theoretical models (no matter if estimated or not[13]) the process for the noise shock has to be specifically defined, which usually implies that the model-implied revision, coincides with the noise shock and, as a result, is orthogonal

[13]See Melosi (2013) for an estimated dispersed information model, albeit with a representative household.

to the true underlying fundamental (x_t^f), a condition not always verified in the data (see Arouba 2008). On the other hand, the flexibility implicit in a VAR specification allows us to make our identification robust to situations in which revisions in the data turn out not to be orthogonal to the underlying fundamentals, as we will show below.

3.1 Classical Noise

We start by considering how our identification applies in the case in which the revision is orthogonal to the fundamentals, a case we will refer to as *classical noise.*

Under this assumption, the early vintage of data (x_t^0) equals the true or fundamental (x_t^f) plus the noise shock:

$$x_t^0 = x_t^f + v_t \qquad v_t \perp x_t^f \tag{3}$$

Appendix A shows that, given the state-space representation in equations (**??**) and (1), the process governing x_t^f can be expressed as:

$$x_t^f = A(L)x_{t-1}^f + B(L)v_{t-1} + \varepsilon_t \tag{4}$$

Where all the elements of equation (4) can be vectors, $A(L)$ and $B(L)$ are finite-order polynomials in the lag operator and ε_t are the other shocks hitting the economy (e.g., in our empirical exercise we will identify demand and supply shocks).

Equation (4) shows how past noise shocks affect the decision-making process of the agents in the economy to the extent that they cannot separate them out from fundamentals. Agents in the models will only observe a combination of noise and fundamentals, otherwise $B(L) = 0$, i.e. they would not respond to noise.

Equations (3) and (4) define the evolution of the two set of variables we are interested in, namely the early and the latest vintages of data.

Combining the two delivers the law of motion for the early relase of economic data (x_t^0):

$$x_t^0 = A(L)x_{t-1}^f + B(L)v_{t-1} + \varepsilon_t + v_t \tag{5}$$

Equation (5) clearly shows how the revision component (consistent with the timeline laid down in Figure 1) affects contemporaneously the early vintage of data and with a lag, i.e. through the decision-making process of the economic agents, the values of fundamental variables.

3.1.1 Identification

As shown above, our identification strategy hinges on the fact that the information set of the econometrician is richer than that of the economic agent who made the decision, because the econometric analysis is carried out at a later time.
Rearranging equation (3) and substituting it into equation (5) yields:

$$x_t^0 = (A(L) - B(L))\, x_{t-1}^f + B(L)x_{t-1}^0 + \varepsilon_t + v_t \tag{6}$$

Using equation (6) to substitute for x_t^0 in equation (3) allows us to re-write the law of motion for the final release as follows:

$$x_t^f = (A(L) - B(L))\, x_{t-1}^f + B(L)x_{t-1}^0 + \varepsilon_t \tag{7}$$

Finally, stacking up equations (7) and (6) produces the following VAR representation:

$$\begin{bmatrix} x_t^f \\ x_t^0 \end{bmatrix} = \begin{bmatrix} A(L) - B(L) & B(L) \\ A(L) - B(L) & B(L) \end{bmatrix} \begin{bmatrix} x_{t-1}^f \\ x_{t-1}^0 \end{bmatrix} + \begin{bmatrix} \mathbf{1} & \mathbf{0} \\ \mathbf{1} & \mathbf{1} \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ v_t \end{bmatrix} \tag{8}$$

The matrix pre-multiplying $[\ \varepsilon_t \quad v_t\ ]'$ simply highlights the timing pattern that emerges in our setup and which is true irrespective of the particular specification of the VAR. We postpone the complete identification of ε_t to our empirical exercise (see Section 4.2.2) because the identification of the other structural shocks inevitably depends on the variables included in the estimated VAR. In particular, we will explicitly identify demand and supply shocks using accepted identification restrictions (Blanchard and Quah, 1989).

3.2 Prediction Error

A vast empirical literature shows that revisions for some series are better characterized as resulting from forecasting errors made by the agency which publishes early releases, e.g. Mankiw and Shapiro (1986). We will sometimes refer to this situation as *news*.

The key difference with respect to the case illustrated above is that the revision is not orthogonal to fundamental x_t^f, which makes it not a suitable candidate for a noise shock.

In this paragraph we illustrate how our VAR procedure actually mitigates this problem as what we call noise shock is *not* (necessarily) the revision of data vintages, because it is orthogonal to the variables included in the VAR.

An exhaustive discussion of this issue would require the knowledge of the prediction models used by the agencies which publish early vintages of data. Since that is not the case, we will proceed with an example and discuss how our procedure is robust to a simple statistical model.

Let us assume that a statistical agency receives a noisy signal on the true underlying economic variable which takes on the following form:

$$x_t^{00} = x_t^f + v_t \tag{9}$$

The key difference with respect to the case above is that now the agency correctly anticipates that the data they collect are noise ridden (e.g. because they only collect a sample of the data of interest) and so perform a filtering procedure before making them public. In particular, it is reasonable to assume that they will consider the linear projection of the true underlying variable onto the known signal so that the early release would take on the following form:

$$x_t^0 = \mathbb{P}[x_t^f | x_t^{00}] = \phi x_t^{00} = \phi x_t^f + \phi v_t \tag{10}$$

Where the projection coefficient ϕ depends on the relative variance of noise in the signal x_t^{00}. The key difference, relative to the case above is that now the data revision is not orthogonal to the final release, in fact:

$$x_t^f - x_t^0 = (1-\phi)x_t^f + \phi v_t \tag{11}$$

As a consequence, it would be incorrect to take the revision as an indicator of the noise shock. However, our VAR strategy provides a simple fix to this potential problem.

Under the maintained assumption that economic agents in the model know the data-generating process (i.e. the state-space representation of the economy), the newly defined early release would simply result in a different set of coefficients in the state-space representation in euqations (**??**) and (1) but would otherwise not change the model which could be summed up as:

$$x_t^f = \tilde{A}(L)x_{t-1}^f + \tilde{B}(L)v_{t-1} + \varepsilon_t \tag{12}$$

Where different filters $\tilde{A}(L)$ and $\tilde{B}(L)$ reflect the different coefficients in the state-space representation.

Following the same steps as above, and using equation (10) as an alternative definition of the early data release, one gets the following formulas for the early release and the fundamental:

$$x_t^0 = \phi(\tilde{A}(L) - \tilde{B}(L))x_{t-1}^f + \tilde{B}(L)x_{t-1}^0 + \phi\varepsilon_t + \phi v_t \quad (13)$$

$$x_t^f = (\tilde{A}(L) - \tilde{B}(L))x_{t-1}^f + \frac{1}{\phi}\tilde{B}(L)x_{t-1}^0 + \varepsilon_t \quad (14)$$

Despite the scaling factor ϕ showing up in the equations and different lag-operator polynomials, reflecting the fact that equilibrium responses will in general be different under this alternative scheme, it is still the case that the noisy component v_t contemporaneously affects only the early release and not the final, thus being consistent with the identification strategy laid down above. Not only that, but this analysis suggests that the resulting noise shock is the share of noise ϕ which is not filtered out by the statistical agency. In other words, it is the portion of noise that impacts the decision makers.

The example above illustrates a situation in which taking the data revision naively would lead to an incorrect assessment of the noise shock because the revision incorporates a component which is not orthogonal to the true value x_t^f. The VAR however cleanses the revision of the component that depends on x_t^f.

While the example assumes a very simple information set of the statistical agency it casts light on the benefits of our strategy, because what we identify as noise shock is orthogonal to the variables included in the VAR.

In fact, the only possible problem with this strategy appears to be in the number of variables and lags included in the VAR. In abstract, since the agents in the model know the data generating process, any variable, or lag thereof, used by the agency would be included in the state equation. In practice, since we do not know the information set and the procedures of the statistical agency, we rely on the standard lag-selection tests to gauge whether our statistical model appears to be correctly specified.

So, while the limited number of data points curtails the number of series and lags we can realistically include in our estimation, we find that using a VAR is more accurate than using data revisions directly (this is somewhat related to Rodriguez-Mora and Schulstad (2007)).

4 VAR

4.1 Baseline

Our baseline VAR specification includes two vintages of quarterly (annualized) output growth and unemployment. Obviusly we need two vintages of output growth if we want to apply the identification scheme we laid down in the previous section, output being the key series subject to revisions. We only have one vintage of unemployment because the unemployment series is essentially never revised. Unemployment serves two key purposes in our context:

I. Precisely because it is not revised it represents a good proxy for the data-publishing agency information set as it is readily available and clearly useful to assess economic conditions in real time. As such, we think it might help us making our identification robust to data revisions being driven by news, in the sense described in the previous section.

II. Moreover, it allows us to identify demand and supply shocks with a long run restriction as in Blanchard and Quah (1989) as one of our goal is to show that using demand shocks as a proxy for noise shocks overestimates the impact of noise.

We will later consider a larger set of variables (which includes a measure of investment), but we aim at keeping this exercise parsimonious for at least two reasons:

1. We want to contribute to identification of noise shocks proposed by Lorenzoni (2009) who used a 2-variable VAR

2. Including other variables subject to revisions would, potentially, increase the number of series (and of estimated parameters) much faster than in a traditional exercise using only the latest data release.

We use de-meaned series so our estimation equation reads:

$$\begin{bmatrix} \Delta y_t^f \\ u_t^f \\ \Delta y_t^0 \end{bmatrix} = \beta_{\mathbf{1}} \begin{bmatrix} \Delta y_{t-1}^f \\ u_{t-1}^f \\ \Delta y_{t-1}^0 \end{bmatrix} + C \begin{bmatrix} \nu_t^1 \\ \nu_t^2 \\ \nu_t^3 \end{bmatrix} \tag{15}$$

Where C is the matrix identifying our structural shock which will be described below.

4.1.1 Data Description

For our empirical analysis, we consider the real GDP and the unemployment rate from the Historical Data Files for the Real-Time Data Set provided by the Federal Reserve Bank of Philadelphia (Croushore and Stark, 2001). The different vintages of data are available only from November 1965 to present. The quarterly vintages and quarterly observations of the Real GNP/GDP (ROUTPUT) is in Billions of real dollars, and seasonally adjusted. We take the first difference logarithmic transformation, so we consider it as a quarterly (annualized) growth rate[14]. Instead, the quarterly vintages and monthly observations of the Unemployment Rate (RUC) is in percentage points, seasonally adjusted. We transform our data from monthly to quarterly frequency considering the first observation of the quarter. We take levels of unemployment rate, without detrending[15] it as discussed in Blanchard and Quah (1989). The investment, used in the robustness analysis, is given by the logarithmic

[14]Using growth rates is motivated not simply by non-stationarity consideration but also by the fact that, as Rodriguez-Mora and Schulstad (2007) point out, it is easy to account for big long-term data revisions in growth rates (because typically affect one value which we substitute with the average of the previous and the following quarter) than in level, because in this case the effect of the revision is essentially permanent.

[15]We do not detrend unemployment since our sample data does not show any deterministic or stochastic trends. Our longer sample from 1966 to 2006 considers different periods, from the Great Inflation to Great Moderation, with an evidence of no trend.

transformation of the ratio between the sum of Gross Private Domestic Investment (GPDI) and Personal Consumption Expenditures: Durable Goods (PCDG) and the Gross Domestic Product, 1 Decimal (GDP) as in Christiano et al. (2010). All these quarterly observations variables used to build the investment are provided by FRED Database of the Federal Reserve Bank of St. Louis.

The VAR analysis, using one lag as suggested by the Schwartz Criterion, considers the quarterly sample from 1966:1 to 2006:4. We limit our sample until 2006, to leave a sufficiently long period after the end of the selected sample to be reasonably confident that the bulk of the revisions has ended by the time we carry out are analysis with a sufficiently long window for the end-of-sample observations. In fact, our final releases of output are those published in the third quarter of 2011[16] so we allow for about five years worth of revisions even for the data at the end of the sample. For the first release, on the other hand, we considered that derived from output level numbers published one quarter after the period of interest[17], using a diagonal difference. That way it seems safe to consider that the agency had some time to collect data, reducing the forecasting component in the release and it also guarantees that such a number cannot affect the decisions of agents in the current period.

4.2 Results

4.2.1 Qualitative Similarities between Noise and Demand Shocks

The discussion in Sections 2 and 3 delivers an identification assumption for the noise shock which is *the shock that contemporaneously affects the early relase of data* ***only***. This, in turn,

[16]Clements and Galvão (2010) entertain both the definition of final release as the latest available or that occurring a fixed number of quarters after the end of the period of interest (in their case 14 quarters, seeming to favor the latter because it is less affected by long-term revisions. On the other hand, Rodriguez-Mora and Schulstad (2007) seem to favor our approach. In any event, we find our approach a sensible benchmark because the standard counterpart of our VAR would be one in which the latest releases available are used, not those published a certain fixed number of quarters after the end of the period of interest.

[17]The computer code we used to elaborate raw data can be requested to the authors.

pins down the third column of matrix C:

$$[C]_3 = \begin{bmatrix} 0 \\ 0 \\ c_{33} \end{bmatrix} \tag{16}$$

where $[.]_j$ refers to the $j-th$ column of the matrix in brackets.

The structure of the third column of matrix C implies that the our estimated noise shock ν_t^3 will be orthogonal to all the variables included in the VAR except the current value of the first release (see the Appendix B for details).

Figures 2 and 3 report the responses of final output (in log-levels) and unemployment to a positve noise shock, i.e. a situation in which the early data release is higher than the surprisingly higher than the fundamentals would imply.

First, both of them are significant. Output appears to be statistically higher than it would otherwise be for about ten quarters, while unemployment is significantly below its long-run level for around three years.

This means that an incorrect and unexpected early release of output figures tends to drive real underlying output in the same direction.

However, it should be noticed that, not only the growth-rate of output converges back to zero but its log-level does as well, which is consistent with the idea that while noise shocks can be expected to produce variability at business cycle frequencies, no long-run effects on output seem likely, consistent with identification scheme in Lorenzoni (2009) who uses demand shocks as a proxy for noise shocks.

Here we find, without imposing it, that, just like demand shocks in the Blanchard and Quah (1989) identification tradition, noise shocks do not affect the level of output in the long run. So, we find a qualitative similarity between noise shocks and demand shocks.

Consistent with the idea of a demand shock is also the fact that the responses of output and unemployment have opposite signs, which one would expect when no productivity shocks are at play.

Having listed the qualitative similarities of noise shocks with demand shocks we now turn to highlighting the important quantitative differences.

4.2.2 Quantitative Differences between Noise and Demand Shocks

To assess the quantitative differences between demand and noise shocks we need to identify both. Because of our variable selection, we can readily do so following Blanchard and Quah (1989). In particular, so far we have imposed two zero restrictions on the C matrix. A third restriction will identify all the shocks. While we leave a detailed derivation for appendix C, to build some intuition we report matric C here as well:

$$C = \left[\begin{array}{cc|c} c_{11} & c_{12} & 0 \\ c_{21} & c_{22} & 0 \\ \hline c_{31} & c_{32} & c_{33} \end{array}\right] \tag{17}$$

The identification of the third column is discussed in the previous section (see equation 15). The third identifying restriction is imposed on the upper-left block of matrix C. Namely a long-run restriction is imposed, which restricts the demand shock not to have any long-run effect on the *level* of output (see Appndix C for details).

The combination of the zero-restrictions to pin down the noise shock and the the long-run restriction to separate out demand and supply shocks also identifies the lower-left block of matrix C (the one that governs the response of the early data release to demand and supply shocks). In particular, given our restrictions, for C to satisfy $CC' = \Sigma$, i.e. for the covariance matrix of the structural shocks to equal the covariance of the estimation residuals, it has to be that:

$$\begin{bmatrix} c_{31} & c_{32} \end{bmatrix} = \left(\begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}^{-1} \Sigma_{1:2,3} \right)' \tag{18}$$

Having identified demand shocks we can now compare them with noise shocks. Figures 4 and 5 report the same one-standard-deviation impulse responses to a noise shock, together with responses to a one-standard-deviation demand shock. In order to make the comparison more robust we report demand-shock responses identified as described in equation (16) and also demand shocks from a two-variable VAR (i.e. our baseline specification without the early output growth release, to be more consistent with Blanchard and Quah (1989) original setup). Interestingly, they deliver very similar results, suggesting that the inclusion of the early vintage of output growth does not materially affect the identification of demand shocks. On the one hand, these figures confirm the qualitative conclusions with drew above: demand and noise shocks both induce negatively correlated responses of output and unemployment (which suggests a sign restriction would not be enough to separately identify both).
However, they also immediately reveal how the latter produce much larger effects on both output and unemployment, the demand shock being well outside the 95 percent confidence bands surrounding the responses to a noise shock. At their peak, responses to a demand shock are about three times as large as those to a noise shock, which gives us an indication of the magnitude of the overestimation of the effects of noise one would run into were they to apply a long-run identification scheme.
This is what we were expecting as, by definition, long-run identification schemes are meant to capture any economic distrubances which do not have a long run effect on the level of output, e.g. most fiscal and monetary policy shocks.

Looking at the variance decomposition for output growth and unemployment stenghtens our point further. Figure 6 illustrates how noise shocks can explain around 5 percent of the output growth dynamics and 7 to 8 percent of the movements in unemployment.

Contrasting those numbers with the variance decompositions shown in Table 1 shows that the variance share of output growth and unemployment explained by the noise shock is about one order of magnitude smaller than that explained by demand shocks[18]. Which, once more, confirms the idea that using demand shocks as a proxy for the effects of noisy data releases, while qualitatively similar, greatly overestimates the impact of data revisions.

This finding is consistent with Lorenzoni (2009) claim that his procedure overestimates the impact of noise shocks and provides a quantification of the overestimation, which appears to be large.

4.2.3 Comparing the responses of different vintages

So far, we have discussed, the differences and similarities in the responses of the final output growth release to demand and noise shocks.

Now we turn to looking at the differences in the responses of the two vintages of output growth we consider in our analysis.

Figure 7 reports, side-by-side, the responses of the final (solid line) and early release (dashed line) of output growthto the Supply, Demand and Noise shocks respectively. Our identification restrictions explain why the final release of output growth does not respond contemporaneously to a noise shock, but they do not directly restrict the response patterns to demand and supply shocks.

Hence it is interesting to consider the striking difference in the two. When it comes to

[18] This is in line with the finding that the impulse response is smaller by a factor of about three. If the MA representations of the responses to two different shocks (i.e. their impulse responses) are scaled by a factor of 3 the variance share of the shock with the bigger impluse response should be 9 times larger than than the other.

demand shocks the response of the early announcement and of the final release essentially overlap, while the early data release seems to underestimate the impact of a supply shock. While this is not conclusive evidence, it is consistent with the idea that because unemployment is known in real time and is very closely linked to demand shocks, demand shocks are correctly reflected in the early data release already. The same is not true for supply shocks, which cannot be recovered by simply looking at unemployment (and even unemployment and the early data release) or, in other words, seem to take longer to be revealed.

More generally, this pattern is consistent with the idea that demand shocks, such as some fiscal intervention, seem easier to spot right away than improvements in technology which are bound to take place at the individual firm level and require some time to become widely known.

4.3 Alternative VAR Setup

Rodriguez-Mora and Schulstad (2007) suggest that investment is a crucial variable when considering the impact of data revisions, which is reasonable given the forward-looking nature of investment decisions.

Long-term projects, such as investment plans tend to be, are more susceptible to data imperfections as they necessarily have to rely on forecasts of future conditions. On top of that, investment decisions are costly to reverse, once undertaken.

Adding a measure of investment in our VAR we want to address two main points. First, we are interested in verifying if investment exhibits a significant response, somewhat along the lines of Rodriguez-Mora and Schulstad (2007). Secondly, introducing investment we can verify if the response of output to a noise shock is significant even when a measure of investment is included in the VAR.

Finally, adding an extra regressor further "cleanses" our definition of noise shock for potential correlations with variables which could enter the data-publishing agency's information set. In particular, we make our noise shock orthogonal to our measure of lagged and current investment as well.

Our definition of investment is similar to that in Altig, Christiano, Eichenbaum, Linde (2004), namely it is the log of the ratio of investment to GDP (in this case the final value of GDP). In other words, it is a measure of the investment-rate as a share of output.
In particular, the investment is given by the logarithmic transformation of the ratio between the sum of Gross Private Domestic Investment (GPDI) and Personal Consumption Expenditures in Durable Goods (PCDG) and the Gross Domestic Product, 1 Decimal (GDP). All the quarterly-observation variables used to build the series for investment were taken from the FRED Database of the Federal Reserve Bank of St. Louis.

4.3.1 Results

Results if Figure 8, 9 and 10 show that, once more, responses to revision shocks appear to be significant at business cycle frequencies.
Interestingly, the size of the responses of output and unemployment is similar to that in the baseline setup we considered above, which appears to rule out the possibility that the response of output had to do with the omission of investment from the setup.
At the same time, the investment rate is higher than average for about two years following an "overly optimistic" early release of output growth numbers.
In this respect, it should be noticed that it is not simply investment per se that increases, but investment as a share of output. Because output itself grows after a positive noise shock, this suggests that the level of investment increases in response to a noise shock more than output, consistent with basic business cycle facts that show how investment is positively correlated but more volatile than output (see King and Rebelo (2000)).
Finally, the sheer size of the responses appears to support the idea that noise shocks produce

real effects even when cleansed from any linear correlation of the revision with lagged and current investment rates. Turning to the analysis of the variance decomposition, Figure 10 displays the variance-decomposition exercise for the specification which includes investment. As in the case above, the charts show the share of the forecast-error variance explained by revision shocks at different points into the future.

Again the share of output growth variance explained levels off just below 5, the corresponding share being around 7 percent for unemployment and 6 percent for investment.

In sum, adding investment does not change the big picture conclusions we drew for the case in which only output growth and unemployment enter the VAR specification. Moreover, broadly consistent with Rodriguez-Mora and Schulstadt (2007), we find that the response of investment is significant and, consistent with business cycle wisdom, we find it is actually larger than that of overall output.

5 Counterfactual Analysis

So far we have taken advantage of the fact that the information set of the econometrician is larger than that of economic agents who do not have the benefit of hindsight, i.e. they cannot observe the revision of the data series (at least by the time they make their decisions).

Now we carry a different experiment which tries to highlight the benefits implicit in the extra information the econometrician has access to. Also, these experiments will allow us to discuss the key conclusion in Blanchard, L'Huillier and Lorenzoni (2013) because, given our estimated setup we can verify to which extent the noise shock can be recovered when revisions are not observed.

Our counterfactual experiment relies on a state-space representation in which the state equation is given by our estimated VAR, while, to keep things simple, the observation equation simply selects a subset of the variables. That means that we study a situation in which some, but potentially not all, of the state variables are observed. To keep things reasonably simple we assume that variables are either unobserved or fully known. The information imperfection aspect of the model comes in play only insofar as it is reflected by the early release being a noisy signal for true output growth.

We will focus on our baseline specification so our state equation reads:

$$\begin{bmatrix} \Delta y_t^f \\ u_t^f \\ \Delta y_t^0 \end{bmatrix} = \beta_{\mathbf{1}} \begin{bmatrix} \Delta y_{t-1}^f \\ u_{t-1}^f \\ \Delta y_{t-1}^0 \end{bmatrix} + \begin{bmatrix} c_{11} & c_{12} & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \begin{bmatrix} \nu_t^1 \\ \nu_t^2 \\ \nu_t^3 \end{bmatrix} \tag{19}$$

Whereas the observation equation will change across the different scenarios but can be represented as:

$$\omega_t \quad = \quad \Lambda \begin{bmatrix} \Delta y_t^f \\ u_t^f \\ \Delta y_t^0 \end{bmatrix} \tag{20}$$

Where the hypothetical agent/econometrician information set will consist of the timeless history of ω_t observables and Λ is a $q \times 3$ matrix of zeros and ones which selects $1 \leq q \leq 3$ of the 3 state variables. We refer to the different scenarios we define this way as observable combinations and, as already mentioned, for the sake of simplicity, we do not consider any additional type of shock/measurement error for this exercise.

Given this setup, the remainder of this paragraph will try to assess whether it is possible to identify noise shocks with data available in real time.

Table 1 reports the output of a simple set of hypothesis tests that try to assess how easy

it is to correctly identify each of the three shocks given different sets of observables.
The experiment works as follows:

- We consider a one-standard-deviation shock for each type which produces three different scenarios (hence three blocks in the table), while all the other shocks are zet to zero.

- For each of the scenarios we test the null hypothesis that each of the shocks is zero, in turn, from the perspective of someone who has received signals ω_t about that shock for four quarters[19].

- We repeat the tests for all the 7 possible combinations of observables.

- We report p-values for all the possible combinations.

To help the intution it is useful to start by considering column (7), i.e. the full information case[20]. Looking at the top section ($\nu_0^S = 1$), the p-values take on value 0 when $H_0 : \nu_0^S = 0$, which is clearly not to be accepted, and one when the other two shocks are tested as being equal to zero. This is just a sanity check that compares our testing strategy against our identification strategy, in the sense that it shows that given the three series we observe the three shocks can be perfectly recovered.
The p-value for the other six observable-combinations, on the other hand, can be taken as indications of how easy it is to recover a shock given incomplete information. Obviously some combinations (e.g. (1) and (4)) are less sensible than others (e.g. (3) and (6)) because they imply the final release of output is known while the first is not, but we report them all

[19]The p-values are not independent of the number of observations agents receive prior to the test being carried out. We decide to consider the test being carried out 4 quarters after the shock but results seem robust to increasing this number (because after a while there is quite little left to learn). Also, the p-values are not independed of the scale of the shock: we think of one-standard-deviation as a reasonable benchmark to illustrate our point.

[20]In terms of the state space representation in equations (18) and (19), this corresponds to $\Lambda = I_{3\times 3}$

for completeness.

Highlighted in yellow are the cells in which the p-value comes out below the customary 5 percent mark. Leaving aside the full information case which, as we said above, represents just a check of our procedure, a few interesting facts can be learnt.

Unemployment reveals demand shocks. Indeed, all the observable-cobinations including unemployment allow to correctly reject the null that there was no demand shock when in fact there was one. Because demand shocks explain a massive share of the variance of unemployment, observing it, even in isolation (observable-combination (3)), reveals what happened to demand. At a more general level, this reinforces our case to introduce unemployment because it shows how it can help identify at least one of the shocks, even when agents do not get to observe all the variables included in the VAR.

Combination (4) is particularly relevant - we could call it the Blanchard-Quah observable combination - because it includes the two variables used in Blanchard and Quah (1989) and is indeed very similar to the pair used in Lorenzoni (2009) which features hours instead of unemployment. On the one hand it shows that the long-run identification scheme they first proposed is robust to a situation in which their VAR specification does not correctly capture the state of the economy, which, in our definition, includes the first release of output growth as well[21].

On the other hand, the bottom entry in the observable-combination (4) column reveals that this pair of observables does not help ”recovering” the noise shock. Hence, it reveals the shortcomings of identification strategies based on one vintage of data.

In particular, the fact that the demand shock can be recovered while the noise shock (which in our controlled experiment is, by definition, contributing to the data-generation process)

[21] This is also consistent with the fact that the demand shock identified in our baseline VAR and in the two-variable Blanchard and Quah specification are very close to each other (see Figure 5).

cannot highlights the dangers of considering demand shocks as a proxy for noise shocks.

If combination (4) is the prototypical econometrician's ex-post observable pair, combination (6) can be thought to best represent real-time information. It turns out that knowing the early release and the unemployment figures allows to recover the demand shock only (because, as mentioned just above, unemployment "reveals" the demand shock) but is no help in recovering a noise shock.

In other words, the noise shock cannot be recovered by observing either real-time or ex-post data but requires both.

Indeed, short of observing the entire three-variable state, the noise shock can only be recovered observing two different vintages of output growth (combination (5)). Once more, this supports the general finding of Blanchard, L'Huillier and Lorenzoni (2013) that it is not possible to identify noise shocks observing just one vintage of data but also shows how the econometrician can take full advantage of a richer information set to uncover the effects of imprecise early data releases.

6 Conclusion

In a world in which there is uncertainty about the underlying state of the economy, early indicators of economic conditions can affect the decision-making process of the economic agents even if they are noise-ridden.

We set out to try and quantify the impact of noise shocks, i.e. the component of early data releases that is unrelated to the contemporaneous true fundamental value. We did so exploiting the econometrician's *benefit of hindsight*, i.e. the fact that she can observe both what in model would be considered the signal and the underlying fundamental on which the noise shock applies. This way we can overcome the impossibility result presented in

Blanchard, L'Huillier and Lorenzoni (2013).

Our identification strategy uses a timing assumption which restricts true economic fundamentals to respond to noise shocks only with a lag, while the early data release is affected contemporaneously. This restriction arises naturally if one considers that early data releases (unless they are forecasts) can only be produced when the period at hand is over or, for our purposes, when the economic decisions have been made already.

By carrying out our analysis in a VAR, we can afford to remain agnostic about the underlying drivers of data revisions, restricting only the timing of the responses as described above. Indeed, we show how our identification strategy can, under certain conditions, uncover the noise shock even when data revisions are driven by news, i.e. the revision is not orthogonal to the fundamentals.

Our empirical exercise shows qualitative similarities between the responses to a noise shock and a demand shock, primarily the negative correlation of output and unemployment reponses, which was the proxy to a noise shock used in Lorenzoni (2009). However, the responses to noise shocks are much smaller (about a third in size at the peak) than those to demand shock, showing that using demand shocks as a proxy for identified noise shocks would over estimate the impact of imprecise data releaes on the business cycle. Our analysis quantifies the contribution of noise shocks to around 4-8 percent of the variance of output growth and unemployment.

Following the analysis of Rodriguez-Mora and Schulstadt (2007), we also study the impact of the noise shock on investment and find that when we introduce a measure of investment in our VAR specification the responses of output and unemployment are roughly unaffected and investment as a positive and significant response.

Finally, we consider a counterfactual experiment based on our estimated VAR, which supports the view that noise shocks cannot be recovered unless different vintages of data are used.

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A Derivation of the VAR from the state-space representation

We now show how the VAR specification we employ relates to the state-space representation in which dispersed-information models are usually cast in.

We will try to keep it general, although obviously there tend to be multiple ways to write the state-space representation of a model which might change the algebra, although the substance of the model would be the same.

Throughout the derivation we will maintain the assumption that $\mathbf{Z}_t$ is defined by stacking up multiple lags of the state variables, which are assumed to comprise x_t^f and x_t^0.

A.1 Derivation of the VAR Representation

First define Ξ^F and Ξ^u such that:

$$x_t^f = \Xi^F \mathbf{Z}_t \tag{21}$$

$$\underline{u}_t = \begin{bmatrix} \Xi^u \underline{u}_t \\ v_t \end{bmatrix} \tag{22}$$

Where Ξ^F selects the current final release of the state vector and Ξ^u a $(m-1) \times m$ matrix of zeros and ones which picks out the $(m-1)$ non-noise shocks from the vector $\underline{u}_t$. For simplicity, we will maintain the assumption that the noise shock we are interested in is the $m-th$ and last entry of the vector of shocks.

Given the state-space representation in equations (**??**) and (1) we have:

$$
\begin{aligned}
x_t^f &= \Xi^F \Psi_1 \mathbf{Z}_{t-1} + \Xi^F \Psi_0 \underline{u}_t & (23)\\
&= \Xi^F \left(\sum_{l=1}^{s} [\Psi_1]_{f,l} x_{t-l}^f + [\Psi_1]_{0,l} x_{t-l}^0 \right) + \Xi^F \Psi_0 \underline{u}_t & (24)\\
&= \Xi^F \left(\sum_{l=1}^{s} [\Psi_1]_{f,l} x_{t-l}^f + [\Psi_1]_{0,l} x_{t-l}^0 \right) + [\Xi^F \Psi_0]_{\forall i<m} \Xi^u \underline{u}_t + [\Xi^F \Psi_0]_m v_t & (25)
\end{aligned}
$$

Where s is the number of lags stacked in the state vector, and $[.]_h$ refers to the $h-th$ column of the matrix in brackets with the understanding that $[.]_{0,l}$ refers to the column multipying the $l-th$ lag of the early release and $[.]_{f,l}$ the $l-th$ lag of the final release.

Given our zero-restriction assumption on Ψ_0:

$$
\begin{aligned}
[\Xi^F \Psi_0]_m &= \Xi^F [\Psi_0]_m & (26)\\
&= \underline{0} & (27)
\end{aligned}
$$

Where the first equality follows from folding out the matrix product and the second because the columns of matrix Ξ^F corresponding to early releases are all zero by construction, while the only non-zero entries in the $m-th$ column of matrix Ψ_0 correspond to early releases by our identification assumption described in the main body of the paper.

Using that and defining $\varepsilon_t \equiv [\Xi^F \Psi_0]_{\forall i<m} \Xi^u \underline{u}_t$, i.e. the rotation of all the other shocks, delivers:

$$
\begin{aligned}
x_t^f &= \Xi^F \left(\sum_{l=1}^{s} [\Psi_1]_{f,l} x_{t-l}^f + [\Psi_1]_{0,l} x_{t-l}^0 \right) + \varepsilon_t & (28)\\
&= \Xi^F \left(\sum_{l=0}^{s} [\Psi_1]_{f,l} x_{t-1-l}^f + [\Psi_1]_{0,l} x_{t-1-l}^0 \right) + \varepsilon_t & (29)\\
&= \mathcal{R}(L) x_{t-1}^f + \mathcal{S}(L) x_{t-1}^0 + \varepsilon_t & (30)
\end{aligned}
$$

Which corresponds to equation (7) given the appropriate matrix definitions.

Now, using the definition of early release[22] we get:

$$
\begin{aligned}
x_t^f &= \Xi^F \left(\sum_{l=0}^{s} [\Psi_1]_{f,l} x_{t-1-l}^f + [\Psi_1]_{0,l} (x_{t-1-l}^f + v_{t-1-l}) \right) + \varepsilon_t && (31) \\
&= \Xi^F \left(\sum_{l=0}^{s} ([\Psi_1]_{f,l} + [\Psi_1]_{0,l}) x_{t-1-l}^f + [\Psi_1]_{0,l} v_{t-1-l} \right) + \varepsilon_t && (32) \\
&= (\mathcal{R}(L) + \mathcal{S}(L)) x_{t-1}^f + \mathcal{S}(L) v_{t-1} + \varepsilon_t && (33)
\end{aligned}
$$

Which is the same as equation (4) when $A(L)$ and $B(L)$ are defined accordingly.

B Orthogonality of the revision shock

The following paragraph illustrates the benefits of using a VAR procedure to study revision shocks. In particular it will show that the revision shock resulting from our analysis is a reasonably close proxy to the classical noise shock employed in models.

We will illustrate the point for our baseline specification, but obviously it generalizes. If we refer to the VAR residuals as $\underline{w}_t$ then, given our identification assumption:

$$
\begin{bmatrix} \nu_t^1 \\ \nu_t^2 \\ \nu_t^3 \end{bmatrix} = C^{-1} \underline{w}_t \tag{34}
$$

[22] At the modeling stage it does not qualitatively matter whether $x_t^0 = x_t^f + v_t$ or $\phi x_t^f + \phi v_t$ as it would just rescale the matrices so the derivation would be the same.

Basic projection theory implies that:

$$Cov\left(\underline{w}_t, \begin{bmatrix} \Delta y^f_{t-1} \\ u^f_{t-1} \\ \Delta y^0_{t-1} \end{bmatrix}\right) = \mathbf{0} \tag{35}$$

So:

$$\begin{aligned} Cov\left(\begin{bmatrix} \nu^1_t \\ \nu^2_t \\ \nu^3_t \end{bmatrix}, \begin{bmatrix} \Delta y^f_{t-1} \\ u^f_{t-1} \\ \Delta y^0_{t-1} \end{bmatrix}\right) &= Cov\left(C^{-1}\underline{w}_t, \begin{bmatrix} \Delta y^f_{t-1} \\ u^f_{t-1} \\ \Delta y^0_{t-1} \end{bmatrix}\right) \\ &= C^{-1}Cov\left(\underline{w}_t, \begin{bmatrix} \Delta y^f_{t-1} \\ u^f_{t-1} \\ \Delta y^0_{t-1} \end{bmatrix}\right) = \mathbf{0} \end{aligned} \tag{36}$$

Besides being orthogonal to past values of both the early and the final data releases, the zero restrictions in the third column of C ensure that ν^3_t, our noise shock, is also orthogonal to the *current* realization of the final data releases, while it affects the early output growth release because $c_{33} \neq 0$.

As a result, as opposed to the plain data revision, our definition of noise shock ensures orthogonality with all the lagged/variables included in our estimation as well as orthogonality to the final releases of period t.

C Identifying Noise, Demand and Supply Shocks

We will now go into the details of our identification[23] strategy. We will focus on our baseline specification and identify all the shocks.

Our complete identification scheme aims at imposing enough restrictions to uniquely pin down the structural-shock matrix C, such that:

$$C\underline{\nu}_t = \underline{w}_t \tag{37}$$

$$CC' = \Sigma \tag{38}$$

$$E\left[\underline{\nu}_t\underline{\nu}_t'\right] = I_3 \tag{39}$$

Where $\Sigma \equiv Cov(\underline{w}_t)$, the covariance matrix of the estimation residuals $\underline{w}_t$ and $\underline{\nu}_t$ are the structural shocks.

To uniquely pin down C , three restrictions are required.

Our discussion in Section 2, provides with two because it restrics the contemporaneous responses to final output growth and unemployment to zero. Hence $c_{13} = c_{23} = 0$ and $c_{33} = \sqrt{\Sigma_{33}}$ so that equations (37) and (38) are satisfied (for what concerns the variance of the third residual)[24] .

In terms of identifying the noise shock this would be enough, which is convenient, because it could extend to alternative VAR specifications (e.g. the one we tried which includes a measure of investment).

Our exercise, however, was concerned with comparing the noise shock with a long-run identified demand shock, for which our baseline specification is very convenient because it allows us to use the Blanchard and Quah (1989) well known identification strategy, the caveat being

[23]We thank Amborgio Cesa-Bianchi for sharing his version of the implementation of a Blanchard-Quah long run restriction

[24]Obviously $c_{33} = -\sqrt{\Sigma_{33}}$ would also do so tha is the sense in which our identification is up to a sign.

that we only use it to identify a block of C[25]

Given our zero restriction, our matrix C looks as follows:

$$C = \left[\begin{array}{cc|c} c_{11} & c_{12} & 0 \\ c_{21} & c_{22} & 0 \\ \hline c_{31} & c_{32} & c_{33} \end{array}\right] \tag{40}$$

The long-run identification applies to the upper-left block so it is convenient to define:

$$\tilde{C} \equiv \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} \tag{41}$$

$$\tilde{\Sigma} \equiv \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix} \tag{42}$$

$$\tilde{\beta} \equiv \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \tag{43}$$

The long-run restriction is then implemented as follows:

$$\tilde{C} = (I_2 - \tilde{\beta})F \tag{44}$$

$$F \equiv Chol\left((I_2 - \tilde{\beta})^{-1}\tilde{\Sigma}(I_2 - \tilde{\beta})^{-1}\right) \tag{45}$$

Which implies that:

$$\tilde{C}\tilde{C}' = (I_2 - \tilde{\beta})FF'(I_2 - \tilde{\beta})' \tag{46}$$

$$= (I_2 - \tilde{\beta})(I_2 - \tilde{\beta})^{-1}\tilde{\Sigma}(I_2 - \tilde{\beta})^{-1}(I_2 - \tilde{\beta})' \tag{47}$$

$$= \tilde{\Sigma} \tag{48}$$

[25] As a robustness check we have also estimated a two-variable VAR (dropping the early release of output growth) and it turns out that the identified demand shocks look remarkably similar as Figure 5 illustrates.

and also that the demand shock will not have any long-run effect on the *level* of output, which follows from the zero restriction in F, which, in turn, implies the sum of the impulse response coefficients of output growth to a demand shock (infinite MA representation) is zero.

The long-run restriction is the last of the three restrictions we could impose on the matrix C. The elements of C we have described so far match up (with reference to equation (37)) four of the six unique elements of Σ (in gray below):

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix} \tag{49}$$

The remaning two elements of C (in the lower-left block) are then pinned down by the restriction implied by the covariances between the first and third residual and that between the second and third.

In particular:

$$\begin{bmatrix} c_{31} & c_{32} \end{bmatrix} = \left(\left((I_2 - \tilde{\beta})F \right)^{-1} \begin{bmatrix} \Sigma_{13} \\ \Sigma_{23} \end{bmatrix} \right)' \tag{50}$$

Which is the same as equation (17), just more explicitly highlighting the link to the estimated cofficients and covariances.

Hence the responses of the final releases of output and unemployment to a noise shock are pinned down as a consequence of the the three restrictions we imposed above, as it should given that three restrictions are required to uniquely pin down (up to sign) the matrix C.

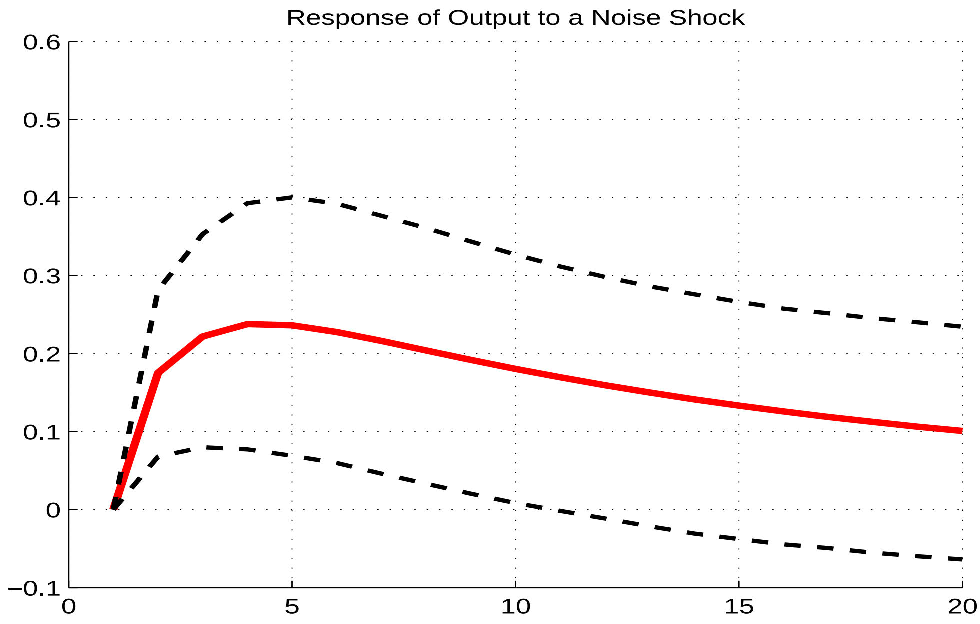

Figure 2: Response of output (in logs) to a one-standard-deviation noise shock.

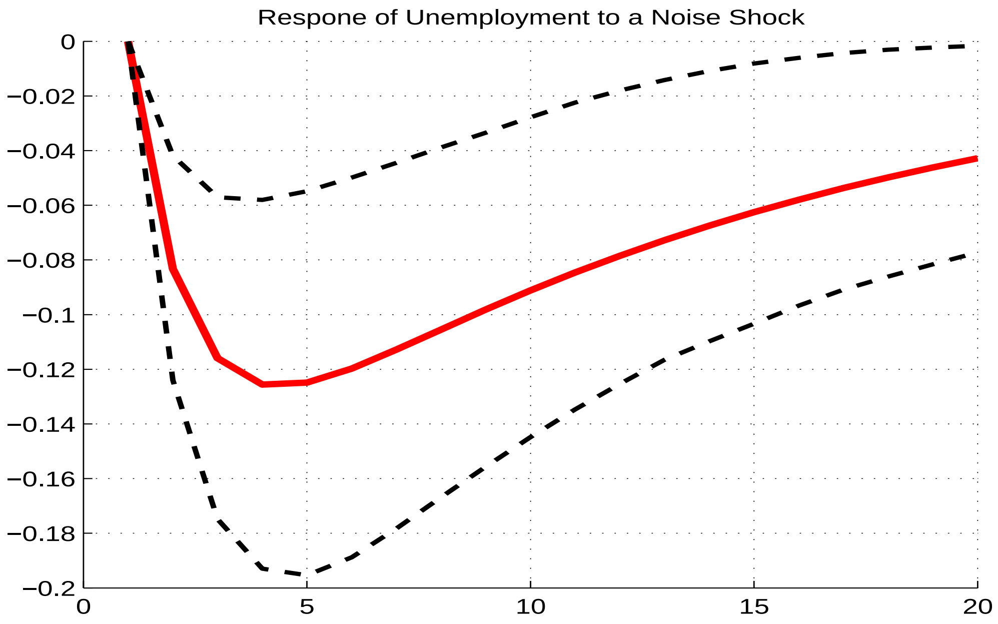

Figure 3: Response of unemployment to a one-standard-deviation noise shock.

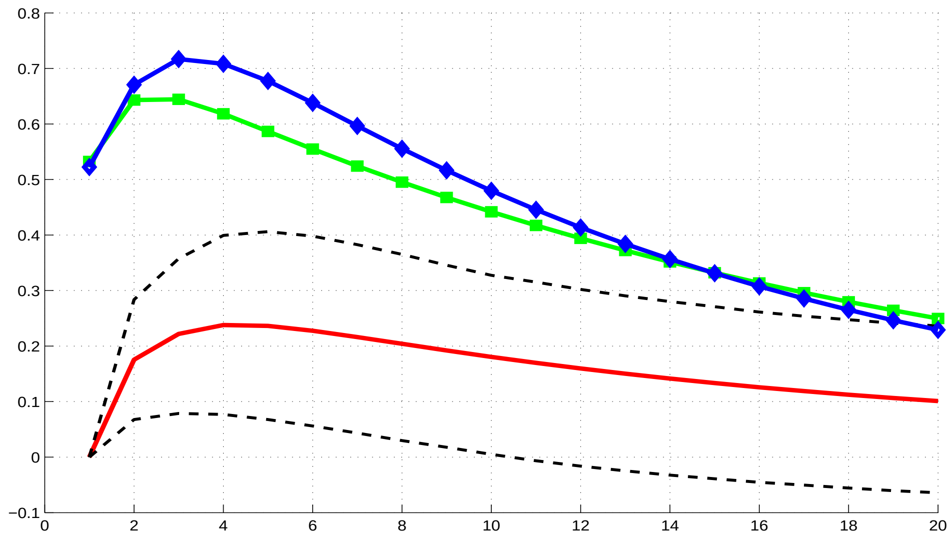

Figure 4: Response of output (in logs) to a one-standard-deviation noise shock (red), to a demand shock identified in our three-variable VAR (blue with diamonds) and to a demand shock identified in a two-variable VAR which excludes the early output growth release (green with squares)

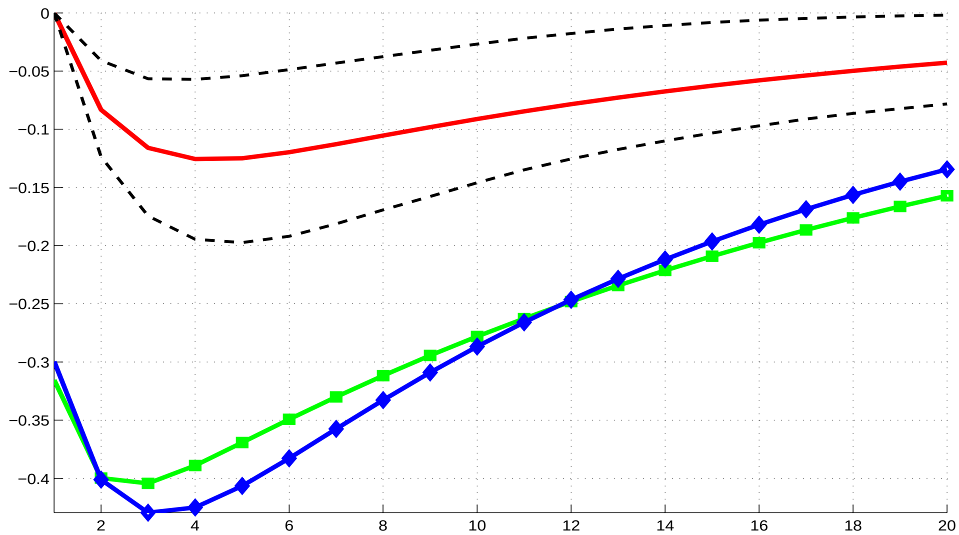

Figure 5: Response of unemployment to a one-standard-deviation noise shock (red), to a demand shock identified in our three-variable VAR (blue with diamonds) and to a demand shock identified in a two-variable VAR which excludes the early output growth release (green with squares)

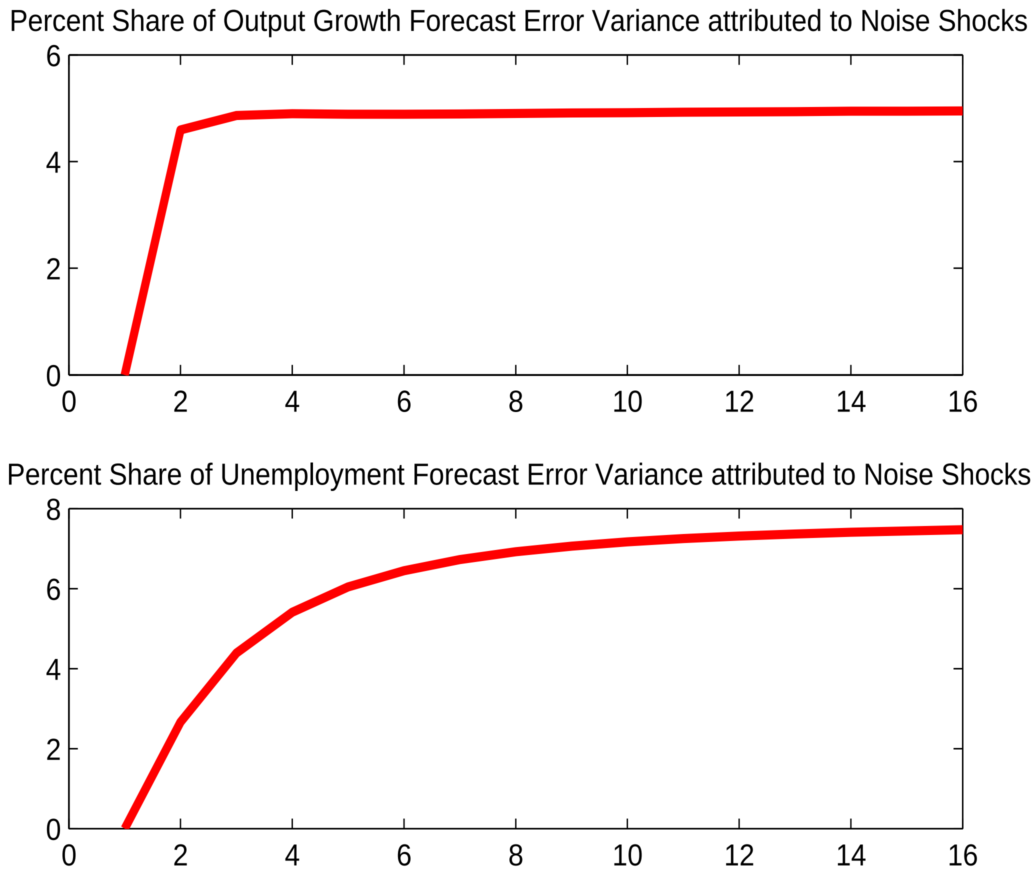

Figure 6: Forecast variance share of output growth (top) and unemployment (bottom) explained by noise shocks.

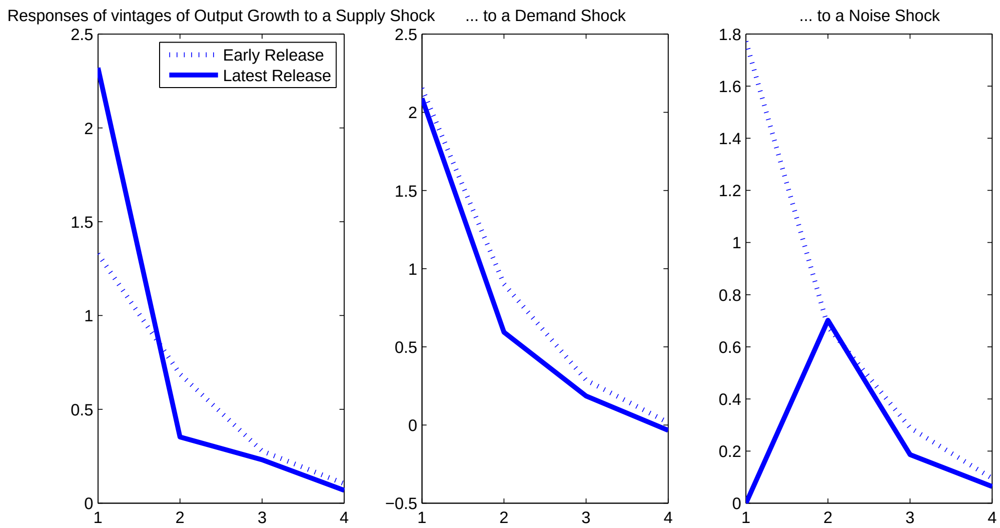

Figure 7: Reponses of the final (solid) and early (dashed) releases of output growth to a supply (left), demand (center) and noise (right) shocks.

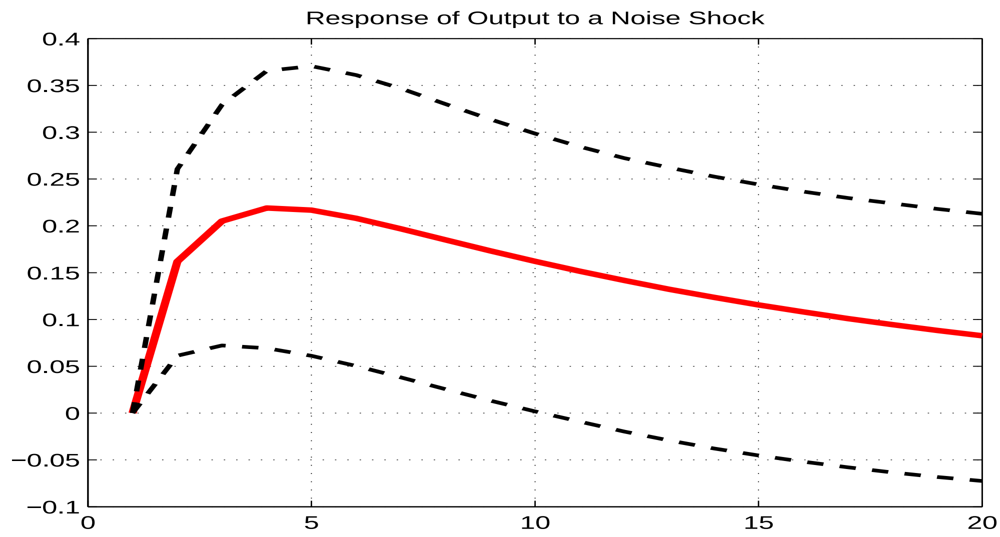

Figure 8: Reponse of final output growth to a one-standard-deviation noise shock when a measure of investment is included in our VAR specification.

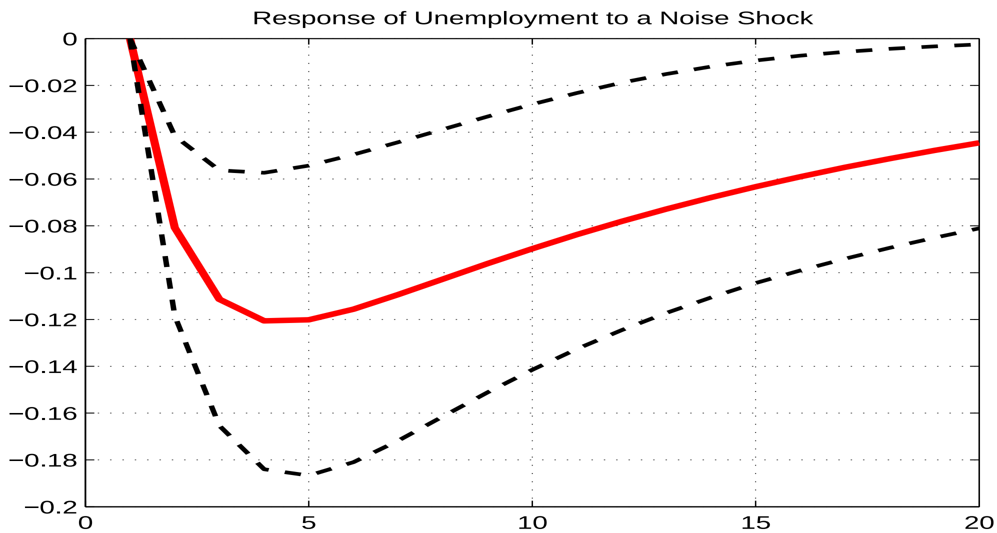

Figure 9: Reponse of unemployment to a one-standard-deviation noise shock when a measure of investment is included in our VAR specification..

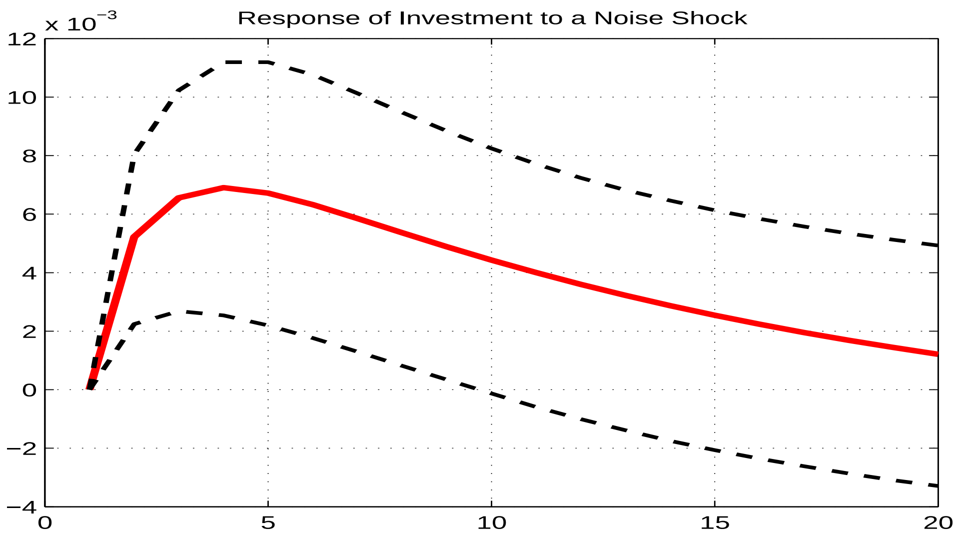

Figure 10: Reponse of our measure of investment to a one-standard-deviation noise shock.

Shock	H_0	Set of Observables						
		One Observable			Two Observables			All
		Δy^f (1)	u (2)	Δy^0 (3)	$\Delta y^f,\ u$ (4)	$\Delta y^f,\ \Delta y^0$ (5)	$u,\ \Delta y^0$ (6)	(7)
	$\nu_0^S = 0$	.45	.93	.84	0	.33	.54	0
$\nu_0^S = 1$	$\nu_0^D = 0$	.54	.81	.68	.96	.54	.50	1
	$\nu_0^N = 0$	.99	.94	.77	1	.53	.46	1
	$\nu_0^S = 0$	.51	.92	.74	.79	.50	.93	1
$\nu_0^D = 1$	$\nu_0^D = 0$	.58	.03	.50	0	.45	0	0
	$\nu_0^N = 0$	.99	1	.63	1	.49	.93	1
	$\nu_0^S = 0$	.99	.94	.79	1	.71	.51	1
$\nu_0^N = 1$	$\nu_0^D = 0$	.99	.99	.58	1	.71	.56	1
	$\nu_0^N = 0$	.96	.95	.69	.94	.03	.40	0

Table 1: The first column indictes the shock hitting the economy in period 0, the second, the null hypothesis (tested after four observations), the other columns report the corresponding p-values. Values below the canonical 5 percent significance level are highlighted.

	Output Growth		Unemployment	
	2-variable VAR	2-variable VAR	2-variable VAR	3-variable VAR
Supply	43.48	41.23	2.08	1.11
Demand	56.52	54.04	97.92	91.16
Noise	n.a.	4.73	n.a.	7.73

Table 2: Variance Decomposition (at infinite horizon) for output growth and unemployment in both our 3-variable baseline VAR specification and in the 2-variable VAR specification which does not include the early realease of output growth (in which the identification of the noise shock is not possible)