

Data Revisions as Shocks

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PRELIMINARY AND INCOMPLETE

Abstract

Recent work has attempted to make use of macroeconomic data revisions as exogenous shocks to beliefs and policy. We discuss some of the challenges researchers face when using this methodology. “Animal spirits”—i.e., revisions in beliefs about the state of the economy and its trajectory—have long been proposed as a potentially important source of business cycle fluctuations. The idea we investigate is whether macroeconomic data revisions provide a useful source of variation for evaluating the role of animal spirits in business cycles by generating noise in beliefs. We demonstrate that omitted variables bias and reverse causation imply that this approach is, unfortunately, uninformative in the business cycle context. Similar concerns arise when data revisions are used as shocks in other contexts.

JEL Classification: E32

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1 Introduction

The initial estimate of macroeconomic statistics such as GDP growth by the Bureau of Economic Analysis (BEA) are frequently revised by large amounts (Mankiw and Shapiro, 1986; Aruoba, 2008). Consider the case of real GDP growth in the third quarter of 1992. While the BEA’s initial estimate was that GDP growth in this quarter was 1.3%, suggesting a modest recovery from the 1990-91 recession, the growth rate in this quarter was later revised to 4.1%! The initial announcement error in this quarter was therefore -2.8%. The idea we investigate in this paper is whether announcement errors like this one can be viewed as exogenous shocks that affect beliefs about the state of the economy.

A long-standing view regarding business cycles is that recessions and booms are driven in part by changing beliefs about current and future economic fundamentals (Pigou, 1927). A large recent literature has formalized how such news and “noise” shocks can drive business cycles and sought to estimate the extent to which business cycles are in fact driven by such shocks.¹ The empirical work in this literature has typically relied on relatively strong structural assumptions to identify news and noise shocks.

If early announcements of macroeconomic data affect beliefs about current and future economic fundamentals, the errors in these early announcements may represent direct measures of exogenous noise shocks to beliefs. This idea suggests a simple instrumental variables strategy for assessing the effect of beliefs on macroeconomic outcomes. Consider the regression

$$\Delta y_t = \alpha + \beta \Delta y_{t,t}^f + \mathbf{X}_t' \gamma + \epsilon_t, \quad (1)$$

where Δy_t denotes “true” output growth in period t (in practice the latest available estimate), $\Delta y_{t,t}^f$ denotes the average nowcast from the Survey of Professional Forecasters of output growth in period t (i.e., the average forecast about period t as of period t) and \mathbf{X}_t' denotes a vector of controls. Here $\Delta y_{t,t}^f$ is being used as a measure of beliefs about the state of the economy. If announcement errors are exogenous, one can estimate the causal effect of beliefs on GDP growth by instrumenting for $\Delta y_{t,t}^f$ in equation 1 with announcement errors about lagged growth, i.e., with the difference between initial announcements about lagged growth and true lagged growth.

This strategy faces at least two empirical challenges. First, announcement errors about lagged GDP growth may affect beliefs about many variables, not only beliefs about current GDP growth.

¹Important contributions to this literature include Beaudry and Portier (2007), Jaimovich and Rebelo (2009), Lorenzoni (2009), Barsky and Sims (2011), Barsky and Sims (2012), Schmitt-Grohé and Uribe (2012), Blanchard et al. (2013), Christiano et al. (2014).

For example, such announcement errors may affect beliefs about inflation. If this is the case, one cannot interpret the estimate of β in equation (1) as the causal effect of beliefs about GDP growth on GDP growth. Rather one should interpret β more cautiously as the ratio of the effect of the announcement error—which one hopes is an exogenous shocks—on GDP growth relative to its effect on beliefs about GDP growth. The IV coefficient is then simply a convenient way of scaling the effect of the shock on GDP growth. Alternatively, one could simply report the first stage and reduced form separately (each of which has a straightforward causal interpretation under the assumption that the announcement errors are exogenous).

The second challenge is that announcement errors may in fact not be exogenous. One concern is that announcement errors may be partially predictable (Aruoba, 2008).

Building on earlier work by Mankiw and Shapiro (1986) and Aruoba (2008), we

If the early releases of GDP growth data affect macroeconomic expectations they may

If macroeconomic expectations react to the initial announcement, then it would be possible to use the response of output growth to such “noise” in macroeconomic data to estimate exogenous “shocks” to beliefs. In turn, it would then be feasible to estimate the response of output growth to expectations.

In this paper, we discuss the problems in this approach and conclude that, unfortunately, it is not possible to cleanly estimate the causal impact of announcement errors upon expectations and realisations of economic data. This poses problems for two recent research areas.

Firstly, the role of expectations in driving business cycles has been formalized in the neoclassical setting in recent work by Beaudry and Portier (2007) and Jaimovich and Rebelo (2009). Lorenzoni (2009) presents a model in which “noise” in economic agents’ signals regarding economic fundamentals can generate sizable business cycle fluctuations. The channel that Lorenzoni emphasises for the generation of “noise” shocks is the presence of measurement error in available data.

As justification for the importance of “noise” shocks, Lorenzoni points to research that estimates the impact of macroeconomic announcement errors on economic activity. Oh and Waldman (1990) study the relationship between initial announcements of the series of “Leading Economic Indicators” and subsequent industrial production growth over the period 1976-1988. They find that the total component of revisions to leading indicators has a limited impact on subsequent industrial production but the late component of these revisions have generally stronger effects².

²Oh and Waldman (1990) consider the late component of revisions on the basis that producers may observe the data

In pioneering work, [Rodriguez Mora and Schulstad \(2007\)](#) show that conditioning on the initial announcement of output growth at a given point in time, “true” output growth has no additional predictive power in forecasting future growth over the time period 1967-1991. They focus on the total announcement error, and include only a minimal set of controls. ? additionally consider the possibility of estimating the importance of noise shocks by mapping the noise shocks in [Lorenzoni \(2009\)](#) to “the transitory shock from an identified VAR”.

Secondly, a recent set of papers have used announcement errors as a source of exogenous change. [Chodorow-Reich and Karabarbounis \(2016\)](#) investigate the impact of lengthening unemployment insurance in US states by estimating the impact of revisions to unemployment upon state-level variables. Revisions have an important impact because if a state has a high initial release of unemployment, it will receive longer unemployment insurance than if the initial release had been correct. [Serrato and Wingender \(2016\)](#) use revisions in census data to estimate the impact of local fiscal multipliers. If initial population estimates for an area are incorrect, it will change the allocations of fiscal spending.

A number of researchers have already discussed the complications in taking announcement errors as exogenous. First, macroeconomic announcement errors are partially predictable ([Aruoba, 2008](#)).³ The predictable component of macroeconomic announcement errors does not affect expectations, and therefore cannot be used in identifying the effect of expectations on growth. Second, initial announcements of macroeconomic data are, in part, rational forecasts of the relevant data for time periods when those data have yet to become available which complicates the interpretation of revisions ([Mankiw and Shapiro, 1986](#)).⁴

We first show that adding controls to regressions using total announcement errors may not overcome sources of endogeneity due to negative bias from seasonal adjustments and (if it is used) smoothing, and additional bias in either direction due to the problem of generating estimates when data for different components of GDP becomes available or is processed at different speeds. Next, we consider an alternative approach using only the late component of announcement errors but, unfortunately, this component appears to demonstrate systematic bias.

after early revisions have already been made. This would suggest the early part of the revision would have less impact upon expectations than the late part. We also break down announcement errors into their early and late components but for quite different reasons.

³[Aruoba \(2008\)](#) estimates the predictability of revisions as a function of particular macroeconomic variables, in contrast to the more reduced-form approach employed by [Mankiw and Shapiro \(1986\)](#) and [Faust et al. \(2005\)](#).

⁴See also [Faust et al. \(2005\)](#) and [Miron and Zeldes \(1989\)](#).

We focus primarily upon determining the impact of GDP announcement errors upon GDP expectations and GDP realisations since it is the most common question that has been studied so far and it strongly relates to the demand shocks literature. However, our findings have implications for other specifications with announcement errors and initial releases as well.

Consequently, our contribution is to highlight additional problems in treating macroeconomic announcement errors as exogenous variables. Ultimately, we conclude that macroeconomic announcement errors are uninformative about the sources of business cycles, since most of the variation in these variables is endogenous and the remaining variation is not large enough to allow for precise identification of the effects of exogenous noise shocks.

The paper proceeds as follows: Section 2 discusses our main sources of data. Section 3 discusses the consistency of regressions of realisations or expectations upon lagged announcement errors. Section 6 concludes.

2 Data

Our main data source is the real-time dataset originally compiled by Dean Croushore and Tom Stark (Croushore and Stark, 2001) and currently maintained by the Federal Reserve Bank of Philadelphia. This dataset contains a complete vintage history of GNP, GDP, and nonfarm payroll employment data from 1965 onwards. We use the quarterly vintage history, which reports a sequence of vintages available at the midpoint of each quarter. For aggregate output, we analyze data for the headline measure produced by the US Bureau of Economic Analysis (BEA) at each point in time—Gross National Product (GNP) before 1991 and Gross Domestic Product (GDP) after 1991. We use the vintage history to construct measures of announcement errors for the variables we study. The sample period in our analysis is from 1965Q3 to 2016Q2.

Figure 1 summarizes the times at which revisions to US GNP/GDP have occurred. The vertical axis gives the time period to which the data pertain, while the horizontal axis gives times when the data were released or revised. For each quarter, the BEA reports an “advance” estimate of aggregate output one month after the quarter ends. This is the estimate the first appears in our dataset (since it is what is available at the middle of the quarter). Following the advance release, the BEA revises the data each month for the next two months (the “second” and “third” releases) and then every year for the next three years as part of the “annual revision” that occurs

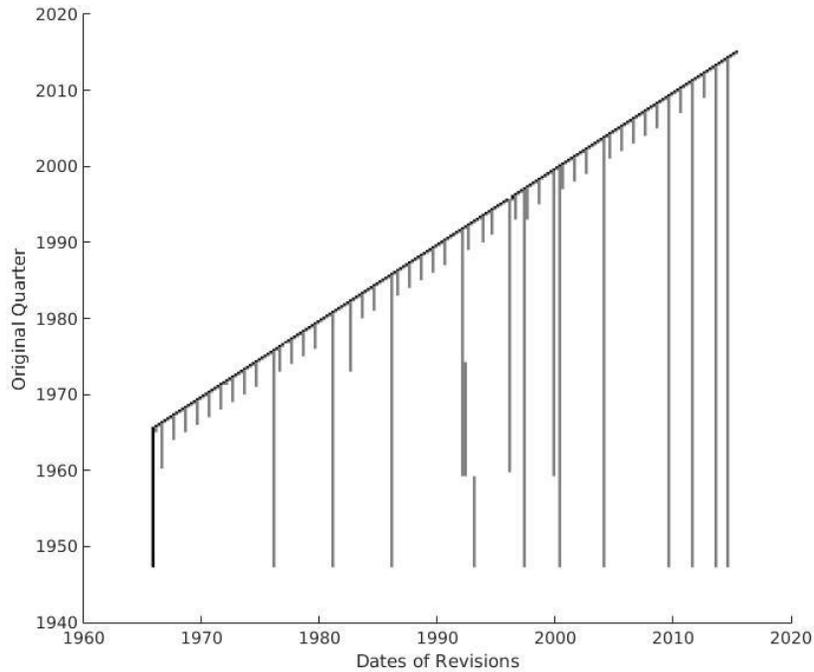


Figure 1: Revisions Over Time

in July.⁵ These early revisions are primarily due to better data availability. The BEA subsequently conducts “benchmark revisions” roughly every 5 years. Thus, GDP observations are periodically revised even many years after their were initially released. These late revisions are primarily due to changes in definitions and methodology.

Our second source of data is the *Survey of Professional Forecasters*. This quarterly survey has polled professional economists on their forecasts for aggregate macroeconomic variables such as output since 1968. The survey includes forecasts of output for the current quarter and subsequent quarters up to a horizon of 4 quarters (recall that current output data are not available until roughly a month after a given quarter ends). Our measure of macroeconomic expectations is the mean forecast across professional forecasters. The data available to forecasters in the Survey of Professional Forecasters when they make their forecast is the initial estimate of GDP for the prior quarter and the initial estimate of employment for the last month of the prior quarter.

⁵The terminology used to refer to different releases has changed over time. For example, the “second” and “third” releases used to be referred to as the “preliminary” and “final” releases.

3 Total Revisions

Our goal is to assess whether announcement errors can be viewed as exogenous shocks. It is useful to start by introducing some notation. We denote by Δy_t the “true” (annualized quarterly) growth rate of real GDP in period t , i.e., the latest available estimate of this growth rate. We denote by $\Delta y_{t+1,t}$ the initial estimate of real GDP growth in period t . This estimate becomes available in period $t + 1$. We denote by $A_t^y = \Delta y_{t+1,t} - \Delta y_t$ the total announcement error for Δy_t , i.e., the difference between the initial announcement and the true value of GDP growth in period t .⁶

Armed with this notation, consider the following two regressions:

$$\Delta y_t = \alpha + \beta A_{t-1}^y + \mathbf{X}_t' \gamma + \epsilon_t, \quad (2)$$

$$\Delta y_t^f = \alpha + \beta A_{t-1}^y + \mathbf{X}_t' \gamma + \epsilon_t. \quad (3)$$

These regressions are the “reduced form” and “first stage” regressions, respectively, in the IV strategy described in the introduction. In addition to these two regressions, we also consider the following regression:

$$\Delta e_t = \alpha + \beta A_{t-1}^e + \mathbf{X}_t' \gamma + \epsilon_t, \quad (4)$$

where Δe_t denotes the true growth rate of employment and A_{t-1}^e is the total announcement error for lagged employment growth. This regression is the reduced form for an analogous IV strategy to the one described in the introduction but for employment growth. We study this third case because the nature of revisions in employment data are quite different from those in NIPA data.

Table 1 presents OLS estimates of β for regressions (2)-(4) with a range of different controls. The first column presents results without any controls. Let’s focus on regression (2) in Panel A for concreteness. The estimate of β in this case is 0.08 and not statistically significantly different from zero. However, there is a strong reason to believe that this estimate of β may be seriously biased. GDP growth rates are serially correlated. If the announcement error for lagged growth is correlated with true lagged growth and we do not control for true lagged growth, then the estimate of β will partly reflect the serial correlation of true GDP growth. Recall that the definition of the announcement error for lagged growth is $A_{t-1}^y = \Delta y_{t,t-1} - \Delta y_{t-1}$, where true lagged growth shows

⁶The announcement error A_t^y is the negative of the revision ($\Delta y_t - \Delta y_{t+1,t}$). We regress outcomes on announcement errors rather than revisions because the intuitive idea behind our empirical strategy is that overly positive initial announcements that result in a positive announcement error should have positive effects on beliefs. We find it easier to work with the case were the desired first stage coefficient is positive.

Table 1: Regressions on Total Announcement Error

	(1)	(2)	(3)	(4)	(5)
<i>Panel A: GDP Growth</i>					
Lagged Total Announcement Error for GDP Growth	0.08 (0.12)	0.30*** (0.12)	0.24** (0.12)	0.21* (0.12)	-0.16 (0.11)
<i>Panel B: Nowcast of GDP Growth</i>					
Lagged Total Announcement Error for GDP Growth	0.10 (0.08)	0.37*** (0.07)	0.25*** (0.06)	0.25*** (0.07)	0.06 (0.05)
<i>Panel C: Employment Growth</i>					
Lagged Total Announcement Error for Employment Growth	-0.36 (0.21)	-0.33** (0.14)	-0.33** (0.14)	-0.42*** (0.14)	-0.72*** (0.26)
2 Lags GDP Growth ^a		*	*	*	*
2 Lags Consumption Growth			*	*	*
2 Lags Investment Growth				*	*
2 Lags Industrial Production Growth ^b					*

^a In Panel C, 2 lags of GDP growth are replaced with two lags of employment growth.

^b In Panel B, Column (5) controls for 2 lags of the nowcast in addition to the other variables listed above.

Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

up with a negative sign. It therefore seems plausible that the announcement error may be negatively correlated with true growth leading the estimate of β in the first column to be downward biased.

In the second column of Table 1 we add two lags of GDP growth as controls. This results in an estimate of β of 0.30 which now is statistically significantly different from zero. The fact that this estimate is substantially larger than the estimate in the first column reveals that lagged true growth is negatively correlated with the lagged announcement error. When lagged true growth is omitted from the regression, the estimate of β falls substantially.

3.1 News versus Noise

Mankiw and Shapiro (1986) discuss two polar characterizations of data revisions that are very useful conceptually:

At one extreme, a provisional estimate of the growth rate of GNP can be regarded as an observation of the revised series, but one that is measured with error; subsequent estimate reduce or eliminate this measurement error, or “noise,” by drawing on larger or

more representative samples, correcting clerical mistakes, and so forth. At the other extreme, the provisional, the provisional estimate can be regarded as an efficient forecast of the revised series, that is, a forecast that reflects all available information; subsequent estimates reduce or eliminate the forecast error by incorporating new information, or “news.”

These two extremes have very different implications regarding the correlation between announcement errors and the true growth rate. If announcement errors are purely noise (measurement error), there will be no correlation between the announcement error and the true growth rate. In this case, the initial announcement is the truth plus noise that is uncorrelated with the truth. However, if announcement errors are purely news, there will be a perfect negative correlation between the announcement error and the truth. In this case, the initial announcement is an unbiased estimate of the truth. This means that announcements will be too optimistic only when the true growth rate turns out to be low.

The difference between our estimates in the first and second columns of Table 1 indicates that announcement errors contain a news component. The estimate in the first column is downward biased because the truth and the announcement error are negatively correlated as in Mankiw and Shapiro’s news case. The fact that we find that announcement errors contain news is consistent with Mankiw and Shapiro’s (1986) earlier results for a much shorter sample period.

The results in column (2) of Table 1 for GDP look promising in that once we have controlled for lagged GDP growth, announcement errors have a positive effect on beliefs (Panel B) and they also have a positive effect on the truth (Panel A). Furthermore, the ratio of these effects has a “reasonable” quantitative magnitude of roughly 0.8 (0.30/0.37). The simple causal interpretation of these results would be that a shock to beliefs that raises beliefs about current growth by one percentage point raises true growth by 0.8 percentage points. If convincing, this would constitute pretty sizable evidence in favor of the “animal spirits” view of business cycles.

3.2 Forecastability

Alas, the world is not that simple. Aruoba (2008) points out that announcement errors may be forecastable using information available at the time of the announcement. This poses a problem if the variables that forecast the announcement error also themselves have an independent effect on true GDP growth since this would be a violation of the exogeneity condition for the announcement

error. Variables that forecast announcement errors include lagged consumption growth and the lagged growth rate of industrial production. It is quite plausible that these variables have an independent effect on current GDP growth.

In columns (3)-(5) of Table 1, we assess the possibility of this type of omitted variables bias by including lags of consumption growth, investment growth, and growth in industrial production as controls in regressions (2)-(4). When we do this, we are using only the residual variation in announcement errors conditional on these sets of controls to identify the effect of announcement errors on the dependent variables.

It turns out that adding controls alters the results substantially. Controlling for lagged consumption growth and investment growth reduces the coefficient estimates in Panels A and B by roughly 30%. But this instability is modest relative to what happens when the lagged growth rate of industrial production is added to the set of controls. In column (5), the coefficient in Panel A has flipped sign to become negative (but statistically insignificantly) and the coefficient in Panel B has dropped to 0.06 (also statistically insignificant).

Taken together, the results in columns (3)-(5) indicate that announcement errors cannot be viewed as exogenous shocks. We have experimented with other sets of controls and found that the coefficient on the announcement error is quite sensitive to the controls included. This high degree of sensitivity to the inclusion of controls has led us to the conclusion that announcement errors are, unfortunately, not a useful source of exogenous variation in beliefs.

[Add discussion of results for employment growth]

4 Early Revisions

There is an additional problem that we do not believe has been discussed in the literature that is induced by the seasonal filter. In order to investigate the implications of the seasonal filter, we consider just the early part of the announcement errors when the seasonal filter is most likely to be updated significantly.

In ??, we observe that the impact of lagged early GDP announcement errors is always negative (the opposite to what we would expect) and significant with many controls. ?? shows that the impact of lagged early GDP announcement errors upon predicted GDP is insignificant and turns negative with many controls.

We have so far focused upon regressions predicting GDP or the GDP ‘nowcast’. However, it’s

Table 2: Regressions on Early Announcement Error

	(1)	(2)	(3)	(4)	(5)
<i>Panel A: GDP Growth</i>					
Lagged Early Announcement Error for GDP Growth	-0.34** (0.14)	-0.20 (0.14)	-0.25* (0.13)	-0.26* (0.13)	-0.41*** (0.12)
<i>Panel B: Nowcast of GDP Growth</i>					
Lagged Early Announcement Error for GDP Growth	-0.06 (0.10)	0.14* (0.09)	0.08 (0.08)	0.07 (0.08)	-0.03 (0.06)
<i>Panel C: Employment Growth</i>					
Lagged Early Announcement Error for Employment Growth	-0.19 (0.12)	-0.16 (0.12)	-0.16 (0.12)	-0.18 (0.12)	-0.84*** (0.17)
2 Lags GDP Growth ^a		*	*	*	*
2 Lags Consumption Growth			*	*	*
2 Lags Investment Growth				*	*
2 Lags Industrial Production Growth ^b					*

^a In Panel C, 2 lags of GDP growth are replaced with two lags of employment growth.

^b In Panel B, Column (5) controls for 2 lags of the nowcast in addition to the other variables listed above.

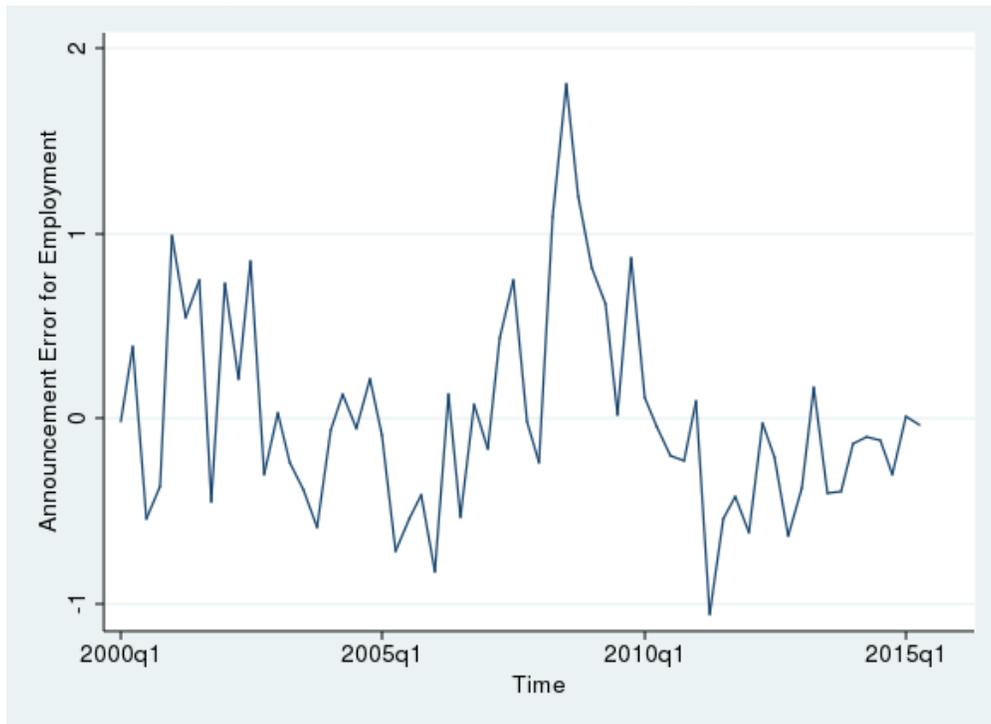
Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

possible to consider the impact of revisions upon other variables. In ??, we consider the impact of announcement errors to employment upon next period employment growth. We see that revisions appear to have a negative impact upon all forms of revisions. We see in ?? that this is significant for early revisions with the inclusion of many controls.

We think that a key factor that can help to explain these surprising results is the implementation of the seasonal filter. Deseasoning is a complicated process. Most deseasoning is done by some variant of X11-ARIMA - X13-ARIMA. These procedures are usually conducted in two steps:

1. Estimate an ARIMA model of the series. Use this ARIMA model to extend the series with forecast data at the start and end. Extra data is useful because otherwise we are estimating the data at the end of the series with only data on one side. For example, the seasonality of the most recent period would be estimated with only data from earlier in time without this adjustment.
2. Break the series down into different components using a form of averaging. Remove the seasonal component.

Figure 2: Announcement Error for Employment



For example: If we wished to find the seasonal adjustment for GDP in 2016Q1 when we have data up to 2016Q1, we could simulate the series forward to 2020Q1 (first step). We would then take the extended series and estimate the seasonal effect for Q1 by averaging across the first quarter of years close to 2016 (second step).

The forecasting step can introduce significant bias. The ARIMA models used in the first step downweight outliers to produce better forecasts. Thus, if growth is significantly lower at time t , and we are making estimates at time $t + 1$, time t will be treated as an outlier and the time t observation will be downweighted in the ARIMA model. Thus, the generated forecasts will not be impacted by the lower value at time t and will continue to show good growth. Consequently, period t will appear to suffer from very large negative seasonal effects (since the periods around period t look fine while period t is very low) so period t will be adjusted upwards a lot.

However, if the raw observation of time $t + 1$ is also significantly lower than the past, time t will no longer be downweighted. Thus, the negative seasonal effect at time t will be reduced and there will be a positive announcement error. Thus, positive announcement errors will naturally be associated with negative future growth in subsequent periods, leading to negative bias. We confirmed this with a BLS statistician who stated that “the big [positive announcement errors]

at turning points into a recessions aren't surprising in the SA data". [2](#) shows the announcement error for employment since 2000. We see that, as predicted, there are large positive announcement errors around the Great Recession. ⁷

In [A](#), we conduct simulations to find the size of the potential bias to announcement errors in periods with large negative shocks (where we calibrate the negative shocks to fit GDP series). Firstly, we consider what happens when we exclude the forecasting step. Without the forecasting step, we have an average positive announcement error of only 0.09%. However, when we include the forecasting step, thus introducing the key form of bias, there is a large average positive announcement error of 2.49%. Therefore, it appears that bias due to the forecasting step of deseasoning is important.

Thus, we observe that in periods with a large negative shock, there are likely to be positive announcement errors. Thus, shocks are clearly not exogenous. Recessions tend to be persistent so a large negative shock, which induces a positive announcement error, will be associated with a negative change in GDP growth in the next period. In our regressions, the coefficient on lagged GDP is small. Then the lagged GDP control will not fully predict the persistence of recessions and instead the negative drop in GDP growth in subsequent periods will be captured by announcement errors so the coefficient on announcement errors will be negatively biased.

A similar problem occurs if variables are smoothed. One example of this is the state unemployment statistics discussed in [Chodorow-Reich and Karabarbounis \(2016\)](#) - there are too few observations of unemployment in each state in the BLS's survey so the results are smoothed across months. If next period's unsmoothed observation is low, today's smoothed observation will be lowered in the smoothing process. Thus, low future observations will be associated with positive early announcement errors (since the initial release will be higher than later releases). Thus, we will again have negative bias.

Therefore, we believe these problems mean that total and early announcement errors may be caused by as well as cause future aggregate economic variables. Consequently, we do not believe we can use the simple approach to identify the impact of total and early announcement errors.

⁷It is also possible that the deseasoning itself could introduce bias: If the non-seasonally adjusted observation drops by a large amount then the drop is attributed partly to a drop in the deseasoned series and partly due to a negative change in the seasonal factor for this part of the year. Thus, if the next time the season occurs, there is not a large decrease, the negative drop is more attributed to a fall in that given quarter rather than a change in the seasonal factor. Thus, there is a positive announcement error. This relates to the discussion in [Wright \(2013\)](#). We do not find much evidence of this form of bias in our simulation.

Table 3: Regressions on Late Announcement Error

	(1)	(2)	(3)	(4)	(5)
<i>Panel A: GDP Growth</i>					
Lagged Late Announcement Error for GDP Growth	0.49*** (0.16)	0.61*** (0.15)	0.52*** (0.15)	0.51*** (0.15)	0.16 (0.14)
<i>Panel B: Nowcast of GDP Growth</i>					
Lagged Late Announcement Error for GDP Growth	0.33** (0.13)	0.46*** (0.10)	0.31*** (0.09)	0.33*** (0.09)	0.15** (0.07)
<i>Panel C: Employment Growth</i>					
Lagged Late Announcement Error for Employment Growth	-0.75 (0.49)	-0.88*** (0.34)	-0.92*** (0.34)	-1.18*** (0.34)	-0.77 (0.63)
2 Lags GDP Growth ^a		*	*	*	*
2 Lags Consumption Growth			*	*	*
2 Lags Investment Growth				*	*
2 Lags Industrial Production Growth ^b					*

^a In Panel C, 2 lags of GDP growth are replaced with two lags of employment growth.

^b In Panel B, Column (5) controls for 2 lags of the nowcast in addition to the other variables listed above.

Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5 Late Revisions

Note that we are using quarterly data so our early announcement error is effectively the change in the observed variable in the five years after the initial release, and the late announcement error is the change afterwards. Late announcement errors primarily reflect changes in the data due to rebasing and new statistical procedures.⁸

Since we do not believe that the early component of announcement errors (and thus total announcement errors) can produce unbiased estimates of the impact of announcement errors on realisations/expectations, this motivates an investigation of whether the late component of announcement errors is exogenous.

It's important to be clear about the channel by which late announcement errors may impact expectations: We are not suggesting that statisticians 21 quarters from today revise GDP and this change in the future impacts people's expectations today. Instead, we are suggesting that a late announcement error means that people today have an imperfect knowledge of the true value of

⁸Revisions data is available only from the late 1960s but we include so the 21st quarter isn't available for some early data. We use later quarters to form the late revisions in this case.

an economic variable today, and this imperfect knowledge was only uncovered many years in the future.

Since late announcement errors are primarily due to definitional and methodological changes, we need to think carefully about what using late announcement errors will imply for coefficients under the simple approach. The expected coefficient will depend upon whether late announcement errors are not just systematic changes but actually improve the accuracy of economic measures and get us closer to the “truth”. To see this, observe that late announcement errors are given by $\Delta Y_{t+21,t} - \Delta Y_{T,t}$ and imagine that $\Delta Y_{t+21,t} < \Delta Y_t^{true}$ so the initial release underestimates true GDP growth. Then if we expect that methodological changes mean that we improve, on average, our estimate, we would expect $\Delta Y_{t+21,t} < \mathbb{E}[\Delta Y_{T,t}|Y_{t+21,t}] \leq \Delta Y_t^{true}$. If, instead, we do not believe that late announcement errors improve accuracy then $\Delta Y_{t+21,t} = \mathbb{E}[\Delta Y_{T,t}|Y_{t+21,t}] < \Delta Y_t^{true}$.

In the first case, observe that the announcement error is expected to be negative whereas in the second case the announcement error is expected to be zero. Therefore, if we are in the first case, late announcement errors will capture some of the impact upon expectations of a low total announcement error. However, unlike early announcement errors, we will not have to worry about seasonal/smoothing/timing issues. Instead, we can treat the late component of announcement errors as exogenous. So if we observe a late negative announcement error at time $t - 1$, we know that there was an exogenous negative shock to expectations at time t .

?? shows the results of running regressions of GDP growth on lagged late GDP announcement errors with controls. Lagged GDP growth appears very significant until we add in industrial production growth when the effect goes away. ?? shows the results of running the equivalent regressions with forecast GDP. Here, we see that the impact of lagged announcement errors upon GDP remains significant as we introduce controls but the impact diminishes substantially after we introduce lagged industrial production growth and lagged forecast GDP.

It is initially surprising that the late announcement errors are impacted by the inclusion of industrial production. The arguments regarding the biased estimates using the early component of announcement errors do not appear to apply after 21 quarters. All data should be available and have been initially processed and the seasonal trend should have settled. The only changes taking place after 21 quarters should be due to changes in methodology. Of course, changes in methodology are not random but our initial hypothesis was that the effects across 45 years would be random. It appears that this may not be the case.

The correlation between industrial production growth and late announcement errors to GDP

is 17.3%. One potential explanation for the positive correlation is that the importance of industrial production in the US has been falling. Therefore, initial releases of GDP may be likely to exaggerate the role of industrial production. Later releases would diminish that role. We would then expect that high industrial production in a given period would generate a positive announcement error in that period.

In basic regressions, lagged industrial production has a significantly positive impact upon GDP growth⁹. This is problematic for our specification since if industrial production is high today, announcement errors are likely to be high and real GDP growth tomorrow is likely to be high. However, the high real GDP tomorrow is due to industrial production not announcement errors. This suggests the coefficient of lagged late announcement errors would be positively biased without the inclusion of industrial production growth.

In ??, we observe the regression of employment growth on lagged employment late announcement errors. It may come as a surprise that there are still revisions to employment data five years after the initial release. The primary cause of the adjustments seems to be that deseasoned aggregate employment is computed by summing deseasoned series for individual industries. The structure for these industries is not constant. When industries change, the sum of the deseasoned individual industries will not necessarily be the same (this is partly because deseasoning removes outliers which may not remain the same). When the structure of industries is changed (for example the conversion from SIC divisions to NAICS supersectors), it affects the deseasoning process. This means the summed deseasoned series for individual industries may change.

Unfortunately, these adjustments may negatively bias the coefficient of lagged employment late announcement errors. This is because if the deseasoned employment level for a period is revised upwards for period 1 due to seasonal adjustment, it is quite likely that it will not be revised upwards for period 2. Then the growth for period 1 will be revised upwards and the growth for period 2 will be revised downwards. Thus, we are likely to find that positive late announcement errors are associated with relatively low growth in the subsequent period.

Therefore, we do not believe that it is possible to get an unbiased estimate of the impact of announcement errors upon realisations or expectations using the late component of the announcement error due to the potential for nonrandom systematic changes in methodology correlating with omitted variables and the continued problems associated with seasonality.

⁹We verified this with basic regression analysis.

6 Conclusion

In this paper, we have broken down announcement errors into their early and late component to analyse the validity of regressions of realisations and expectations of economic variables upon announcement errors. We have demonstrated that a regression of realisations or expectations using the lagged early component of the announcement errors is likely to suffer to suffer substantial bias due to seasonality, smoothing and the fact that data may become available/processed at different speeds. We do not believe that it is possible to add controls to prevent these problems. Thus, we believe that it does not appear possible to identify the impact of early/total announcement errors upon economic variables by the simple approach. We have also shown that a regression of realisations or expectations upon the lagged late component of the announcement errors may be biased due to the fact that the late announcement errors are likely to be methodological changes which are nonrandom.

Therefore, we believe that we have established that it is not possible to estimate in an unbiased manner the impact of realisations or expectations upon announcement errors. This poses problems for two strands of literature: the impact of expectational shocks captured in [Lorenzoni \(2009\)](#) which was implicitly estimated in [Rodriguez Mora and Schulstad \(2007\)](#) and the recent use of announcement errors as exogenous shocks to realisations/expectations, seen recently in [Chodorow-Reich and Karabarbounis \(2016\)](#).

A Seasonality Simulation

To estimate the impact of different types of deseasoning upon the size of announcement errors, we consider the size of announcement errors made in a period with a large shock. We need to simulate unadjusted data to do this since, as far we are aware, there is no real-time data for unadjusted employment (or a similar series where deseasoning is important). We simulate a variable where growth typically grows steadily but where there is a large negative shock in one period. We use the following model for the variable where T_0 is the period with a large negative shock:

$$\log Y_t = \beta \log Y_{t-1} + \gamma \mathbb{1}_{t=T_0} + \epsilon_t$$

where $\epsilon_t \sim N(0, \sigma^2)$

We need to pick values for β, γ, σ in order to simulate the data ¹⁰. We try computing the regression for T_0 at any possible date for total nonfarm payrolls (PAYEMS) data from FRED. We select β, γ, σ from the regression where \tilde{T}_0 maximised the R^2 of the regression given that $\gamma < 0$ (since we're generally more interested in negative shocks). We find that: $\beta = 1.00015, \gamma = -0.01367, \sigma = 0.00400$. We pick $T = 120, T_0 = 60$ for the simulations.

We consider two types of deseasoning using X-13 ARIMA:

1. Basic deseasoning: This involves no forecasting or removal of outliers.
2. Advanced deseasoning: We use the BLS deseasoning code which is used to deseason the series employment in the management of companies and enterprises. Aggregate employment is computed by summing the deseasoned employment for different industries. This is why we use the deseasoning codes for a specific industry rather than aggregate employment. This deseasoning code includes more advanced options including forecasting and the removal of outliers. The removal of outliers is particularly important since this is the step that we believe induces positive revisions in periods with large negative shocks.

For each type of deseasoning, we do the following 1,000 times:

1. Generate the series.

¹⁰The value for Y_0 is unimportant because we can rewrite the model as $\log \frac{Y_t}{Y_{t-1}}$. We don't think it makes sense to calibrate when a big recession happens in a simulation based upon when the biggest recession was when data was available so we just set the large negative shock to be in the middle of our sample.

Table 4: Announcement Errors in a Period with a Large Shock under Different Forms of Deseasoning

	Basic Deseasoning	Advanced Deseasoning
Initial Growth	-12.91	-10.66
Final Growth	-12.99	-13.14
Total Announcement Error	0.09	2.49

2. Use the deseasoning process to generate the deseasoned data only for periods $1 - T_0$. This gives the initial deseasoned observation of T_0 .
3. Use the deseasoning process to generate the deseasoned data for all periods $1 - T$. This gives the final observation of T_0 .
4. Compute the total announcement error to growth that occurs from the initial to the final observation. We use annualised percentages so we multiply by 1,200 since we calibrated to employment data which is monthly.

The average of initial observation, final observation and announcement error to growth are given in 4 for each type of deseasoning.

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