Expectations Shocks with Uncertain Data

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Abstract

We consider the effects of expectations shocks on the US macroeconomy. We show that the estimation of expectations shocks, and of their effects on the economy, are sensitive to the assumptions we make about forecasters' information sets. If we falsely assume forecasters know the final values of recent values of real GDP when they form their expectations, the importance of expectations shocks will be under-estimated. In addition, the VAR needs to include key monthly indicators on the current state of the economy to correctly identify the effects of expectations shocks. Expectations shocks are largely uncorrelated with technology news shocks.

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1 Introduction

There is a venerable literature on the effects of expectations on economic fluctuations dating back at least to Pigou (1927) and Keynes (1936). Our paper focuses on the role of expectational shocks when there is uncertainty about 'where we are now', because the national accounts data on the current state of the economy are only provisional and are subject to (sometimes substantial) revision. There are a number of papers that explore the effects of exogenous shifts in consumer confidence, or survey expectations, including Barsky and Sims (2012), Leduc and Sill (2013), Lambertini, Mendicino and Punzi (2013), Levchenko and Pandalai-Nayar (2017) and Fève and Guay (2016), *inter alia*. However, these papers either ignore or attempt to finesse the issue of data uncertainty. For example, Leduc and Sill (2013) choose their measure of economic activity, the unemployment rate, precisely because data revisions are small and can be ignored.[1] One of our key interests is whether the uncertainty surrounding the activity data affects the way in which expectational shocks affect the economy.

Leduc and Sill (2013) find that positive expectations shocks about the future (specifically, the unemployment rate) lead to increases in current activity and inflation, and a contemporaneous tightening in monetary policy. They leave open the question of how their expectational shocks are related to anticipated or 'news' shocks such as the future technology innovations of Beaudry and Portier (2006) and Barsky and Sims (2011), or the 'animal spirits' (autonomous shocks to expectations when all the fundamental factors have been included) of Barsky and Sims (2012). Economic-activity forecasts might be revised in response to anticipated future productivity shocks, so that changes in the expectations of professional macro-forecasters in part reflect news shocks. This would contrast with Milani (2011), who associates expectational shocks with changes in the private sector's degree of optimism or pessimism.

In this paper we consider the effects of data revisions to macroeconomic aggregates on the determination of expectations shocks, and on the estimated response of the macro-economy to those shocks. We compute expectation shocks from the revisions by professional forecasters to their previous forecasts which are not made in response to changes in their information set. To measure the effect of expectation shocks, the use of final data (i.e., latest available at the time

[1] However, it is unlikely that data uncertainty can be side-stepped by choice of variable on the part of the investigator. Forecasters will surely condition their expectations on a range of variables and indicators, many of which are revised over time. So modelling shocks to expectations requires that we include the intial estimates of relevant variables (such as non-farm payroll and industrial production).

the study is undertaken) on economic activity variables may lead to misleading findings given that agents act on the basis of the then-available data.[2] We consider expectations of the future values of macroeconomic variables which are subject to data revisions, but we use only the vintages of data that would have been available at each moment. This is in stark contrast to all previous studies that consider the effects of confidence and expectations shocks.[3] The literature uses the latest-vintage of data available at the time the study is undertaken. Hence we identify expectations shocks using the data that agents would have had access to at the time the forecasts were made. The vector autoregression (VAR model) used to identify the impact of one-year-ahead expectation shocks is estimated only using real-time data. There are a number of ways this could be done. The approach we use includes two time series on the macroeconomic variable of interest in the empirical model: a time series of first releases (advance estimates) and a time series for 'first-finals' (the vintage of data published after initial revisions have been incorporated by the statistical office).

Another feature of our paper is to use the key information available to the forecasters at the time to estimate expectations shocks. Some of the data available at the time the expectation is formed pertains to the current quarter - it is of a higher frequency than the macroeconomic variable being forecast. This is recognized in the forecasting literature by terming current-quarter forecasts 'nowcasts'. For forecasting GDP, key indicators such as monthly data on industrial production and non-farm payroll employment for the current quarter will generally be available before the forecasts for the quarterly variable of interest are recorded (see, e.g., Bańbura, Giannone, Modugno and Reichlin (2013)). Ignoring this monthly-indicator information on the current quarter would omit potentially relevant information from the survey respondent's information set, leading to an incorrect estimate of the expectations shock. To correctly estimate expectations shocks and their impacts, we consider mixed-frequency VAR (MF-VAR) models (see, e.g., Ghysels (2016)) so that the monthly information can be included.

Using a mixed-frequency VAR model, we find that expectations shocks explain only 6% of the variation of aggregate output at a two-year horizon if we use the latest-available vintage data on GDP. This is in agreement with the effects of sentiment shocks in Fève and Guay (2016). If instead we use real-time GDP data (as briefly described above and detailed in section 2.2), we find

[2] This mirrors the literature on the real-time estimation of output gaps and inflation trends. Estimates based on final data may provide misleading assessments of the historical efficacy of monetary policy: see, e.g., Orphanides (2001), Orphanides and van Norden (2002) and Clements and Galvão (2012).

[3] Including those cited above, such as Barsky and Sims (2012), Leduc and Sill (2013), Lambertini *et al.* (2013), Levchenko and Pandalai-Nayar (2017) and Fève and Guay (2016), *inter alia*.

that expectation shocks explain 22% of the variation of aggregate output two-years ahead. When we consider how expectations and confidence react to technology news shocks, we find that news shocks explain 44% and 48% of the variation of these variables at the two year horizon, but if we use only the latest available vintage, these proportions decline to 38%. These results suggest that by effectively assuming that agents are able to predict future data revisions (as is implicit in the use of the latest-available-vintage data on real GDP), previous studies may have under-estimated the impact of expectations and confidence shocks on aggregate output, and may also have under-estimated the impact of news shocks on expectations and confidence measures.

We also show that expectation shocks and technology news shocks are largely uncorrelated. Levchenko and Pandalai-Nayar (2017) make news and expectations shocks orthogonal by construction to measure the effects of non-technology expectations shocks. We implement their identification strategy to a quarterly VAR model. We show that the use of latest-available-vintage data instead of real-time data reduces the proportion of the forecast error variance of output explained by non-technology expectations shocks from 73% to 40% at one-year horizon.

The plan of the rest of the paper is as follows. Section 2 discusses the calculation of expectations shocks for activity variables such as real GDP growth which are only available quarterly, and are subject to substantive revisions. Section 3 briefly discusses the literature on new shocks. Section 4 describes the estimation of the model, and section 5 presents our results. Finally, section 6 offers some concluding remarks.

2 Identification of the Expectations Shock

In this section, we show how to measure the transmission of expectation-driven shocks using the U.S. Survey of Professional Forecasts (SPF) as the source of expectations.[4] We start with the identification of the expectations shock while ignoring the impact of data uncertainty, then we progress to models that accommodate the impact of data uncertainty. Finally, we show how to allow for forecasters use of intra-quarter monthly indicators when computing their forecasts.

[4] Freely available at https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/

2.1 Measuring Expectations shocks

We measure expectation shocks as the innovations to forecast revisions that cannot be explained by the updating of the information set of the forecaster. SPF forecasts are made around the middle of the middle month of the quarter (survey questionnaires are required to be returned by around the end of the third week of the middle month). At quarter t, the value of the target variable Y_t is not available because of publication delays. Hence, in response to a survey at time t, there is a nowcast $Y_{t|t}$ and forecasts for next three quarters $Y_{t+1|t}$, $Y_{t+2|t}$, $Y_{t+3|t}$ where the conditioning is on the survey t information.[5] Forecasts revisions are then defined as:

$$Y_{t+n|t} - Y_{t+n|t-1},$$

where $Y_{t+n|t}$ is the cross-sectional median of respondents' forecasts at time t of Y at $t+n$. Because of possible links with anticipated shocks, we are particularly interested in changes in longer horizon forecasts. We will make use of the SPF forecasts $Y_{t+2|t}$ and $Y_{t+3|t}$.[6]

We use a VAR that includes the target variable and forecasts as endogenous variable to measure and compute responses to expectation shocks, as in Leduc and Sill (2013), Barsky and Sims (2012), Levchenko and Pandalai-Nayar (2017) and Fève and Guay (2016). We use the time series of forecasts $Y_{t+2|t}$ and $Y_{t+3|t}$, and the time series for the target variable Y_t, all for $t = 1, ..., T$. We will explain our identification strategy using a VAR with autoregressive order equal to 1 and ignoring intercepts for simplicity. Details of our VAR specification and estimation procedure are described in section 4. To capture exogenous changes to forecasts, we use the following VAR:

$$\begin{bmatrix} Y_{t+2|t} \\ Y_{t+3|t} \\ Y_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} Y_{t+1|t-1} \\ Y_{t+2|t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{rt} \\ \varepsilon_{ft} \\ \varepsilon_{yt} \end{bmatrix}, \tag{1}$$

where ε_{rt}, $\varepsilon_{ft}, \varepsilon_{yt}$ are (potentially) correlated reduced-form disturbances. In this reduced-form, the first reduced-form shock captures the forecast shock:

$$\varepsilon_{rt} = (Y_{t+2|t} - a_{12}Y_{t+2|t-1}) - a_{11}Y_{t+1|t-1} - a_{13}Y_{t-1}. \tag{2}$$

[5] From 1982, the SPF also includes predictions for $Y_{t+4|t}$. Our baseline results in this paper use forecasts from 1968.

[6] These are 2 and 3 quarter ahead forecasts, relative to the forecast origin, t. Because at quarter t the last quarterly data value is for $t-1$, we will sometimes refer to $Y_{t+3|t}$ as a year-ahead forecast.

We calculate structural shocks by assuming a Cholesky decomposition, with the ordering as shown, so that the first reduced-form shock estimates the structural expectations shock, as in Leduc and Sill (2013). The structural expectations shock is allowed to have a contemporaneous effect on all the other variables, but none of the other structural shocks are permitted to have a contemporaneous effect on expectations.

If, as in Leduc and Sill (2013), we include only one time series of rolling-event forecasts, that is, we include $Y_{t+2|t}$, say, but exclude $Y_{t+3|t}$, then the innovation ε_{rt} still measures a change in expectations, only it compares a forecast $Y_{t+2|t}$ with a forecast of a previous period $Y_{t+1|t-1}$, rather than with a longer horizon forecast of the same target period ($Y_{t+2|t-1}$), as in (2). The use of $Y_{t+3|t}$ in addition to $Y_{t+2|t}$, therefore, might provide a more accurate estimate of the forecast revision, because we are controlling for the forecast of the same target made in the previous period.

The target variable Y_t is ordered after the forecasts, because it is published after the forecasts are made. Hence we can assume that shocks to Y_t do not affect the forecasts at impact. The ordering also implies that the expectation shock (equal to ε_{rt} under the assumptions made) has a direct spillover to the next step forecast.

When computing responses of expectations to shocks, we are mainly interested in the responses of the second variable in (1), which measures responses of one-year-ahead expectations. We also look at responses of forecast revisions to shocks, where the forecast revision is defined as the change in the forecast of a given target period. In our setup, we look at the revision between the forecasts of Y_t made at times $t-2$ and $t-3$, say. Hence the responses of forecast revisions are measured as follows. The response at impact, that is, at $t+1$, is computed from the response of the first variable in the VAR at horizon $h = 1$, that is, $E[Y_{t+3|t+1}]$, because the forecast conditional on period t is fixed. Then for subsequent periods, $t+2, ..., t+h$, we use the difference between the responses for the first and second variables at horizons h and $h-1$, that is, $E[Y_{t+4|t+2} - Y_{t+4|t+1}], ..., E[Y_{t+h+2|t+h} - Y_{t+h+2|t+h-1}]$.

Two key issues that arise in the study of expectations of quarterly macroeconomic variables are: the fact that the macro data are typically revised, although expectations are necessarily real-time, and the final values of (current and past) macro data will not be known to the forecaster; and that monthly indicators (and other data) will typically be available to the forecaster which are informative about the outlook when the forecasts are made. Leduc and Sill (2013) solve the first problem by using expectations of a variable that is not subject to revisions, and the second problem by aligning data and forecasts by using monthly data to re-define the 'quarters' of the year (described more fully below). If the target variable Y_t is real GDP, or an alternative national-account-based macroeconomic aggregate, then we cannot disregard data revisions. Because our target variable is sampled quarterly and only quarterly data is available, we also need an alternative solution to the second issue. We discuss these solutions in the two sections that follow.

2.2 Expectations Shock when Data is Uncertain

The literature on the relevance of news and confidence shocks as explanations of business cycle fluctuations typically employs the latest-available vintage on Y_t to estimate models.[7] Were we to download the latest-available data vintage, say the 2017Q1 vintage, Y_t^{17Q1} for $t = ..., 16Q3, 16Q4$, and estimate the VAR on this data vintage, then the forecast innovation would be given by:

$$\varepsilon_{rt} = (Y_{t+2|t} - a_{12}Y_{t+2|t-1}) - a_{11}Y_{t+1|t-1} - a_{13}Y_{t-1}^{17Q1}.$$

As consequence, the reduced-form disturbance ε_{rt} is estimated with data not available to the forecaster at t, because the data revision includes the term Y_{t-1}^{17Q1} - the 2017Q1 vintage estimate of Y_{t-1}. This will be at least in part unpredictable. This is particularly important because we are trying to measure the effect of expectation shocks, and care is required not to confound these with data revisions. By using the latest vintage we may compute estimates of the reduced-form innovations that are either too large, or too small, depending on the impact of data revisions on the time series properties of Y_t. At time t, the survey forecaster would have had access to Y_{t-1}^t, not Y_{t-1}^{17Q1}, and we assume the forecaster takes Y_{t-1}^t at face value. In the data revisions literature, a useful dichotomy is between revisions which add news, and those which remove noise (see, e.g., Mankiw and Shapiro (1986)). When they add news, the unconditional variance of Y_{t-1}^{17Q1} would exceed that of Y_{t-1}^t, and vice versa for noise revisions.

To the best of our knowledge, we are the first to consider the issue of data revisions when measuring the impact of expectations shocks. We will proceed by providing an alternative way to specify the reduced-form VAR. In section 5, we compare the empirical results of the conventional approach, which is called the end-of-sample (EOS) approach, with our suggested 'release-based' (RB) approach.

It may be tempting to discount the importance of accounting for data revisions, but data revisions can be large relative to the variability in the series (see, e.g., Aruoba (2008)). Croushore

[7] This literature is surveyed by Beaudry and Portier (2014).

(2011b, 2011a) provide good review articles, and Jacobs and van Norden (2011), Cunningham, Eklund, Jeffery, Kapetanios and Labhard (2009), Kishor and Koenig (2012) and Garratt, Lee, Mise and Shields (2008) are key papers considering various ways of modelling data subject to revision. Following Garratt *et al.* (2008) and Kishor and Koenig (2012), we assume that the second quarterly release of the macroeconomic aggregate, that is, the 'first-final', is an efficient estimate of the true underlying national account aggregate value. This implies that we observe efficiently-revised real GDP for observation t at time $t+2$. In the earlier quarter, $t+1$, we observe an advance estimate of real GDP in quarter t.

Real GDP initial releases are published with about a 30-day delay (so at the end of the first month of the following quarter). At the time expectations are surveyed, during the middle of the second month of the quarter, we have both Y_{t-1}^{t}, the first release for $t-1$, and Y_{t-2}^{t}, the first-final release for $t-2$. We allow the professional forecaster at time t to draw on a time series of revised (first-final) data with observations available up to $t-2$, as well as the advance-release series, up to $t-1$. The release-based version of the reduced-form VAR in equation (1) is then:

$$\begin{bmatrix} Y_{t+2|t} \\ Y_{t+3|t} \\ Y_{t-1}^{t+1} \\ Y_{t}^{t+1} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} Y_{t+1|t-1} \\ Y_{t+2|t-1} \\ Y_{t-2}^{t} \\ Y_{t-1}^{t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{rt} \\ \varepsilon_{ft} \\ \varepsilon_{yt} \\ \varepsilon_{yft} \end{bmatrix}. \tag{3}$$

And the forecast innovation is:

$$\varepsilon_{rt} = (Y_{t+2|t} - a_{12}Y_{t+2|t-1}) - a_{11}Y_{t+1|t-1} - a_{14}Y_{t-1}^{t} - a_{13}Y_{t-2}^{t}. \tag{4}$$

Note that in (4) the included data (Y_{t-1}^{t} and Y_{t-2}^{t}) were available at t (and so would have been known when the forecasts, $Y_{t+2|t}$ and $Y_{t+3|t}$, were made). Our proposal then is to use the two observed time series of the target variable to estimate the model: the time series of first releases Y_{t}^{t+1}, and the first-finals Y_{t}^{t+2}. The Cholesky decomposition can again be applied to identify the expectations shocks since both Y_{t-1}^{t+1} and Y_{t}^{t+1} are released after the forecasts are made, so we can assume that shocks to these observables have no contemporaneous impact on the forecasts. The identification scheme allows all the other variables to respond contemporaneously to the expectations shock.

We will be mainly interested in the responses of first-final Y_t as a measure of aggregate output. This implies that to compute the response of $E[Y_{t+1}^{t+3}], ..., E[Y_{t+h-1}^{t+h+1}]$ to shocks, we need to look at responses of the third variable in the VAR (3). The impact of the shock is then measured with the horizon 2 response. A similar approach is employed when computing variance decompositions for Y using the release-based approach.

The model above also allows us to compute the responses of data revisions to shocks. Because Y_t^{t+1} is included, then at $t+1$ (impact), the effect on the third variable Y_t^{t+2} measures the response of GDP revisions. To compute data revisions responses for $t+2, ..., t+h$, we use responses for the third and the fourth variables as $E[Y_{t+1}^{t+3} - Y_{t+1}^{t+2}], ..., E[Y_{t+h}^{t+h+2} - Y_{t+h}^{t+h+1}]$.

In general, one might hope that the use of real-time data would provide more accurate estimates of expectational errors. This would be the case if agents' decisions and forecasts are based on early estimates of variables - such as real GDP - which are subject to revision. Because we want to estimate actual expectations shocks - when data is uncertain - it does not make sense to include the final-vintage estimate of Y_t in the VAR, for example. We want to analyze the behaviour of forecasters and have to restrict our information set accordingly.

Our baseline release-based VAR model is as equation (3) but includes also the time series of CPI, P_t and the short-term interest rate, R_t. These additional variables are not subject to revisions (or subject to only minor revisions as in the case of CPI) and are an important part of the forecaster information set as suggested by Leduc and Sill (2013). They may help us understand whether expectation shocks are demand shocks (they raise prices and interest rates while increasing activity) or predominantly have the characteristics of supply shocks (decrease prices and interest rates while increasing activity). Leduc and Sill (2013) and Levchenko and Pandalai-Nayar (2017) suggest expectations shocks are in general demand-type shocks.

This implies that we use a VAR(p) in the following vector of endogenous variables:

$$\mathbf{y}_t^{RB} = \begin{bmatrix} Y_{t+2|t} \\ Y_{t+3|t} \\ Y_{t-1}^{t+1} \\ Y_t^{t+1} \\ P_t \\ R_t \end{bmatrix} \tag{5}$$

where the RB superscript indicates the use of release-based actual data, where relevant.

2.3 Identification with the Mixed-frequency VAR

The identification strategy in section 2.2 deals with the impact of data revisions when identifying expectations shocks, but the assumption that shocks to the actual activity variable (in our case GDP growth) do not contemporaneously affect forecasts is less convincing than in Leduc and Sill (2013), since we are unable to adopt their trick of re-defining the quarters.[8] There will typically be information on the current quarter t available to the forecaster which is not captured by the data on previous quarters ($t-1$, $t-2$, $\dots$). Hence the identifying assumptions which place Y_{t-1}^{t+1} and Y_t^{t+1} below the forecasts ($Y_{t+2|t}$, $Y_{t+3|t}$) when the Cholesky decomposition is applied are suspect.

Consider the SPF GDP forecasts. These are made around the middle of the middle month of the quarter (survey questionnaires are required to be returned by around the end of the third week of the middle month). In our case, when the forecast is surveyed, the forecaster will have access to first-month of the quarter data on P_t and R_t, as well as first-month of the quarter data on variables closely correlated to Y_t, such as industrial production (IP) and non-farm payroll (NF), as well as daily data on financial variables. Of these, first-month data on industrial production and payroll are perhaps most likely to be relevant for quarterly predictions of $Y_{t+n|t}$ for horizons $n = 2, 3$, because they are timely indicators and suggested by the literature surveyed by Bańbura *et al.* (2013).

Our solution is to augment model (3) with monthly data $IP_{t,m}$ and $NF_{t,m}$, where $X_{t,m}$ denotes month m in quarter t, $m = 1, 2, 3$. That is, we move to a mixed-frequency set of variables in the VAR, as in Ghysels (2016). Although both industrial production and non-farm payroll are subject to data revisions, we use only the first releases of both monthly variables. First releases are published up to 30 days after the end of the observational month. We let $IP_{t,1}^{t,2}$ denote the first-release for the data in the first month of the quarter, $IP_{t,2}^{t,3}$ the first-release for the second month, and so on. Given the timing of the forecasts relative to the releases of the monthly data,

[8] Leduc and Sill (2013) redefine the quarters of the year so that the first quarter consists of months February to April, the second quarter of May to July, etc. Hence the SPF forecasts are made at the beginning of each quarter (or more accurately, within 2 or 3 weeks of the beginning of the quarter). This means that when the unemployment forecasts they consider are made at the beginning of quarter t (of period $t+h$), say, there will be little information on U_t, P_t and R_t (the unemployment rate, CPI inflation, and the Treasury Bill rate) in 'quarter' t. Hence shocks to these data variables can be assumed not to affect $U_{t+h|t}$. We cannot use this trick because there is no monthly data for GDP. P_t and R_t could be re-defined, but they would then be out of sync with Y.

we use the following vector of endogenous variables in the VAR:

$$\mathbf{y}_t^{MF-RB} = \begin{bmatrix} IP_{t,1}^{t,2} \\ NF_{t,1}^{t,2} \\ Y_{t+2|t} \\ Y_{t+3|t} \\ IP_{t,2}^{t,3} \\ NF_{t,2}^{t,3} \\ IP_{t,3}^{t+1,1} \\ NF_{t,3}^{t+1,1} \\ Y_{t-1}^{t+1,1} \\ Y_t^{t+1,1} \\ P_t \\ R_t \end{bmatrix}, \tag{6}$$

where MF-RB indicates we employ a mixed-frequency release-based VAR model.

We have purposefully placed $IP_{t,1}^{t,2}$ and $NF_{t,1}^{t,2}$ before the expectations variables. This ordering, allied with a Cholesky decomposition to identify the expectations shock, means that the structural expectations shock is no longer identified with the reduced form shock ε_{rt}, but instead is calculated using an information set which includes $IP_{t,1}^{t,2}$ and $NF_{t,1}^{t,2}$. This provides a more realistic depiction of the environment faced by the forecaster than assuming forecasters do not have access to such information.[9] As shown, observations for the subsequent months in the quarter - the second and third months - are only published after the forecasts are surveyed, so these variables are ordered after the forecasts.

In general, we use release-based ordering to support the identification of expectations shocks. We expect that expectations shocks in (6) may explain a smaller part of the variation of output measured as revised GDP than in the baseline model (5) because of the larger information sets and

[9] To see this, note that the structural model is

$$B(L)\, y_t = u_t$$

(where we use y_t in place of $\mathbf{y}_t^{MF-RB}$ for convenience), which corresponds to the reduced form VAR,

$$A(L)\, y_t = \varepsilon_t.$$

From the Cholesky decomposition, B_0 is lower triangular, so that the third element of y_t, $Y_{t+2|t}$, depends on the contemporaneous values of the first two elements of y_t, i.e., $IP_{t,1}^{t,2}$ and $NF_{t,1}^{t,2}$.

alternative sources of shocks.

3 Relation between Expectations and News shocks

The previous section proposes a method to identify expectation-driven shocks using SPF expectations data even when the macroeconomic variable is sampled quarterly and subject to data revisions. Are expectations shocks an additional source of explanation of business-cycle variation: 'expectations-driven business cycles', or simply a reflection of technology news shocks? Barsky and Sims (2012) suggest confidence shocks are mainly driven by technology news shocks. Related arguments might suggest that expectations shocks are linked to technology news shocks. We address this possibility in the paper.

We estimate a VAR model that allows us to measure how much of the variance of expectations can be explained by technology news shocks. News shocks in Beaudry and Portier (2006) and Barsky and Sims (2011) are future technological changes that are anticipated today. We assume 'future' relates to a medium term horizon, and use our one-year-ahead expectations series $Y_{t+3|t}$. As before, we use expectations of real GDP, and the VAR is estimated in log-levels to allow that the variables may exhibit cointegration, as in Beaudry and Portier (2006) and Barsky and Sims (2011).

Following the news shocks literature surveyed in Beaudry and Portier (2014), we use two forward-looking variables to identify news shocks. The first one is an equity market index, namely, the S&P500 index. The second is the confidence variable, 'E5Y', from the Michigan survey, used as a measure of consumer confidence by Barsky and Sims (2012). And following the literature, we use the Fernald (2014) utilization-adjusted total factor productivity to identify technology news shocks. As argued by Cascaldi-Garcia (2017) and Kurmann and Sims (2017), some of the empirical results currently available in the literature turn on the way TFP is calculated, and no longer hold if the revisions and methodological changes suggested by Fernald (2014) are applied. Unfortunately we are not able to apply the real-time data strategies described in section 2 to the TFP variable, because a quarterly real-time dataset on utilization-adjusted TFP is not currently available. As a consequence, we ignore the uncertainty in the measurement of the TFP series when we measure the impact of news shocks on expectations.

The benchmark VAR used to measure the impact of news shocks on expectations is a modification of the VAR model in section 2.2, and has the following vector of endogenous variables:

$$\mathbf{y}_t^{News,EOS} = \begin{bmatrix} TFP_t \\ SP500_t \\ Conf_t \\ Y_{t+2|t} \\ Y_{t+3|t} \\ Y_t^{17Q1} \\ P_t \\ R_t \end{bmatrix}. \tag{7}$$

The news shocks are identified by the twin requirements that i) they maximize the forecast error variance decomposition of TFP after 40 quarters, and ii) they have a zero effect on TFP at impact (i.e., only affect future values). This is the identification scheme proposed by Barsky and Sims (2011), which also allow us to compute unexpected technology shock (or 'surprise' technology shocks) which are allowed to have an impact effect on technology. Because the identification scheme does not identify the sign of the shock, the restriction that the impact effect of news shocks on $SP500$ is non-negative is also imposed.

The VAR based on (7) ignores data uncertainty by using the latest-available vintage (the 2017:Q1 vintage) data on Y, i.e., Y_t^{17Q1}. We also consider a VAR model that takes into account data uncertainty on Y when we measure news shocks, and estimate their impact on the expectations variables: one-year-ahead expectations $Y_{t+3|t}$ and the confidence variable $Conf_t$. We apply the release-based approach to the VAR model to account for data uncertainty on GDP, and to measure responses to (first-final) revised GDP. The VAR is estimated for the following vector of endogenous variables:

$$\mathbf{y}_t^{News,RB} = \begin{bmatrix} TFP_t \\ SP500_t \\ Conf_t \\ Y_{t+2|t} \\ Y_{t+3|t} \\ Y_{t-1}^{t+1} \\ Y_t^{t+1} \\ P_t \\ R_t \end{bmatrix}. \tag{8}$$

As in section 2, responses and variance decompositions for revised GDP as measure of aggregate output are computed using Y_{t-1}^{t+1}. We can compute responses of forecast revisions and data revisions to news shocks using estimates of a VAR(p) based on (8).

4 Model Estimation

The VAR models described in sections 2 and 3 are estimated in levels as Barsky and Sims (2011) so we do not rule out cointegration, but nor do we impose specific cointegration relations as Beaudry and Portier (2006) and Garratt *et al.* (2008). Our models consist of a reasonably large number of variables (the MF-VAR with the RB approach has 12 endogenous variables). To deal with parameter uncertainty arising from the size of the VAR, we use the Bayesian VAR MCMC estimation approach proposed by Giannone, Lenza and Primiceri (2015). We set $p = 5$, and adopt both the Minnesota prior and the 'dummy-initial-observation' prior, while prior hyper-parameters are estimated in a MCMC algorithm calibrated to accept around 40% of the candidate draws.[10]

Table 1 describes our data sources. Throughout we use real GDP (formerly GNP) median forecasts from the US Survey of Professional Forecasts. We use forecasts from the quarterly surveys from 1968Q4 to 2016Q3. Forecasts are for real GDP in dollars and for horizons from t up to $t + 4$, although the last horizon is not available for all surveys, and we set our longest forecast horizon to $t+3$. We use the real-time data on real GDP from the Philadelphia Fed real-time data database up to 2017Q1. We re-base the real-time real GDP series to remove changes of base using the method

[10] We thank Giorgio Primiceri for making the code for Giannone *et al.* (2015) available from his website. We also thank Danilo Cascaldi-Garcia for sharing his code to identify news shocks.

described in Clements and Galvão (2013). We use the same GDP factor values to remove the effects of the re-basings from the SPF forecasts. We also use forecasts for aggregate consumption and non-residential investment. They are also re-based using factors computed using real-time data on consumption and non-residential investment.

We use monthly real-time data from the Philadelphia Fed real-time database for industrial production (IP) and non-farm payroll employment.

5 Results

In section 5.1 we consider the effects of expectation shocks on real activity in the economy, as measured by real GDP. The results we report allow us to determine the importance of allowing for data uncertainty, and of supplementing the information set used to calculate expectations shocks with monthly information on the current state of the economy. In section 5.2 we investigate news shocks, and the extent to which they account for the variation in survey expectations and consumer confidence. Section 5.3 relates our findings to the literature.

5.1 The Effects of Expectations Shocks

We begin by evaluating the effect of expectational shocks to aggregate output using the baseline VAR model in (5) that ignores monthly information. Figure 1 shows the effects of a one-unit change in the expectations shock (the size of the shock has been standardized) on one-year ahead expectations ($Y_{t+3|t}$), aggregate output (Y), prices (P) and the short-term interest rate (R) for horizons from 1 up to 40 quarters (10 years). The plots include 68% confidence bands computed using retained MCMC draws from the model estimation. The first two panels (1A up to 1B) are based on different ways of using the real GDP data. The first panel uses the end-of-sample (EOS) data (that is, data taken from the vintage available at the time of the study: here, the 2017Q1 vintage). The second panel uses the release-based (RB) approach as in (5). The third panel 1C presents responses for forecast revisions and data revisions computed using retained MCMC draws obtained from estimation of the baseline released-based VAR. Finally, the last panel compares the output responses to expectations shocks using the RB and the EOS approaches (with the confidence intervals drawn for (first-final) revised GDP from the RB approach).

Figure 1A shows that expectations shocks have a significant positive short-term (up to two years) effect on aggregate output, a significant positive effect on prices, and a positive short-term effect on the short-rate. This suggests that expectations shocks are a demand-type shock as also argued (but using a different identification scheme) by Levchenko and Pandalai-Nayar (2017). If we take into account GDP data uncertainty, the results in Figure 1B suggest that the short-term output responses are significantly larger than in Figure 1A. A direct comparison is given in Figure 1D, which shows that the response of output peaks after one-year in both cases, but that the measured response with the release-based approach is twice as large. The price level response is instead attenuated during the first year in the released-based approach, while the response of the short rate is roughly the same for both approaches. Figure 1C shows that the impact of the expectation shock on forecast revisions is short-lived, as suggested by Leduc and Sill (2013) and Levchenko and Pandalai-Nayar (2017).

A new result is that data revisions responses to expectations shocks are significant and positive at the first horizon, suggesting that GDP data revisions and GDP forecast revisions are related. This might be explained as in Sargent (1989), by supposing that the statistical agency filters the data before publishing an initial release, implying that later data revisions are correlated with underlying structural shocks.

Figure 2 is structured as Figure 1, but shows the results for the mixed-frequency VAR described in section 2.3. Comparing Figure 2 to Figure 1 highlights the importance of allowing for information on the current quarter. The inclusion of the monthly variables reduces the contemporaneous impact of expectations shocks on output. In the case of EOS, the impact value declines from 0.3 to 0.1, and in the case of RTV from 0.45 to 0.35, although it is still statistically different from zero in both cases. Hence it continues to be true that the use of data not available at the time the forecasts were surveyed attenuates significantly the responses of aggregate output to expectational shocks. The attenuation effect of data uncertainty on the price responses is now stronger, to the extent that expectation shocks have no significant effect on prices using the release-based approach.

In summary: the standard approach of using fully-revised data leads to an under-estimation of the response of aggregate output to expectations shocks, and the false finding of a significant (positive) response of prices at medium horizons.

Table 2 shows the variance decomposition for output to GDP expectation shocks at impact ($h = 1$) and for $h = 4, 8, 12, 16, 40$. The forecast-error variance decomposition was computed with the baseline (section 2.2) and the mixed-frequency (section 2.3) specifications, using EOS and RB data on GDP. The values are computed for VAR parameters at the posterior mean. These decompositions serve to highlight the importance of i) using real-time data, and ii) using monthly data to extend the information set. At a short-horizon such as $h = 4$, expectations shocks explain only around 10% of the variation of GDP if we use EOS data in the MF-VAR. This small share of business cycle variation explained by expectation shocks supports the results obtained using consumer confidence by Fève and Guay (2016). We conjecture that confidence shocks might explain a larger proportion of the variation if considered in a model estimated using real-time data, as in our release-based model.[11] However, our forecast-error variance decompositions attribute a markedly smaller proportion of output variation to 'non-technology expectations shocks' than Levchenko and Pandalai-Nayar (2017) find at short horizons. In section 5.3 we briefly review the identification scheme of Levchenko and Pandalai-Nayar (2017) and reasons for the difference in findings.

The main novel empirical result in Table 2 is that taking into account data uncertainty when estimating the VAR model suggests expectation shocks are much more important: we find that expectation shocks explain around 23% of the revised GDP variation at short horizons (of 1 and 2 years-ahead, $h = 4, 8$). Table 2 provides evidence that expectation-shock effects are under-estimated if we use data that was not available to the forecaster in real-time.

The SPF also provides information on forecasts for other important macroeconomic aggregates such as consumption and investment. We estimate the mixed frequency VARs of Table 2 using forecasts of consumption ($C_{t+2|t}$ and $C_{t+3|t}$) or non-residential investment ($Inv_{t+2|t}$ and $Inv_{t+3|t}$) in the place of the real GDP forecasts. As described in Table 1, these forecasts are only available from 1981Q3, so we change our estimation sample accordingly. The first two columns of Table 3 replicate the results in the last two columns of Table 2 for this shorter sample. In this shorter sample, we still find that with the released-based approach expectations shocks explain around 20% of output variation at short horizons, 3 or 4 times as much as when the fully-revised data is used. The next columns show equivalent results using either consumption or investment forecasts. In both cases, we confirm that expectations shocks have larger effects if we use the release-based approach. Investment expectations shocks explain only a small share of output variation, but the consumption expectation shocks are broadly similar to the GDP expectations shocks in terms of accounting for output business cycle variation.

Our results so far suggest that expectation shocks are essentially aggregate consumer demand-type shocks, and explain a sizeable proportion of business cycle variation at horizons up to two

[11] This conjecture is based on our findings that expectation shocks are two to three times as large when we use real-time data, compared to fully-revised data, and that the same might be true for confidence shocks. Levchenko and Pandalai-Nayar (2017) find that expectations and confidence can be used more or less interchangeably in their analysis.

years. There is also evidence that expectations shocks lead GDP data revisions.

5.2 Expectations and News Shocks

Figure 3 presents responses to a news shock estimated using the eight-variable VAR described in section 3. In addition to the responses of the four variables in Figures 1 and 2, we include responses of TFP and of the consumer confidence measure used by Barsky and Sims (2012). The organization of the figure follows the previous ones.

The response of TFP to the news shock matches the finding in the literature (see, e.g., Beaudry and Portier (2014)). The aggregate output responses are not significantly different from zero during the first quarters but there is a large effect after 3 years (12 quarters). As in Barsky and Sims (2012), consumer confidence jumps at impact, but the response is not significantly different from zero after 3 years. The responses of prices and the short-term rate suggest that the TFP shock is indeed a 'supply-type' shock: both variables exhibit negative responses.

The use of real-time GDP data has an effect on how expectations and confidence respond to news shocks. The peak response of output to news shocks is now at 10 quarters instead of 13 quarters when using EOS data. The response of consumer confidence at impact increases from 5.8 to 6.8 percent. As suggested by Figure 3D, responses of output to news shocks are attenuated at medium horizons (3 years) but the effect is small. The use of the release-based approach also does not change results for the price index and the short-rate.

Table 4 provides forecast-error variance decompositions, and shows the proportion of the variation in aggregate output, GDP Expectations and consumer confidence attributable to news shocks. As before, we consider both the EOS and the release-based approaches. As previously reported in the literature, news shocks explain a sizeable share of output variation, about 50% at the 10 year horizon. The use of real-time data on GDP has very little impact on the output variation explained by news. Table 4 confirms the Barsky and Sims (2012) results that news explains a large share of the long-term variation in consumer confidence. Our results indicate however that news shocks explain an even larger share of GDP expectations (60% compared to 40%). The main reason is that, in contrast with consumer confidence, news shocks have a more persistent effect on GDP expectations.

A novel empirical result in Table 4 is that the importance of news shocks as an explanation of both consumer confidence and GDP expectations is enhanced at short horizons ($h = 4, 8$) when the VAR is estimated using real-time data. For consumer confidence, the percentage of the variation attributable to news shocks increases from 29% (EOS) to 42% at $h = 4$. This suggests that not only is real-time data important to correctly measure the effects of expectations shocks, but it should also be used to measure the effects of news shocks on variables such as macroeconomic expectations and sentiment.

5.3 Discussion of Findings and Related Literature

A natural question is the relationship between our news shocks and expectations shocks, considered in sections 5.1 and 5.2. Although they are estimated separately, it turns out that they are largely uncorrelated. The correlation is small at around 11%, suggesting news and expectations shocks are quite distinct, consistent with that aspect of the identification scheme of Levchenko and Pandalai-Nayar (2017). Figure 4 plots the time series of news and expectations shocks. Both shocks series were computed using the release-based approach. For expectations shocks we use the MF-VAR model of Figure 2B, and for news shocks the VAR of Figure 3B.

By comparing the responses to the expectations and news shocks in Figures 2 and 3, we can clearly see that although both shocks have positive, significant effects on aggregate output, expectation-shock effects peak at one year and are demand-type shocks, while news-shock effects peak around 3 years, and are supply-type shocks. This reinforces the low empirical correlation, and suggests they are different shocks. Expectation shocks constitute a supplementary source of business cycle variation. Whereas technology news shocks are anticipated shocks about economic fundamentals, our expectations shocks might be more linked to sentiment, 'animal spirits' and waves of optimism, as in Milani (2011), than fundamental changes, or at least to fundamental changes that refer to technology. Of course, expectations shocks could be related to news about other fundamentals, as in Schmitt-Grohé and Uribe (2012) and Christiano, Motto and Rostagno (2014).

The expectations shocks have larger effects at horizons up to one year, with news shocks becoming more prominent as the horizon lengthens. In contrast to the findings of Barsky and Sims (2012) and Fève and Guay (2016), who use consumer confidence rather than survey expectations, we find that GDP expectations shocks explain a substantial part of business cycle variation at a two year horizon (around 20%). We also find that consumption expectation shocks explain roughly the same proportion of business cycle variation in the short term.

Our expectations shock accounts for a smaller percentage of output variation at short horizons than the 'non-technology expectations shock' (NTE shock) of Levchenko and Pandalai-Nayar

(2017). Levchenko and Pandalai-Nayar (2017) suggest their NTE shock can be interpreted as an expectations shock. Their identification strategy first identifies technology surprise and news technology shocks, as in Barsky and Sims (2011). They then calculate the NTE shock as the linear combination of the reduced form residuals which maximizes the forecast-error variance of their expectations variable (or, alternatively, a sentiment indicator) subject to the shock being orthogonal to the two technology shocks. Their shock is able to explain 60% of the variation of output at a one-year horizon, where output is meaured by the latest vintage real GDP per capita.

We implement their approach to identify a non-technology expectations shock to the EOS VAR in (7) and the RB VAR in (8). The strategy assumes that technology news and surprise shocks are as in Figure 3 and Table 4. The non-technology expectations shock is then orthogonal to these news and surprise shocks and maximizes the forecast error decomposition of $Y_{t+2|t}$ at a horizon of four quarters.[12] Responses computed using only the latest-vintage of real GDP and using the release-based approach on real GDP are presented in Figure 5. Responses are computed for the same set of variables as in Figure 4. Expectations shocks have only a minor short term effect on TFP, as expected. The shape of the reponses from one-year-expectations, output, prices and the interest rate are similar to the responses to the expectations shock identified using the recursive identification approach of Section 2. As in the case of the mixed frequency VAR in Figure 2D, Figure 4C shows how the use of the latest-vintage data on real GDP implies that responses to expectations shock are attenuated when compared with responses estimated using only data actually available at the time professional forecasters devise their expected values.

Table 5 shows the variance decomposition for non-technology expectation shocks using the same variables, horizons and VAR models as in Table 4. Because the expectations shock is now identified by maximizing the FEDV for $Y_{t+2|t}$ at $h = 4$, the shock now explains 64% of the variation of one-year-ahead expectations instead of the 22% share in Table 2. The share of the variation in output is strongly affected by the data on real GDP. If we use only the latest available vintage, we find that the expectations shock explains 40% of output variation at one-year horizon. But if we use the release-based approach, then the expectations shock accounts for 73% of the variation of first-final output.

In summary, although news about technology changes explains 50% of aggregate output varia-

[12] Levchenko and Pandalai-Nayar (2017) say their results are robust to different short term horizons. Their benchmark results are for a two quarter maximization, but we prefer to use four quarters because of our use of one-year-ahead expectations.

tion at long horizons, at horizons up to one year expectations shocks are more important, explaining either 20% of the variation of output using a recursive identification scheme or 73% of output variation using the Levchenko and Pandalai-Nayar (2017) identification scheme.

6 Conclusions

We show that data uncertainty matters for measuring the effects of expectations shocks on aggregate output, using both a recursive and the Levchenko and Pandalai-Nayar (2017) identification scheme, and for computing responses of expectations variables (including consumer confidence) to news shocks. Using the latest-available vintage on real GDP would lead one to conclude that expectations shocks are relatively unimportant in terms of explaining aggregate output variation using a recursive identification scheme, whereas when data revisions are taken into account, expectations shocks explain in excess of 20% of the variation one and two years ahead. Data uncertainty is taken into account by a release-based approach. This is a real-time approach - expectations shocks are constructed only using vintages of data available at the time to estimate the shocks. It also allows us to track the response of 'revised' real GDP to shocks, where revised real GDP is estimated by 'first-final' data.

Our results also point to the importance of including relevant information in the VAR to correctly identify expectations shocks. Professional forecasters will be aware of the state of the economy when they submit their forecasts. Simply using quarterly data will not lead to a correct specification of expectations shocks when forecasters have access to more up-to-date readings on the state of the economy, such as knowledge of the latest month's non-farm payroll and industrial production figures.[13]

Expectations shocks are shown to be quite distinct from news shocks. The two shocks are largely uncorrelated. Expectations shocks are essentially demand shocks, whereas news shocks give rise to characteristic supply-shock responses. Expectations shocks are more prominent at shorter horizons, whereas news shocks become increasingly important as the horizon lengthens.

[13] Faust and Wright (2009) show the importance of knowledge of the current state of the economy for macroeconomic forecasting in their comparison of the Greenbook and model forecasts.

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