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Nowcasting Gross Domestic Output*

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Abstract

A recent literature in macroeconomic forecasting studies models that estimate real GDP growth at high frequencies and at very short forecast horizons, known as nowcasts. However, there are two official measures of U.S. economic output, real GDP and real GDI. Although conceptually the same, in practice each is measured with error. This paper evaluates whether the measurement error present in sequential releases of GDP and GDI can be measured more precisely within a mixed-frequency nowcasting framework that accounts for 'news' and 'noise' in real-time GDP and GDI. We develop a model that produces high-frequency forecasts of the common component to the growth rates of GDP and GDI, real gross domestic output (GDO). The mixed-frequency dynamic factor model extracts the common component to roughly 30 additional monthly macroeconomic indicators. We produce, using a fully real-time dataset, GDO nowcasts. We compare the properties of GDO revisions to those of GDP and GDI, evaluate the model's nowcasts of GDP and GDI themselves and examine the properties of news and noise in the measurement errors for output in the context of real-time, mixed-frequency data.

- *Keywords*: Nowcasting; macroeconomic forecasting; mixed-frequency factor model; Bayesian estimation; news and noise; real-time data.
- *JEL Codes*: C11, C22, C53, C55, E37.

Travis J. Berge and **Kurt F. Lewis**
Board of Governors of the Federal Reserve
20^{th} and C St, NW
Washington, DC 20551
e-mail (Berge): travis.j.berge@frb.gov
e-mail (Lewis): kurt.f.lewis@frb.gov

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1 Introduction

Early assessments of economic activity are of critical importance to the successful implementation of economic policy. This paper builds a measure of Gross Domestic Output (GDO) with the goal of improving our real-time understanding of economic activity, allowing policymakers to make better decisions and provide researchers with measurements of output to facilitate more accurate statements about the nature and timing of economic shocks.

Our study is at the junction of the nowcasting (e.g. Giannone et al. 2008, Camacho & Perez-Quiros 2010, Bańbura et al. 2011) and data revision literatures (e.g. Jacobs & van Norden 2011, Aruoba et al. 2016, Jacobs et al. 2018). Nowcasts are high-frequency forecasts for very near-term macroeconomic data. The most prominent nowcasts tend to forecast the very near-term growth rate of real Gross Domestic Product, largely because it is the broadest measure of economic activity and therefore of interest to policymakers, businesses and households. However, the Bureau of Economic Activity (BEA) produces two distinct gross output measures for the United States, real Gross Domestic Product and real Gross Domestic Income (GDP/GDI, respectively). While the two measures measure the same conceptual object—real output—in practice the two measures derive from different surveys and therefore can diverge notably.

We therefore develop a model that nowcasts not GDP or GDI, but the underlying conceptual object, which we denote Gross Domestic Output, GDO. Our baseline nowcast model is in the vein of Bańbura & Modugno (2012). The model includes two quarterly measures of output growth, real GDP and real GDI. These two variables are included with a panel of monthly macroeconomic indicators that constitute a large cross-section, from which a common factor is extracted. We compare the ability of our baseline nowcasting model to produce accurate near-term projections for upcoming BEA releases of real GDP and real

GDI. Further, we consider the degree to which our measure of GDO revises *ex-post* to real GDP and GDI.

In recent years there has been increasing interest in leveraging the revisions process which occurs across data vintages of the two output measures to get a better sense of the true level of GDP.[1] Measures like GDP^{+} from Aruoba et al. (2016) and GDP^{++} from Jacobs et al. (2018) are more recent elements of the growing literature that attempts to use the history of revisions in the data to improve the accuracy of the measurement of historical GDP. This investigation involves modeling the observable data from quarter q as the sum of the truth and a measurement error.

$$Y_q^v = Y_q^{\text{TRUTH}} + \varepsilon_q^v,$$

where v represents a vintage of the estimate (and therefore also the error). Thus, over different vintages of the data for Y in quarter q, a revision process occurs for the data which presumably brings it ever closer to the truth. That revision process, as discussed at the level of the official statistical agency in Mankiw & Shapiro (1986), then more academically by (among others) Faust et al. (2005), could be due to measurement error resulting from either "news" or "noise." If ε_q^v is driven by noise, it is measurement error in the truest sense: ε_q^v is uncorrelated with the true Y. In such a case, where Y is GDP or GDI agents in the economy face a filtering problem in forming their beliefs about output in quarter q based on the available data.[2] If the statistical agency optimally uses all available information in forming the estimate at each point in time, revisions must then reflect news that arrives

[1] *Vintages* refers to different measurements of the same object at alternative points in time. For example, in January 2009, the BEA's measurement of real GDP growth in the fourth quarter of 2008 indicated that 'growth' was -3.8%. By April 2009, the estimate for 2008-Q4 had almost doubled in magnitude to -6.3% and the current estimate is -8.4%. Each of these would represent a different $Y_{2008:Q4}^v$ in the dataset described above. For more information on vintages of real-time data see Croushore & Stark (2001), van Cleve (Forthcoming).

[2] Such filtering problems are discussed in de Jong (1987), Mariano & Tanizaki (1995) and others).

after the announcement.[3] Under an extreme case where all error was noise, ε's would be orthogonal to the true value Y^{TRUTH}, and under the corresponding case in which all error was news, ε's would be orthogonal to their corresponding vintaged estimates, the Y^v's. The data on revisions suggests, as noted by and modeled in Jacobs et al. (2018), that each of the individual estimates of true output at any given point in time are affected by both news and noise, or more explicitly:

$$Y_q^v = Y_q^{\text{TRUTH}} + \nu_q^v + \zeta_q^v = \text{`Truth'} + \text{`News'} + \text{`Noise'}.$$

By explicitly modeling the news-noise relationship in our structure, we can improve on the existing nowcast literature. What makes a "better" nowcast? First, the variable of interest ought to be less-revised and less volatile than either the expenditure (GDP) or income (GDI) measurements, which have been shown to have markedly different cyclical behavior (Nalewaik 2012). A good nowcast would experience small revisions over time while providing clear real-time signals of significant changes in output. As in other studies (e.g. Boivin & Ng 2006, Bok et al. 2018), our estimate will be informed by other, more frequently released, data series. However, we examine these series in the context of their contributions to the GDO nowcast and their relationship to the way in which output measures such as GDP and GDI are revised to account for errors in prior releases which were due to both "news" and "noise." The insight gained through examining "news" and "noise" shocks can help refine the weights given to higher-frequency series.

Because of its high-frequency nature, nowcasts are typically evaluated against early releases of the target variable, for example the BEA's advance release of GDP for a given quarter. However, the revisions of these earlier official estimates are frequently sizable, making comparison along multiple dimensions important. Two examples of such additional

[3] This "news" view would be the correct view if, for example, each statistical release was constructed to minimize a symmetric loss function which was increasing in the size of revisions.

dimensions could be the magnitude of mutual revision (GDO and data) and whether that revision brought the data toward, or away from the GDO nowcast. We find that the one-month and one-year revision of GDO are smaller than the revisions in the data itself.

The paper proceeds as follows. Section 2 presents our baseline nowcasting the model and provides results of our forecast experiment. Section 3 links our nowcasting model to the news-noise literature, and shows how our baseline model can be extended to account for the news content in macroeconomic releases. Section 4 describes the empirical relevance of these news. Section 5 concludes. Technical details and data description are provided in the Appendix.

2 A Mixed-Frequency GDO Model

This section describes a model that provides estimate of the latent, monthly growth rate of "true" output. Our model follows the work of Mariano & Murasawa (2003), Giannone et al. (2008), and Camacho & Perez-Quiros (2010).

2.1 Gross Domestic Output

In the U.S., the Bureau of Economic Activity produce two measures of real output, GDP and GDI. In principal, GDP and GDI measure the same concept, albeit using different approaches. Where GDP measures expenditures, GDI measures income, but both do so with notable measurement error. To mimic the task of macroeconomic forecasters and policymakers, who track the news relating to the state of the economy in real-time and on a daily basis, we wish to utilize a large dataset that contains data of mixed frequency. Since most macroeconomic variables are measured at a monthly frequency, let t denote time, in months. We observe N_m monthly macroeconomic indicators, $y_{mi}, i = 1, ..., N_m$. Let $y_t = [gdp_t, gdi_t, y_{mt}]'$ be a vector that collects the three-month changes of GDP and GDI alongside the vector of monthly indicators, y_{mt}. Because we observe GDP and GDI at a quarterly frequency, we assume that the vector y_t contains missing values for GDP and GDI when t is the first or second month of the quarter. In real-time, the matrix $Y = [y_1', y_2', ..., y_T']'$ will have a ragged edge, since many macroeconomic indicators are released with a lag.

The dynamics real GDP, real GDI, and the vector of monthly indicators is captured by a common latent factor, which we label GDO:

$$y_t = \alpha + \beta gdo_t + e_t \tag{1}$$

We follow Mariano & Murasawa (2003) and assume that the quarterly output variables are the geometric mean of the unobserved values of each month within the quarter. Then the growth rate of the quarterly variable (q_t) is a weighted average of the latent month-on-month growth rates, y^*:

$$q_t = w(L)q_t^*; \quad w(L) = \frac{1}{3} + \frac{2}{3}L + L^2 + \frac{2}{3}L^3 + \frac{1}{3}L^4$$

Finally, the latent output measure GDO and the vector of measurement errors e_t follow autoregressive processes:

$$\begin{aligned} (1 - \Phi(L))gdo_t &= \varepsilon_{gdo,t}; \quad \varepsilon_{gdo,t} \sim N(0, \sigma^2) && (2) \\ (1 - \rho(L))e_t &= \varepsilon_t; \quad \varepsilon_t \sim N(0, \Omega). && (3) \end{aligned}$$

A number of papers have used models akin to this one to produce nowcasts of real GDP, including Giannone et al. (2008) and Camacho & Perez-Quiros (2010). By imposing sensible parameter restrictions, we can give the common factor the interpretation of 'true output,' in the sense of Aruoba et al. (2016), who define true output as the common component of

GDP and GDI, or, equivalently, as GDP (or GDI) excluding measurement error. We denote GDP less measurement errors as *Gross Domestic Output*, or GDO. Specifically, we impose in equation 1 that $\alpha_{GDP} = \alpha_{GDI}$ and $\beta_{GDP} = \beta_{GDI}$.

The model described above can be written compactly in state-space form:

$$y_t = \alpha + \mathbf{Z}\mathbf{s_t} \tag{4}$$

$$\mathbf{s_t} = \mathbf{T}\mathbf{s_{t-1}} + \mathbf{R}\varepsilon_t \tag{5}$$

where y_t is as defined above, the state vector S_t collects the common factor and measurement errors, ε_t collects the shocks to the common factor and each measurement error, and $\mathbf{Z}$, $\mathbf{T}$ and $\mathbf{R}$ are matrices that collect model parameters.

2.2 Data

The variables entering the proposed model are listed in Table 1. We have aimed to incorporate a wide number of leading macroeconomic indicators in the data set, while recognizing that factor models are not immune to the curse of dimensionality. Further, increasing the number of observables included in the model may well decrease forecast accuracy, as found in Boivin & Ng (2006). In total, our dataset contains 31 macroeconomic indicators. We group the data into 9 categories: real output, consumption, manufacturing, the labor market, surveys, housing and construction, inventories, net exports, and prices. The real output category consists of our two quarterly indicators, real GDP and real GDI. Indicators for consumption, manufacturing, labor market, housing and construction, inventories and net exports were largely chosen following Bańbura et al. (2011) and Bok et al. (2018), and consist of the most important monthly indicators for the U.S. economy.

[Table 1 about here]

The majority of the data in the model have a publication lag. This has two important implications. First, since the lags are series-specific, the data will contain a "ragged-edge," meaning that the most recent observation in each series will not be for the same period. The estimation procedure we use is compatible with missing data, but this variable arrival rate of data presents a challenge for high-frequency analysis.

Fortunately, we are able to make use of a real-time dataset constructed and maintained by the Federal Reserve Board (van Cleve Forthcoming). The dataset was produced by the nightly backups done by the staff at the Federal Reserve Bank of St. Louis and the Federal Reserve Board, and therefore consists of *daily* real-time data vintages for a very large panel of macroeconomic variables. The real-time data for the variables that we consider begins in 2006 (*Note: Soon to be 1999*). The high degree of specificity in the vintage data allows us to look at a snapshot of the data as it would have been available to a policymaker in real-time as of the close of business on a specific *day*. This level of real-time precision in defining the conditional information set can provide us with considerable opportunities for analysis of revisions to the unobserved GDO measure.

2.3 Model estimation

The model above is a linear Gaussian state-space model, which we estimate using Bayesian methods. We leave the details of to the appendix but briefly describe the estimation procedure here. We sample from the posterior distribution of model parameters using a Gibbs sampler that consists of the following steps:

1. Conditional on the data, a draw of states and the variance-covariance matrix Ω, draw the parameters associated with the observation equation—α and β. See de Wind & Gambetti (2014) for details on the imposition of parameter restrictions.

2. Conditional on the states, draw the parameters associated with the transition equation,

ϕ.

3. Conditional on the states, draw the AR parameters of the errors and the variance-covariance matrix Ω.

4. Conditional on the states and draws of the model parameter—α, β, ϕ, ρ and Ω—draw the state vector using a state-space representation of the model. We use the forward-filter backward sampler algorithm of Carter & Kohn (1994).

2.4 Priors

Our priors and the resulting conditional posterior distributions are of standard form. We choose conjugate but flat priors for α, β, ϕ, ρ and Ω. The state vector is initialized assuming a Gaussian distribution with mean 0 and variance-covariance matrix of $10 \times I$, where I is the identity matrix of proper dimension.

[Table 2 about here.]

2.5 Estimation results

The full-sample estimate of the monthly GDO is shown in figure 1. The estimate is notably pro-cyclical, showing sharp declines in the NBER-defined recessions present in the series. Although the estimated factor is mean-zero by construction, we add to it the unconditional mean value implied by the draw of $\alpha_{GDP/GDI}$. We estimate the posterior mean of $\alpha_{GDP/GDI}$ to be 0.68, which implies an unconditional annualized growth rate of real output of 2.7 percent. Latent monthly GDO is also quite persistent. When we assume that GDO follows an AR(1) process, we estimate the autoregressive coefficient to be 0.85.

The model also estimates sizable measurement error present in real GDP and real GDI. Figure 2 shows these estimates, plotted as 12 month changes. There are a couple of features of GDP and GDI measurement error worth commenting on. First, the measurement errors show a modest degree of autocorrelation. Secondly, these measurement errors concern the *current vintage* output data, not the BEA initial estimate. In the next section we will evaluate whether the inclusion of monthly data can help to identify the news and noise in the variable-specific releases of data.

[Figures 1 and 2 about here.]

The variables with the highest factor loading are shown in figure 3. Since the variables themselves have different volatilities, we divide factor loadings by the standard deviations of the corresponding series. After this normalization, we find that capacity utilization and industrial production have the largest factor loading, followed by our two quarterly output indicators.

2.6 Out-of-sample analysis

In this section we present an out-of-sample forecasting exercise. As previously described, our source dataset consists of daily real-time vintages for the variables that we include in our model. Nevertheless, because our data consists of indicators that are typically released on a monthly basis, we choose to produce weekly real-time estimates from our model. Specifically, we produce estimates of the annualized growth rate of quarterly real Gross Domestic Output for the previous, current and next quarters. Our first out-of-sample forecast is produced in the first week of 2006, and we produce weekly forecasts through the final week of 2017.

Because our model estimates gross output, we must choose a numeraire to which we compare our nowcast estimates. To that end, tables 4 and 5 present root mean squared errors for our nowcast estimates relative to four different output measures: the second release and the June 2018 vintages of real GDP and real GDI, respectively. For comparison, we also include real-time RMSEs from univariate AR(p) models, with lag length determined by the BIC.

Our estimate of GDO is notably more accurate than the autoregressive null model when forecasting GDP (table 4) and GDI (table 4). Although GDI appears to be somewhat less predictable than GDP, the qualitative pattern of the forecast performance of GDO is similar for both GDP and GDI. For both releases and at each of the three forecast horizons, we compare the posterior median estimate from our model to the forecast from the autoregressive forecast. We find that GDO outperforms the AR model in a statistically meaningful way. For backcasts, the improvement in RMSE is statistically meaningful both the second GDP release as well as the June 2018 vintage. For all forecast horizons, the RMSE deteriorates when one uses the 2nd release versus the current vintage value. The deterioration of the GDO estimate, however, is less pronounced than that of the autoregressive model. This result seems to suggest that the model can correctly anticipate some degree of measurement error in real GDP and real GDI in real-time.

[Tables 4 and 5 about here.]

2.7 Comparison of GDP, GDI and GDO vintages

Estimated revisions to GDO appear to be smaller than to GDI and GDP. Table 6 shows that the one month revisions to the growth rate of GDO are smaller than the equivalent measures from GDP and considerably smaller than those of GDI. The disparity appears to increase when we consider revisions over one year.

[Table 6 about here.]

These revisions can be seen in Figures 3 and 4. From these pictures it is clear to see that the revisions are also two-sided and that the recession associated with the financial crisis resulted in some of the largest revisions for each series. The changes to GDO represent, like GDI and GDP, the effects of both news and noise disturbances.

3 Measurement Error: News vs. Noise

The model presented in the previous section is ignorant of the fact that most macroeconomic data undergo revisions. For example, the measures of real GDP and GDI used in the estimation above are simply the most recent estimate of the history for that series. However, statistical agencies typically produce several estimates of a given macroeconomic variable in a particular time period. Given the mixed-frequency nature of the model, we wish to test whether the data revisions are news or noise, and whether we can distinguish between the two in real-time.

It is important to note that there are different reasons for data revisions. A primary reason why data are revised in the near term is that data collection occurs with a lag. Surveys are conducted to accumulate this data and those can be received with a lag and also require processing. Thus, while some information allows for an advance read on GDP growth within several weeks of the end of a quarter, a significant amount of information has yet to be collected at that point. One could think of this as the "data-arrival" issue for revisions. A second issue which occurs over a longer period is that important and subtle factors involved in the production of official statistics are revised over time, for example seasonal factors; one could think of this concern as the "data-context" issue. Wright (2013) shows that the application of outdated, or perhaps incorrectly updated seasonal factors can distort the readings of a given data set. Given the near-term focus of a nowcasting exercise such as our own, the data-arrival issue may feel more salient, but the data-context issue may loom just as large given the real-time issue of identifying the differences between cyclical variation and potentially misallocated seasonal factors.

Jacobs & van Norden (2011) provide a framework for jointly estimating news and noise from multiple estimates of a given variable. They do not consider a mixed-frequency environment, but instead evaluate the signal for a latent variable present in multiple estimates thereof. For example, consider the problem of understanding the latent annualized growth rate of Gross Domestic Output. Following Jacobs & van Norden (2011), one could stack the releases of GDP and GDI into a vector, y_t. For example, if one considered only the first and second releases of each, we would define the 4×1 vector $y_t = [y_t^{GDP,1}, y_t^{GDP,2}, y_t^{GDI,1}, y_t^{GDI,2}]'$. It is worth emphasizing that the vector y_t is static, in the sense that it contains multiple measures of output in period t, but does not impose any relation to how the elements of the vector relate to one another or evolve.

As in the mixed frequency framework above, these observations can be linked to a latent 'true' growth rate, GDO within a state-space framework:

$$y_t = Z s_t \tag{6}$$

$$s_{t+1} = T s_t + R \eta_t. \tag{7}$$

The Z and T matrices are standard and map states into observables and states into their own lags, respectively. The vector η consists of three elements $[\varepsilon_t, \nu_t, \zeta_t]'$, and $\eta_t \sim N(0, I)$. Here ε is the innovation to GDO, ν is a vector of *news* shocks, and ζ is a vector of *noise* shocks. The matrix R is the crux of the Jacobs & van Norden (2011) framework: it defines the structure of the variance-covariance matrix for the shocks, and therefore whether a particular revision contains news or noise.

Noise shocks are uncorrelated with truth, and therefore have the property that $\text{cov}(\varepsilon_t, \zeta_t)$ is zero, which implies that future estimates are predictable. A new release has news, in contrast, if the measurement error associated with that release is correlated with the truth. Thus, in contrast to noise shocks, news shocks imply revisions not predictable, which would mean that the complete information set available for that period of time was being fully utilized by statistical agency (as discussed in Nordhaus 1987).

3.1 A Mixed-Frequency Model of News and Noise

A joint estimation and nowcast exercise to be added...

4 Discussion and Conclusion

To be added...

5 Tables and Figures

Table 1: Data description and transformations.

Variable	Category	Freq	Trans.
Real GDP	Real output	Quarterly	dlog
Real GDI	Real output	Quarterly	dlog
Retail sales (ex motor vehicles)	Consumption	Monthly	dlog
Real PCE	Consumption	Monthly	dlog
Real disposable personal income	Consumption	Monthly	dlog
Light vehicle sales	Consumption	Monthly	dlog
Industrial Production	Manufacturing	Monthly	dlog
Capacity utilization, manufacturing	Manufacturing	Monthly	dlog
New orders, durable goods	Manufacturing	Monthly	dlog
New orders, nondef capital goods	Manufacturing	Monthly	dlog
ISM composite	Manufacturing	Monthly	diff
ISM manu, new orders	Manufacturing	Monthly	diff
ISM manu, employment	Manufacturing	Monthly	diff
Employment, non-farm payrolls	Labor market	Monthly	diff
Unemployment rate	Labor market	Monthly	diff
Initial jobless claims	Labor market	Monthly	dlog
Philadelphia Fed survey	Surveys	Monthly	diff
Conference Board confidence	Surveys	Monthly	diff
University of Michigan sentiment	Surveys	Monthly	diff
Housing starts (total)	Housing and const.	Monthly	diff
Housing starts (1-fam)	Housing and const.	Monthly	diff
New 1-fam sales	Housing and const.	Monthly	dlog
Total new home sales	Housing and const.	Monthly	dlog
Housing permits	Housing and const.	Monthly	dlog
Private construction put in place	Housing and const.	Monthly	dlog
ISM manufacturing survey, inv.	Inventories	Monthly	diff
Real inventories, all industries	Inventories	Monthly	dlog
Census total exports	Net exports	Monthly	dlog
Census total imports	Net exports	Monthly	dlog
Total CPI	Prices	Monthly	dlog
Core CPI	Prices	Monthly	dlog

NOTE: Transformation *dlog* is the difference of the log of the data where *diff* is the difference of the level.

Table 2: Nowcast Model Parameters, Prior Distributions

Object	Prior Distribution	Parameter 1	Parameter 2
α	Normal	$\bar{y}$	$2 \cdot I_{N_{\text{obs}}}$
β	Normal	$N_{\text{obs}}^{-1} * \iota_{N_{\text{obs}}}$	$I_{N_{\text{obs}}}$
ϕ	Normal	0.7	0.25
ρ	Normal	0	$\frac{1}{2}$
Ω	Inverse Gamma	3	12

NOTE: For the Normal distributions, parameter 1 is the mean and parameter 2 is the variance; for the inverse gamma distributions, parameter 1 is degrees of freedom (ν) and parameter 2 is scale (Ψ). N_{obs} is the number of observable variables in the model and $\iota_{N_{\text{obs}}}$ is a vector of ones of length N_{obs}; $\bar{y}$ indicates that the prior mean of each α^i is the sample mean of the corresponding observable series.

Table 3: Variables with largest factor loading.

	15%	50%	85%
Capacity utilization	1.55	1.74	1.90
Industrial production	1.50	1.69	1.86
GDP	1.25	1.49	1.73
GDI	1.19	1.41	1.62
Unemployment rate	-0.98	-0.85	-0.72
New orders, durable goods	0.55	0.64	0.72
Retail sales	0.52	0.62	0.73
Non-farm payrolls	0.36	0.44	0.53
Light vehicle sales	0.31	0.39	0.49
Housing permits	0.27	0.36	0.44

NOTE: Quantile estimates from posterior estimate of factor loading, β. To facilitate comparison, entries divided by the standard deviation of series.

Table 4: Nowcasting Gross Domestic Product.

Numeraire	2^{nd}	c.v.	2^{nd}	c.v.	2^{nd}	c.v.
Forecast horizon	-1		0		1	
GDO	1.44	1.98	2.26	2.42	2.34	2.51
AR(p)	2.43	2.48	2.46	2.84	2.64	3.01
p-value	0.01	0.01	0.29	0.03	0.11	0.02
N.obs	144	144	144	144	144	144

Note: Table shows RMSE for backcast, nowcast and 1-quarter ahead forecast of real GDP. Numeraire denotes estimate used to calculate forecast error in each quarter; 2^{nd} denotes the second release and *c.v.* denotes the June 2018 vintage. P-value is Diebold-Mariano test of equal predictive ability under squared error loss and using Newey-West standard errors.

Table 5: Nowcasting Gross Domestic Income.

Numeraire	2^{nd}	c.v.	2^{nd}	c.v.	2^{nd}	c.v.
Forecast horizon	-1		0		1	
GDO	1.86	2.77	2.46	2.74	2.47	2.70
AR(p)	2.54	2.56	2.68	3.16	2.85	3.28
p-value	0.00	0.31	0.28	0.03	0.05	0.00
N.obs	144	144	144	144	144	144

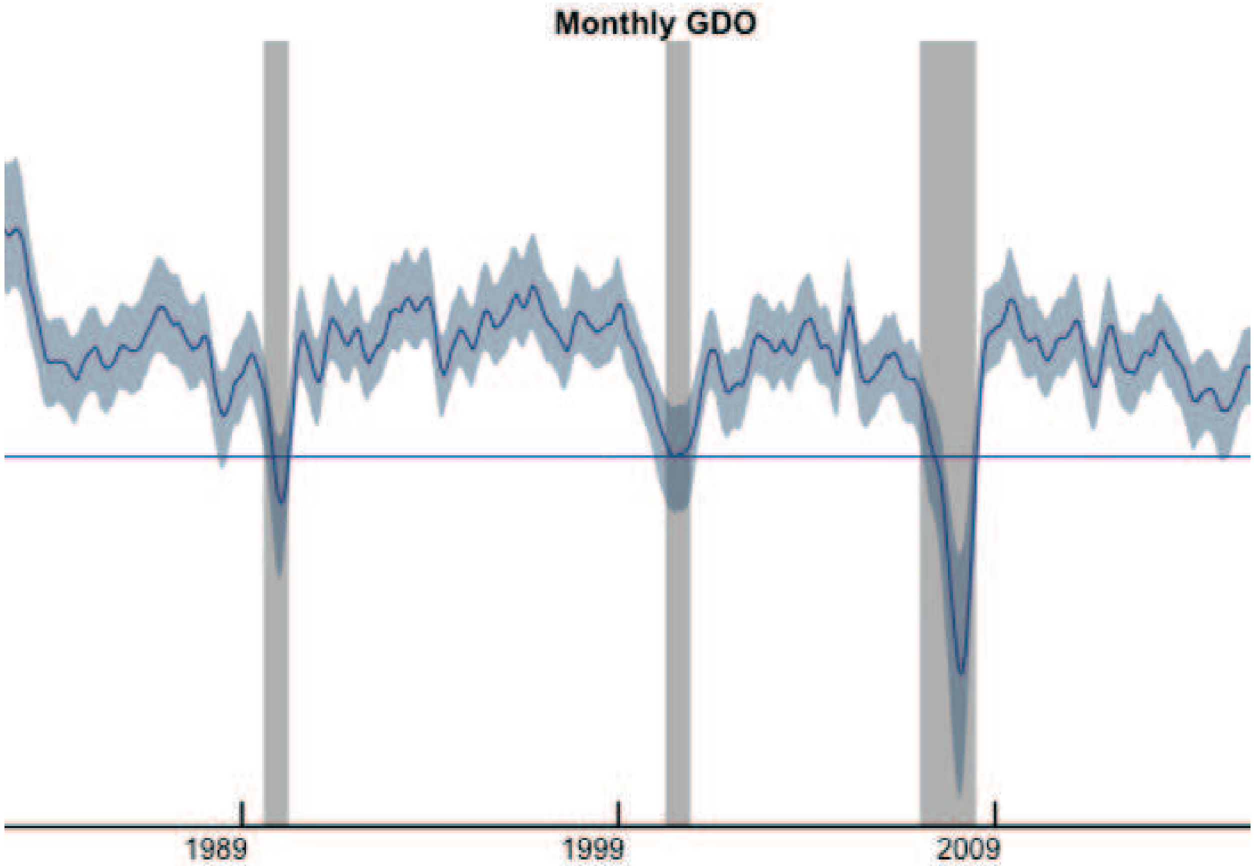
Note: Table shows RMSE for backcast, nowcast and 1-quarter ahead forecast of real GDP. Numeraire denotes estimate used to calculate forecast error in each quarter; 2^{nd} denotes the second release and *c.v.* denotes the June 2018 vintage. P-value is Diebold-Mariano test of equal predictive ability under squared error loss and using Newey-West standard errors.

Table 6: Revisions to GDO, GDP and GDI

	One Month	One Year
Estimated GDO	0.70	0.96
Real GDP	0.89	1.23
Real GDI	1.07	1.79

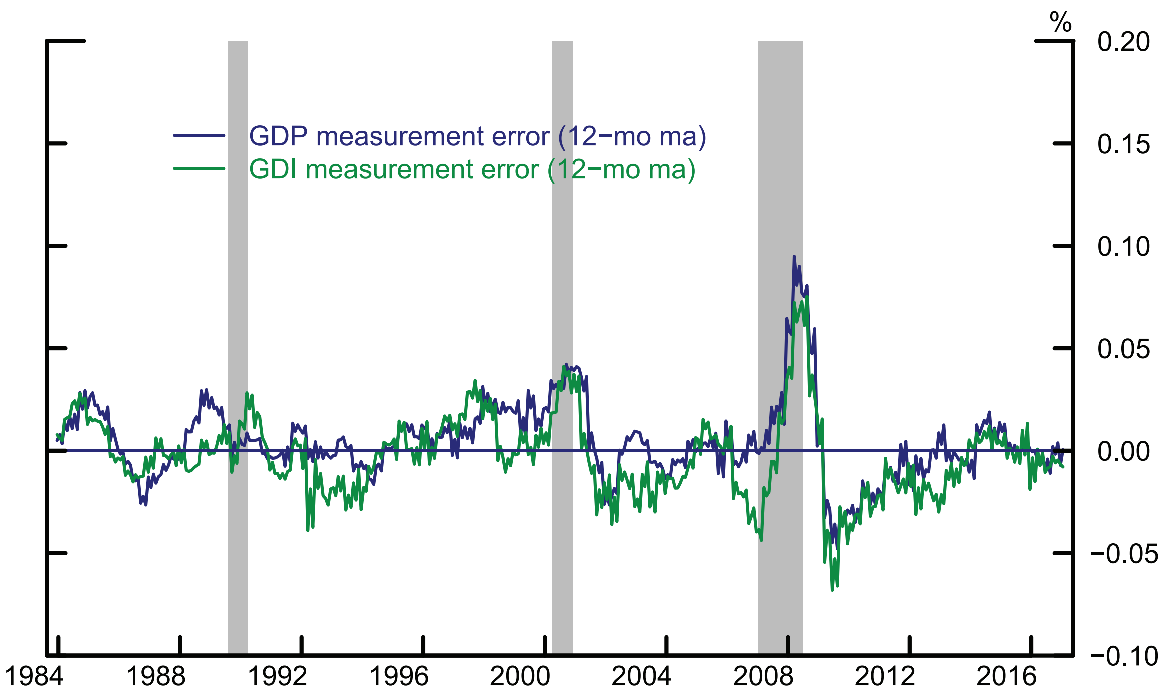
Note: Numbers reported are the standard deviation of revision to annualized growth rates of GDO, real GDP and real GDI.

Figure 1: Monthly measure of GDO, January 1983–June 2018.



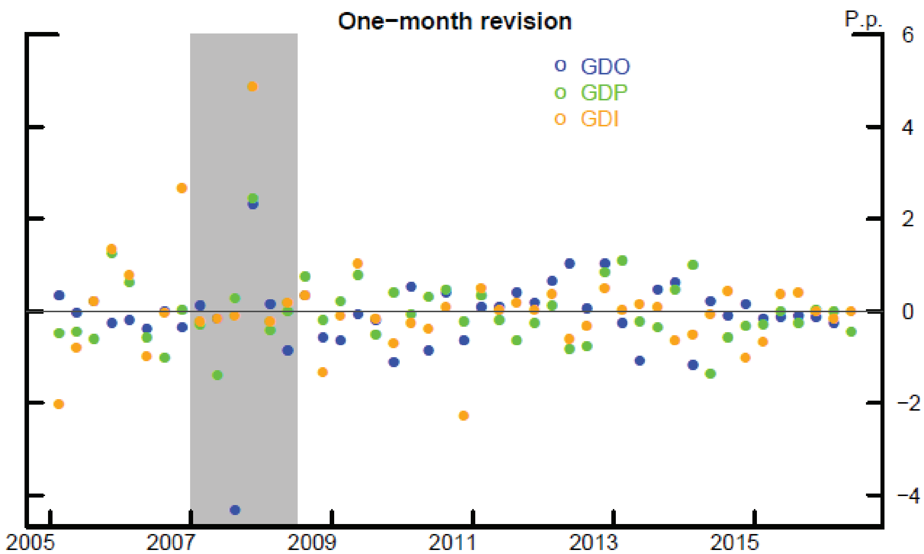
NOTE: Figure shows latent monthly measure of GDO, plotted as a monthly change. Since the true factor is mean zero, we add the unconditional mean implied by our estimate of α_{GDP} and α_{GDI} to the estimate. Shaded area denotes 70 percent credible set.

Figure 2: Estimated measurement error in GDP and GDI.



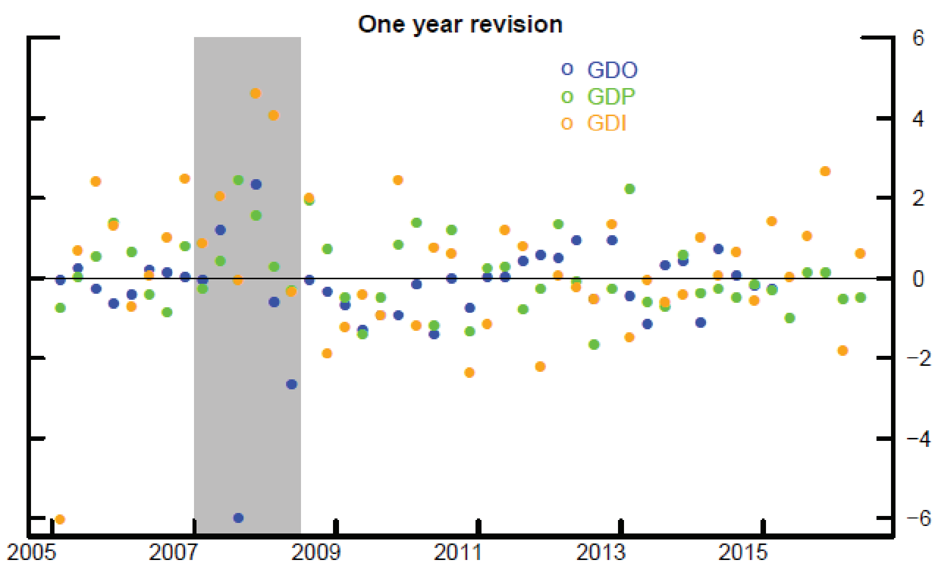
NOTE: Figure shows posterior median estimate of the latent measurement error in real GDP and real GDI. Measurement errors shown as 12-month changes.

Figure 3: One-Month Revisions to Output Measures.



Note: Figure shows the revisions over a one-month period for each of the estimates of GDO, GDP and GDI over the 2006-2017 period.

Figure 4: One-Year Revisions to Output Measures.



Note: Figure shows the revisions over a one-year period for each of the estimates of GDO, GDP and GDI over the 2006-2017 period.

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Appendix

The Gibbs sampler

Here we give the details of the sampler. For simplicity, we consider the case where $p = q = 1$, i.e., both the common factor and idiosyncratic measurement errors follow AR(1). We further assume a single factor.

Recall that we can cast the model in state space form:

$$\begin{aligned} y_t &= \alpha + \mathbf{Z}\mathbf{s_t} \\ \mathbf{s_t} &= \mathbf{T}\mathbf{s_{t-1}} + \mathbf{R}\varepsilon_t \end{aligned}$$

Draw parameters of observation equation

We have:

$$y_{it} = \alpha_i + \beta_i f_t + e_{it} \tag{1}$$

with $e_{it} = \rho_i e_{it-1} + \varepsilon_t$, $\varepsilon_t \sim N(0, \omega_i^2)$. At this point in the sampler, we can treat f, ρ_i and ω_i^2 as observed, and this equation is a standard linear regression with autocorrelated errors. Thus, let $x_t = [1, f_t]'$, and then filter both sides of equation 1 by $1 - \rho_i(L)$ to obtain

$$\tilde{y}_t = \tilde{\beta}_i \tilde{x}_t + e_t, \quad e_t \sim N(0, \omega_i^2). \tag{2}$$

In the case of the monthly variables, since our priors for α and β are Gaussian, the posterior is also Gaussian from which we draw.

The draw is slightly complicated for the quarterly variables, since the regression error enters as a moving average and also follows an autoregressive process:

$$y_{qt} = \alpha_i + \beta_i w(L) f_t + w(L) e_{qt}, \tag{3}$$

with $w(L) = \frac{1}{3} + \frac{2}{3}L + L^2 + \frac{2}{3}L^3 + \frac{1}{3}L^4$. To draw the factor loading for quarterly observables, we use the auto-covariance function to work out the variance of the error term in 3. We then divide each observation of $\tilde{x}$ by this variance. The unrestricted posterior of $\beta_{\mathbf{i}} = [\alpha_i, \beta_i]$ is

$$\begin{aligned} &\beta_i \sim N(\mu_\beta, V_\beta), \text{ where} \\ &\mu_\beta = V_\beta \left(\underline{V}_{\beta,i} \underline{\mu}_\beta + \tilde{x}'\tilde{y} \right) \\ &V_\beta = \left(\underline{V}_{\beta,i}^{-1} + \tilde{x}'\tilde{x} \right)^{-1}, \end{aligned} \tag{4}$$

and $\underline{\mu}$ and $\underline{V}$ denote the prior mean and variance. Lastly, the α and β parameters for GDP and GDI are assumed to be the same in order to identify GDO. We impose the restriction, expressed as $R[\alpha', \beta']' = 0$, by drawing from the posterior

$$\begin{aligned} &\beta_i^R \sim N(\mu_\beta^R, V_\beta^R), \text{ where} \\ &\mu_\beta^R = \beta^u - V_\beta^u R' \left(R V_\beta^u R' \right)^{-1} \left(R\beta^u - r \right) \\ &V_\beta^R = V_\beta^u - V_\beta^u R' \left(R V_\beta^u R' \right)^{-1} R V_\beta^u \end{aligned} \tag{5}$$

where β^u and V^u denotes the unrestricted mean and variance.

Draw parameters of transition equation

To draw the autoregressive parameters of the factor and idiosyncratic shocks notice that, conditional on the state, the common factor gdo_t and the residuals e_{it} are known. The transition equations are also standard linear regressions, and drawing these parameters is standard. We employ normal priors and rule out explosive roots by discarding explosive draws of ϕ or ρ_i.

Draw innovation variances

The law of motion for the measurement errors is:

$$(1-\rho(L))e_{it} = \varepsilon_{it} \quad \varepsilon_{it} \sim N(0, \omega_i^2)$$

Our prior for ω_i^2 is inverse-Gamma, $\omega_i^2 = IG(\frac{\underline{\nu_i}}{2}, \frac{\underline{\delta_i}}{2})$. The posterior is then also inverse-Gamma:

$$\begin{aligned} &\omega_i^2 \sim IG(\frac{\nu_i}{2}, \frac{\delta_i}{2}), \text{ where} \\ &\nu_i = T + \underline{\nu_i} \\ &\delta_i = \underline{\delta_i} + ((1-\rho(L))e_{it})'((1-\rho(L))e_{it}) \end{aligned} \tag{6}$$

Draw state vector

Conditional on the model parameters and the data, the model is a standard linear Gaussian state-space system. We make draws using the algorithm of Carter & Kohn (1994).