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Anticipating Early Data Revisions to US GDP and the Effects of Releases on Equity Markets

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Abstract

The effects of data uncertainty on real-time decision-making can be reduced by predicting early revisions to US GDP growth. We show that survey forecasts efficiently anticipate the first-revised estimate of GDP, but that forecasting models incorporating monthly economic indicators and daily equity returns provide superior forecasts of the second-revised estimate. We consider the implications of these findings for analyses of the impact of surprises in GDP revision announcements on equity markets, and for analyses of the impact of anticipated future revisions on announcement-day returns.

Key words: survey forecasts, data revisions, economic indicators, stock returns, macro announcements.

JEL code C53.

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Anticipating Early Data Revisions to US GDP and the Effects of Releases on Equity Markets

The effects of data uncertainty on real-time decision-making can be reduced by predicting early revisions to US GDP growth. We show that survey forecasts efficiently anticipate the first-revised estimate of GDP, but that forecasting models incorporating monthly economic indicators and daily equity returns provide superior forecasts of the second-revised estimate. We consider the implications of these findings for analyses of the impact of surprises in GDP revision announcements on equity markets, and for analyses of the impact of anticipated future revisions on announcement-day returns.

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1 Introduction

Orphanides (2001) brought to the attention of economists the difference between taking policy decisions in real-time using the early estimates of real output and inflation that are then available compared to using the final-revised data only available a number of years later. Revisions to national accounts data are large enough that the policy rate implied by the real-time Taylor rule may differ significantly from the one computed with revised data. Data uncertainty also affects financial market participants. The calendar of 'market-moving' indicators published on the Econoday website[1] includes not only the initial release of real GDP published up to one month after the end of the observation quarter, but also the second and the third estimates released, respectively, two and three months after the end of the observation quarter. Indeed the results of Gilbert, Scotti, Strasser and Vega (2010) on the impact of macroeconomic news on bond and currency markets establish that markets react to surprises (differences between the published values and the market expectation) in the second release of real GDP. Gilbert (2011) also provides evidence that equity markets react not only to surprises in the initial release, but also to expected future revisions, indicating that markets care about the revised values of economic activity measures.

Data uncertainty decreases with the publication of revised estimates which incorporate new information, and which may also reduce the measurement noise component of the initial estimates. Following Mankiw and Shapiro (1986), economists classify data revisions as news when they add new information, and noise when they reduce measurement error. If data revisions are noise, they can be predicted based on the current estimate. Mankiw and Shapiro (1986) and Faust, Rogers and Wright (2005) provide empirical evidence that data revisions to US real GDP are largely news, while Aruoba (2008) and Corradi, Fernandez and Swanson (2009) found some limited predictability of data revisions, in particular of initial revisions. Clements and Galvão (2012) exploit multiple-vintage models to show that real-time estimates of output and inflation gaps can be improved by using predictions of data revisions following the encouraging results of Garratt,

[1] See www.econoday.com.

Lee, Mise and Shields (2008). Predictable data revisions suggest that we are able to reduce current data uncertainty in real time.

However, much of the literature has used the quarterly vintages recorded in the Real Time Data Set for Macroeconomists (RTDSM: see Croushore and Stark (2001)), where the first estimate is the 'advance' estimate, published around one month after the end of the observation quarter, and the second estimate is the 'final' estimate published four months after the end of the quarter. Hence the predictability of the monthly revisions to the first (advance) estimate has not been addressed.

The nature of the process by which the national accounts data are revised suggests that the initial monthly revisions may be predictable even if the revisions are 'news' in the sense that they are unpredictable based on information at the time the first estimate (or an earlier estimate more generally) was made. As described by Landefeld, Seskin and Fraumeni (2008), 25% of the GDP components at the time of the release of the first estimate are trend-based data obtained from extrapolations supported by related indicator series. The proportion of trend-based data in the second and third estimates is 23% and 13% respectively. As a consequence, it might be possible to exploit data on the economic indicators that are published prior to the release of the GDP figure to anticipate that figure.

We evaluate different methods of forecasting the US statistical agency's early releases of GDP data: survey data, forecasting models with economic indicators, and models with financial indicators. The quality of survey forecasts of *new* observations has been extensively evaluated (see, e.g., Ang, Bekaert and Wei (2007) for a recent appraisal), but we are not aware of any explicit assessments of survey forecasts of the *revisions* to initial releases.[2]

In the burgeoning event studies literature which investigates the response of financial markets to new information provided by the release of measures of economic activity (see, e.g., Andersen, Bollerslev, Diebold and Vega (2003) and Faust, Rogers, Wang and Wright (2007)), market expectations are typically proxied by the median forecasts of a survey of professional forecasters. Our

[2] Evans (2005) compares model-based real-time measures of output growth with the MMS (International Money Market Services) survey median forecasts of the three initial releases of GDP growth. However, the comparison was made to evaluate the models, with the MMS forecasts taken as the target values.

findings suggest the availability of sources of information - not incorporated in survey expectations - which might influence market expectations. We provide an assessment of the effects of surprises in the second and third releases of GDP on daily equity returns, allowing that market expectations may not be accurately measured by survey expectations. We also consider the evidence for whether investors respond to the information the GDP release carries about the true value of GDP. We calculate model-based estimates of the expected revision generated by the announcement-day release.

The plan of the rest of the paper is as follows. In section 2 we describe the survey data, and the accuracy of the median forecasts of the second and third estimates of output growth. Section 3 evaluates the forecast accuracy of forecasting models exploiting information sets comprising monthly economic indicators and daily financial data. Section 4 analyses the impact of the mis-measurement of market expectations on estimates of the effects of data release announcements on equity returns. Section 4 analyses whether announcement-day returns are affected by future expected revisions to the GDP figures induced by the announced value. Section 5 offers some concluding remarks.

2 Using Surveys to Anticipate Revised Data Releases

When predicting the second and the third GDP releases in real time, we are able to use an earlier release. The initial release (the 'advance' estimate, published on average 30 days after the end of the quarter, and denoted $y_t^{t+1/3}$) can be used to predict the second release (the 'preliminary' estimate $y_t^{t+2/3}$, published on average 60 days after the end of the observational quarter).[3] So if either no revision is expected, or the revision is not predictable, the appropriate forecast is the no-change forecast: $\hat{y}_t^{t+2/3} = y_t^{t+1/3}$. For a short-horizon forecast, such that $y_t^{t+2/3}$ has been released, the no-change forecast of the third release (the 'final estimate') is simply $\hat{y}_t^{t+1} = y_t^{t+2/3}$. The accuracy of no-change forecasts serve as a benchmark for the forecasting models in section 3, and also for the survey forecasts in the remainder of this section. Note that if we are able to predict GDP revised

[3] Note the supercripts are the release dates, and the subscripts are the date the observation refers to.

estimates more accurately than the benchmark, we are effectively reducing the data uncertainty surrounding real-time policy and economic decision-making.

Before the announcement of 'market moving' economic data, business websites such as Bloomberg (www.bloomberg.com) and Econoday (www.econoday.com) provide the 'consensus forecast' of the pre-announcement value of output growth. The consensus forecasts are the medians of surveys made on the Friday before the announcement. These determine the forecast horizon we consider. Aggarwal, Mohanty and Song (1995) and Hess and Orbe (2011) have evaluated survey forecasts of the releases computed by the MMS (International Money Market Services). Our preliminary results suggested that the choice of survey provider mattered little - the accuracy of the forecasts for overlapping periods is generally similar. (We compared MMS, Bloomberg, Econoday and Action Economics). As a consequence, we use the survey median provided in the Econoday report for the first, second and third releases of US GDP growth. This covers 2001:M1 to 2013:M12, and so includes both the 2001 and the 2008-9 recessions, and the post Financial Crisis recovery period.

Figure 1 presents the forecast errors from predicting the second (preliminary) and the third (final) release of US GDP growth. We compute forecast errors for the no-change forecasts and the survey forecasts. The actuals are the released values and the dates refer to the release dates, for example, 2005M2 refers to the preliminary release of GDP growth for 2004Q4. No-change forecast errors for the third release are between -0.6 and 0.6%, but the range is -2.5 to 1.5% for the second release. The size of these initial revisions is reasonably large given that the average GDP growth rate is 3% (computed with latest-available vintage data for the period 1985-2007). The improvements offered by the professional forecasters for the second release are evident from the figure, but equally clear is that their forecast errors for the third release are similar to those of the no-change forecasts.[4]

We use the root mean squared forecast error (RMSFE) to measure forecast performance. Table 1 records the RMSFEs of no-change forecasts as benchmarks against which the survey forecasts

[4] Although the survey forecasters made a large error in calling the 3rd release value for 2010:Q3 that was not made by the benchmark.

can be assessed. For completeness, we also report the accuracy of forecasts of the first release, using last quarter's final estimate as the benchmark: $\hat{y}_t^{t+1/3} = y_{t-1}^t$. Table 1 includes a test of the null of equal forecast accuracy. The alternative hypothesis is that the no-change benchmark is less accurate than the survey median (i.e., a one-sided test). This is the t-statistic of Diebold and Mariano (1995). Rejections at 1, 5 and 10% significance levels are indicated by ***, *** and *, respectively.

As expected, the survey forecasts are much more accurate for the advanced estimate. But the results also indicate startling improvements in accuracy for the survey forecasts for the second release of GDP growth. The RMSFE is a half of that for the no-change benchmark. By contrast, the third estimate is not predicted any more accurately by the survey forecasters than if we were to assume no revision to the second estimate, consistent with the visual impression provided by Figure 1.

We investigate possible dependence of the results on the business cycle phase (see, e.g., Swanson and van Dijk (2006)) by evaluating forecasts separately for observations that fall in expansions and contractions. The split is based on the observation date as determined by the NBER business cycle chronology. The results in Table 1 indicate that the survey forecasts of the third release are equivalent to the no-change forecasts independently of the business cycle phase. In contrast, the survey forecasts of the second release record a larger reduction in RMSFE relative to the no change during contractions. Second release estimates are also more variable during contractions (compare the no-change RMSFEs for second estimates across phases). In short, the first revision (i.e., the second release) is both larger and relatively more predictable using survey forecasts during contractions.

3 Using Forecasting Models to Predict Data Revisions

The results in the previous section show that survey forecasts are significantly more accurate than 'no change' forecasts for the second release of GDP growth but not for the third release. In this section we consider forecasting models that exploit the predictive power of monthly economic indicators and daily financial indicators to anticipate the second and third estimates of US GDP.

We use monthly vintages of US real GDP from 1966:M1 up to 2013:M12 from the Real-Time Dataset for Macroeconomists (RTDSM) of the Philadelphia Fed (see Croushore and Stark (2001)) to estimate the forecasting models.[5],[6]

We assess which information is useful to predict data revisions in a real-time out-of-sample forecasting exercise. In-sample evaluations (such as Aggarwal *et al.* (1995), amongst others) may be misleading, especially if there are parameter instabilities. Against this, out-of-sample evaluations require longer spans of historical data because separate in-sample estimation and out-of-sample forecast periods need to be defined, but nevertheless we choose to conduct an out-of-sample evaluation. We evaluate forecasts from autoregressive models in section 3.1, from models with monthly economic indicators in section 3.2, and with daily financial data in section 3.3.

Table 2 summarizes the forecasting models used in this paper for ease of reference, with detailed explanations in what follows. We aim to forecast the second and the third estimates, that is, y_t^{t+v} for $v = 2/3, 1$. Note that $t = 1, 2, ...$ in quarters, varying for both vintages (superscripts) and observations (subscripts). All forecasting models use the revision $y_t^{t+v} - y_t^{t+v-1/3}$ on the left-hand side. At each point in time, we use data from the most recent vintage available at that time to estimate the given forecasting model, and then compute forecasts using the model estimated parameters and the required right-hand-side predictor variables.

Hence we present a real-time analysis of forecasting early GDP releases. The out-of-sample periods match the release dates covered by the survey (2001:M2-2013:M12). At each new forecast origin we re-estimate each model with an expanding window of data. As in section 2, we provide results for the whole period and also the split by business cycle phase.

[5] The one exception is the 2003 benchmark revision. One week after the second release of 2003:Q3 GDP, the BEA published a benchmark revision. The RTDSM records the benchmark revision estimates as the 2003M11 vintage. This creates a mismatch with the actual release published in November 2003. For this reason we use the vintage published in 2003M11 obtained from the St Louis Fed ALFRED database.

[6] The RTDSM contains the data available at the middle of each month. The advance estimate (vintage $t + 1/3$) is published in the first month following the end of the quarter, the preliminary (vintage $t + 2/3$) is published in the following month, and the final (vintage $t + 1$) a month later.

We assess whether model forecasts are more accurate than the random walk using the t-test of Diebold and Mariano (1995) (DM), assuming quadratic loss. An alternative test for nested models is the encompassing statistic of Clark and West (2007) (CW), which makes an allowance for the effect of parameter estimation uncertainty (in estimating the nesting model). Effectively the CW test assumes that we have an infinitely large sample, that is, that we are able to use the population values of the nesting (alternative) model's parameters to generate forecasts. The DM approach tests whether the model is more accurate than the random walk allowing that the model needs to be estimated, and unlike CW, will only reject the null when the mean squared forecast error of the model's forecasts is smaller than that of the random walk. Thus the DM approach seems preferable for our purposes. We use heteroscedasticity-consistent standard errors.

3.1 Information from Past Vintages

We start by considering forecasting models with an information set restricted to past-vintage data on the variable in question. If past data vintages help predict data revisions in comparison with the no-change forecast benchmark, then revisions at least in part embody a reduction in noise or measurement error.

The first panel of Table 2 summarizes the five forecasting models which exploit the real-time dataset for US GDP. The first model assumes that data revisions are serially uncorrelated with possible a non-zero mean. The second model adds an autoregressive term related to the 'spillover effect': see e.g., Jacobs and van Norden (2011). The third model allows revisions to depend on the value of the initial release. Similar regressions are commonly used to test whether revisions are news. If $\beta_0 = \beta_1 = 0$ then data revisions are unpredictable (news) as defined by Mankiw and Shapiro (1986). Note that by comparing the out-of-sample forecasting performance of the 'Previous Release' model of Table 2 with a no-change forecast, we are assessing the out-of-sample predictability of data revisions. If the modified t-test described previously rejects the null, we conclude that revisions are not pure news.

Clements and Galvão (2013) have shown that models of multiple data vintages are able to predict *quarterly* data revisions to output growth and inflation by exploiting information on past revisions, and in particular, the annual revisions which take place in the third quarter of each year. The 'Vintage-Based' model of Table 2 describes a simplified single-equation version of their model (see also Koenig, Dolmas and Piger (2003), and Croushore (2011a) for a recent survey of forecasting with data vintages). We experiment with $q = 5, 14$.

Swanson and van Dijk (2006) report that the biases of the revisions to industrial production depend on the state of the business cycle. To capture possible business cycle asymmetric effects, we consider a threshold specification that allows the response of the revision to the earlier release to depend on the sign and size of the earlier release: the 'Threshold Model' of Table 2. Note that $I()$ is an indicator function and c is the value of the threshold. The threshold is jointly estimated with the slope parameters by conditional least squares. The estimation employs a grid search for the threshold value c based on the restriction that each regime must have at least 15% of the observations (see, e.g., Hansen (2000)).

Table 3 presents the ratio of the RMSFE of each autoregressive model with respect to the no-change benchmark. By and large, there is little indication that any of these 'own-information' models offer much improvement over the benchmark for these early data revisions. There is some evidence that past vintages could anticipate the second release during recessions. Finally, there is no evidence to support the use of a threshold specification. Broadly, these findings are in agreement with the literature suggesting there is limited predictability of revisions to US GDP growth.

3.2 Information from Monthly Economic Indicators

As discussed in the Introduction, the early monthly estimates of real GDP are based on extrapolations, and the GDP releases incorporate new information as it becomes available (see e.g., Landefeld *et al.* (2008)). Forecasters might be expected to anticipate upcoming data revisions by using the new information released since the previous release (first, second) but before the target release (second, third) is announced. We consider the monthly economic indicators categorized as 'market moving' by Econoday. These variables are listed in Table 4, with the Econoday descriptions of their economic importance. This is mainly to do with their correlations with components of GDP: consumption, investment, and the trade balance. The set of variables examined is constrained by the availability of a real-time data set with monthly vintages such that we use only information that would have been available to the forecaster at each forecast origin. Our data sources are indicated in Table 4.

Taking a closer look at Table 4, the first two indicators, industrial production and employment, are alternative measures of economic activity, and the market expects that the announcement of these variables will anticipate the GDP growth announcement later in the month. The nonfarm payroll announcement in particular receives much media attention as the first aggregate measure of economic activity to be announced.

Looking at the GDP components, retail sales is an important measure of current consumption, while the production manufacturing index (NAPM) and durable good orders measure current aggregate production. An alternative measure of consumer spending is consumer sentiment, which is published at the end of the month but refers to the consumers' mood for the next month. Consumer confidence is generally regarded as a leading indicator, while the other measures we have referred to are coincident indicators.

We also include two housing activity measures, housing starts and new home sales. These measures also help anticipate domestic investment and production; however, the Econoday comments on the new home sales releases suggest that new home sales may also be a measure of consumer confidence. Although the timing of the release of GDP deflator inflation means it cannot be used as a predictor (it is released at the same time as the output data), we use as an alternative inflation measured by the consumer price index.

Exports and imports are components of real GDP that are subject to initial revisions that are five times larger than aggregate consumption revisions, even though their proportion in the aggregate output measure is small (see, e.g., Fixler and Grimm (2006)). A 'market moving' monthly indicator that could anticipate these revisions is the trade balance computed from Balance of Payment accounting.

We consider each indicator separately. Given the poor performance of models with autoregressive components (see Table 3) we omit such terms, while non-zero mean revisions are accommodated by the inclusion of intercepts in the regressions. The second panel of Table 2 describes the regression models of this section.

Notice that the majority of the variables in Table 4 are subject to revision. This means that for such variables we typically have (*i*) data published after the announcement of the current GDP estimate, including new observations and revisions to the past data; and (*ii*) values and observations already available before the announcement of the current GDP estimate ('past' information). We can organize the new information into: 'new revision', 'new observation' and 'updated observation'. By comparing the relative forecasting accuracy of models which exploit new, updated and past information, we can assess the efficiency of early GDP releases for later releases, and which information is useful in predicting those releases. Note that in contrast with much of the literature, our short forecast horizon of up to one-week-ahead suggests that data revisions may be news - unpredictable based on past information - but nevertheless predictable ahead of the time of their release based on new and updated information

Five indicators (including industrial production and employment) are published with a delay shorter than 21 days from the end of the observational month, so we can use their revisions to predict both the second and the third releases of GDP growth. The 'New Revision' regression model uses the published revision of the indicator $x_t^{t+v} - x_t^{t+v-1/3}$ to predict the future releases of output growth for $v = 2/3, 1$.[7] For the three indicators published with a longer delay, $x_t^{t+2/3}$ indicates their first release, and the 'New Revision' model is only applicable for forecasting the third release of GDP ($v = 1$). We also consider the 'updated observation' x_t^{t+v}, release subsequent to the publication of the current release. For the variables with the longer publication lags, the 'updated observation' is the initial release for predicting the second release of output growth, but

[7] We could use revisions to monthly observations $t - 1/3$ and $t - 2/3$, which also refer to quarter t. However, we will consider only revisions of the last month of the quarter (t) for simplicity, since we use quarterly differences for many of the variables ($x_t^{t+1/3} = (X_t^{t+1/3} - X_{t-1}^{t+1/3})$, where X_t is level of monthly nonfarm payroll in the last month of quarter t, for example).

is the revised value otherwise.

Another way of exploiting new information is to use the new observation published before the release we would like to anticipate but after the current release of GDP growth. The 'New Observation' regression model employs $x_{t+v-1/3}^{t+v}$ as a predictor. Note that this information is only available for the five indicators published with a short delay.

We also consider models based on data available at the time of the publication of the current release $x_t^{t+v-1/3}$. As before, we have to be careful when applying the 'Previous Release' regression model to regressor variables with long publication delays. If 'Previous Release' forecasts are significantly more accurate than no-change forecasts, early GDP estimates are not efficient since they do not use all available information. If data revisions are not predictable from 'past information', then revisions are classified as news (see, e.g., Croushore (2011b)). Note that a given release may be news, in the sense of being unpredictable based on data at the time of the earlier release, but may still be predictable from more recent information: the new revisions, observations, or updated information. By exploiting economic releases between the current and target GDP release, we consider whether the target release is predictable up to one-week in advance.

For the two survey-based variables in Table 4 that are not subject to revisions and are published with short delays (NAPM and consumer confidence), we apply the 'New Observation' model with $x_{t+v-1/3}$ to exploit new information, and the 'Previous Release' model with $x_{t+v-2/3}$ to consider past information.

The RMSFE ratio to the benchmark of all regression models in Table 2 with the indicators in Table 4 are presented in Table 5. The first panel shows the results for the second GDP estimate, and the second panel the results for the third estimate. For both releases, we generally find more evidence of predictability during recessions. Newly-released data revisions to monthly economic indicators do not help to predict the first revision, but the second revision can be forecast by trade balance revisions. Significant improvements over the no-change benchmark are obtained for forecasting the second release using updated observations and previous-release values of sales and housing, and the new release of durable orders.

Neither survey forecasts nor forecasts based on past vintages improve on the no-change forecast for predicting the third release. But the results in Table 5 indicate that by exploiting new information (on the trade balance and consumer confidence) released after the second release, the third release can be anticipated in real time. However, while survey forecasts of first-revised GDP growth releases improve on the benchmark by 50% on RMSFE, for the third estimate the model-based gains are capped at 20% (for recessions).

All in all, both GDP revisions are predictable from a combination of past and new information.[8]

3.3 Information from Daily Financial Variables

Our third broad information set consists of daily financial variables. That financial variables may have predictive content for growth data revisions is suggested by Andreou, Ghysels and Kourtellos (2010), who show daily financial indicators help to nowcast revised values of GDP growth. They find short-term interest rates, bond spreads and stock returns are among the indicators with the best forecasting accuracy for output growth one-quarter-ahead. Secondly, Gilbert (2011) argues that on days that advance estimate announcements are made, equity returns respond to incorporate information on expected future data revisions to measures of economic activity such as nonfarm payroll employment and output growth. This implies that equity returns (observed during the first month of the current quarter, $t+1/3$) might help predict the revised values released in $t+2/3$ and $t+1$.

We use Mixed Data Sampling (MIDAS) regressions to exploit the information in daily financial variables for predicting the quarterly data releases (see for example the review article by Andreou, Ghysels and Kourtellos (2011) on MIDAS). The MIDAS regression is described in the third panel of Table 2. The lag operator is applied to daily data, and we assume that there are m daily observations per quarter. The number of daily lags is set to K. The weighting function $w_j(\boldsymbol{\theta}, K)$ is a beta function with two parameters in the vector $\boldsymbol{\theta}$. The aggregation weights $w_j(\theta, m)$ sum up to 1

[8]These qualitative results do not change if we consider more sophisticated forecasting models such as MIDAS regressions, to exploit longer lags, and nonlinear regressions. These additional results are available on request.

to guarantee the identification of the slope parameter α_1. Galvão (2013) shows that beta functions work better than an exponential function when m is large. The parameters of the weighting function are jointly estimated with the slope and intercept parameters by nonlinear least squares. When using information up to t, the parameter l is set to v, and $K = 60$, that is, we use all the daily data from the observation quarter t. When using information up to $t + 1/3$, $l = 1/3$ for $v = 2/3$, and $l = 2/3$ for $v = 1$, while in both cases $K = 20$, so only data from the month of the first GDP announcement is considered.

Instead of estimating the function to aggregate high frequency data, we can also assume flat aggregation (equal weighting) and set $w_j(\boldsymbol{\theta}, K) = 1/K$ for all the daily lags, giving the 'Linear' model of Table 2.

Galvão (2013) suggests that regime changes in the slope parameters may have a larger effect on the accuracy of output growth forecasts than the use of high frequency data. The slope coefficients in models which use financial variables to predict output growth may shift because of market regimes (bull/bear) and monetary policy regimes (loose/tight). Therefore, we also employ the Smooth Transition MIDAS (STMIDAS) regression as a forecasting model to extract information from daily financial variables. The MIDAS model is modified such that the slope parameters are weighted by a logistic function. The values of the logistic function (between 0 and 1) at each point in time depend on the difference between the aggregated high frequency data and a threshold c. The smoothness of the function depends on the parameter γ. The STMIDAS regression is described in the last row of Table 2. Note that the parameters of the aggregation function $w_j(\boldsymbol{\lambda}, m)$ of the transition function may differ from the parameters of the aggregation function of the indicator as a predictor $(w_j(\boldsymbol{\theta}, m))$.

We need a long historical sample on each financial variable to estimate these models for out-of-sample forecasting. This restricts us to the four financial variables described in Table 6 with data from early 60's. The empirical results of Andreou *et al.* (2010) suggest the use of stock returns (both SP500 and DJIA) and the short–rate as predictors of economic activity variables. Gilbert (2011) uses the SP500 to capture the market reaction to the first release of GDP growth. As well as these variables, we include a measure of the interest rate spread (computed as the difference between the 10-year Treasury bond and a 3-month Treasury bill), as suggested by Galvão (2013).

Table 7 presents the RMSFE ratios with respect to the benchmark using the three daily-data specifications (MIDAS, linear and STMIDAS) with each financial variable for predicting the second (first panel) and the third (second panel) releases. Table 7 compares the accuracy of models using daily data through quarter t and with daily data from the month of the first announcement $t+1/3$. From 1975, we have the dates of the real output releases. This means that for this shorter in-sample period, we can estimate specifications that use daily data up to the day before the second and third release announcements. The results for this specification with $K = 60$ are presented in the last columns of Table 7 ($t + db$).

The measures of relative accuracy clearly show that equity returns from the month of the first announcement have predictive power for both releases, whereas daily data through quarter t and using information up the day before the release is of no value. Daily stock returns (in particular DJIA) for the month of the initial release of GDP growth are able to anticipate the second revision during both business cycle phases, and result in forecasts of a similar accuracy to those that use trade balance revisions (see Table 5). The STMIDAS provides more accurate forecasts of the second estimate, and the MIDAS is best for the third release.

It is possible that the predictive content of equity returns stems solely from their embodying news on the economic indicators released during the month. To see whether this is the case, in Table 8 the accuracy of the best forecasting models and indicators from Table 5 is compared with that of forecasting models which combine the economic indicators with daily equity returns (either SP500 or DJIA). The daily returns are included via a beta weighting function $w_j(\boldsymbol{\theta}, 20)$, with all the parameters being estimated jointly by nonlinear least squares. Statistically significant reductions of RMSFE from the inclusion of daily financial variables are detected for predicting the third release of GDP growth during both business cycle phases, and for predicting the second release during recessions. The results in Table 8 indicate that equity returns contain additional information to that in the economic variables, and are especially informative for recession quarters.

4 Data Revisions and Equity Markets

The literature has identified two main problems with estimating the effects of macroeconomic surprises on equity returns. First, Rigobon and Sack (2008) argue that if survey forecasts are a noisy proxy for market expectations, the estimates of the impact of macroeconomic surprises on asset returns will be attenuated. Second, 'good news may be bad news for stock returns'. An unexpected increase in growth may presage a tightening of monetary policy to allay fears of a build up of inflationary pressure. In general, this is solved by considering the impact of surprises during expansions and contractions separately (see, e.g., Gilbert (2011)). Good news may have negative effects during expansions and positive effects during contractions.

In this section we address both of these issues. We look at the effect of surprises emanating from second and third releases of GDP figures on daily equity returns, allowing differential impacts across business cycle phases by running separate regressions for recessions and expansions. For market expectations we use both the Econoday survey median (following Andersen *et al.* (2003)) and a model-based measure motivated by our earlier results. We also reassess the evidence for Gilbert's assertion that investors respond to the information the GDP release carries about the true value of GDP. As well as the replication of the Gilbert (2011) event study on our dataset using both SP500 and DJIA returns, we also explicitly decompose future revisions into an expected and a 'surprise' component to further investigate the response of the stock market to information about the final value conveyed by the announcement-day release. This expected/surprise decomposition, together with measures of market expectations of forthcoming GDP releases that draw on daily stock returns, help to further our understanding of how GDP revision announcements affect the equity market.

4.1 The Impact of Announcement Surprises

Our empirical results suggest that the model forecasts are superior to the survey forecasts for the third release, although the survey forecasts perform better for the second release. However, a combination of model and survey forecasts might perform even better, and potentially provide a superior measure of market expectations. We calculate regression-based forecast encompassing tests (see e.g., Clements and Harvey (2009) for a recent review) to investigate the potential for combination, but find that survey forecasts encompass model forecasts for the second release, in both business cycle phases, and that the model forecasts encompass the survey forecasts for the third release. This supports the use of the model forecasts as a proxy for market expectations for the third release to lessen the impact of error in the expectations measure. The model forecasts are generated from the MIDAS regression model (see section 3.3) with daily stock returns for the month of the initial release of GDP.

We estimate the effects of surprises in GDP release announcements on daily stock returns (measured by the SP500 and the DJIA) on the day of the announcement. Preliminary results suggest that the size of the effect is similar for both measures. Given the relatively small sample for this event study analysis (52 quarterly observations), we estimate the two equations by pooled ordinary least squares to obtain a more accurate estimate of the effects of surprises.

Announcement surprises are standardized and measured as:

$$S_{t,k}^{t+v} = \frac{y_t^{t+v} - \hat{y}_{t,k}^{t+v}}{std(y_t^{t+v} - \hat{y}_{t,k}^{t+v})},$$

where $\hat{y}_{t,k}^{t+v}$ is the forecast using method k (either a model or survey expectations) of the second release (if $v = 2/3$) or of the third release (if $v = 1$). Let $ret_{t+v,i}$ denote the return to stock index i on the day of the announcement of a revised figure. Then we evaluate the impact of data revision surprises by estimating:

$$ret_{t+v,i} = \beta_0 + \beta_1 S_{t,k}^{t+v} + \varepsilon_{t,i}, \tag{1}$$

where $i \in \{\text{SP500, DJIA}\}$ and t runs over the 52 events. Note that the explanatory variable surprises are calculated for the survey median, or for the MIDAS models using either the SP500 or the DJIA returns (so $k = i$, i.e., so that SP500 returns are regressed on surprises calculated using SP500 predictor variables, and similarly for DJIA returns).

Table 9 reports the estimates of the slope coefficients (β_1) in equation (1), and the R^2 statistics. The results for the survey forecasts confirms previous results in the literature (e.g., Gilbert (2011)) that third-release surprises have no impact on stock returns. Second-release surprises are shown to have an impact on stock returns, but only during recessions. The sign of the coefficient implies that 'good news' has a positive impact during recessions. These results could be interpreted as suggesting that equity markets pay more attention to data revision releases during recessions, when their relative size and predictability is larger (see section 2).

The use of the model-based measure of market expectations increases the magnitude of the estimated response of returns to second-release surprises (see the second panel of Table 9). The size of the response to third-release surprises triples when we do not differentiate by business cycle phase. Although the coefficient is not significant at conventional levels (t-statistic of 1.6), this may simply reflect the small sample size. These increased estimated responses are consistent with the greater accuracy of the model forecasts for the third release, and with these forecasts proving better proxies of market expectations.

4.2 The Impact of Future Revisions

Gilbert (2011) argues that investors 'respond to the information conveyed by the initial release about the correct value and not only its preliminary estimate'. Gilbert (2011) defines the 'total' surprise as the difference between the final value ($y_t^{t+\infty}$) and the forecast of the announcement ($\hat{y}_{t,k}^{t+v}$), which can be written (in our notation) as:

$$TS_{t,k}^{t+\infty} = y_t^{t+\infty} - \hat{y}_{t,k}^{t+v} = \underbrace{\left(y_t^{t+\infty} - y_t^{t+v}\right)}_{R_t^{t+\infty}} + \underbrace{\left(y_t^{t+v} - \hat{y}_{t,k}^{t+v}\right)}_{S_{t,k}^{t+v}} \tag{2}$$

that is, as the (non-standardized) revision $R_t^{t+\infty}$ plus the (non-standardized) 'announcement surprise' $S_{t,k}^{t+v}$ (which we will continue to refer to as the surprise). By including a standardized version of $R_t^{t+\infty}$ in the regressions of section 4.1 (e.g., $\widetilde{R}_t^{t+\infty} = R_t^{t+\infty}/std\left(R_t^{t+\infty}\right)$) we are able to gauge the response of announcement-day returns to future revisions, as well as to announcement surprises ($S_{t,k}^{t+v}$). The first of these terms allows returns to respond to the true value.

In the first panel of Table 10, we replicate Gilbert's regression using our panel dataset, and report results for announcement surprises calculated using survey-consensus forecasts, and including in the regression the actual revisions, $R_t^{t+\infty}$.[9] Our results for second-release announcements match Gilbert (2011, Table 8 and 9, p.128). Future revisions have a significant negative effect on stock returns during recessions, but no (significant) effect during expansions. However, our results for third-release announcements differ. Gilbert finds a significant negative effect of third-release revisions on returns during recessions, and a positive effect in expansions, whereas we only find a significant effect in contractions, and the effect is positive.

If we instead measure announcement surprises $S_{t,k}^{t+v}$ using model-based forecasts (see the second panel of Table 10), we again find evidence that equity markets respond to surprises in third-release announcements (confirming the findings reported in Table 9). This is consistent with the superior accuracy of the stock-returns-based model forecasts (relative to the survey forecasts), as discussed in section 4.1, which provide more accurate estimates of the surprises experienced by the market. Future revisions to third releases continue to have a significant effect, as when survey forecasts are used to define surprises, but future revisions to second-releases no longer have an impact.

These results imply that, controlling for announcement day surprises, upward revisions in third-release GDP figures boost equity markets during recessions. However, the use of actual future revisions, as in Gilbert, may be suspect. An obvious issue with the use of $R_t^{t+\infty}$ to measure future revisions is that the true value $y_t^{t+\infty}$ will not be realized until many years later, and will include benchmark revisions and changes in the methodology of data collection and compilation, which will be unforeseen at period t. We decompose the revisions term $R_t^{t+\infty}$ in (2) into the expected

[9] We approximate $y_t^{t+\infty}$ using data from the 2013M12 vintage, and consequently shorten our sample of data releases. We remove the last two years so that the 2013M12 vintage can be used to provide a reasonable measure of future revisions, $R_t^{t+\infty}$.

revision, ER, and the surprise revision, SR. That is,

$$\underbrace{\left(y_t^{t+\infty} - y_t^{t+v}\right)}_{R_t^{t+\infty}} = \underbrace{\left(E_{t+v}y_t^{t+\infty} - y_t^{t+v}\right)}_{E_{t+v}R_t^{t+\infty}} + \underbrace{\left(y_t^{t+\infty} - E_{t+v}y_t^{t+\infty}\right)}_{SR_t^{t+\infty}}. \tag{3}$$

One might suppose that the announcement-day return would only respond to the predictable revision, $E_{t+v}R_t^{t+\infty}$, i.e., how far the current release is from the predicted true GDP value. However, the validity of using $E_{t+v}R_t^{t+\infty}$ rests on the forecasts of the true values accurately representing the unknown market expectations of the true values. Hence we consider regressions which include the announcement day surprises $S_{t,k}^{t+v}$ (as in section 4), as well as $E_{t+v}R_t^{t+\infty}$ and $SR_t^{t+\infty}$, as a way of determining whether the expected revision or the actual future revision drives announcement-day returns.[10]

Our expectations of $y_t^{t+\infty}$ are generated by vintage-based vector autoregressive models of real GDP growth (as in Clements and Galvão (2013)) assuming that the true value $y_t^{t+\infty}$ is well approximated by the value in the quarterly vintage released 14 quarters after the observational quarter. The model is estimated on quarterly vintages of data up to an including the $t+v$ vintage, and exploits the predictive content of past vintages for future vintages. The results in Table 3 suggest that a simplified version of this approach was the only autoregressive specification able to improve upon the random walk, at least during recessions.

The third panel of Table 10 records the results of regressing returns on (standardized versions of) $S_{t,k}^{t+v}$, $E_{t+v}R_t^{t+\infty}$ *and* $SR_t^{t+\infty}$. We find that neither expected or surprise future revisions have significant effects on stock returns for second releases. In contrast to the results in the first two panels using only $R_t^{t+\infty}$, the response to expected revisions in recessions is positive, as might be expected, but not significant.

The evidence that future revisions affect equity markets on the day of the third GDP release is confirmed. The finding that the expected and surprise future revisions are of the same sign and

[10] In population, at least, if the coefficient on the surprise revision is not significantly from zero, the results would favour the expected revision. In practice of course we have a relatively small sample of data for teasing out the importance of these different factors.

a similar magnitude indicates that third-release announcement-day returns respond to the actual future revision (as opposed to the expected future revision). This may be evidence that markets know more about upcoming third releases than is captured by our model forecasts (and the survey consensus expectations).

In general, the publication of better than expected early GDP revised figures provide a fillip to equity markets. And if the market expects future upward revisions (especially to the third release figures), the effects are enhanced. By and large, the use of model-based expectations provides more evidence that equity markets react to data revisions than when survey forecasts are used to measure market expectation, principally for third releases. The models are used to measure market expectations of the upcoming announcement and of future revisions to the announced value.

5 Conclusions

Data revisions clearly contribute to the uncertainty about the current state of the economy, and about the current conditions of macroeconomic fundamentals, which in turn may affect economic activity. An early contribution was Oh and Waldman (1990), who considered the macroeconomic effects of 'false' announcements (see also Oh and Waldman (2005)), and argued that an upbeat estimate of the current state of the economy which was subsequently revised down would lead to stronger output growth than would otherwise have transpired (with the reverse being true of an ex post pessimistic assessment). Rodriguez-Mora and Schulstad (2007) find that first announcements of GDP growth are a more important determinant of subsequent actual GDP growth than the true value of GDP growth in the earlier period (see also Clements and Galvão (2010)). A recent strand of the literature has considered the role of 'noise shocks' in generating aggregate fluctuations (Lorenzoni (2009), Blanchard, L'Huillier and Lorenzoni (2013)). Blanchard *et al.* (2013) estimate that noise shocks account for more than half of the forecast error variance of output growth at short horizons: changes in the fundamentals explain a smaller proportion of this variance. Measurement errors in initial estimates of GDP and related macro variables (such as productivity growth) may constitute one source of noise shocks, and as such the extent to which subsequent revisions are predictable may have important implications for business cycle analysis.

Our empirical investigation focuses on determining the predictability of early data revisions to US output growth at short horizons. Specifically, on the predictability of the second and the third estimates of US GDP at horizons as short as one week. The horizon is determined by the nature of the survey forecasts of the early releases, and we line up the data underlying the model-based forecasts to ensure our exercises are feasible in real time. We find that the survey forecasts of the second GDP release are far more accurate than the model-based forecasts, but that the survey forecasts of the third GDP release are relatively poor in that there are sources of information which could be tapped, and which might inform market expectations.

Our findings suggest that an economic agent seeking to reduce data uncertainty when taking decisions in real time ought to use survey forecasts to anticipate the second release (in agreement with the literature on forecasting inflation, see, e.g., Ang *et al.* (2007)), but would do better to anticipate the third release with a forecasting model which combines information on economic indicators and equity returns from the month of the first release. A novel finding is that data revisions can be partially anticipated at short horizons even when they add new information relative to an earlier release.

Studies of the impact of macro news on financial variables rely on market expectations being well approximated by the median forecast of a survey of professional forecasters (Rigobon and Sack, 2008). The use of the survey median as a proxy for the market expectation of the third release value of GDP is problematic if, as seems likely, market participants exploit all the information relevant to predicting the final estimate. We use models to measure market expectations of the upcoming announcement, and to generate expectations of future revisions to the announced value. We show that the publication of better than expected third-release GDP figures provides a fillip to equity markets, and that if the market expects future upward revisions the effects are enhanced. This is a novel finding: equity markets respond to unanticipated news about the second revision, and not just to the advance estimate, and the release of the first revision one month later. But this only becomes evident when appropriate estimates of expectations are used: here model-based estimates of GDP releases which exploit daily returns data.

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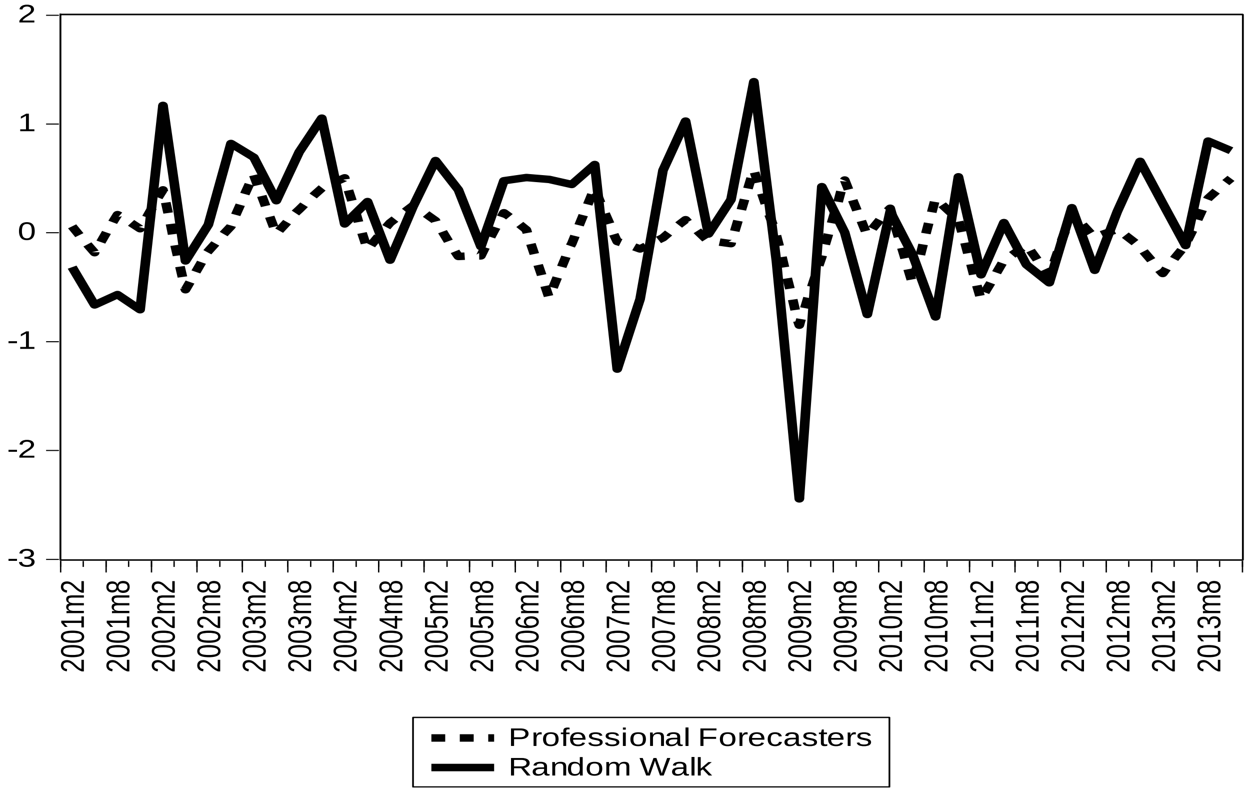
A) Forecasts of the Second Release



B) Forecasts of the Third Release

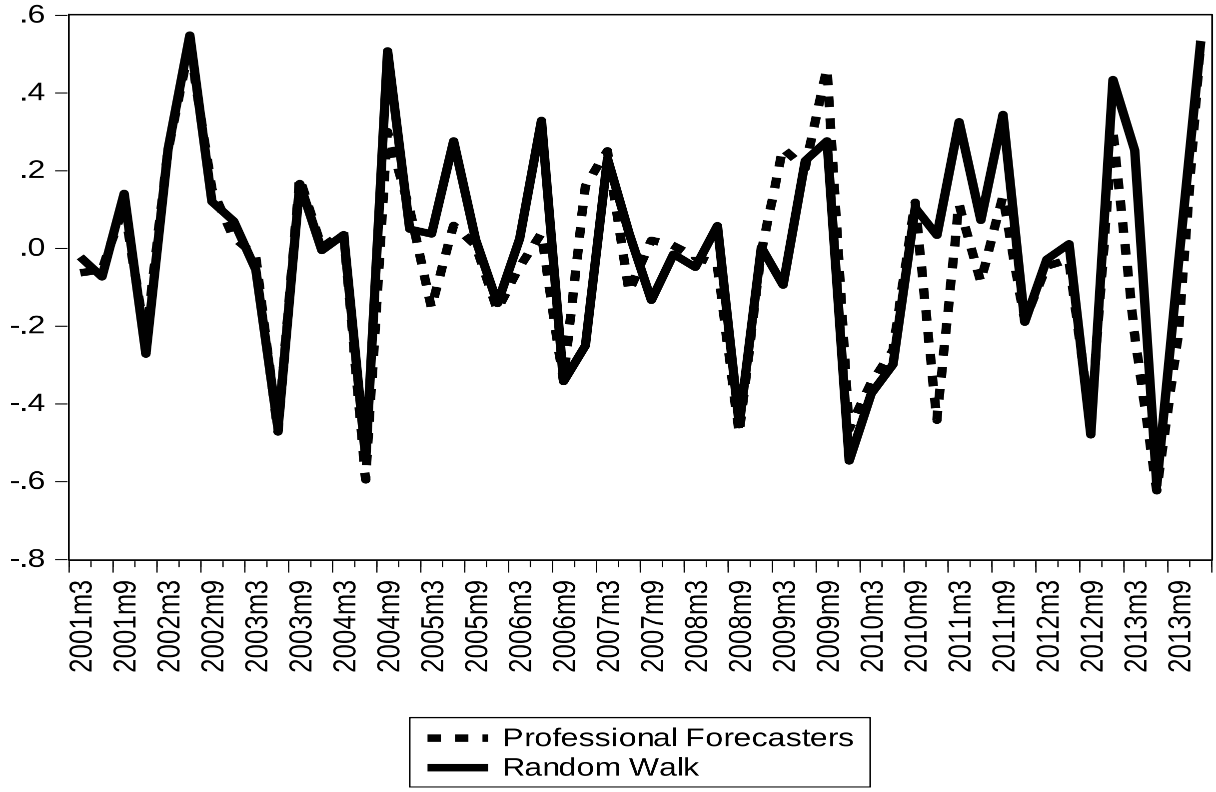


Figure 1: Errors in Forecasting the Monthly GDP Releases. (The Random Walk forecast is a no-change in the growth rate forecast).

Table 1: Forecasting Accuracy of Survey Forecasts versus No-Change Forecasts, measured by RMSFE.

	All (N=52)	Contractions (N=9)	Expansions (N=43)
First Release (Advance)			
No-Change Forecast	2.220	2.221	2.219
Survey Median [ratio]	0.711 [0.320]	0.912[0.411]	0.437 [0.298]
Equal Accuracy t-stat	4.851***	1.727**	4.500***
Second Release (Preliminary)			
No-Change Forecast	0.671	1.077	0.549
Survey Median [ratio]	0.310 [0.462]	0.413 [0.383]	0.284 [0.517]
Equal Accuracy t-stat	3.170***	1.741**	4.046***
Third Release (Final)			
No-Change Forecast	0.279	0.237	0.287
Survey Median [ratio]	0.268 [0.960]	0.275 [1.160]	0.266 [0.928]
Equal Accuracy t-stat	0.801	-1.174	1.374

Note: Release Dates: 2001M1-2013M12. Values in [] are the ratio of the Survey forecast RMSFE to the No-Change forecast.

Table 2: Forecasting Models for the Second and Third Releases ($v = 2/3, 1$).

	Autoregressive Models:
Only revision mean	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \beta_0 + \varepsilon_t$
AR model	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \beta_0 + \beta_1\left(y_{t-1}^{t+v-1} - y_{t-1}^{t+v-\frac{4}{3}}\right) + \varepsilon_t$
Previous release	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \beta_0 + \beta_1 y_t^{t+v-\frac{1}{3}} + \varepsilon_t$
Vintage-based	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \beta_0 + \sum_{i=0}^{q-1} \beta_{i+1} y_{t-i}^{t+v-\frac{1}{3}} + \varepsilon_t$
Threshold model	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \left[\beta_0 + \beta_1 y_t^{t+v-\frac{1}{3}}\right] I\left(y_t^{t+v-\frac{1}{3}} \le c\right) + \left[\beta_2 + \beta_3 y_t^{t+v-\frac{1}{3}}\right] I\left(y_t^{t+v-\frac{1}{3}} > c\right) + \varepsilon_t$
	Regression Models:
New Revision	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \delta_0 + \delta_1\left(x_t^{t+v} - x_t^{t+v-\frac{1}{3}}\right) + \varepsilon_t$
New Observation	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \delta_0 + \delta_1 x_{t+v-1/3}^{t+v} + \varepsilon_t$
Updated Observation	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \delta_0 + \delta_1 x_t^{t+v} + \varepsilon_t$
Previous Release	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \delta_0 + \delta_1 x_t^{t+v-1/3} + \varepsilon_t$
Previous Release (survey data)	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \delta_0 + \delta_1 x_{t+v-2/3} + \varepsilon_t$
	Models with Daily Financial Data: $m = 60; l = v, \frac{1}{3}, and\ \frac{2}{3}\left(if\ v = \frac{2}{3}\right)$.
MIDAS	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \alpha_0 + \alpha_1 \sum_{j=0}^{K-1} w_j(\boldsymbol{\theta}, K) x_{t+v-l-\left(\frac{i}{m}\right)} + \varepsilon_t;$
Linear	As MIDAS, but $w_j(\theta, K) = 1/K$ for all j.
STMIDAS	$y_t^{t+v} - y_t^{t+v-\frac{1}{3}} = \alpha_0 + \alpha_1 x_{t+v}(\boldsymbol{\theta}, K, l, m)[1 - G(\gamma, c, x_{t+v}(\boldsymbol{\lambda}, K, l, m)] + \alpha_2 x_{t+v}(\boldsymbol{\theta}, K, l, m)[G(\gamma, c, x_{t+v}(\boldsymbol{\lambda}, K, l, m)] + \varepsilon_t$ where: $G(\gamma, c, x_{t+v}(\boldsymbol{\lambda}, K, l, m)] = \left[1 + \exp\left(-\gamma(x_{t+v}(\boldsymbol{\lambda}, K, l, m) - c)\right)\right]^{-1}$ $x_{t+v}(\boldsymbol{\theta}, K, l, m) = \sum_{j=0}^{K-1} w_j(\boldsymbol{\theta}, K) x_{t+v-l-\left(\frac{j}{m}\right)}$ $x_{t+v}(\boldsymbol{\lambda}, K, l, m) = \sum_{j=0}^{K-1} w_j(\boldsymbol{\lambda}, K) x_{t+v-l-\left(\frac{j}{m}\right)}$

Table 3: Using Past Vintages to Predict GDP revisions in Real Time.

Forecast Target:	second (preliminary): $y_t^{t+2/3}$			third (final): y_t^{t+1}		
Using info up to:	$y_t^{t+1/3}$			$y_t^{t+2/3}$		
	All	Con.	Exp.	All	Con.	Exp.
Only revision mean	0.990	1.019	0.965	1.014	1.008	1.015
AR model	1.009	1.028	0.993	1.024	1.024	1.024
Previous release	0.970	0.980	0.962	1.016	1.018	1.015
Vintage-based (q=5)	0.986	0.984	0.988	1.071	0.991	1.082
Vintage-based (q=14)	0.979	0.936*	1.013	1.118	1.104	1.120
Threshold model (previous release)	0.975	0.990	0.963	1.000	0.982	1.002

Note: Release period 2001:M2-2013:M12. Entries are RMSFEs ratios to No-Change (random walk) forecast. The tests for equal forecast accuracy between the model and the no-change benchmark were computed using the Diebold and Mariano (1995) t-stat (using heteroscedasticity-consistent standard errors) and asterisks imply that the null hypothesis is rejected at significance Levels: *1%, **5%, ***10%. Vintages since 1966:M1 are employed to estimate the described models. Models are re-estimated at each forecast origin with increasing windows of data during the out-of-sample period (2001-2013).

Table 4: Monthly Economic Indicators

Variable	Description	Transf.	Vintages Available	Source	Initial Release delay:	Econoday Explained Importance
			Market Moving Variables –Data Subject to Revision			
Ind. Prod.	Total Industrial Production	Quarterly difference; growth rate	1966:M1-2013:M12	RTDSM – Philadelphia Fed	15-18 days	"It is a measure of current output for the economy and helps to define turning points in the **business cycle**."
Empl.	Employees on non-agricultural payrolls	Quarterly difference;	1966:M1-2013:M12	RTDSM – Philadelphia Fed	3-9 days	"It is the primary monthly indicator of aggregate economic activity because it encompasses all major sectors of the economy. It provides **clues about other economic indicators** reported for the month."
Sales	Retail and Food Services Sales; Retail Sales before vintage 1992:M1.	Quarterly difference; growth rate	1966:M1-2013:M12	ALFRED – St Louis Fed.	12-15 days	"A major indicator of **consumer spending** trends because they account for nearly one-half of total consumer spending and approximately one-third of aggregate economic activity."
Housing	New Privately Owned Houses Started	Levels	1968:M2-2013:M12;	RTDSM – Philadelphia Fed	15-21 days	"It is the most closely followed report on the housing sector. Housing starts reflect the commitment of builders to **new construction activity**."
Home Sales	New One Family Houses Sold	Levels	1999:M7-2013:M12;	ALFRED – St Louis Fed.	27-32 days	"This provides a gauge of not only the demand for housing, but the **economic momentum**. People have to be feeling pretty comfortable and confident in their own financial position to buy a house."
Durable Orders	Manufacturers' New Orders of Durable Goods (2nd release)	Quarterly difference; growth rate	1999:M11-2013:M12	ALFRED – St Louis Fed.	30-35 days	"Durable goods orders tell investors what to expect from the **manufacturing sector**, a major component of the economy. "
Trade Balance	Trade Balance of Goods and Services (from BP) (BEA data for pre-1992M1)	Quarterly Growth rate of quarter's accumulated defict.	1997:M2-2013:M12	ALFRED – St Louis Fed.	45-53 days	"Measured separately, inflation-adjusted imports and exports are important components of **aggregate economic activity**, representing approximately 17 and 12 percent of real GDP, respectively."
CPI	Consumer Price Index for Urban Wage Earners and Clerical Workers	Annual difference; growth rate	1972:M7-2013:M12.	ALFRED – St Louis Fed.	15-21 days	"The CPI is considered a cost-of-living measure since it is used to **adjust contracts** of all types that are tied to inflation.."
			Market Moving Variable –Data not Subject to Revision			
NAPM	Production Manufacturing Index: ISM since 2002, but previously NAPM.	Levels	Obs: 1959:M1-2013-M2	ALFRED – St Louis Fed	3 – 6 days	A PMI reading above 50 % indicates that the manufacturing economy is generally expanding; below 50% is declining. "It indicates **overall factory sector trends**.."
			Merit Extra Attention Indicators - – Survey Data not Subject to Revision			
Cons. Conf.	University of Michigan: Consumer Sentiment	Quarterly Difference of quarter average.	Obs: 1978:M1-2013:M12.	FRED- St Louis Fed	-3 - -1 days	"Consumer spending accounts for more than two-thirds of the economy, so the markets are always dying to know what **consumers are up** to and how they might behave in the near future."

Note: Econoday comments available at www.econoday.com

Table 5: Predicting GDP Revisions in Real Time with Economic Indicators.

Table 5A: Forecasting the Second Release ($y_t^{t+2/3}$)

	New revision: $x_t^{t+2/3} - x_t^{t+1/3}$			New Observation: $x_{t+1/3}^{t+2/3}$			Updated Observation: $x_t^{t+2/3}$			Previous Release: $x_t^{t+1/3}$			Previous Release: x_t		
	All	Con.	Exp.	All	Con.	Exp.	All	Con.	Exp.	All	Con.	Exp.	All	Con.	Exp.
Ind. Prod	0.989	1.008	0.971	0.986	0.992	0.981	0.988	1.007	0.972	0.990	1.010	0.973			
Empl.	0.996	1.024	0.972	0.985	1.019	0.956*	0.995	1.028	0.967	0.996	1.028	0.969			
Sales	0.980	0.994	0.969	0.999	1.016	0.985	0.875*	0.758*	0.959	0.904**	0.836*	0.955			
Housing	0.974	1.006	0.947	0.964*	0.996	0.937**	0.971*	1.005	0.942*	0.974*	1.008	0.945*			
CPI	0.994	1.020	0.972	0.987	1.012	0.967	0.988	1.014	0.967	0.988	1.014	0.967			
	Indicators with publication delay > 27 days														
Home Sales							0.98	1.005	0.967						
Durable Orders							0.913**	0.877*	0.940*						
Trade Balance							0.990	1.021	0.965						
	Indicators that are not subject to revision														
NAPM				0.970*	0.974**	0.967							0.984	1.001	0.970
Cons. Conf.				0.998	1.015	0.985							1.002	1.030	0.978

Table 5B: Forecasting the Third Release (y_t^{t+1})

Using info up to:	New revision: $x_t^{t+1} - x_t^{t+2/3}$			New Observation: $x_{t+2/3}^{t+1}$			Updated Observation: x_t^{t+1}			Previous Release: $x_t^{t+2/3}$			Previous Release: $x_{t+1/3}$		
	All	Con.	Exp.	All	Con.	Exp.	All	Con.	Exp.	All	Con.	Exp.	All	Con.	Exp.
Ind. Prod	1.049	1.091	1.042	1.008	0.981	1.011	1.018	1.023	1.018	1.016	1.019	1.016			
Empl.	1.022	1.011	1.023	1.038	1.135	1.023	1.018	1.017	1.019	1.019	1.014	1.020			
Sales	1.017	0.984	1.022	1.027	1.094	1.017	1.009	0.956	1.016	1.009	0.964	1.015			
Housing	1.014	1.039	1.071	1.017	1.018	1.017	1.040	1.045	1.040	1.037	1.040	1.037			
CPI				1.014	1.008	1.015	1.021	1.119	1.006	1.021	1.119	1.006			
	Indicators with publication delay > 27 days														
Home Sales	1.007	1.041	1.002				1.061	1.070	1.060	1.061	1.070	1.060			
Durable Orders	1.033	1.054	1.030				1.065	0.980	1.076	1.065	0.980	1.076			
Trade Balance	0.929*	0.777**	0.949				1.051	1.162	1.035	1.051	1.162	1.035			
	Indicators that are not subject to revision														
NAPM				1.016	1.010	1.017							1.014	1.004	1.016
Cons. Conf.				1.023	0.854**	1.045							0.980	0.776**	1.006

Note: Release period 2001:M2-2013:M12. The CPI observed in t is revised in vintage t+2/3, but not in vintage t+1. For variables with publication delay >27, $x_t^{t+2/3}$ is their first release. See notes to Table 3. The models are described in Table 2.

Table 6: Financial Indicators.

Variable	Description	Transformation	Observations	Source
SP500	Standard & Poor's 500 Leading Companies	Daily Percentage Returns	1959-M1-02: 2013-M12-30.	FRED- St Louis Fed
DJIA	Dow Jones Industrial Average	Daily Percentage Returns	1959-M1-02: 2013-M12-30.	
Spread	10-year Treasury Constant Maturity Rate – 3-month Treasury Bill (Seconday Market)	10-year rate – 3-month rate.	1962-M1-02-2013-M12-30.	
Short-rate	3-month Treasury Bill (Seconday Market)	Levels (rate)	1962-M1-02-2013-M12-30.	

Table 7: Predicting GDP Revisions in Real Time with Daily Financial Indicators.

Table 7A: Forecasting the Second Release ($y_t^{t+2/3}$)

Information up to:		x_t (K=60)			$x_{t+1/3}$(K=20)			x_{t+db}(K=60)		
Variables	Models	All	Con.	Exp.	All	Con.	Exp.	All	Con.	Exp.
SP500	MIDAS	0.972	0.944*	0.994	0.989	1.027	0.958*	1.024	1.083	0.974
	Linear	1.001	1.032	0.976	0.993	1.016	0.973	1.008	1.062	0.963
	STMIDAS	1.027	1.037	1.019	0.955*	0.958**	0.952	1.057	0.990	1.109
DJIA	MIDAS	0.974	0.962	0.983	0.986	1.015	0.961	1.043	1.118	0.979
	Linear	1.002	1.035	0.973	0.994	1.023	0.970	1.023	1.097	0.959
	STMIDAS	0.992	1.001	0.984	0.970	0.957*	0.980	1.021	1.021	1.022
Spread	MIDAS	0.999	1.024	0.978	0.999	1.029	0.974	0.994	1.030	0.964
	Linear	0.999	1.035	0.969	0.998	1.028	0.974	0.997	1.032	0.967
	STMIDAS	0.967	0.981	0.955	0.994	1.003	0.986	0.998	1.032	0.970
Short-rate	MIDAS	1.001	1.039	0.969	1.002	1.050	0.962	1.005	1.056	0.962
	Linear	0.998	1.035	0.967	1.000	1.044	0.962	1.003	1.051	0.963
	STMIDAS	1.129	1.170	1.094	1.044	1.142	0.958	1.100	1.201	1.012

Table 7B: Forecasting the Third Release (y_t^{t+1})

Information up to:		x_t (K=60)			$x_{t+1/3}$(K=20)			x_{t+db}(K=60)		
Variables	Models	All	Con.	Exp.	All	Con.	Exp.	All	Con.	Exp.
SP500	MIDAS	1.019	0.985	1.023	0.929**	0.870	0.937*	1.064	1.380	1.011
	Linear	1.029	1.092	1.020	1.018	0.993	1.021	1.025	1.039	1.023
	STMIDAS	1.135	1.275	1.113	0.928*	0.919	0.929*	1.076	1.068	1.077
DJIA	MIDAS	1.035	1.171	1.014	0.918**	0.772*	0.937*	1.028	1.127	1.013
	Linear	1.034	1.147	1.016	1.016	1.006	1.017	1.012	1.050	1.007
	STMIDAS	1.132	1.556	1.058	0.931**	0.804**	0.948*	1.026	1.071	1.019
Spread	MIDAS	1.025	1.022	1.025	1.029	1.028	1.029	1.021	1.015	1.021
	Linear	1.018	1.012	1.019	1.018	1.013	1.019	1.017	1.010	1.019
	STMIDAS	1.103	1.188	1.091	1.055	1.091	1.050	1.087	1.160	1.077
Short-rate	MIDAS	1.046	1.109	1.037	1.051	1.121	1.041	1.065	1.142	1.053
	Linear	1.036	1.088	1.029	1.047	1.112	1.038	1.055	1.123	1.045
	STMIDAS	1.072	1.348	1.026	1.072	1.349	1.027	1.071	1.347	1.026

Notes: Release period 2001:M2-2013:M12. See notes to Table 3. The forecasting models are described in Table 2. x_{t+db} refers to the value of the indicator on the business day immediately before the release date (release dates only from 1975).

Table 8: Evaluating the Predictive Power of Daily Stock Returns ($x_{t+1/3}$) to Predict Data Revisions in Real Time.

Forecast Target:	second (preliminary): $y_t^{t+2/3}$			Forecast Target:	third (final): y_t^{t+1}		
	All	Contr.	Exp.		All	Contr.	Exp.
Revisions to GDP growth							
Sales (upd release)	*0.587*	*0.817*	*0.527*	Trade(New Revision)	*0.261*	*0.189*	*0.274*
Sales + SP500	0.990	0.958*	1.005	Trade + SP500	0.939*	0.878**	0.945*
Sales + DJIA	0.996	0.973*	1.007	Trade + DJIA	0.937*	0.797**	0.951

Note: Release period 2001:M2-2013:M12. For each variable, the first line has the RMSFE for the best regression model with a single economic indicator. The remaining two lines are ratios to the first line RMSFE. For GDP, a MIDAS specification is employed to add the daily financial variables to the model with the economic variable. See notes to Table 3.

Table 9: The Impact of Announcement Surprises on Equity Returns.

	Second Release			Third Release		
	All	Con.	Exp.	All	Con.	Exp.
Consensus	0.038	0.632**	-0.134	0.036	0.270	-0.025
	(0.125)	(0.238)	(0.111)	(0.086)	(0.293)	(0.095)
R^2	0.003	0.298	0.024	0.001	0.025	0.001
MIDAS	0.165	0.881***	-0.091	*0.118*	0.275	0.094
	(0.165)	(0.174)	(0.096)	(0.075)	(0.300)	(0.076)
R^2	0.031	0.576	0.010	0.013	0.026	0.011

Note: The dependent variable is the daily return on the day of the announcement. Estimates obtained from pooled OLS, with White standard errors reported in brackets. Number of cross sections: 2 (SP500 and DJIA). Number of observations for each cross-section: 52 (the number of quarterly data releases 2001-2013). The MIDAS forecasts use daily data up to the month of the advance estimate.

Table 10: The Impact of Announcement Surprises and Expected Revisions on Equity Returns.

	Second Release			Third Release		
	All	Con.	Exp.	All	Con.	Exp.
AS (Consensus)	0.053	0.783**	-0.146	0.083	0.103	0.051
	(0.137)	(0.281)	(0.129)	(0.106)	(0.336)	(0.110)
Future	0.067	-0.403*	0.143	0.121	1.041**	-0.136
Revision	(0.113)	(0.235)	(0.126)	(0.171)	(0.365)	(0.141)
R^2	0.008	0.400	0.038	0.019	0.381	0.022
AS (MIDAS)	0.213*	0.880***	-0.070	0.187*	0.252	0.232**
	(0.119)	(0.184)	(0.111)	(0.101)	(0.322)	(0.101)
Future	0.111	-0.107	0.110	0.097	1.052**	-0.182
Revision	(0.115)	(0.149)	(0.131)	(0.182)	(0.357)	(0.147)
R^2	0.048	0.584	0.022	0.019	0.400	0.077
AS (MIDAS)	0.219*	0.901***	-0.070	0.186*	-0.148	0.208**
	(0.125)	(0.203)	(0.112)	(0.101)	(0.288)	(0.103)
Expected	0.093	0.160	0.033	0.102	1.118***	-0.172
Revision	(0.129)	(0.207)	(0.176)	(0.134)	(0.197)	(0.138)
Surprise	0.110	-0.126	0.109	0.096	1.132**	-0.156
Revision	(0.125)	(0.141)	(0.143)	(0.194)	(0.382)	(0.189)
R^2	0.051	0.615	0.022	0.045	0.548	0.096

Note: See notes to Table 9. AS(Consensus) is the announcement surprise, calculated using the consensus forecasts. AS(MIDAS) is the announcement surprise, calculated using MIDAS forecasts (using daily data up to the month of the first-release). The calculation of Expected Revision and Surprise Revision is fully explained in the main text, section 4. Sample period: 2001M1-2011M12 (total of 44 observations for each cross-section).