



Title	Identifying Noise Shocks: A VAR with Data Revisions
Authors(s)	Masolo, Riccardo Maria, Paccagnini, Alessia
Publication date	2019-12
Publication information	Masolo, Riccardo Maria, and Alessia Paccagnini. "Identifying Noise Shocks: A VAR with Data Revisions." Wiley, December 2019. https://doi.org/10.1111/jmcb.12585 .
Publisher	Wiley
Item record/more information	http://hdl.handle.net/10197/10644
Publisher's statement	This is the peer reviewed version of the following article: Masolo, R. M. and Paccagnini, A. (2018), Identifying Noise Shocks: A VAR with Data Revisions. Journal of Money, Credit and Banking. . doi:10.1111/jmcb.12585, which has been published in final form at https://doi.org/10.1111/jmcb.12585 . This article may be used for non-commercial purposes in accordance with Wiley Terms and Conditions for Self-Archiving.
Publisher's version (DOI)	10.1111/jmcb.12585

Downloaded 2026-05-01 23:41:40

The UCD community has made this article openly available. Please share how this access benefits you. Your story matters! (@ucd_oa)



© Some rights reserved. For more information

Identifying Noise Shocks: a VAR with Data Revisions*

Riccardo M. Masolo[†] Alessia Paccagnini[‡]

October 20, 2018

JEL CODES: E3, C10, D8.

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

*We are particularly grateful to Larry Christiano, Giorgio Primiceri, Roberto Motto, Efrem Castelnuovo, editor Pok-sang Lam and an anonymous referee. We also thank Kate Reinold, Federico Di Pace, Abi Haddow, Lena Boneva, Francesca Monti, Michele Piffer, Kostas Theodoridis, and Matt Waldron for their comments on 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, Barcelona GSE Summer Forum and seminar participants at Maynooth University, Università degli Studi Federico II, and 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.*

[†]Senior Economist, Monetary Analysis, Bank of England and Centre for Macroeconomics. Email: Riccardo.Masolo@bankofengland.co.uk

[‡]Permanent Lecturer, University College Dublin, Michael Smurfit Graduate Business School and Centre for Applied Macroeconomic Analysis, E-mail : alessia.paccagnini@ucd.ie

Abstract

We propose a new VAR identification strategy to study the impact of noise, in the early releases of output growth figures, which exploits the informational advantage of the econometrician. Economic agents, uncertain about the underlying state of the economy, respond to noisy early data releases. Econometricians, with the benefit of hindsight, have access to data revisions as well, which we use to identify noise shocks. A surprising report of output growth produces qualitatively similar but quantitatively smaller effects than a demand shock. We also illustrate how a noise shock cannot be identified unless ex-post information is used.

1. INTRODUCTION

The constant stream of revisions in many macroeconomic data series challenges the commonly-held perfect-information assumption (Smets and Wouters 2007). Orphanides (2003) and Altavilla and Ciccarelli (2011), among others, study the effects of imperfect information for policy, while dispersed information DSGEs, e.g. Lorenzoni (2009), illustrate the consequences of relaxing the assumption of full information in microfounded models.

Data revisions are the manifestation of a particular form of information imperfection, namely information imperfection about the past and current state of the economy. This marks a difference with respect to the "noisy news" literature (Forni et al. 2017), which focuses on noisy signals about future events, like the future level of TFP.

In this paper, we focus on information imperfections about the past and current state of the economy, which is often overlooked, and which can be more readily measured with no need for specific behavioral assumptions, by exploiting data revisions. In particular, we investigate the effects of noise in the early releases of output growth figures.

We do so by developing a structural VAR that exploits the econometrician's informational advantage relative to economic agents. Our novel identification strategy relies on the timing of output data releases and is robust to alternative modeling assumptions. Indeed, our identification scheme rests on three simple considerations:

- i. economic agents respond to information about past economic conditions;
- ii. since the earliest data release for output in quarter t is published in quarter $t + 1$, agents cannot respond to it contemporaneously, but only with a lag;
- iii. econometricians have an information advantage relative to economic agents: *the benefit of hindsight*. Since they typically carry out their analysis years after the reference period t , they can observe both early and mature vintages for the series of interest, which enables them to disentangle noise from fundamental shocks more accurately than economic

agents making decisions in real time.

Our first assumption is supported both by dispersed-information theory, which we discuss below, and real-world practice, while the second and third are a consequence of the process by which information about macroeconomic series is disseminated.

Our structural VAR analysis shows that the responses of output and unemployment to the noise shocks we identify are qualitatively in line with those to a demand shock, which Lorenzoni (2009) used as a proxy for noise shocks. However, the impact of noise in the output growth release is much smaller than that of a demand shock, identified with a long-run restriction à la Blanchard and Quah (1989). For our baseline specification, noise shocks explain about 3 percent of the variance of output growth and 17 percent of the variance of unemployment, while demand shocks explain 52 and 71 percent respectively.

We provide three main insights about the effects of noise in the early release of output growth figures. First, this type of noise produces a negative co-movement between output and unemployment, just like the demand shocks proposed by Lorenzoni (2009). Second, quantitatively, these shocks produce much smaller responses than demand shocks identified with a long-run restriction. Third, in line with the impossibility result presented by Blanchard, L’Huillier and Lorenzoni (2013), these shocks can only be identified if the econometrician has an informational advantage, relative to economic agents. Namely, the econometrician has access to mature vintages of the output growth series, which are not available to economic agents when they make their decisions.

Related Literature. In the dispersed-information literature, Mendes (2007) studied the propagation of a noise shock on output growth in a calibrated model. Lorenzoni (2009) combined a theoretical model with a VAR in which the effects of demand shocks – identified with a long-run restriction along the lines of Galí (1999) and Blanchard and Quah (1989) – are attributed to noise.¹ Our aim is to relax any specific assumption about the data-generating process for noisy signals and to identify noise shocks as separate from other demand shocks.

We do so by focusing on a key common feature of all dispersed information models: the state of the economy is not perfectly known and information differs across agents. As a consequence, aggregate economic indicators, albeit measured with noise, reduce the degree of uncertainty about the state of the economy and prompt agents to act on them. For example, a noise shock to the early release of output growth (Mendes 2007) will have an impact on economic decisions *not because it reveals something about the future* – as is the case in the Barsky and Sims (2012) and Blanchard, L’Huillier and Lorenzoni (2013) – but because it provides useful information about the current state of the economy.

By using a structural VAR, we do away with what we believe to be the main drawback of dispersed information models in this context: the need to specify the data-generating process for the early output growth release, and, implicitly, for the revision process. Data revisions for macroeconomic series are not easy to model (see Mankiw and Shapiro 1986, Croushore and Stark 2001, and Arouba 2008, among others). So a VAR is better suited, in the spirit of Sims (1980), to study the effects of noise in the early releases of output growth, as it captures the key economic mechanism at play while accommodating alternative data-revision processes, as we discuss in Section 3.

Lorenzoni (2009) demonstrates how a VAR can be used to identify the effects of noise shocks without imposing specific assumptions about the revision process. Lorenzoni estimates a VAR in the tradition of Galí (1999) and Blanchard and Quah (1989). This class of VARs identifies a demand and a supply or productivity shock by assuming that only the latter affects the level of output in the long run. Lorenzoni 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 because it works against his model, but leaves open the possibility of finding a more accurate quantification of the effects of noise shocks on macro aggregates, which is what we set out to do.

Related to our analysis is work by Blanchard, L’Huillier and Lorenzoni (2013), 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. Blanchard, L’Huillier and Lorenzoni identify an *impossibility result*:² a noise shock cannot be identified in the context of a VAR. However, this crucially depends on the assumption that the econometrician has access to the same information as the agents or less. In our analysis, we exploit what we call the econometrician’s *benefit of hindsight*. Indeed, we set up a counterfactual exercise to show that the Blanchard, L’Huillier and Lorenzoni impossibility result would apply to our analysis if it was not for the informational advantage of the econometrician.

Complementary to Blanchard, L’Huillier and Lorenzoni (2013) is work by Forni et al. (2017) that proposes a way to identify the effect of noise shocks by exploiting the agents’ learning process to uncover the impact of what they call ”noisy news”. This brings us to an important difference between the analysis of Blanchard, L’Huillier and Lorenzoni, Forni et al., and our own. Both other papers assume that noise corrupts a signal about some future exogenous process (technology), while we focus on noise in the early releases of *past* output growth.

By focusing on noise about past data, our analysis complements that in the ”noisy news” literature. Clearly, noise about the past is only part of the noise affecting the economy. However, focusing on this definition of noise has two important advantages. First, we do not need to define a signal and a variable it insists on (typically TFP): we observe the signal in the data. Second, as a consequence, we can assess the impact of this disturbance on the macroeconomy with no assumptions, other than those that pertain to the data-release process.

Our paper is also related to Déés and Zimic (2016), Enders, Kleeman and Müller (2016), and Benhima and Poilly (2017). Enders, Kleeman and Müller identify optimism shocks in a VAR using SPF data to quantify the agents’ misperceptions. In particular, they study the impact of differences between professional forecasts and early data releases. Déés and Zimic

exploit the econometrician’s informational advantage in a setting which primarily differs from that in Enders, Kleeman and Müller in that it includes forecast errors regarding trend output. The work by Benhima and Poilly aims at identifying multiple noise shocks, for which they need a theoretical model to derive the implications that different noise shocks have on the macroeconomy. Our strategy is different, as we explore the effects of the noisy early data releases by simply assuming that all the agents have observed the early vintage of data and updated their expectations accordingly. We do not use a model to derive sign restrictions, as Déés and Zimic, but strive to be as robust as possible to alternative modeling choices.

The remainder of the paper is organized as follows. Section 2 presents our setup. The derivation of the VAR representation is discussed in Section 3, while Section 4 is devoted to the specification of the VAR. Section 5 illustrates our results. Section 6 provides concluding remarks.

2. SETUP

Let us consider an economy described by the following state-space system:

$$z_t = \Psi_1 z_{t-1} + \Psi_0 u_t, \tag{1}$$

$$s_{ht} = \Gamma_1 z_t + \Gamma_0 \zeta_{ht}, \tag{2}$$

where (1) is the aggregate law of motion for the state of the economy, represented by vector z_t , (2) is the observation equation for agent h at time t , u_t is a vector of aggregate shocks, ζ_{ht} a vector of idiosyncratic disturbances, and Ψ_0 , Ψ_1 , Γ_0 , and Γ_1 conformable matrices.

Linearized dispersed information models, e.g. Lorenzoni (2009), can be readily cast in this form. Information imperfection means that agents do not exactly know the state of the economy, dispersion refers to the fact that information sets differ across agents. As a result, agents will base every decision on their expectation for the state of the economy, $\mathbb{E}_{ht} [z_t]$,

which can be expressed as a linear function of the history of signals:

$$\mathbb{E}_{ht} [z_t] = \mathbb{E} [z_t | s_{ht}, s_{h,t-1}, s_{h,t-2}, \dots] = \mathcal{A}(L) s_{ht}, \quad (3)$$

where the polynomial $\mathcal{A}(L)$ is known and the same for all agents in the economy, given that the data-generating process for the observables is the same for all.

Modeling the exact data-generating process would require a lot of assumptions. Most notably, for our purposes, it would require positing a process for the signal about output growth, which may not accurately reflect the actual properties of early data releases.

So, we adopt only two uncontroversial implications of this setup and otherwise take advantage of the flexibility of a VAR to capture the effects of noise shocks.

The first implication is that information about past realizations of macro variables is valuable to economic agents. The amount of attention paid to the release of GDP figures for the previous quarter confirms that this is a realistic assumption. Yet, standard macroeconomic models (e.g. Christiano, Eichenbaum and Evans 2005 or Smets and Wouters 2003) maintain that the state of the economy is known, so that agents should not devote attention to, let alone act upon, information about past economic developments.

The second implication is that, trivially, agents can only respond to information that is actually known to them, which implies that they will act on noisy early output growth indicators only after they are released.

These two assumptions are all we need to derive the identifying restriction for our VAR.

We can see this by noting that, in the context of the state-space representation in equations (1) and (2), the noise shock is an entry in vector u_t , since it affects the information set of all agents in the economy. Specifically, our noise shock will corrupt the observation of the previous period's output growth, 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 (Mendes 2007).

Importantly, given that the noise shock will impact all agents' information sets, we can

study its effects using aggregate variables.

2.1 Timeline

We now briefly describe how the data-release process for output is consistent with our timing restriction – more details can be found in Appendix A.

The *Bureau of Economic Analysis* (BEA), which is responsible for GDP data in the US, publishes the first release for quarter t GDP during the first month of quarter $t + 1$.

It thus follows immediately that any information contained in an early release cannot affect decisions made during quarter t . Most notably, it cannot affect the consumption and investment decisions that ultimately determine GDP.

Any noisy component present in the early release of GDP for quarter t can only affect macro variables from periods $t + 1$ onwards, when it enters the agents' information set.

Formally, $x_t^0 \in s_{h,t+1}$, $\forall h$, where we indicate with x_t^0 the early release of our variable of interest. As a consequence, the true underlying final value x_t^f , which is a function of the expected value of the state of the economy (see equation (3)), can only respond to the noisy early indicator from period $t + 1$ onwards.

This results in the following timeline, represented graphically in Figure 1:

1. During period t , the true realization x_t^f is determined as a function of the agents' expectations of the state of the economy, so, ultimately, as a function of $s_{h,t-j}$, $\forall h$, $\forall j \geq 0$.
2. The noise-ridden measure of x_t^f , $x_t^0 = x_t^f + v_t$, is released after all economic decisions for period t have been made, i.e. in period $t + 1$, where we denote with v_t the difference between the two measures.³
3. $x_t^0 \in s_{h,t+1}$, $\forall h$, so the expectation of the state of the economy from period $t + 1$ onwards will be affected by the noise shock. As a consequence, x_{t+j}^f , $j \geq 1$ will be a function of v_t .

When one thinks of x_t^f , x_t^0 and v_t as elements of the state-space system in equations (1) and (2), the timeline we just described translates into a set of zero-restrictions in Ψ_0 . In particular, if the early data release x_t^0 is the j -th entry in z_t and the noise shock is the m -th entry in u_t , then the m -th column of Ψ_0 will comprise all zeros except on row j , which delivers our timing restriction, as we discuss in Appendix B.

3. VAR REPRESENTATION

So far, we have described how noise affects the early data release and, in turn, economic decisions in theory. When it comes to empirical analysis, however, there are two main competing models for data revisions known as *noise* and *news*, after the definition in Mankiw and Shapiro (1986). Indeed, one key advantage of using a VAR is that we do not need to make a specific assumption on this process. Rather, we show in this section that our identification restriction is robust both.

3.1 Classical Noise

We start by considering how our identification applies to the case in which the revision is orthogonal to underlying fundamentals. This case arises more naturally in theoretical models (e.g. Mendes 2007) and we will refer to it as *classical noise*.

Under this assumption, the noise component v_t is assumed to be orthogonal to the fundamental value x_t^f :

$$x_t^0 = x_t^f + v_t, \quad v_t \perp x_t^f. \quad (4)$$

Appendix B shows that, given the state-space representation in equations (1) and (2), the process governing x_t^f can be expressed as:

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

where all the elements of equation (5) can be vectors, $A(L)$ and $B(L)$ are polynomials in the lag operator and ε_t is a linear combination of all the other shocks hitting the economy.

Equation (5) shows that past noise shocks affect the decision-making process of the agents in the economy while the current realization does not.

It is then immediate to derive the implied law of motion for the early data release (x_t^0):

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

which shows that the revision component v_t contemporaneously affects the early vintage of data only.

Finally, by combining equations (5) and (6), the following VAR representation can be derived:

$$\begin{bmatrix} x_t^f \\ x_t^0 \end{bmatrix} = \begin{bmatrix} A(L) - B(L) & B(L) \\ A(L) - B(L) & B(L) \end{bmatrix} \begin{bmatrix} x_{t-1}^f \\ x_{t-1}^0 \end{bmatrix} + \begin{bmatrix} \mathbf{1} & \mathbf{0} \\ \mathbf{1} & \mathbf{1} \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ v_t \end{bmatrix}. \quad (7)$$

The matrix pre-multiplying $[\varepsilon_t \ v_t]'$ simply highlights the timing identification scheme that emerges in our setup.

3.2 Prediction Error

A vast empirical literature (see Mankiw and Shapiro 1986, among others) shows that revisions for some series are better characterized as resulting from forecasting errors made by the agency which publishes early releases. We refer to this revision process as *news* driven.

The key difference with the *classical noise* case is that the revision is not orthogonal to the fundamental x_t^f , which makes it not a suitable candidate for a noise shock. Our VAR procedure, however, can overcome this problem because what we call the noise shock is *not necessarily* the revision of data vintages. Indeed, it is orthogonal to the variables included in the VAR by definition.

As we cannot know the exact models used by statistical agencies, we will illustrate this

point with an example and later discuss the role played by our VAR specification.

Let us assume that a statistical agency receives a noisy signal (for example due to sampling errors) on the true underlying value for GDP, x_t^{00} , which we can describe as:

$$x_t^{00} = x_t^f + v_t. \quad (8)$$

To the extent that the agency anticipates that the data that it collects is ridden with noise, it will perform a filtering procedure before releasing it to the public. It is reasonable to assume that it will consider the linear projection of the true underlying variable onto the known signal. In this case the early release would correspond to:

$$x_t^0 = \mathbb{P}[x_t^f | x_t^{00}] = \phi x_t^{00} = \phi x_t^f + \phi v_t, \quad (9)$$

where the projection coefficient ϕ depends on the relative variance of noise in the signal x_t^{00} .

An immediate consequence of this projection procedure is that the data revision will not be orthogonal to the final release. In fact:

$$x_t^f - x_t^0 = (1 - \phi)x_t^f + \phi v_t. \quad (10)$$

So it would be incorrect to take the revision as an indicator of the noise shock. Fortunately, our VAR strategy is robust to this possibility.

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 equations (1) and (2), but would otherwise not change the structure of the problem.

Indeed, using equation (9) as an alternative definition of the early data release, it is

possible to express the early release and the underlying fundamental values as:

$$x_t^0 = \phi(\tilde{A}(L) - \tilde{B}(L))x_{t-1}^f + \tilde{B}(L)x_{t-1}^0 + \phi\varepsilon_t + \phi v_t, \quad (11)$$

$$x_t^f = (\tilde{A}(L) - \tilde{B}(L))x_{t-1}^f + \frac{1}{\phi}\tilde{B}(L)x_{t-1}^0 + \varepsilon_t. \quad (12)$$

Despite the scaling factor ϕ showing up in the equations and different lag-operator polynomials, it is still the case that the noisy component v_t contemporaneously affects only the early release and not the final, consistent with our identification strategy. In fact, the resulting noise shock is precisely the part of noise ϕ which is not filtered out by the statistical agency and thus ends up affecting the agents' information sets.

So our VAR strategy is effective even in a situation in which taking the data revision naively would lead to an incorrect assessment of noise shocks and their effects. The VAR cleanses the revision of the component that depends on x_t^f and, indeed, on any of the variables included in the VAR specification. So, it allows us to study the impact of noise shocks with no need to be specific about the underlying data revision process.

The only possible limitation with this strategy is 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 our VAR specification as a proxy for that information set and experiment with different set of variables and number of lags.

4. VAR SPECIFICATION

Our baseline VAR specification includes an early vintage of (annualized) quarterly output growth (Δy_t^0), its mature counterpart (Δy_t^f), and unemployment (u_t^f). We need two vintages of output growth if we want to apply the identification scheme that we laid down above. The series for unemployment, however, is essentially never revised so we only use one vintage.

Unemployment is key in our VAR for two main reasons:

- i. it is a readily available indicator of current economic conditions not subject to revisions. As such, it represents a good proxy for the data publisher’s information set and can help us to make our identification robust to data revisions being driven by *news*.
- ii. Unemployment allows us to identify demand and supply shocks with a long run restriction as in Blanchard and Quah (1989), which is useful since we can compare our noise shock to a demand shock.

We will also consider a larger set of variables (which includes measures of investment, consumption and inflation), but we keep our baseline parsimonious as we aim to contribute to the identification of noise shocks proposed by Lorenzoni (2009), who used a 2-variable VAR.

We use de-meanded series so our VAR reads:

$$\begin{bmatrix} \Delta y_t^f \\ u_t^f \\ \Delta y_t^0 \end{bmatrix} = \beta(L) \begin{bmatrix} \Delta y_{t-1}^f \\ u_{t-1}^f \\ \Delta y_{t-1}^0 \end{bmatrix} + C \begin{bmatrix} \nu_t^1 \\ \nu_t^2 \\ \nu_t^3 \end{bmatrix}, \quad (13)$$

where $\beta(L)$ is matrix polynomial in the lag operator and C is the matrix identifying our structural shock that we describe below.

4.1 Shock Identification

The discussion in Section 2 describes our identification of the noise shock, which we can sum up as: *the shock that contemporaneously affects the early release of data **only***.

In our three-variable VAR specification, our identification thus pins down the third column of matrix C :⁴

$$[C]_3 = \begin{bmatrix} 0 \\ 0 \\ c_{33} \end{bmatrix}. \quad (14)$$

The structure of the third column of matrix C implies that our estimated noise shock, ν_t^3 , will be orthogonal to all the variables included in the VAR except for the current value of the first release (see the Appendix C for details). We will be using this timing restriction in all the VAR specifications that we will consider.

Our baseline setup lends itself to identifying shocks ν_t^1 and ν_t^2 as demand and supply shocks à la Blanchard and Quah (1989). We do so by partitioning C :

$$C = \left[\begin{array}{cc|c} c_{11} & c_{12} & 0 \\ c_{21} & c_{22} & 0 \\ \hline c_{31} & c_{32} & c_{33} \end{array} \right], \quad (15)$$

and imposing a long-run identification restriction on the upper-left block, which restricts the demand shock not to have any long-run effect on the *level* of output.

The combination of the zero-restriction to identify the noise shock and the long-run restriction to separate out demand and supply shocks also pins down the lower-left block of C , which governs the response of the early data release to demand and supply shocks, as we detail in Appendix D.

4.2 Data Description

We now describe the data we use for our baseline as well as for our alternative specification, which we will present as a robustness check.

The real GDP and unemployment data come 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 from November 1965 to present. We use data published in the third quarter of 2015 and a sample that runs from the first quarter of 1966 to the end of 2007. The quarterly vintages and quarterly observations of the Real GNP/GDP (ROUTPUT) are in Billions of real dollars, and seasonally adjusted. We take the first difference logarithmic transformation, to get the quarterly (annualized)

growth rate⁵. The quarterly vintages of the Unemployment Rate (RUC) are in percentage points, seasonally adjusted. We transform our unemployment data from a monthly to a quarterly frequency by considering the first observation of the quarter. We take levels of the unemployment rate, without detrending⁶ it, as discussed in Blanchard and Quah (1989).

Our early output release corresponds to the second-earliest vintage published in the Philadelphia Fed's dataset. The rationale for this can be better understood by the following example. Our assumption means that for the early release for output in, say, the first quarter of 1980 (1980q1), we use the vintage reported in the Philadelphia Fed's dataset in 1980q3. The vintage reported in the Philadelphia Fed's dataset as the 1980q2 vintage for 1980q1 output refers to the output data released by the BEA in April 1980, the first month after the conclusion of the quarter. During the second quarter of 1980, the BEA would have produced two more releases for output (in May and June). Using the 1980q2 vintage would thus potentially overestimate the amount of noise agents were subject to with regards to output for 1980q1, during the course of 1980q2. It would capture their information set at the beginning of the period but would disregard the extra information that they would have had access to during the quarter. We think that the vintage published in 1980q3 is a better proxy for the information available to agents towards the end of 1980q2. Moreover, this assumption works against us as it tends to make the effects of noise shocks less significant.⁷

We end our sample in 2007 to leave a sufficiently long period after the end of the sample for data revisions. Our mature release of output is that published in the third quarter of 2015⁸ so we allow for almost 8 years worth of revisions even for the data at the very end of the sample.

In our robustness analysis, we add measures of investment, consumption, and inflation. Investment is given by the logarithmic transformation of the ratio between the sum of Gross Private Domestic Investment (GDPI) and Personal Consumption Expenditures: Durable Goods (PCDG) and the Gross Domestic Product, 1 Decimal (GDP) as in Christiano, Trabandt and Walentin (2010). Consumption is given by the logarithmic transformation of the

ratio between the sum of Nondurables Consumption (PCND) and Consumption Services (PCESV) and the Gross Domestic Product, 1 Decimal (GDP), as in Christiano, Trabandt and Walentin.

Inflation is defined as the (annualized) first difference logarithmic transformation of the Personal Consumption Expenditures (PCE).⁹ The data series used for consumption, investment, and inflation are provided by FRED Database of the Federal Reserve Bank of St. Louis. We use quarterly data from the vintage published in the third quarter of 2015.

5. RESULTS

Baseline. We first estimate our three-variable specification. We estimate a VAR(4) as our baseline, a choice which trades off parameter proliferation, associated with an increase in the number of lags, and concerns regarding a possible lag-truncation bias (see Chari, Kehoe and McGrattan 2008).¹⁰

Figure 2 reports the responses of final output (in log-levels) and unemployment to a positive noise shock, a situation in which the early data release is surprisingly higher, given the underlying fundamentals.

Output displays a persistent increase peaking at about a quarter of a percentage point, while unemployment falls in excess of .15 percent. Responses are hump-shaped and persistent, peaking about 2 years after the shock. They are both significant, at least at the 68 percent level.

This supports our working assumption that the economy responds to early releases of output figures. In particular, an unexpectedly high early release of output numbers tends to drive real underlying output in the same direction.

It is important to notice, though, that, not only does the growth-rate of output converge back to zero but so does its log-level, consistent with the idea that, while noise shocks can be expected to produce variability at business cycle frequencies, the effects die out in the long run.

In other words, we find, without imposing it, that the behavior of our identified noise shock is consistent with that identified in Lorenzoni (2009), where a Blanchard and Quah (1989) type demand shock is used as a proxy for noise.

Our finding that output and unemployment move in opposite directions is also qualitatively consistent with the response to a demand shock. In our setting, a positive noise shock gives the economic agents the impression that activity is high, leading to an increase in demand. Underlying productivity, however, is not affected, so the increased demand for output has to be met by a fall in unemployment.

At a quantitative level, though, important differences emerge between noise and demand shocks. Figure 3 overlays demand-shock responses to the responses to a noise shock presented in Figure 2.¹¹

It is evident that both demand and noise shocks induce negatively correlated responses of output and unemployment. However, Figure 3 also immediately reveals that the former produces 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.

As a consequence, identifying noise shocks with a long-run identification scheme would incur a sizable overestimation. This finding is reasonable if one considers that long-run identification schemes are meant to capture, by definition, any economic disturbance that does not have a long run effect on the level of output, e.g. most fiscal and monetary policy shocks, besides noise in output growth figures.

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

Figure 4 reports, side-by-side, the responses of the final (solid line) and early release (dashed line) of output growth to supply, demand and noise shocks respectively. Our identi-

fication restrictions explain why the final release of output growth does not respond contemporaneously to a noise shock, but do not directly restrict the response patterns to demand and supply shocks in the short run.

Hence it is interesting to consider the striking difference between the two. When it comes to demand shocks, the response of the early and mature vintages essentially overlap. In response to supply shocks, however, the early data release responds much less on impact than the underlying fundamental.

This is consistent with the idea that, because unemployment is known in real time and 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 seem to take longer to be revealed, according to our VAR analysis.

More generally, this pattern suggests that demand shocks, such as fiscal interventions, are easier to spot right away than improvements in technology, which are more likely to take place at the individual firm level and require some time to become known.

Variance Decomposition. Figure 5 illustrates the share of the forecast-error variance for output growth and unemployment explained by our identified noise shock. Table 1 presents variance decomposition in a more systematic way. Overall, noise explains about 3 percent of the variability in output growth and 17 percent of the variance of unemployment.

For both variables, the variance share explained by the noise shock is way smaller than that explained by demand shocks. This confirms the idea that using demand shocks as a proxy for the effects of noisy data releases, while qualitatively sensible, overestimates the impact of the shocks, consistent with Lorenzoni (2009) claim that his procedure overestimates the impact of noise shocks.

Our VAR also allows us to study the variance decomposition of the early release of output growth and of the subsequent revision.¹² As one would expect, the noise shock affects the

early release much more than the late vintage. Table 1 shows that the noise shock explains almost 30 percent of the early release. The ten-fold difference in the share of the variance of the early and mature vintage explained by noise shocks can be ultimately considered a measure of the efficiency of the process by which agents filter out noise from early output releases.

Importantly, noise shocks explain more than two thirds of the variance of the revision in output growth. On the one hand, this shows that the revision and the noise shocks are tightly related. It also demonstrates, though, that it would be a mistake to consider the revision, at face value, as a noise shock. Almost one third of the variance in revisions is explained by other shocks. As the impulse responses in Figure 4 illustrate, the response of the early and mature vintage to demand shocks is very similar, which is reflected in the share of the variance of the two vintages explained by demand being very close. Consequently, demand shocks explain a small share of the revision. Conversely, supply shocks are not reflected much in the early vintage while they explain more than 40 percent of the variability in the mature vintage, again in line with the responses presented in Figure 4. This explains why supply shocks are responsible for almost 30 percent of the variability in the revisions.

Counterfactual. We perform a counterfactual exercise to illustrate the role of the extra information that the econometrician has access to, and to discuss the key conclusion in Blanchard, L’Huillier and Lorenzoni (2013) that noise shocks cannot be identified in a VAR.

We set up scenarios in which some, but potentially not all, of the state variables are observed. We consider a state-space representation in which the state equation is represented by our baseline VAR (equation (13)), while the observation equation selects a subset of the variables:

$$\omega_{jt} = \Lambda_j \begin{bmatrix} \Delta y_t^f \\ u_t^f \\ \Delta y_t^0 \end{bmatrix} \quad j = \{1, 2, \dots, 7\}, \quad (16)$$

where ω_{jt} is the vector of observables, and Λ_j is a $q \times 3$ matrix of zeros and ones which selects $1 \leq q \leq 3$ of the 3 state variables. This results in 7 distinct combinations. For each of them, we maintain that the economic agent's information set consists of the timeless history of ω_{jt} . To keep things reasonably simple, we assume that variables are either unobserved or fully known. The information imperfection aspect of the model comes into play insofar as it is reflected by the early release being a noisy signal for true output growth.

The experiment works as follows:

- We consider a one-standard-deviation shock of each type, while all the other shocks are set to zero. This produces three different scenarios, hence three blocks in Table 2.
- 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_{jt} about that shock for four quarters.
- We repeat the tests for all the 7 possible combinations of observables.
- Table 2 reports p-values for all the possible combinations. Rejection of the null-hypothesis means that the shock is identified.

To help with the intuition, it is useful to start by considering column (7) of Table 2, i.e. the full information case.¹³ Looking at the top section ($\nu_0^S = 1$), the p-values equal 0 when $H_0 : \nu_0^S = 0$ and very close to 1 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 scheme. It simply shows that, given the three series, the hypothesis is rejected for the shock that actually occurs but not for the others.

The p-value for the other six observable-combinations can be taken as an indication of how easy it is to recover a shock given incomplete information.

Demand shocks turn out to be easy to identify even when the information set is incomplete.

Supply shocks, however, can be correctly identified only when the late output growth vintage and unemployment are included. That corresponds to combinations (4) and (7). The former includes the same two variables Blanchard and Quah (1989) consider for their long-run identification scheme and is the prototypical econometrician’s ex-post set of observables. The latter is the full information case. So, our counterfactual shows that the long-run identification scheme of supply and demand shocks is robust to the fact that the true underlying model might be including the early vintage of output growth.

Most importantly, however, this counterfactual shows that noise shocks cannot be identified unless all three variables are observed.

So, ultimately, this experiment supports the general finding of Blanchard, L’Huillier and Lorenzoni (2013) that it is not possible to identify noise shocks by observing just one vintage of data, but also illustrates how the econometrician, with the benefit of hindsight, can take full advantage of a richer information set to uncover the effects of imprecise early data releases.

5.1 Robustness Analysis

Variable Selection. 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, are more susceptible to data imperfections, as they necessarily have to rely on forecasts of future conditions, and are costly to reverse.

For this reason we add a measure of investment to our VAR specification. We also consider two more headline macroeconomic variables: consumption and PCE inflation.¹⁴ Figure 6 reports responses to a noise shock for this VAR specification.

It is immediately evident that consumption and investment responses display a marked comovement with output. In terms of magnitudes, however, the investment response is larger than that of output which, in turn, is larger than the consumption response. This is

consistent with both the insight from Rodriguez-Mora and Schulstad (2007), who suggest that the behavior of investment is key to understanding the impact that data revisions have on GDP, and with the well-established business cycle stylized fact positing that investment is more volatile than output, while consumption is less so (see King and Rebelo 2000). Importantly, inflation increases in the wake of the output, consumption and investment increase, which is a staple of a demand-like shock.

Lag Selection. Our results are robust to selecting the number of lags with the two most commonly used statistical procedures. The Schwarz Information Criterion (or BIC) selects a VAR(1) specification, while the Akaike Information Criterion, known to favor the inclusion of more lags, suggests a VAR(8).

Figure 7 reports the responses of output and unemployment to a noise shock when we estimate a VAR(1) and VAR(8) respectively. The responses are qualitatively the same as in our baseline VAR(4). The VAR(8) specification, in particular, produces very similar responses. The VAR(1) produces less persistent and somewhat smaller but more sharply estimated responses. Both of which can be explained by the smaller number of lags and, consequently, of parameters.

Finally, Figure 8 presents the impulse responses from a VAR(1) that includes our measures of investment, consumption and inflation. Just as above, the response of investment exceeds that of output, while the consumption response is smaller. Including more variables increases the number of estimated parameters by less when we estimate a VAR(1) and impulse responses display tighter confidence bands.¹⁵

6. CONCLUSION

Noise can affect information about the past as well as the future state of the economy. The "noisy news" literature has concerned itself with the latter, while we focus on the former.

Our work exploits the econometrician's *benefit of hindsight*, i.e. the fact that she can observe both what in model terms would be considered the signal and the underlying fundamental on which the noise shock applies.

By carrying out our analysis in a VAR, we can afford to remain agnostic about the underlying drivers of data revisions. We only restrict the timing of the responses.

Our identification strategy relies on a timing assumption that 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 are produced when the period at hand is over.

We show that noise about past output growth induces demand-like responses in the macroeconomy. However, responses are quantitatively smaller than those resulting from a demand shock identified with a traditional long-run identification scheme à la Blanchard and Quah (1989).

Also, we illustrate how this additional information is key to identifying the effects of noise shocks. A counterfactual experiment demonstrates that agents cannot separately identify the effect of a noise shock in real time, as suggested by Blanchard, L'Huillier and Lorenzoni (2013).

APPENDIX A: DATA RELEASE DETAILS

The discussion in this section relies on detailed information provided the *General Notes on the Philadelphia Fed's Real-Time Data Set for Macroeconomists (RTDSM) - Variables from the National Income and Product Accounts*, pp. 2-3.

For quarterly vintages, like those that we use for GDP, the *last* observation in each column of the real time data set captures the advance estimate for the *previous* quarter. For concreteness, let us consider GDP for 1980 quarter 1. The first vintage for which a number for GDP in 1980q1 is available is the vintage released in the *second* quarter of 1980 (1980q2). This is critical in that it justifies our assumption that the economic agents' information set does not include an observation for GDP in the current quarter. This, in turn, justifies our timing assumption and, indeed, makes it hold by default (as the earliest of releases is made public after the quarter). In keeping with our example, our identifying restriction implies that a noise shock to 1980q1 GDP will impact GDP and all the other economic variables, from 1980q2 onwards, i.e. from when data is released onwards.

Going back to our example, in 1980q2 the BEA would release three successive numbers for the 1980q1 GDP (near the end of April, May and June respectively). The 1980q2 vintage of 1980q1 output in the Philadelphia Fed's real-time dataset records the information available to agents *in the middle* of 1980q2, that is the first of the BEA releases (that released in April).

For our baseline set of results, as the early output release for 1980q1 we use the release published in 1980q3 (so the second one available). First, this should better capture information available *throughout* the 1980q2 quarter (as mentioned above the 1980q2 vintage release for 1980q1 refers to the first of three BEA releases within the same quarter). Second, when we use the first first available vintage for all quarters in our sample, one observation is missing, which we have to interpolate.

We think this is a more conservative approach, as it amounts to assuming that agents

can make their economic decisions for 1980q2 at the very end of the quarter, while in reality some decisions will be made earlier than that. In practice, our assumption should reduce the significance of a noise shock.

For robustness purposes, we also considered the first available vintage, though it requires interpolating one observation. The correlation between the two series is .973. In terms of variance decomposition, when we use the first available vintage, the noise shock explains 5.57 percent of the the late output growth release, 11.3 percent of unemployment and 32.3 percent of the variation in the early output release. These numbers are about 1 to 2 percentage points higher than those we obtain in our baseline setup, but do not alter any of our conclusions.

APPENDIX B: 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 equations (1) and (2).

Throughout the derivation we will maintain the assumption that z_t is defined by stacking up multiple lags of the state variables. Since in equation (7) we derive a 2-variable VAR in Section 2, and since adding variables does not change the identification, we will maintain, for the rest of this section that the state variables are x_t^f and x_t^0 only.¹⁶

B.1 Derivation of the VAR Representation

First define Ξ^F and Ξ^u such that:

$$x_t^f = \Xi^F z_t \tag{B1}$$

$$u_t = \begin{bmatrix} \Xi^u u_t \\ v_t \end{bmatrix}, \tag{B2}$$

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 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 (1) and (2) we have:

$$x_t^f = \Xi^F \Psi_1 z_{t-1} + \Xi^F \Psi_0 u_t, \quad (\text{B3})$$

$$= \Xi^F \left(\sum_{l=1}^s [\Psi_1]_{f,l} x_{t-l}^f + [\Psi_1]_{0,l} x_{t-l}^0 \right) + \Xi^F \Psi_0 u_t, \quad (\text{B4})$$

$$= \Xi^F \left(\sum_{l=1}^s [\Psi_1]_{f,l} x_{t-l}^f + [\Psi_1]_{0,l} x_{t-l}^0 \right) + [\Xi^F \Psi_0]_{\forall i < m} \Xi^u u_t + [\Xi^F \Psi_0]_m v_t, \quad (\text{B5})$$

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

Given our zero-restriction assumption on Ψ_0 :

$$[\Xi^F \Psi_0]_m = \Xi^F [\Psi_0]_m, \quad (\text{B6})$$

$$= \underline{0}, \quad (\text{B7})$$

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 $\varepsilon_t \equiv [\Xi^F \Psi_0]_{\forall i < m} \Xi^u u_t$, i.e. the rotation of all the other shocks,

delivers:

$$x_t^f = \Xi^F \left(\sum_{l=1}^s [\Psi_1]_{f,l} x_{t-l}^f + [\Psi_1]_{0,l} x_{t-l}^0 \right) + \varepsilon_t, \quad (\text{B8})$$

$$= \Xi^F \left(\sum_{l=0}^s [\Psi_1]_{f,l} x_{t-1-l}^f + [\Psi_1]_{0,l} x_{t-1-l}^0 \right) + \varepsilon_t, \quad (\text{B9})$$

$$= \mathcal{R}(L)x_{t-1}^f + \mathcal{S}(L)x_{t-1}^0 + \varepsilon_t, \quad (\text{B10})$$

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

Now, using the definition of early release¹⁷ we get:

$$x_t^f = \Xi^F \left(\sum_{l=0}^s [\Psi_1]_{f,l} x_{t-1-l}^f + [\Psi_1]_{0,l} (x_{t-1-l}^f + v_{t-1-l}) \right) + \varepsilon_t, \quad (\text{B11})$$

$$= \Xi^F \left(\sum_{l=0}^s ([\Psi_1]_{f,l} + [\Psi_1]_{0,l}) x_{t-1-l}^f + [\Psi_1]_{0,l} v_{t-1-l} \right) + \varepsilon_t, \quad (\text{B12})$$

$$= (\mathcal{R}(L) + \mathcal{S}(L))x_{t-1}^f + \mathcal{S}(L)v_{t-1} + \varepsilon_t, \quad (\text{B13})$$

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

APPENDIX C: ORTHOGONALITY OF THE REVISION SHOCK

Here we will illustrate how the revision shock resulting from our analysis is not simply a data revision but is orthogonal to variables included in the VAR. We will illustrate the point for our baseline specification, but obviously it generalizes. If we refer to the VAR residuals as w_t then, given our identification assumption:

$$\begin{bmatrix} \nu_t^1 \\ \nu_t^2 \\ \nu_t^3 \end{bmatrix} = C^{-1}w_t. \quad (\text{C1})$$

Basic projection theory implies that:

$$Cov \left(w_t, \begin{bmatrix} \Delta y_{t-1}^f \\ u_{t-1}^f \\ \Delta y_{t-1}^0 \end{bmatrix} \right) = \mathbf{0}. \quad (\text{C2})$$

So:

$$\begin{aligned} Cov \left(\begin{bmatrix} \nu_t^1 \\ \nu_t^2 \\ \nu_t^3 \end{bmatrix}, \begin{bmatrix} \Delta y_{t-1}^f \\ u_{t-1}^f \\ \Delta y_{t-1}^0 \end{bmatrix} \right) &= Cov \left(C^{-1}w_t, \begin{bmatrix} \Delta y_{t-1}^f \\ u_{t-1}^f \\ \Delta y_{t-1}^0 \end{bmatrix} \right) \\ &= C^{-1}Cov \left(w_t, \begin{bmatrix} \Delta y_{t-1}^f \\ u_{t-1}^f \\ \Delta y_{t-1}^0 \end{bmatrix} \right) = \mathbf{0}. \end{aligned} \quad (\text{C3})$$

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_t^3 , 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 .

APPENDIX D: IDENTIFYING NOISE, DEMAND AND SUPPLY SHOCKS

Our identification scheme¹⁸ aims at imposing enough restrictions to uniquely pin down the structural-shock matrix C , such that:

$$C\nu_t = w_t \tag{D4}$$

$$CC' = \Sigma \tag{D5}$$

$$E[\nu_t\nu_t'] = I_3, \tag{D6}$$

where $\Sigma \equiv Cov(w_t)$, the covariance matrix of the estimation residuals w_t and ν_t are the structural shocks.

To pin down C , three restrictions are required.

Our discussion provides two, in that it restricts the contemporaneous responses to final output growth and unemployment to zero. Hence $c_{13} = c_{23} = 0$ and $c_{33} = \sqrt{\Sigma_{33}}$.¹⁹

In terms of identifying the noise shock this would be enough, which is convenient, because we can easily apply this to our alternative specifications.

In our main exercise, though, we want to identify demand and supply shocks with a long-run identification scheme. Given our zero restriction, our matrix C looks as follows:

$$C = \left[\begin{array}{cc|c} c_{11} & c_{12} & 0 \\ c_{21} & c_{22} & 0 \\ \hline c_{31} & c_{32} & c_{33} \end{array} \right] \tag{D7}$$

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

$$\tilde{C} \equiv \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}, \quad \tilde{\Sigma} \equiv \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}, \quad \tilde{\beta} \equiv \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$$

The long-run restriction is then implemented as follows:

$$\tilde{C} = (I_2 - \tilde{\beta})F, \quad (\text{D8})$$

$$F \equiv \text{Chol} \left((I_2 - \tilde{\beta})^{-1} \tilde{\Sigma} (I_2 - \tilde{\beta})^{-1} \right). \quad (\text{D9})$$

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 four of the six unique elements of Σ (in gray below):

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix} \quad (\text{D10})$$

The remaining 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:

$$\begin{bmatrix} c_{31} & c_{32} \end{bmatrix} = \left(\left((I_2 - \tilde{\beta})F \right)^{-1} \begin{bmatrix} \Sigma_{13} \\ \Sigma_{23} \end{bmatrix} \right)' \quad (\text{D11})$$

LITERATURE CITED

Altavilla, Carlo, and Matteo Ciccarelli. (2011) "Monetary Policy Analysis in Real-Time. Vintage Combination from a Real-Time Dataset." CESifo Working Paper Series 3372, CESifo Group Munich.

Arouba, S. Boragan. (2008) "Data revisions are not well behaved." *Journal of Money, Credit and Banking*, vol. 40(2-3), pages 319-340, March.

Barsky, Robert B., and Eric R. Sims. (2012) "Information, animal spirits, and the meaning of innovations in consumer confidence." *American Economic Review* 102, 4,1343(1377).

Benhima, Kenza, and Céline Poilly. (2017) "Do Misperceptions about Demand Matter? Theory and Evidence." *Cahiers de Recherches Economiques du Département d'Econométrie et d'Economie politique (DEEP)*, Université de Lausanne.

Blanchard, Olivier, and Danny Quah. (1989) "The Dynamic Effects of Aggregate Demand and Supply Disturbances." *American Economic Review*, American Economic Association, vol. 79(4), pages 655-73, September.

Blanchard, Olivier, Jean-Paul L'Hullier, and Guido Lorenzoni. (2013) "News, noise and fluctuations: An empirical exploration." *American Economic Review*, 103(7): 3045-70.

Chari, V. V., Patrick Kehoe, and Ellen McGrattan. (2008) "Are structural VARs with long-run restrictions useful in developing business cycle theory?" *Journal of Monetary Economics*, volume 55, pages 1337-1352.

Clements, Michael P., and Ana B. Galvão. (2010) "First announcements and real economic activity." *European Economic Review* 54, 6, 803(817).

Christiano, Lawrence, Martin Eichenbaum, and Chris Evans. (2005) "Nominal Rigidities and the Dynamic effects of a Shock to Monetary Policy." *Journal of Political Economy* 113, 1-45.

Christiano, Lawrence J, Mathias Trabandt, and Karl Walentin. (2010) "DSGE Models for Monetary Policy Analysis." *Handbook of Monetary Economics*, in: Benjamin M. Friedman & Michael Woodford (ed.), *Handbook of Monetary Economics*, edition 1, volume 3, chapter 7, pages 285-367 Elsevier.

Croushore, Dean, and Tom Stark. (2001) "A real-time data set for macroeconomists." *Journal of Econometrics*, Elsevier, vol. 105(1), pages 111-130, November.

Dées, Stephen, and Srećko Zimic. (2016) "Animal Spirits, Fundamental Factors and Business Cycle Fluctuations." Working Paper Series 1953, European Central Bank.

Enders, Zeno, Michael Kleemann, and Gernot Müller. (2016) "Growth Expectations, Undue Optimism, and Short-run Fluctuations." CEPR Discussion Paper No. DP11521.

Forni, Mario, Luca Gambetti, Marco Lippi, and Luca Sala. (2017) "Noisy News in Business Cycles, *American Economic Journal: Macroeconomics*." 9 (4): 122-52.

Galí, Jordi. (1999) "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?" *American Economic Review*, American Economic

Association, vol. 89(1), pages 249-271, March.

King, Robert, and Sergio Rebelo. (2000) "Resuscitating real business cycles." NBER Working Paper 7534.

Lorenzoni, Guido. (2009) "A theory of demand shocks." The American Economic Review.

Mankiw, Gregory, and Matthew Shapiro. (1986) "News or noise? an analysis of gnp revisions." NBER Working Paper, 24.

Melosi, Leonardo. (2014) "Estimating Models with Dispersed Information." American Economic Journal: Macroeconomics, Volume 6(1), 2014, p. 1-31.

Mendes, Rhys. (2007) "Information expectations and the business cycle." Bank of Canada, Mimeo.

Orphanides, Athanasios. (2003) "Monetary policy evaluation with noisy information." Journal of Monetary Economics, Elsevier, vol. 50(3), pages 605-631, April.

Rodriguez-Mora, Jose V., and Paul Shulstad. (2007) "The effect of GNP announcements on fluctuations of GNP growth." European Economic Review, 1(19).

Sims, Christopher A. (1980) "Macroeconomics and Reality." Econometrica, Econometric Society, vol. 48(1), pages 1-48, January.

Smets, Frank, and Rafael Wouters. (2003) "An Estimated Stochastic Dynamic General Equilibrium Model of the Euro Area." Journal of the European Economic Association, 1,

1123-1175.

Smets, Frank, and Rafael Wouters. (2007) "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review*, Vol. 97 No. 3 June 2007.

FOOTNOTES

1. Melosi (2014) estimated a structural model with dispersed information but the information friction is limited to firms.
2. Blanchard, L’Huillier, and Lorenzoni (2013) section 2.2.
3. We will discuss the properties of v_t in detail in Section 3.
4. We use the $[\cdot]_j$ notation to the j -th column of the matrix in brackets.
5. Using growth rates is motivated not simply by non-stationarity considerations but also by the fact that, as Rodriguez-Mora and Schulstad (2007) point out, it is easier to account for big long-term data revisions in growth rates than in levels.
6. We do not detrend unemployment since our sample data does not show any deterministic or stochastic trends.
7. We estimated our baseline specification using the first vintage available in the Philadelphia Fed’s dataset. Results are very close to those we present in the next Section and, to the extent that they differ, they tend to produce slightly larger, though not statistically different, impulse responses. Exactly what one would expect given that the first available vintage is an even noisier indicator than the one we use.
8. 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.
9. Chain-type Price Index, Index 2009=100, Quarterly, Seasonally Adjusted.
10. In Section 5.1, we present results from a VAR(1) and a VAR(8) for the sake of robustness.
11. We report both the responses to demand shocks identified in the context of our three-

variable baseline specification and in a two-variable VAR which does not include the early output release and is thus more in the spirit of Blanchard and Quah (1989). They are remarkably similar, though the response to a demand shock is somewhat smaller when a noise shock is separately identified, in line with our variance-decomposition findings.

12. The revision is a simple linear combination (difference) of two variables included in our VAR, so it is immediate to compute a variance decomposition for that measure as well.

13. In terms of the observation equation (16), this corresponds to $\Lambda_7 = I_{3 \times 3}$.

14. Detailed description of each of these series is presented in Section 4.2.

15. We also estimated a VAR(8) with investment, consumption and inflation. Results are similar to our VAR(4) specification.

16. Having extra variables in the state would add more terms to the sum in brackets in equation (B4) but would not affect the orthogonality result.

17. 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.

18. We thank Amborgio Cesa-Bianchi for sharing his version of the implementation of a Blanchard-Quah long run restriction

19. Obviously $c_{33} = -\sqrt{\Sigma_{33}}$ would also be a solution, so, strictly speaking, we also make a sign normalization as for every structural VAR identification.

Table 1: Variance Decomposition

	Δy_t^f		u_t^f		Δy_t^0	$\Delta y_t^f - \Delta y_t^0$
	2-var	3-var	2-var	3-var	3-var	3-var
Supply	46.8	45.6	12.6	12.0	21.6	28.4
Demand	53.2	51.9	87.4	71.4	49.9	2.9
Noise	n.a.	2.6	n.a.	16.6	28.5	68.6

Note: Variance decomposition (at infinite horizon) for output growth and unemployment in both our 3-variable baseline VAR specification (3-var) and in the 2-variable VAR specification (2-var) which does not include the early release of output growth. Variance decomposition (at infinite horizon) for the early release of output growth and for the revision (difference between late release and early release) in our 3-variable baseline VAR specification.

Table 2: Counterfactual Exercise

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)	
$\nu_0^S = 1$	$\nu_0^S = 0$	0.89	0.98	0.96	0*	0.56	0.45	0*
	$\nu_0^D = 0$	0.94	0.77	0.83	0.99	0.99	0.86	0.97
	$\nu_0^N = 0$	0.99	0.99	0.97	0.99	0.71	0.54	0.97
$\nu_0^D = 1$	$\nu_0^S = 0$	0.97	0.95	0.92	0.99	1	0.97	0.89
	$\nu_0^D = 0$	0.05*	0*	0.09	0*	0.01*	0*	0*
	$\nu_0^N = 0$	0.98	0.99	1	0.98	0.92	0.96	0.89
$\nu_0^N = 1$	$\nu_0^S = 0$	0.99	0.99	0.97	0.97	0.76	0.52	0.98
	$\nu_0^D = 0$	0.94	0.94	0.99	0.89	0.85	0.81	0.98
	$\nu_0^N = 0$	1	0.99	0.96	0.98	0.30	0.51	0*

Note: The first column indicates 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 denoted with an asterisk.

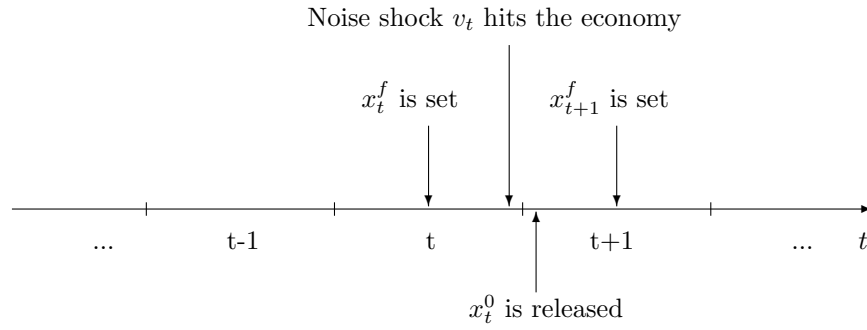


Figure 1: Timeline of decision making and data releases.

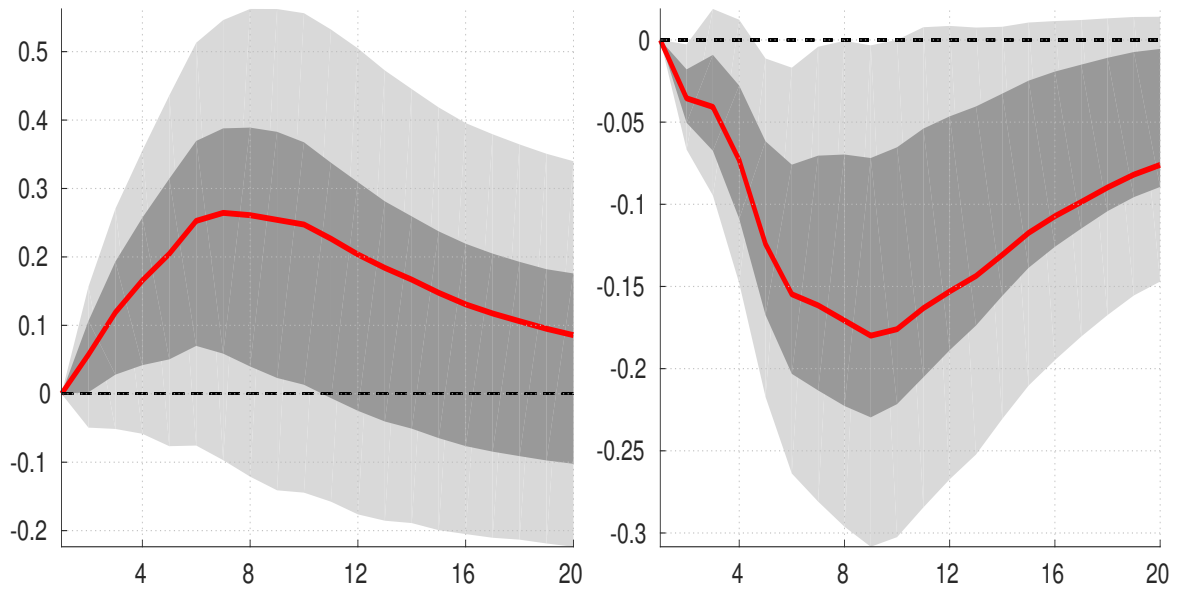


Figure 2: Responses of output (in logs) and unemployment to a one-standard-deviation noise shock. The shaded area represents a 95 percent confidence band.

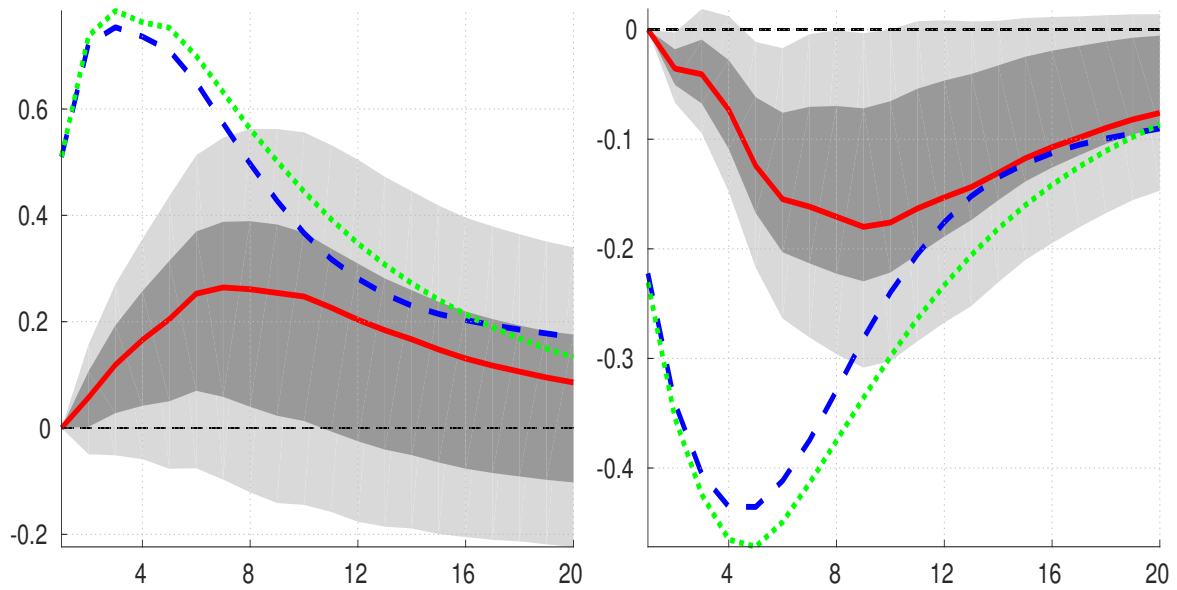


Figure 3: Responses of output (in logs) and unemployment to a one-standard-deviation noise shock (red solid), to a demand shock identified in our three-variable VAR (blue dashed) and to a demand shock identified in a two-variable VAR which excludes the early output growth release (green dotted). The shaded area represents a 95 percent confidence band. Shocks are equally likely because each corresponds to a one-standard deviation shock.

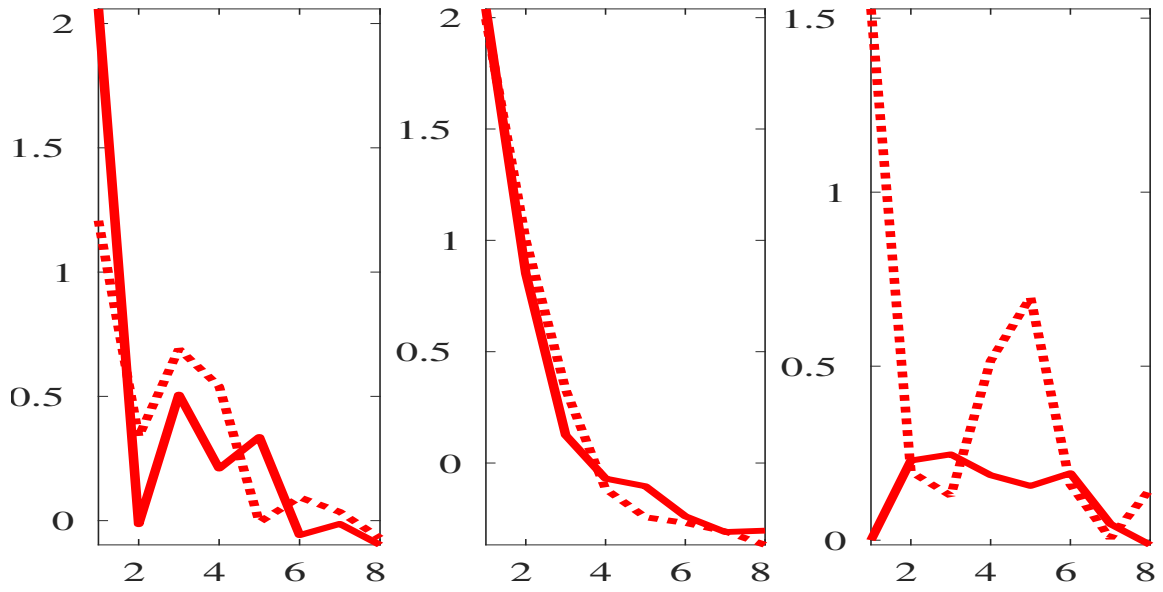


Figure 4: Responses of the final (solid) and early (dotted) releases of output growth to a supply (left), demand (center) and noise (right) one standard-deviation shocks.

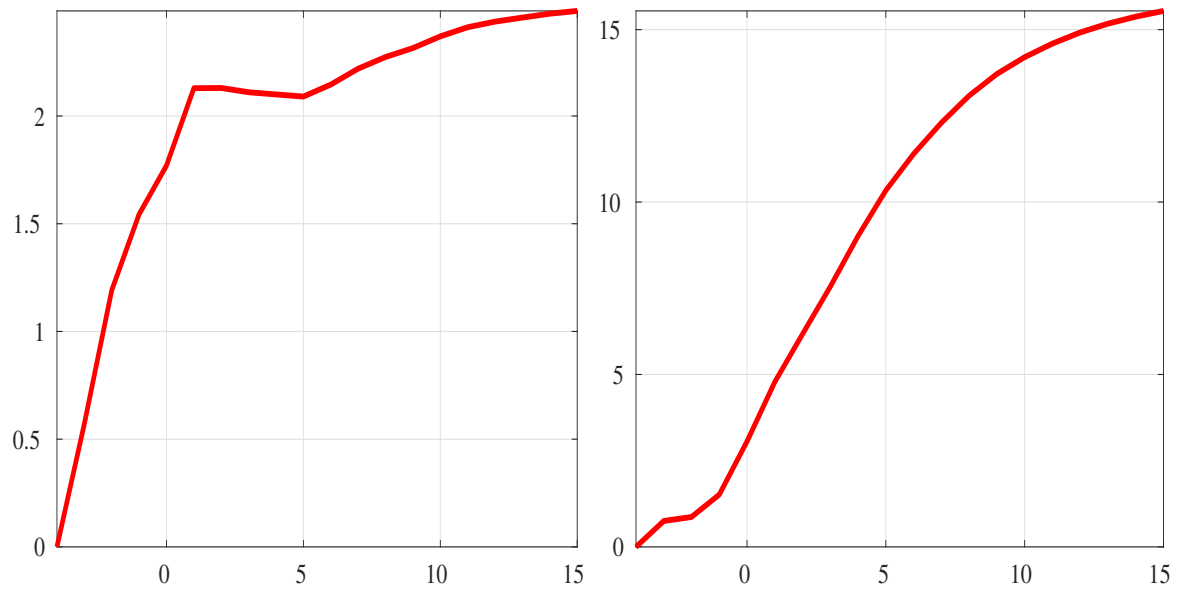


Figure 5: Forecast error variance share of output growth and unemployment explained by noise shocks.

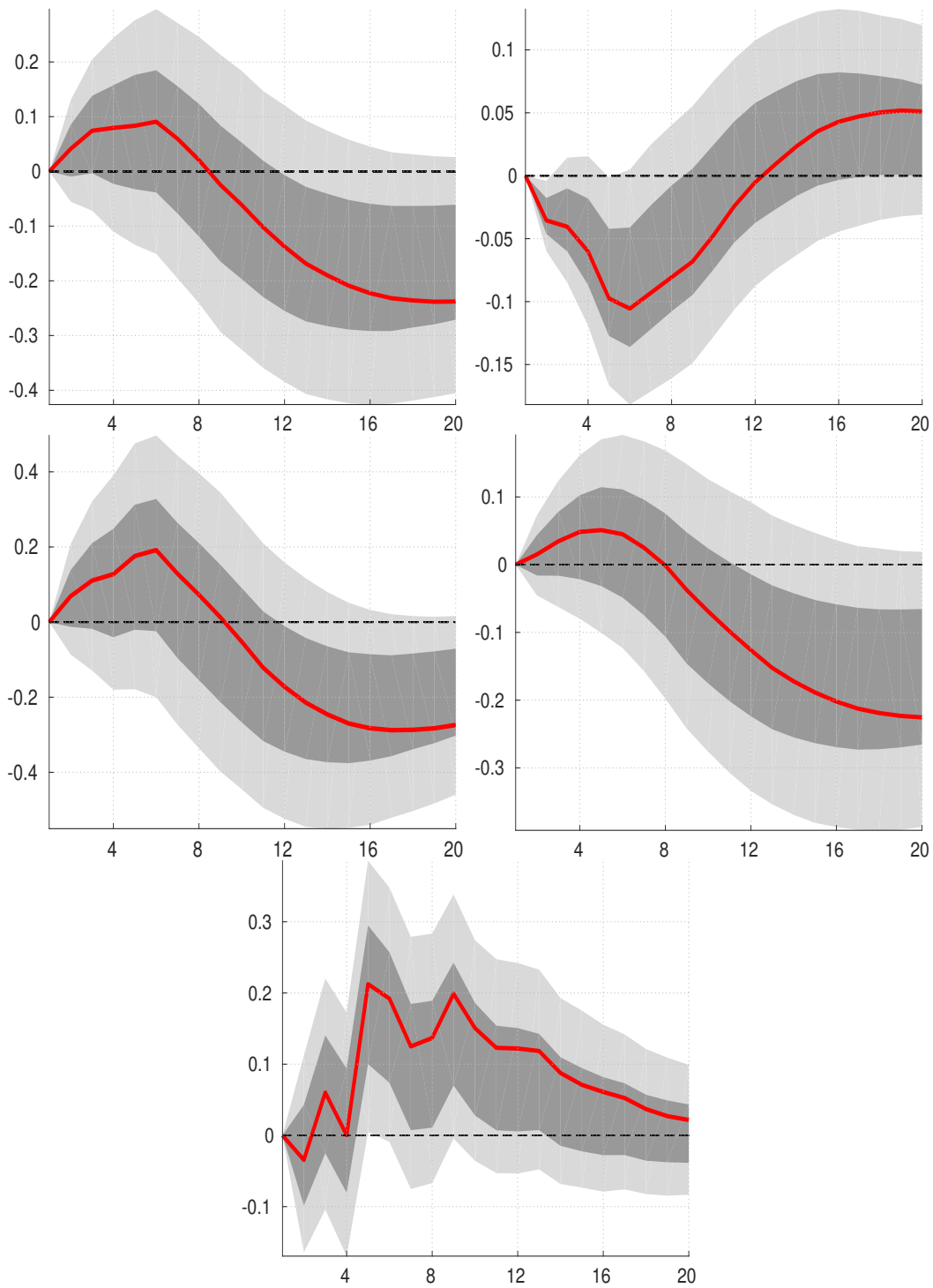


Figure 6: Response of output (top left), unemployment (top right), investment (mid left), consumption (mid right), and inflation (bottom) to a one-standard deviation noise shock. The dark shaded area represents a 68 percent confidence band. The lighter shaded area represents a 95 percent confidence band.

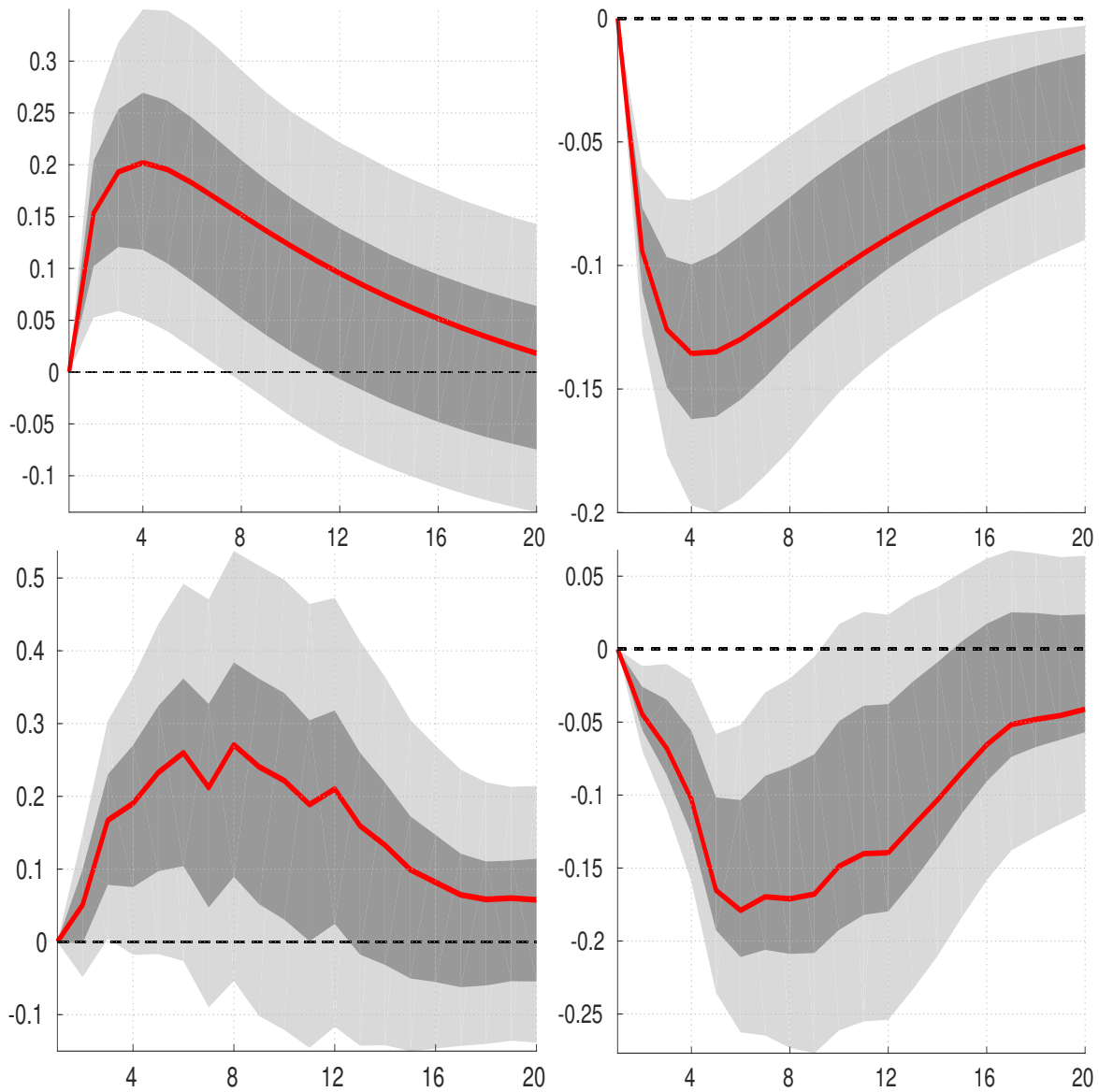


Figure 7: Response of output (left) and unemployment (right) to a one- standard-deviation when we estimate an VAR(1) (top) and a VAR(8) (bottom). The dark shaded area represents a 68 percent confidence band. The lighter shaded area represents a 95 percent confidence band.

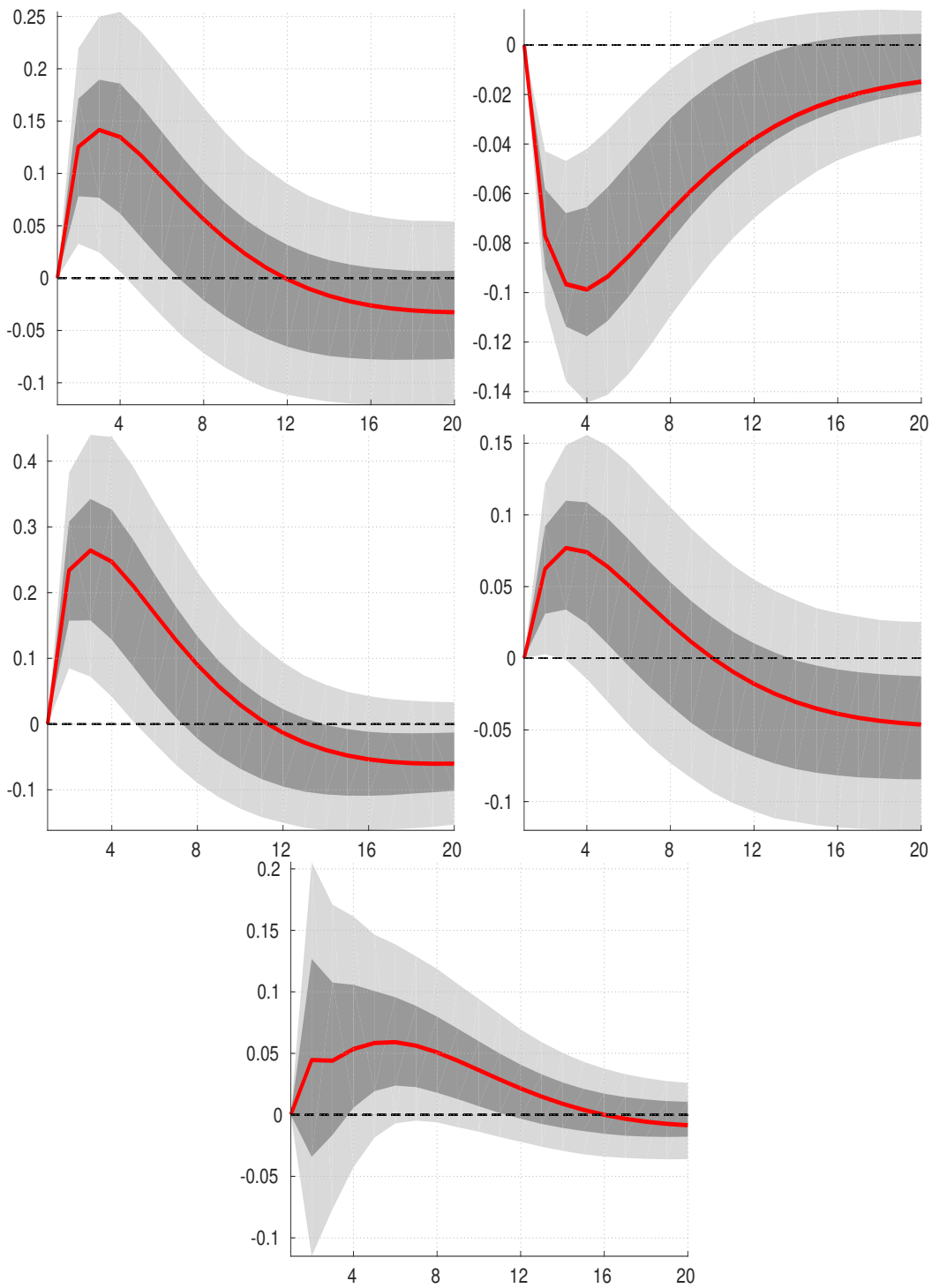


Figure 8: Response of output (top left), unemployment (top right), investment (mid left), consumption (mid right), and inflation (bottom) to a one-standard deviation noise shock from a VAR(1) specification. The dark shaded area represents a 68 percent confidence band. The lighter shaded area represents a 95 percent confidence band.