Forecasting GDP: Do Revisions Matter?

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Abstract

This paper investigates the informational content of regular revisions to real GDP growth and its components. We perform a real-time forecasting exercise for the advance estimate of real GDP growth using dynamic regression models that include GDP and GDP component revisions. Echoing other work in the literature, we find little evidence that including aggregate GDP growth revisions improves forecast accuracy relative to an AR(1) baseline model; however, when we include revisions to components of GDP (i.e. C, I, G, X, and M) we find improvements in forecast accuracy. Overall, nearly 68% of all models that contain subsets of component revisions outperform our baseline model. The "best" component-augmented model forecasts roughly 0.2 percentage points better, and a large subset of models improve RMSFE by more than 5%. Finally, we use Bayesian model comparison to demonstrate that differences in forecast performance are unlikely to be the result of statistical noise. Our results imply that component revisions, in particular to consumption, contain important information for forecasting GDP growth.

Keywords: Data revisions, real-time data, forecasting

JEL Classification Numbers: E01, C11, C53, C82

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1 Introduction

The revision process for many macroeconomic time series has led to an explosion of work focusing on the use of real-time data. Two aspects of real-time data are particularly important for forecasting. First, many studies investigate how the use of real-time data impacts the evaluation of forecast performance (e.g. Robertson and Tallman, 1998; Croushore and Stark, 2003; Faust et al., 2003). Estimating a forecasting model using post-revision data available to the researcher *today* may create a misleading comparison with forecasts from a model based on the best available data *at the time they were made*. Second, real-time data has given rise to approaches that use multiple vintages of the same time series to improve forecast performance (e.g Howrey, 1978; Clements and Galvão, 2012).

In light of this important work with real-time data, we ask whether revisions to GDP growth contain information that can help forecast advance estimates of GDP growth. We investigate the informational content of both aggregate revisions to GDP and revisions to its components. Echoing other work in the literature, we find that revisions to GDP growth have no impact on short-run forecast accuracy. However, there is strong evidence that revisions to certain GDP components, principally consumption, have important information for forecasting economic growth. Further, the improvement in forecast accuracy can be substantial over an AR(1) benchmark model. Nearly 68% of all models that contain subsets of component revisions outperform the baseline model. The "best" component-augmented model forecasts roughly 0.2 percentage points closer to the advance estimate of GDP growth than an AR(1).

There is a well-developed literature that has attempted to incorporate preliminary data into coherent forecasting frameworks.[1] Much of its focus has been on forecasting

[1] Croushore (2011) provides an excellent summary of the broader literature on real-time data.

post-revision releases and measuring the efficiency of early data releases. In this vein, Howrey (1978) outlines a method to efficiently use preliminary data when errors in measuring GDP are serially correlated. Kishor and Koenig (2012) generalize Howrey (1978) by also allowing data revisions to be efficient estimates with white-noise errors as in Sargent (1989). State-space forecasting models have also had mixed results in forecasting post-revision data using data revisions (Croushore, 2006). Finally, Clements and Galvão (2012) investigate the use of vintage-based VARs (V-VARs) to forecast post-revision data.

Our work more closely aligns with a strain of the literature that has looked at forecasting early or advance estimates of macroeconomic time series. We incorporate the findings of Koenig et al. (2003) who emphasize that forecasting advance releases of GDP growth is best done using only advance releases in the estimation of forecasting models. Two other studies align closely with our objectives in that they attempt to incorporate information from revisions and forecast advance GDP growth: Clements and Galvão (2013a) and Clements and Galvão (2013b). The former paper concludes that several variants of vintage-based VAR (V-VAR) models show little improvement in forecast accuracy. Clements and Galvão (2013b) suggest a real-time vintage approach to forecasting. Using this approach, they estimate models using lightly revised data while their forecasts are conditioned on the same data as traditional approaches to forecasting that utilize the most recent vintage. Their approach yields small improvements in forecast accuracy. Our method contrasts nicely with Clements and Galvão (2013b) in that we also forecast the advance estimate of GDP growth, but our forecasts are conditioned on the same series used for estimation.

Our first set of results are established in a straight-forward forecasting exercise. We use dynamic regression models to produce one-period ahead forecasts of advanced GDP growth. We augment a baseline AR(1) model with subsets of revisions (aggregate or components) and estimate the model using maximum likelihood. We evaluate forecast performance using root mean squared forecasting error (RMSFE) and check for robustness across other accuracy measures, data assumptions, and test periods. Our forecasting framework is simpler than previous approaches in that we do not attempt to estimate using multiple vintages of GDP, but rather incorporate revisions themselves as additional right-hand side variables in our dynamic regression models.

We refrain from an *a priori* elimination of component-based models leaving us with a large set of potential models to consider. Given our priors and the existing literature, there was little justification for concluding that some components were more important than others. Our second set of results addresses this large model space problem. To test the significance of our findings in the presence of many alternative models, we turn to Bayesian model comparison. Even with strong priors that our baseline model should outperform component-based models, we find that the posterior probability of our baseline model falls. There is a high probability that the superior forecasting model (in the large set that we consider) contains at least one component revision. Our Bayesian analysis demonstrates that the difference in forecast performance is unlikely to be the result of statistical noise.

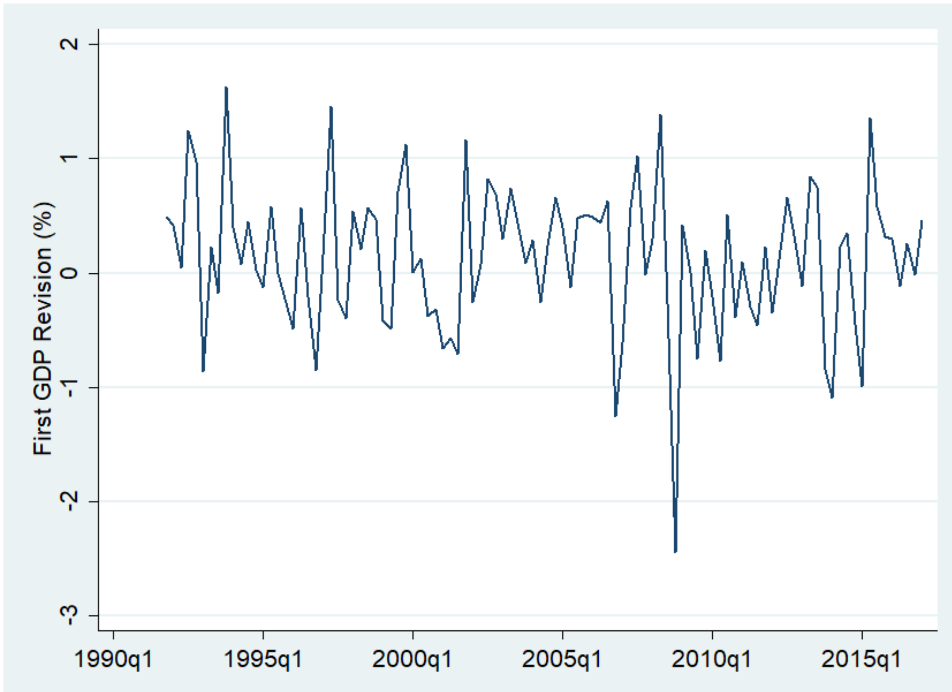
Beyond highlighting the fact that component revisions contain information that improves forecast performance, these results may have important implications for other questions on real-time data including the efficiency of early estimates and whether revisions contain news or reflect statistical noise. The remainder of this paper is organized as follows. Section 2 outlines our data and how we evaluate forecast performance in both frequentist and Bayesian frameworks. Section 3 presents our primary findings and tests their robustness. It also addresses the significance of our findings in the context of our large set of alternative models. Finally, Section 4 provides a brief discussion of the findings and their importance to future research.

2 Data and Estimation

We use advance estimates of real GDP growth over the period 1991Q4:2017Q1. Beginning in 1991Q4, the BEA began to follow the current release schedule composed of three regular releases of GDP: advance, second, and third. The advance estimate of real GDP growth is calculated as the percentage change between the new advanced estimate of GDP and the third estimate of the previous quarter's GDP. We use this standard construction as it is the headline measure reported by the Bureau of Economic Analysis (BEA), and therefore the most likely to impact markets and monetary policy. All of our real-time data is from the Real-Time Data Set for Macroeconomics which is housed at the Federal Reserve Bank of Philadelphia. A brief description of the construction for our variables is available in Appendix A. Relevant summary statistics for our data can be found in Appendix B.

We supplement our GDP growth data with data on aggregate GDP revisions (henceforth simply aggregate revisions) and revisions to consumption, government spending, investment, imports, and exports (denoted as c, g, i, m, and x respectively). The advance components for quarter t are measured as the percentage change in the expenditure category between the third release for quarter $t-1$ and the advance release for quarter t. Therefore, they are measured in an equivalent way to our advance GDP growth measure. However, we do not use these components directly, since the goal of our study is to determine if revisions contain useful information for future values of GDP growth. Therefore, in our estimation procedure, we instead include up to two revisions for GDP growth or each component's growth. First revisions are the difference between the advanced estimate of growth and the second estimate, and second revisions are the difference between the second estimate of growth and the third estimate. This distinction is documented in the subscript

Figure 1: First GDP Growth Revision (r_1)



The first revision to GDP is measured as the difference in the annualized growth rates of the advance and second releases of GDP.

for each revision. For example, the first consumption revision, c_1, is the percentage point difference between consumption growth in the advance release and consumption growth in the second release. As an example, Figure 1 plots the first revision to GDP growth. In total, we have two aggregate revisions and ten different component revisions that can be used to augment our dynamic regression models of GDP growth.

Our main goal is to investigate whether the inclusion of revisions in a linear regression model increases forecast performance relative to a baseline AR(1) model.[2]

[2] The single auto-regressive term, with no moving average terms, is preferred by AIC with a sample-size correction (AICc). AICc will often suggest more complex ARMA models for all post-war data or fully revised data. It also forecasts advanced GDP growth better than other candidate models, notably an AR(2) and an ARMA(1,1), in our preferred test period.

The use of ARMA(p,q) models as a baseline is quite common (e.g Koop and Potter, 2004; Koenig et al., 2003), although the mechanism for choosing the lag lengths depends on the application. We do not argue that our baseline is the *best* model for forecasting GDP growth, but rather that forecast improvements beyond this baseline are evidence of revisions containing information about future GDP growth. To do so, we consider models spanning all possible combinations of component revisions. With $k = 10$ total types of component revisions, we have $R = 2^{10} = 1,024$ possible models to consider.[3] Let any specific model be denoted by $M_r \in \{M_1, M_2, \cdots, M_{1024}\}$. Under a specific model, M_r, we consider one unique subset of revisions, X^r, with coefficient estimates, μ_r and β_r, and AR(1) persistence estimate, ρ_r. Our state-space model with AR(1) errors under model r at time t is then given by:

$$y_t = \mu_r + X^r_{t-1}\beta_r + \eta^r_t \tag{1}$$

$$\eta^r_t = \rho_r \eta^r_{t-1} + \varepsilon^r_t \tag{2}$$

where $\varepsilon^r_t \sim N(0, \sigma_r)$. In our baseline model we do not include any revisions, so X^r_{t-1} is empty and equations (1) and (2) represent a standard AR(1) process.

All models are initially estimated on the sample period 1991Q4:2004Q3. This period roughly splits our data, so that we use the second half of the data as our test sample. Beginning our test sample in 2004Q4 allows us to measure forecast performance during the Great Recession (2008Q1:2009Q2). It also leaves a relatively large amount of time between the start of our sample in 1991Q4 and the beginning of our test data in 2004Q4. This gap in time helps to diminish the impact of the coefficient priors in our Bayesian model comparison exercise. While we think that

[3] In the case of aggregate revisions, we consider 4 possible models including each of the revisions, both of the revisions, and excluding the revisions entirely.

beginning the forecasting exercise in 2004Q4 is sensible, we also show that our results are robust to the choice of test sample.

When forecasting, we use both frequentist and Bayesian techniques. First, we investigate forecast performance of various revision-augmented models as measured by RMSFE under maximum likelihood estimation, since this is a standard way to assess forecasting performance. We then switch to using Bayesian techniques for two primary reasons: (1) most frequentist statistical tests of forecast performance require that the forecast models be non-nested, and (2) Bayesian techniques provide a relatively simple and theoretically justified way to compute posterior model probabilities using the forecast performance of the models. Since maximum likelihood estimation of conditionally linear ARMA models is widely understood, we omit further discussion. Instead, we focus on our Bayesian estimation procedure.

2.1 Bayesian Estimation

As is well documented in the Bayesian literature, for each model M_r, we can compute the model probability, $p(M_r|Y)$ as:

$$p(M_r|Y) = cp(Y|M_r)p(M_r) \tag{3}$$

where $p(M_r|Y)$ is the probability of model r conditional on the data, Y. This is commonly called the *posterior probability* of model r. Defined in this way, the posterior probability represents the probability that, of the set of models under consideration, model M_r is the *best* model for explaining the data. There are three terms on the right-hand side that together determine this probability: c is a constant, $p(Y|M_r)$ is the marginal likelihood of model r, and $p(M_r)$ is the prior probability assigned to model r. The marginal likelihood includes a reward for model fit and a punishment for the inclusion of irrelevant variables.[4]

2.1.1 Model Priors

Before computing model probabilities, we need to specify the model priors, $p(M_r)$ for each model. Since parsimonious models, like an AR(1), have shown relatively strong forecast performance in many studies of various macroeconomic indicators, we set 50% of our prior belief on the AR(1) model. The other 50% prior probability is spread across all remaining models in a geometrically declining fashion according to model size. That is, we believe with roughly 25% prior probability that a model that includes any single component revision by itself will be the superior forecasting model, with roughly 12.5% probability that a model with any combination of two component revisions will be the superior forecasting model, etc. This is consistent with our belief that parsimonious forecasting models are preferred to more complex ones.

Mathematically, the prior probability of model M_r depends on the number of component revisions, k_r, that are included in that model. For all models with at least one revision included, we set:

$$p(M_r|k_r = j) \propto \frac{0.5^{j+1}}{N_j}$$

$$N_j = \binom{10}{j}$$

$$j \in \{1, \cdots, 10\}.$$

For example, the group of models with only one component revision have a collective

[4] It may be helpful to think of $p(Y|M_r)$ as akin to AIC or BIC, as it includes a built in penalty for large models. In fact, the large sample approximation to $p(Y|M_r)$ under linear regression is $-\frac{1}{2}$ times the Bayesian Information Criterion (BIC).

prior probability of roughly 25%. We divide this prior probability equally across all models that include only one revision. Since there are 10 of these models, each one-component revision model receives a prior probability of roughly 2.5%. In addition to the model priors, each particular model has priors on the regression coefficients and the AR(1) term in the error equation. Since we are considering 1,024 models, this is hard to do in a model-by-model way. Instead, we assign these prior beliefs in an automatic and fairly standard fashion. Additional details can be found in Appendix C.

2.1.2 Forecast Performance

Since this study is primarily concerned with forecast accuracy and the informational content of revisions, we alter Equation (3) so that the posterior model probabilities are based on forecast performance rather than in-sample fit. To do this, we replace the marginal likelihood, $p(Y|M_r)$, in Equation (3) with a measure of forecast performance: the one-step-ahead predictive density, a measure of the performance of the entire forecast distribution. As shown in Amisano and Geweke (2017), the sum of the log of one-step-ahead predictive densities starting from the first in-sample observation is actually equal to the log marginal likelihood:

$$\ln[p(Y|M_r)] = \sum_{t=0}^{T} \ln[p(y_{t+1}|M_r, y_t)]$$

where the forecast made at $t = 0$ for the data in period $t = 1$ comes solely from the priors of the model. Therefore, if used over the entire sample, the two measures will produce identical model probabilities. However, to maintain consistency with the previous section, we focus on our test period of 2004Q4:2017Q1. Instead of using the entire marginal likelihood, we compute the log one-step-ahead predictive density from each model, denoted as pd_r, starting after $\tau = 2004\text{Q}3$:

$$\text{pd}_r = \sum_{t=\tau}^{T} \ln[p(y_{t+1}|M_r, y_t)]$$
$$\text{PD}_r = \exp\{\text{pd}_r\}$$

This measure: (1) summarizes forecasting performance, (2) diminishes the impact of the priors that we place on the regression coefficients, and (3) can be used to form model probabilities. An additional benefit of using the log predictive density instead of the marginal likelihood is that it prevents the probability on any single model from approaching 100% too quickly, which can be sub-optimal if the "true" model is not under consideration.[5]

To form the model probabilities with this measure, we compute:

$$p(M_r|Y) = c \ \text{PD}_r \ p(M_r) \tag{4}$$

We use these model probabilities to determine the strength of evidence for the baseline AR(1) model relative to dynamic regression models that are augmented with GDP or component revisions. If the component revisions are not important for forecasting GDP growth, we would expect the posterior probability of the AR(1) model to either increase from its prior probability or to at least remain large relative to the posterior probabilities of models that include component revisions.

The estimation process is as follows. First, we focus on one model, M_r from the set $\{M_1, M_2, \cdots, M_{1024}\}$. This model will have a unique set of regressors, X^r. Given that our test sample starts in 2004Q4, we use the subset of our data from the first observation through 2004Q3 to estimate the posterior distribution regres-

[5] See Eklund and Karlsson (2007) for more detail.

sion coefficients, $Pr(\beta_{r,t}|, y_t, M_r)$. Using this distribution of coefficient estimates, along with the posterior distribution for the AR(1) coefficient and the variance of the error term, we form the one-period-ahead out-of-sample forecast distribution, $p(y_{t+1}|M_r, y_t)$. We then forward the end-date of the training sample by one period, so that it runs through 2004Q4, and repeat the estimation and forecasting process. We continue in this fashion until we reach the end of our sample. We then move to the next model, M_{r+1} and repeat the process. This process yields point-forecasts and forecast distributions under each possible model that are used to evaluate Equation (4).

3 Results

We present our results in four sections. The first two document the main results of this paper: aggregate revisions do not improve forecast performance, while component revisions have important information regarding future real GDP growth. The third section investigates the robustness of our main results, and the final section addresses the statistical significance of these results given the large number of models considered.

3.1 Aggregate Revisions

Our first set of results investigates whether aggregate revisions to real GDP growth can improve forecast performance over our baseline model. Table 1 presents the relative forecast performance for three models that are augmented with aggregate revisions. None of the three models show meaningful improvements in forecast performance. This result echoes the findings of Clements and Galvão (2013b) who find the vintage-based VARs do not improve forecast accuracy for advance estimates of real GDP growth. It is important to note that these aggregate revisions are themselves composed of component revisions that may be the result of very different data generating processes. This aggregation process may obfuscate the important information contained in any individual component revisions. Hence, it is worth investigating the contribution of individual components to forecasting real GDP growth.

Table 1: Forecasting with Aggregate Revisions

Model	Relative RMSFE
First Revision (r_1)	1.021
Second Revision (r_2)	0.994
First and Second Revision ($r_1 + r_2$)	1.005

The first column indicates the covariates that are included in Equation (1). RMSFE is reported relative to the baseline AR(1) model.

3.2 Component Revisions

In comparison to aggregate revisions, revisions to individual components increase forecast performance and therefore appear to contain information that is important for forecasting the advance release of real GDP growth. Table 2 highlights the relative forecast performance for several models. The best model in terms of forecast performance has RMSFE that is nearly 13% below that of the baseline model. This improvement is not limited to a small subset of models. More than half of all component-based models outperformed the baseline model by at least 3.1%. These results are surprising and important on two fronts. First, they indicate the revisions contain important information about the future path of real GDP growth *beyond* what is captured by past GDP growth. Second, this information is typically hidden through the aggregation process.

Table 2: Forecasting with Component Revisions

Performance	Relative RMSFE
Best	0.873
10th percentile	0.904
25th percentile	0.922
50th percentile	0.969
Worst	1.071

Performance refers to how a model did relative to the entire distribution of 1024 component-based models. For instance, the 10th percentile model is the 102nd best performing model in terms RMSFE. Relative RMSFE in column two reports each model's forecast performance relative to the baseline AR(1) model. The "best" forecasting model contains revision to components $c_1, g_1, i_2,$ and x_1.

The principle challenge of interpreting these component results stems from the number of models we consider. There was no compelling *a priori* evidence to suggest which components ought to be important. In fact, our priors were that component revisions do not contain important information for forecasting. This hypothesis seemed to be underscored by the findings with respect to aggregate revisions in the previous section. Given this, we felt that excluding certain components or revisions (i.e. first vs. second) in our analysis was unjustified. With such a large number of alternative models, it is reasonable to assume that *some* subsets of components could outperform the baseline based on statistical chance alone.

The remainder of our results address this large-model-space problem. Beyond the results in Table 2 that show that a large percentage of component-based models outperform the baseline, we also investigate the primary drivers of the improvement in forecast performance. Of the 695 models that outperform the baseline model, 73.7% of them include the first revision to consumption. All other components are included in between 43.9% and 59.3% of models that outperform the AR(1) baseline. More importantly, *every* model that contains the first revision to consumption outperforms the baseline model. This result can be seen visually in our Bayesian model comparison section below.[6] Beyond the large set of models that outperform the baseline, this evidence suggests that the results in Table 2 are driven by more than just randomness. However, we are hesitant to conclude that c_1 is the *only* component revision that contains pertinent information for forecasting.

3.3 Robustness

In this section we re-estimate the universe of component-based models and compare them over different test periods to evaluate whether the results in the previous section are robust to the choice of test period. Table 3 reports the results of this exercise. As the test period becomes shorter (moving left to right across rows), the ranking of the baseline model (lowest RMSFE to highest RMSFE) remains very consistent. Within each test period, the baseline model is outperformed by 59.9% to 87.9% of all models.[7] In addition, the second row highlights the fact that there is a substantial set of models that outperform the baseline in *all* of the test periods. In total, there are 495 models that outperform an AR(1) across every test period we consider. There is noticeable drop in the percentage of models that outperform the baseline when the test period starts later than 2009, which is the first test period that excludes the Great Recession. There are a substantial number of models that forecast relatively well during the Great Recession, but were mediocre under more normal economic

[6] A more complete accounting of these results can be found in Appendix D.

[7] For clarity, if the baseline percentage is 68.0%, the baseline model is the 696th best model. This also means that 695 models outperformed it, or 67.9% of models.

conditions.

Table 3: Robustness of Forecasts with Component Revisions

	Start of Test Period						
	2004	2005	2006	2007	2008	2009	2010
Baseline Percentile	68.0%	67.6%	66.1%	67.6%	75.4%	59.9%	87.9%
Cumulative % of outperforming models	67.9%	67.4%	65.9%	65.7%	65.7%	48.3%	48.2%

From left to right each column increases the estimation period by one year. Column 2 represents our primary estimation period through 2004Q3 with column 3 advancing the estimation period to 2005Q3. Baseline percentile reports the performance of the baseline model relative to all 1024 models (ranked from lowest to highest RMSFE). Row 2 reports the percentage of all models that outperform the baseline model conditional on *also* outperforming the baseline in all previous test periods.

Our results are robust to two other changes. First, the results are robust to different measures of forecast accuracy. Calculating mean absolute forecast error (MAFE) in place of RMSFE yields a similar ranking of models.[8] We also investigate the role of outliers in component revisions. In each component revision series there are one to three large outliers (greater than three standard deviations). Censoring these outliers at 3 standard deviations actually *increases* the relative performance of the component models. After censoring outliers, 69.3% of component-augmented dynamic regression models outperform the baseline model, up from 67.9% when the outliers are not censored.

[8] This is in addition to the measures used in the Bayesian section below.

3.4 Bayesian Model Comparison

The results above suggest that at least one of our component-augmented models outperforms the baseline AR(1) model in terms of forecasting accuracy. However, since we are testing over 1,000 different models, it may not be surprising that at least one of these models should have outperformed the baseline. Our results above indicate that a large number of our component-augmented models outperform the AR(1) model. Additionally, the first revision of consumption appears especially important, suggesting that this result is being driven by something meaningful. In this section, we show, in a theoretically rigorous manner, that the superior forecast performance of component-augmented models is likely not driven by statistical noise.

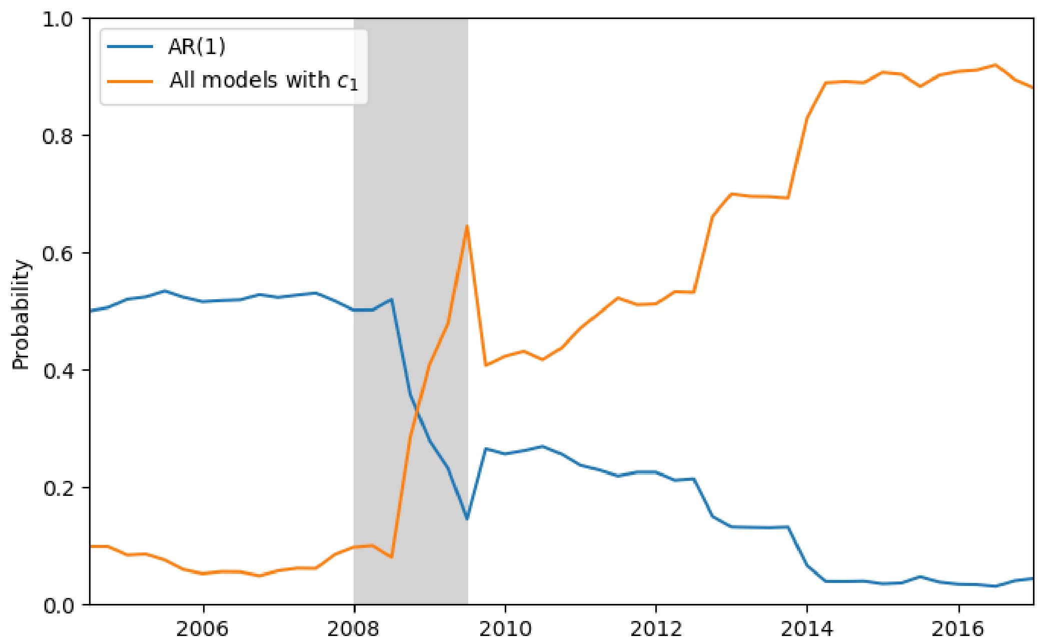
Using our Bayesian framework outlined in Section 2.1 we find that the probability of the AR(1) model being the best forecasting model decreases substantially, from a prior probability of 50% to a posterior probability of only 4.5%. In addition, the findings in this section reinforce the frequentist results — we find that models that include the first revision of consumption growth outperform all other models and that the first revision of consumption growth likely belongs in the forecasting model for GDP growth.[9]

Figure 2 shows the model probabilities for the AR(1) model and the sum of model probabilities over all models that include the first revision of consumption growth, c_1. Given our priors, since we have 10 variables, there is a prior probability of roughly 10% on the mass of models that includes c_1. As time progresses and the probabilities are revised based on forecast performance, we see a large increase in the posterior probability of models that include c_1. This increase is substantial during the Great

[9] These results are robust to our choice of model priors. For example, under a 50% prior on the AR(1) model and 50% spread evenly across all other models, the posterior probability on the AR(1) model drops to roughly 2% and inclusion of the first revision of consumption is vitally important for forecasting gains.

Recession, with smaller, but persistent, gains accruing largely between 2010 and 2015. At the last date in the test sample, the models containing c_1 accounted for 88.1% of the posterior probability, with the AR(1) model falling from 50% to 4.5% probability over the same horizon. Table 4 provides inclusion probabilities for each component revision. It again highlights the important role of the first revision to consumption.

Figure 2: Selected Model Probabilities over Time



The vertical axis reports the posterior probability. As more test sample data accrues, the probability that the best forecasting model includes c_1 increases while the probability of the AR(1) model being the best forecast model shrinks.

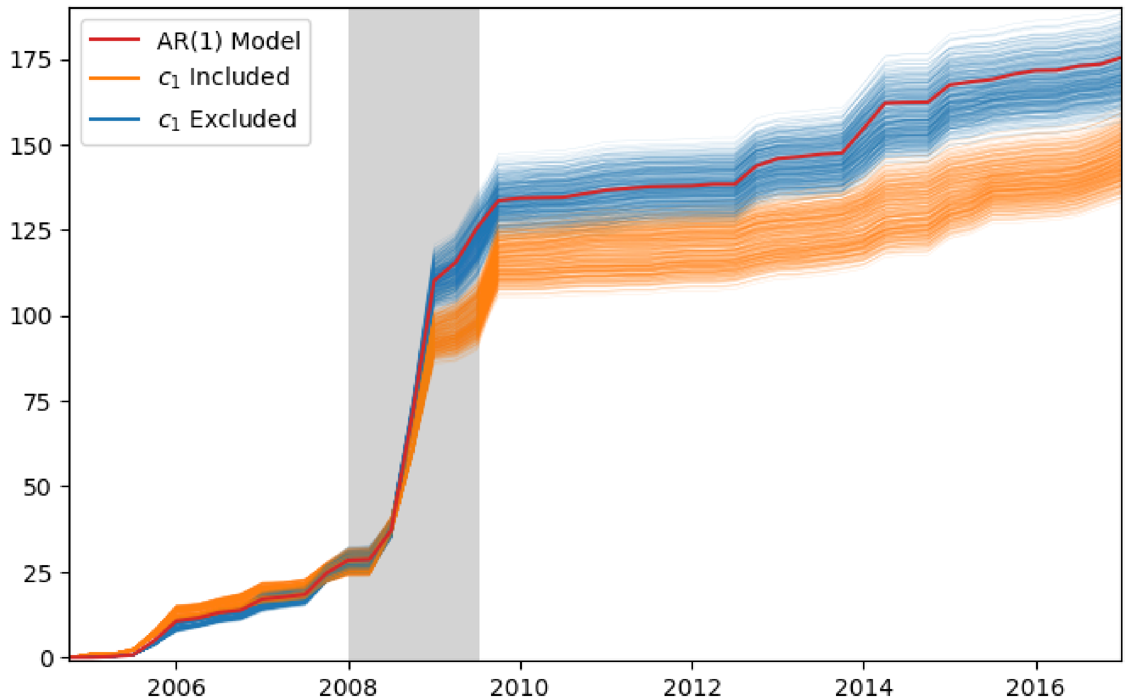
Table 4: Inclusion Probabilities for Component Revisions

Component	Inclusion Probability
c_1	88.1%
c_2	17.9%
i_1	16.8%
i_2	31.7%
g_1	51.8%
g_2	21.3%
x_1	19.5%
x_2	26.9%
m_1	35.0%
m_2	21.8%

Inclusion probability for each variable is based on the model probabilities derived using the Bayesian predictive density as of 2017Q1.

More strikingly, Figure 3 plots the cumulative squared forecast error, where smaller values indicate superior forecast performance. The point forecasts from models that include the first revision of consumption generally outperform models that exclude it. The baseline model is outperformed by every model in which the first revision of consumption is present; this is also true for the cumulative sum of the log posterior density, which is qualitatively similar. Our Bayesian model comparison underscores, in a statistically rigorous way, that it is highly likely (95.5% probability) that the best forecasting model in the large set that we consider includes at least one component revision. Moreover, according to our posterior model probabilities there is roughly an 88% probability that the best model contains the first revision to consumption. In combination, these facts imply that we both identify that there is information pertinent for forecasting in component revisions and that the first revision to consumption is a strong candidate for the source of the information.

Figure 3: Cumulative Sum of Squared Forecast Error, All Models



The vertical axis is the cumulative sum of squared forecast errors. Smaller values indicate superior point-forecast performance. All models including c_1 outperform the baseline AR(1) model.

4 Conclusion

This paper conducts a real-time forecasting exercise for advance estimates of real GDP growth where we compare the forecast performance of dynamic regression models that are augmented with data revisions. Similar to previous work in the literature, we find no increase in forecast performance using aggregate GDP revisions. Surprisingly, component revisions appear to improve forecast performance with nearly 68% of such models outperforming an AR(1) model. The best of these models would predict advanced GDP growth about 0.2 percentage points more accurately than our baseline.

Without an *a priori* reason to exclude certain revisions, we consider a large set of alternative models. Because of this, we conduct an extensive investigation into the significance of our results. Component-augmented models outperform our baseline in a variety of test periods, and a large percentage (48%) of component-augmented models outperform the baseline in all of our seven test periods (2004Q4:2010Q4 advanced in one year increments). We perform Bayesian model comparison to illustrate that the increase in forecast performance goes beyond statistical noise. Despite a 50% prior probability on the AR(1) model, its posterior probability falls to 4.5%. This implies that there is a 95.5% probability that at least one of the component revisions belongs in the most accurate forecasting model for the advance estimate of GDP growth. Finally, we identify the strong role of the first revision to consumption, c_1, in improving forecast performance. Models that include c_1 generally outperform models that exclude it (see Figure 3). Of all the component revisions, c_1 has by far the highest inclusion probability at 88.1%.

On the whole, we feel that the results paint a compelling picture that GDP component revisions improve forecast accuracy. The most direct implication of this finding is that some GDP revisions contain information about future GDP growth. This research suggests several potential paths for future research. While we have identified the role of consumption, the exact mechanism and the importance of other components could be a fruitful line of inquiry. Our results may also have important implications for other strains of the real-time forecasting and data revisions literature. In particular, there may be implications for the debate surrounding whether data revisions contain news or noise (e.g. Mankiw and Shapiro (1986)) and the efficiency of government data releases (e.g. Aruoba (2008)). The value of this research lies in illustrating the informational content of GDP component revisions. This content highlights their potential importance in a wide array of economic planning and forecasting applications.

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Appendix A Data Construction

Our primary series of interest is the advanced estimate of real GDP growth. We utilize the series directly from the Real-Time Data Set for Macroeconomists, hosted at the Federal Reserve Bank of Philadelphia. For convenience, we outline some of the critical aspects of constructing the data. Interested readers should consult the extensive documentation that accompanies the data set.[10] The advanced estimate of annualized quarter over quarter GDP growth is constructed as

$$y_t^T = \left[\left(\frac{Y_t^T}{Y_{t-1}^T} \right)^4 - 1 \right] \times 100, \tag{5}$$

where T represents the first vintage that contains an observation of t. For our purposes the difference between T and t will always correspond to about 1 month or the release lag from the end of a quarter until the advance release of real GDP. A more concrete example is shown below:

$$y_{1991Q4}^{1992m1} = \left[\left(\frac{Y_{1991Q4}^{1992m1}}{Y_{1991Q3}^{1992m1}} \right)^4 - 1 \right] \times 100, \tag{6}$$

where y_{1991Q4}^{1992m1} would be the advance estimate of real GDP growth for 1991Q4 based on the vintage released in January 1992. We calculate revisions to GDP as the difference in growth rates between monthly releases for t. Therefore, the first revision r_1 is the difference between growth rates for the first (T) and second ($T+1$) releases of period t GDP growth:

$$r_{1,t} = y_t^{T+1} - y_t^T. \tag{7}$$

The second revision then is:

$$r_{2,t} = y_t^{T+2} - y_t^{T+1}. \tag{8}$$

We omit the vintage superscript and time subscripts from revisions for clarity. It is understood that first revisions can only exist after a second vintage containing t has been released. Its superscript is therefore $T + 1$ and the second revision's is $T + 2$. Typically level changes in GDP due to definitions and measurement occur in advance releases. Since our growth rates are calculated within vintages and subsequent revisions (i.e. second and third) use the same definitions as the advance release, we

[10] Documentation can be found at `https://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/`.

do not make any additional changes to our data to account for revisions beyond the advance, second, and third releases.

Our component data for real personal consumption expenditures, real exports of goods and services, real imports of goods and services, and real government consumption and gross investment are also directly from the Philadelphia Federal Reserve's Real-Time Data Set for Macroeconomists. Our data for component revisions is constructed in the same way as for revisions to GDP. For example, let C be the level of consumption in GDP (measured in real terms), then the annualized growth rate of C is:

$$c_t^T = \left[\left(\frac{C_t^T}{C_{t-1}^T} \right)^4 - 1 \right] \times 100. \tag{9}$$

The data we use for estimation are the first and second revisions to c, which are again measured as differences in consumption growth:

$$c_{1,t} = c_t^{T+1} - c_t^T. \tag{10}$$

The second revision then is:

$$c_{2,t} = c_t^{T+2} - c_t^{T+1}. \tag{11}$$

As with the aggregate revisions, we drop the vintage superscript and time subscripts in order to refer to revisions generally. We also tolerate the abuse of notion (using c for revisions and growth) in order to present a simpler composition in the text. The notation for government spending, investment, import, and export expenditures follow an identical construction and are designated g, i, m, and x, respectively.

For real gross private domestic investment we use the sum of real non-residential investment, real residential investment, and real change in private inventories. Note that since some of our data occurs after the BEA changed to chain-weighting rather than fixed-price weighting, summing the component elements of real gross private domestic investment will not equal real gross private domestic investment from other sources like the Archival Federal Reserve Economic Database (ALFRED). Given that the two series are highly correlated, we opted to use a consistent data source and rely on the considerable documentation provided by the Philadelphia Federal Reserve's Real-Time Data Set for Macroeconomists.

Appendix B Summary Statistics

Table 5 provides summary statistics for the advance estimates of real GDP growth. It begins in 1991Q4 to coincide with the BEA's change from GNP to GDP as its primary measure of output. Of our 101 observations, we withhold 50 for out-of-sample comparisons between models. The single gap in our sample stems from the lack of an advance release of real GDP in 1995Q4.[11] For comparison, the post-war (1947Q2:2017Q1) real GDP growth rate, using the most recent vintage (September 28th, 2017), is 3.22% with a standard deviation of 3.91%.

Table 5: Advance Estimates of Real GDP Growth

Period	Dates	N	Mean	Std. Dev.	Gaps
Full Sample	1991Q4 - 2017Q1	101	2.51%	1.95%	1
Estimation Sample	1991Q4 - 2004Q3	51	3.13%	1.74%	1
Test Sample	2004Q3 - 2017Q1	50	1.88%	1.97%	0

We also utilize the differences in growth rates between advance and second estimates (first revision) and second and third estimates (second revision). Summary statistics for these revisions are presented in Table 6. As has been documented by others, the first revision to GDP and GDP growth tends to be much larger than the second revision (roughly 6 times larger in our full sample).[12] However, the difference between first and second revisions is considerably lower in the second half of our sample (27 times larger vs. 2 times larger). There is also a greater variance in first revisions than second revisions. Our revision data has an additional gap (beyond what was presented in Table 5) resulting from a missing second release of GDP growth in 2003Q3.

[11] For greater explanation on these types of data eccentricities see the extensive documentation that accompanies each series in the Real-Time Data Set for Macroeconomists.

[12] Additional information on the revision process for aggregate output can be found in Zellner (1958), Young (1993), Fixler et al. (2011), Croushore (2011), Fixler et al. (2014), and U.S. Bureau of Economic Analysis (2015)

Table 6: Revisions to Real GDP Growth

Period	Mean r_1	Mean r_2	Std. Dev. r_1	Std. Dev. r_2	Gaps r_1	Gaps r_2
Full Sample	0.129%	0.022%	0.641%	0.370%	2	1
Estimation Sample	0.191%	0.007%	0.591%	0.313%	2	1
Test Sample	0.068%	0.038%	0.688%	0.424%	0	0

r_1 and r_2 refer to the first and second revisions to real GDP growth, respectively.

Tables 7 and 8 present summary statistics for the revisions to GDP components. These revisions share many of the characteristics of the revisions to aggregate GDP. Mainly, within each component, first revisions tend to be larger than second revisions, and there is more volatility in first revisions than second revisions. First revisions tend to be positive across each of the components as would be expected given that revisions to overall growth also tend to be positive. Second revisions see more heterogeneity with respect to their sign, but are very small in relative magnitude. In line with the two gaps in aggregate revisions, our first set of component revisions also have two gaps in 1995Q4 and 2003Q3, while our second revisions only have a gap in 2003Q3 (the first release in 1995Q3 is missing while the second release is missing for 2003Q3).

Table 7: First Revisions to GDP Components

Component	Mean	Std. Dev.	Gaps
Full Sample			
c_1	0.066%	0.369%	2
i_1	0.661%	3.332%	2
g_1	0.119%	0.854%	2
x_1	0.916%	2.591%	2
m_1	0.956%	3.142%	2
Estimation Sample			
c_1	0.180%	0.364%	2
i_1	0.810%	3.425%	2
g_1	0.253%	1.038%	2
x_1	1.170%	3.047%	2
m_1	1.691%	3.716%	2
Test Sample			
c_1	-0.049%	0.339%	0
i_1	0.511%	3.263%	0
g_1	-0.015%	0.598%	0
x_1	0.661%	2.037%	0
m_1	0.220%	2.244%	0

c, i, g, x, m refer the real GDP components of consumption, investment, government spending, exports, and imports, respectively. The first revision is the difference in each component's growth rate between the advance and second estimate. See Equation (10).

Table 8: Second Revisions to GDP Components ($r_{k,2}$)

Component	Mean	Std. Dev.	Gaps
Full Sample			
c_2	0.014%	0.358%	1
i_2	-0.001%	1.415%	1
g_2	-0.075%	0.475%	1
x_2	0.127%	1.389%	1
m_2	-0.126%	1.486%	1
Estimation Sample			
c_2	0.039%	0.236%	1
i_2	-0.081%	1.433%	1
g_2	-0.181%	0.595%	1
x_2	0.068%	1.424%	1
m_2	-0.215%	1.744%	1
Test Sample			
c_2	-0.012%	0.451%	0
i_2	0.081%	1.405%	0
g_2	0.032%	0.276%	0
x_2	0.187%	1.365%	0
m_2	-0.035%	1.179%	0

c, i, g, x, m refer to the real GDP components of consumption, investment, government spending, exports, and imports, respectively. The second revision is the difference in each component's growth rate between the second and third estimate. See Equation (11).

Appendix C Coefficient Priors

In addition to the model priors, each particular model has priors on the regression coefficients and the AR(1) term in the error equation. For each model, we place priors on the regression coefficients, β_r, and the AR(1) term, ρ_r. For the $k \times 1$ vector of regression coefficients, β_k, in model r, we follow convention and set $p(\beta_r) = N(0, V_r)$. Our prior is that each regressor has no effect, with the tightness of that belief controlled by the covariance matrix, V_r. Put another way, our prior is that past revisions to GDP growth do not contain information important to forecasting future GDP growth.

Since we are considering a large set of models, we set these priors in an automatic fashion. Our prior belief is that each coefficient is independent, so all non-diagonal elements of V_r are zero. We assume that each coefficient is given as:

$$p(\beta_r^k) = N(0, \sigma_\beta^2)$$
$$\sigma_\beta^2 = 1$$

where β_r^k is the coefficient corresponding to the k^{th} regressor in model r.

For the AR(1) term, ρ_r, we set:

$$p(\rho_r) = N(0.5, \sigma_\rho^2)$$
$$\sigma_\rho^2 = 0.5^2$$

We center the AR(1) coefficient at 0.5 since most economic variables have positive autocorrelation at the first lag. Since the AR(1) coefficient should always lie between -1 and 1, the variance of 0.25 is fairly wide. To estimate the model, we use the method of Koop (2003), and we enforce the restriction that $-1 < \rho < 1$ via rejection sampling.

Appendix D Additional Results

Table 9: Forecasting with Component Revisions

Component	Outperforming Models with component (%)	Performance of models with component (%)
c_1	73.7%	100%
g_1	59.3%	80.5%
i_2	53.4%	72.5%
m_2	52.8%	71.7%
x_1	51.1%	69.3%
x_2	50.1%	68.0%
m_1	46.6%	63.3%
g_2	46.0%	62.5%
c_2	45.6%	61.9%
i_1	43.9%	59.6%

Table 9 includes data on two separate conditional statements. Column two reports the percentage of models that outperform the baseline which include each component. Column three reports the percentage of models with a component that outperform the baseline. There are 695 models that outperform the baseline model using our preferred test period.