Tracking U.S. GDP in Real Time

By Taeyoung Doh and Jaeheung Bae

Measuring the current state of the U.S. economy in real time is an important but challenging task for monetary policymakers. A more accurate assessment of the current state of the economy helps policymakers make better projections for the future and, accordingly, set policy best suited to achieving the mandated goals of maximum employment and stable prices. However, capturing the state of the economy in real time is difficult because the most comprehensive measure—real gross domestic product—is available at a relatively low frequency (quarterly) and with a significant delay (one month). While several indicators used to estimate GDP are available at higher frequencies, using them to track GDP in real time requires researchers to make choices about how to combine and weight these indicators. These choices may introduce errors.

Recent advances in econometric methods have made it feasible to track GDP in real time with fewer human judgments using the historical relationship between the official quarterly GDP numbers and economic indicators available at higher frequencies. The Federal Reserve Bank of Kansas City has incorporated these new methods into a GDP tracking model (henceforth referred to as the "KC Fed model") that combines two conventional approaches to estimating GDP to obtain better assessments of the current state of the economy.

In this article, we explain the model's underlying details and illustrate its performance by comparing the model's daily tracking estimates of 2019:Q1 GDP with those from the Federal Reserve Bank of New

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York and the Federal Reserve Bank of Atlanta. Our results suggest that the KC Fed model's tracking estimate is comparable to tracking estimates from the other two Reserve Banks. In addition, our results lend support to the KC Fed model's dynamic weight-shifting assumption, which adjusts the weights placed on GDP estimates from the two approaches as information from monthly indicators accumulates.

Section I explains the policy relevance of tracking GDP in real time as well as some practical challenges. Section II introduces the general methodologies used to track GDP in real time and discusses their pros and cons. Section III reviews the underlying details of the KC Fed model and compares its real-time tracking performance with other Reserve Bank models based on the models' estimates of 2019:Q1 GDP.

I. The Challenges of Tracking GDP in Real Time

Tracking current-quarter macroeconomic conditions based on recent indicators is important for the conduct of monetary policy and medium-term forecasting. Members of the Federal Open Market Committee (FOMC) have increasingly communicated to the public that policy decisions are "data dependent," meaning policymakers take into account new information as economic conditions and the outlook evolve (Powell 2019; Williams 2019). Although most macroeconomic data are released with a lag, incomplete data can provide a reasonable starting point for assessing current-quarter economic conditions. For this reason, the FOMC's post-meeting statement typically begins by discussing the implications of the data released between meetings. In addition, researchers have shown that initial-period forecasts play a key role in the accuracy of forecasts at subsequent horizons in the medium term (Carriero and Clark 2015).

While obtaining an accurate estimate of current-quarter GDP is useful in making policy decisions and medium-term forecasts, the official estimate is released with a significant lag. The Bureau of Economic Analysis (BEA) releases the first estimate of GDP only at a quarterly frequency and with a one-month delay.[1] However, this first estimate is often revised in subsequent months because not all underlying source data are available at the time of the initial release. The final estimate of GDP that incorporates more than 90 percent of the underlying source data is usually released three months after the end of the quarter.

To overcome these data limitations and lags, policymakers consider a wide range of information provided by other economic and financial indicators available at higher frequencies. Some of these indicators are "hard" data that directly feed into the official estimate of GDP— namely, monthly retail sales and industrial production. Others are "soft" data, which include consumer and business surveys or financial asset prices. According to Williams (2019), data-dependent policy means taking into account such policy-relevant data at higher frequencies.

However, considering all available higher-frequency indicators requires policymakers to make substantial judgments. For example, estimating overall consumption in a given quarter may require policymakers to estimate how much a positive surprise in one month's retail sales will persist into the next month's retail sales. In addition, incorporating survey data into an assessment of current macroeconomic conditions may require policymakers to estimate the effect of changes in consumer sentiment on consumer spending. Quantifying this effect can be especially challenging because sentiment sometimes changes even without new information on economic fundamentals.

Recent advances in econometric methods may allow policymakers to automate some of these judgments in a consistent way using statistical models. For example, Giannone, Reichlin, and Small (2008) explain how to address "unbalanced" data sets in which the release dates of monthly data differ by indicator.[2] In particular, they provide the statistical tools used to aggregate various components of GDP with different frequencies and release dates into the tracking estimate of GDP. While these methods do not eliminate all human choices—for example, which criterion function to use to evaluate different models—they allow policymakers to largely automate the process of tracking GDP in real time using mixed-frequency data (Banbura and others 2013).

II. The "Bottom-Up" and "Top-Down" Methods for Tracking GDP

Two popular ways of estimating GDP in real time are the "bottom-up" and "top-down" methods. The bottom-up method aggregates the effect of each economic indicator on each subcomponent of GDP. The top-down method extracts the statistical factors driving the co-movements of economic indicators and predicts GDP or its subcomponents based on estimates of these factors.

Forecasters using the bottom-up method make a current-quarter forecast for each subcomponent of GDP using bridging equations that link monthly indicators with quarterly forecasts of GDP subcomponents. Then, they aggregate the quarterly forecasts of GDP subcomponents to obtain the current-quarter estimate of headline GDP. For example, a forecast of current-quarter services consumption would aggregate forecasts for relevant indicators such as electric and gas utilities in monthly industrial production. The aggregation is typically based on the subcomponents' accounting identities and closely mimics the methodology used by the BEA to calculate each subcomponent of GDP from underlying details.

The bottom-up method offers researchers a few key benefits. Because the bottom-up method makes projections at the indicator level, it can easily identify surprises in data releases and determine their effect on GDP. In this way, the bottom-up method provides transparency in how the tracking estimate of GDP responds to data releases. For example, consider the following autoregressive prediction model for monthly retail sales for food services:

$$x_t = (1-\rho_x)\mu_x + \rho_x x_{t-1} + \epsilon_{x,t},$$

where x_t represents monthly retail sales for food services in month t, ρ_x represents the degree of persistence, μ_x represents the historical average, and $\epsilon_{x,t}$ represents an unanticipated surprise. If the indicator follows a highly persistent autoregressive model (ρ_x close to 1), a positive surprise in the latest reading of the indicator (a big positive realization of $\epsilon_{x,t}$) is more likely to shift up the current-quarter estimate of the services consumption subcomponent of GDP. In contrast, if the indicator follows an autoregressive model with a negative coefficient ($-1 < \rho_x < 0$), one month's strong reading is more likely to shift down the estimate in the following month within the same quarter with relatively little influence on the current-quarter estimate.

The bottom-up method has two key disadvantages. First, the method cannot easily incorporate information from soft data, such as surveys, that are not part of the official GDP estimate. In addition, the method can yield estimates of GDP that are overly sensitive to individual data points early in the quarter, when fewer indicators are available. This sensitivity arises from the fact that the tracking model relies more on extrapolated values than actual data to obtain early-quarter estimates of GDP. As more data become available, the model relies more on the realized data and less on extrapolated values, and the volatility of the tracking estimate tends to decline accordingly.

In contrast, the top-down method tends to generate much smoother and less volatile estimates. In the top-down method, we aggregate information from high-frequency indicators into a few statistical factors before using the factor estimates to predict GDP. We extract the statistical factors by identifying the common components that explain most of the covariations of the high-frequency indicators. This aggregation process smooths out the idiosyncratic volatility of individual indicators. Then, we project current-quarter GDP by regressing headline GDP growth on the factor estimates.

Another benefit of the top-down method is that the statistical factor model is not restricted by accounting identities and can thus include soft data as well as hard data as input variables. This flexibility allows researchers to include hard data such as employment that may help predict GDP but are not a direct input into the calculation of GDP. For example, the BEA uses the monthly employment report to estimate only two components of GDP—services consumption and government spending. However, labor market conditions in the employment report might also influence business investment. The flexibility of the top-down method allows us to examine how hard data might influence variables outside of the bottom-up method's rigid accounting identities.

In addition, researchers have the flexibility to include relevant soft data as additional inputs when releases of hard data are unexpectedly or systematically delayed. Even when hard data releases are not delayed, soft data may offer benefits to researchers. For example, the effect of news about future fiscal policy on current spending may show up in hard data with a delay but in survey and financial market data immediately. This feature can be useful for predicting future macroeconomic conditions beyond the current quarter.

However, the top-down method has one key disadvantage. Because factor estimates are based on a purely statistical relationship, it is difficult to explain why the tracking estimate of GDP changes in response to data releases. For example, a strong data point in the manufacturing survey may change the estimated factor that affects the tracking estimates of GDP components, such as consumption, that are not directly tied to the manufacturing survey. A strong data point in a consumer survey that moves the factor estimate by the same amount can affect consumption to the same degree. The top-down method cannot isolate which data release drove the change in consumption, even though the consumer survey is more likely to affect consumption and the manufacturing survey is more likely to affect investment. For this reason, the top-down method is not a good tool for interpreting the underlying economic forces behind data surprises.

III. The KC Fed Model

Although the bottom-up and top-down approaches have discrete advantages and disadvantages, they are not mutually exclusive. In fact, the two approaches can be combined to generate more accurate forecasts. For example, researchers can take the weighted averages of forecasts generated by the two approaches and incorporate factor estimates into bridging equations.

The KC Fed model follows this process, combining forecasts from two different models.[3] The first model, which follows the bottom-up method, is the accounting-based model. This model generates quarterly forecasts of indicators by filling in observations for missing months and aggregating them to make a quarterly projection for each subcomponent of GDP. The second model, which follows the top-down method, is the factor model. This model generates forecasts for the nine major subcomponents of GDP by aggregating information from high-frequency indicators into a few statistical factors and then making corresponding projections using these factor estimates.[4]

The two models address the varying availability of monthly data used as inputs in different ways. The accounting-based model generates a forecast using a specified selection function for each data series yet to be released. Namely, the model selects its forecasting method based on the recent forecast accuracy of four univariate methods.[5] Whichever method and parameterization produces the smallest root mean square error (RMSE) for its one-step-ahead forecast over the preceding six months is used to forecast missing values for that data series. Under this approach, forecasts are based only on the observed variables so far. In contrast, the factor model can allow the unobserved latent variables to affect forecasts. The factor model has two sets of parameters: those governing the dynamics of observed or unobserved factors and those linking factors with observed variables. To estimate the factor model, we first estimate model parameters from a balanced panel containing data for all input indicators up to the date of the latest common release. Then, the model updates the estimated factor using parameter estimates and monthly indicators already released but not included in the balanced panel. Finally, we run an ordinary least squares (OLS) regression of past quarterly data on past estimates of the factor to produce current-quarter estimates of each subcomponent of GDP. We then aggregate these subcomponent estimates to construct GDP.

Once quarterly forecasts are obtained from both models, we can generate alternative forecasts that combine these forecasts by imputing weights. For example, the KC Fed model aggregates the forecasts from the two models for the nine subcomponents of GDP using calendar-based weights. For each subcomponent (x) in quarter t, the tracking model combines the forecasts from the factor model (x_t^F) and the accounting-based model (x_t^{act}) according to the corresponding weight ($w_{x,t}$) to obtain the final forecast of x_t as follows:

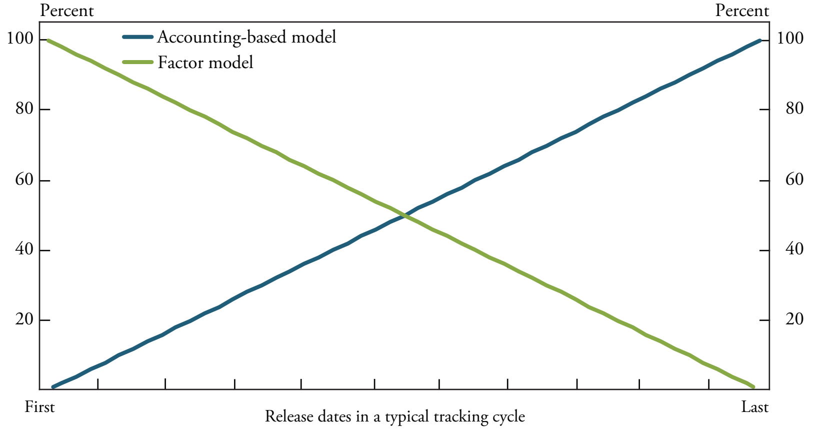
$$x_t = w_{x,t} x_t^{act} + \left(1 - w_{x,t}\right) x_t^F.$$

Chart 1 shows how the KC Fed model weights the forecasts from the two models over time. The horizontal axis shows the calendar dates in which economic indicators for a particular tracking quarter are released. The first date, following the first release date of the BEA's first estimate of the previous quarter GDP, usually occurs early in the second month of the quarter. The last date, corresponding to the last relevant release date, usually occurs in the first month of the subsequent quarter. Table 1 shows the release schedule for some of the key data sources used in the KC Fed model. In a tracking cycle of approximately 12 weeks, three monthly observations of each indicator are incorporated into the model.

The KC Fed model weights forecasts from the factor model more heavily early in the tracking cycle, when many data are not yet available and forecasts from the accounting-based model are more sensitive to surprises in high-frequency indicators. The KC Fed model then increases the weight on forecasts from the accounting-based model over time. One day before the release of the BEA's first estimate of quarterly GDP, the model places the entire weight on the accounting-based model's

Chart 1

Weights Assigned to the Two Models for Components of GDP for a Given Quarter



Notes: The blue and green lines represent the weights assigned to the accounting-based model and factor model, respectively, in computing the final estimate of the subcomponent. The entire weight is assigned to the accounting-based model forecasts one day before the release of the BEA's first estimate of quarterly GDP for the current tracking quarter.
Source: Authors' calculations.

Table 1

Typical Release Weeks for Major Source Data in the KC Fed Model

Week of release	Data
First	Construction spending, factory orders, international trade, motor vehicle sales, employment situation
Second	Wholesale trade, import/export prices, retail sales, consumer price index
Third	Business inventories, producer price index, industrial production, residential construction
Fourth	New home sales, durable goods, personal income and personal outlays

Note: Table represents typical release weeks for the relevant series; the actual week of release may differ from month to month.

forecasts. Because the accounting-based model follows the same guidelines used in the BEA's actual calculation of GDP, the model-based tracking estimate is likely to be a good proxy for the official estimate as the date approaches the release date (given that both estimates include the same amount of information provided by high-frequency indicators).[6]

Table 2 provides summary information for input variables used in each model. The accounting-based model includes 148 indicators, 107 of which are available at a monthly frequency. The factor model includes 198 indicators, 197 of which are available at a monthly frequency. Because it follows the top-down method, 11 of the 198 indicators are soft data.

Table 2
Source Data in the KC Fed Model

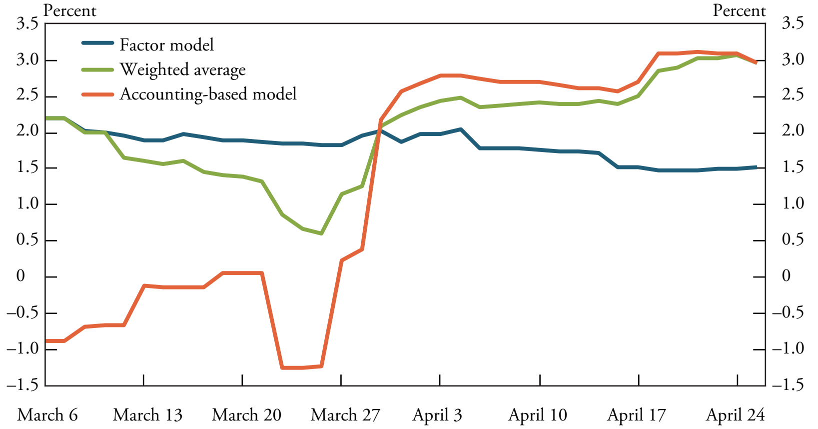
Accounting-based model				Factor model			
Category		Frequency		Category		Frequency	
Personal consumption expenditures	23	Quarterly	38	Soft	11	Quarterly	1
Business fixed investment	40	Monthly	107	Hard	187	Monthly	197
Residential investment	19	Weekly	2				
Change in private inventories	19	Daily	1				
Net exports of goods and services	25						
Government consumption expenditures and gross investment	25						
Total	148		148		198		198

Source: Authors' calculations.

Chart 2 shows the real-time tracking estimates of 2019:Q1 headline GDP growth from the KC Fed model from March 6, 2019, to April 25, 2019. Typically, we would begin tracking first-quarter GDP in late January or early February rather than March. However, due to the partial government shutdown that began in December 2018, the BEA did not release its first estimate of 2018:Q4 GDP until the end of February—one month later than usual. The GDP tracking estimate from the factor model (blue line) slowly moves down from 2.2 percent to 1.5 percent, with a standard deviation of 0.2 percent. In contrast, the estimate from the accounting-based model (orange line) exhibits substantially higher volatility during the same period. Indeed, the corresponding standard deviation is an order of magnitude larger at 1.66 percent. The estimate from the weighted average of the two forecasts (green line) has a standard deviation between the two extremes at 0.67 percent.

The difference in the volatility of the models' forecasts reflects the difference in the models' sensitivity to high-frequency data releases. Although the tracking estimate of 2019:Q1 GDP from the accounting-based model starts below that of the factor model, it quickly rises above the factor model. Specifically, the accounting-based model's estimate of headline GDP growth jumps up by 1.46 percent on March 27, coinciding with the release of January international trade data showing a narrowing of the trade deficit spurred by a substantial decline in imports. The estimate jumps up by another 1.77 percent on March

Chart 2
KC Fed Model Tracking Estimates for 2019:Q1 GDP



Source: Authors' calculations.

29, coinciding with the release of much stronger than expected January manufacturing and wholesale inventories data. In contrast, the factor model estimates change little on these dates.

Table 3 shows that the accounting-based model's final estimates of quarterly inventory investment and international trades (exports and imports) are much closer to the BEA's official estimates than those from the factor model, suggesting the accounting-based model correctly identified the signals from monthly indicators. The accounting-based model also captured the weakness in private domestic final sales masked by the strength in inventory investment and net exports. By generating forecasts for the subcomponents of GDP, the KC Fed model helps isolate the subcomponent that is more likely to be persistent (here, private domestic final sales) before the BEA's official estimate of GDP is available.

However, the sizable adjustments in the accounting-based model on March 27 and 29 suggest that the model might have underestimated the strength of inventories and net exports early in the quarter simply because it lacked relevant monthly data. These adjustments justify the KC Fed model's use of time-varying weights, allowing the factor model to be more influential early in the quarter, when many high-frequency indicators are not available.

To further evaluate the KC Fed model's performance, we compare the model's forecasts to those from other available GDP tracking models.

Table 3
Comparison of 2019:Q1 GDP Tracking Estimates

Component	Factor model (April 25)	Accounting-based model (April 25)	Atlanta GDPNow (April 25)	New York Nowcast (April 25)	BEA (April 26)
GDP	1.5	3.0	2.7	1.4	3.2
Private domestic final sales	3.2	0.9	1.4		1.3
Personal consumption expenditures	3.0	0.6	1.1		1.2
Business fixed investment	3.9	2.3	3.1		2.7
Structures	3.8	−1.6	−0.3		−0.8
Equipment	1.7	1.7	2.0		0.2
Intellectual property products	6.8	5.8	6.8		8.6
Residential investment	−2.0	1.6	1.3		−2.8
Change in private inventories	52.0	128.0	117.0		128.0
Net exports of goods and services		−902.0	−929.0		−899.0
Exports	1.6	4.0	3.4		3.7
Imports	2.9	−3.2	−0.5		−3.7
Government consumption expenditures and gross investment	2.4	3.8	3.2		2.4

Note: All components are annualized quarterly rates of change except net exports and change in private inventories, which are in billions of chained 2012 dollars.
Sources: BEA, Federal Reserve Bank of Atlanta, Federal Reserve Bank of New York, and authors' calculations.

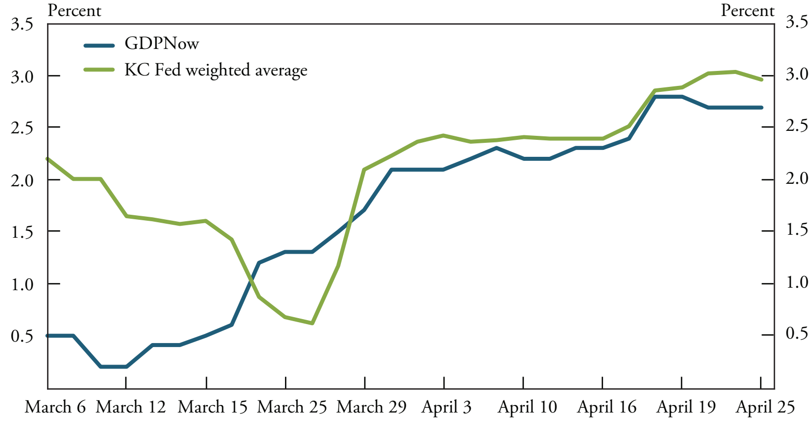
Specifically, we consider two publicly available tracking estimates from the Federal Reserve Bank of Atlanta and the Federal Reserve Bank of New York. These models provide good benchmarks because they use two different approaches to tracking GDP.

Chart 3 compares estimates from the KC Fed model with estimates from the Atlanta Fed's tracking model, also known as "GDPNow." The GDPNow model is similar to the KC Fed model in that it combines a factor model with bridging equations. However, the GDPNow model differs from the KC Fed model in that it adds factor estimates as predictors in the bridging equations (Higgins 2014). In addition, the GDPNow model uses forecasts from a Bayesian vector autoregression of 13 subcomponents of GDP as additional inputs for the tracking model estimates. Despite these differences, the KC Fed model's tracking estimate of GDP closely follows the estimate from GDPNow.

In contrast, Chart 4 shows that estimates from the New York Fed's tracking model appear to differ substantially from estimates from the KC Fed model. This difference can be attributed to different goals. According to Bok and others (2017), the New York Fed's model targets the systematic

Chart 3

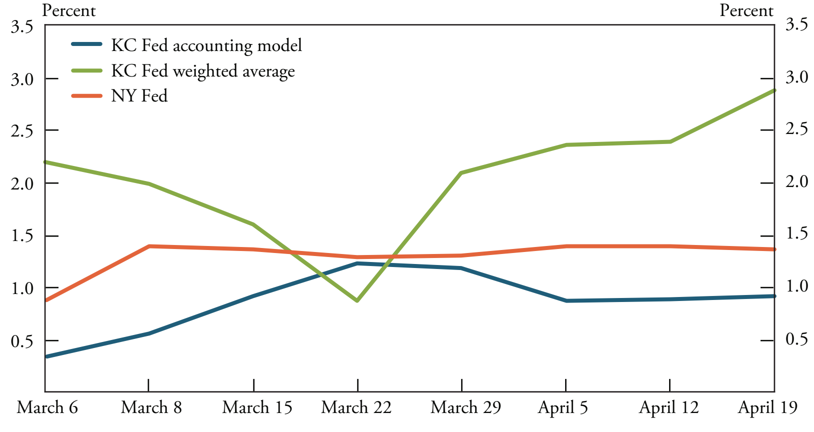
Tracking Estimates of 2019:Q1 GDP from KC Fed Model and GDPNow



Note: Dates correspond to releases of the Federal Reserve Bank of Atlanta's tracking estimates.
Sources: Federal Reserve Bank of Atlanta and authors' calculations.

Chart 4

Tracking Estimates of 2019:Q1 GDP from KC Fed and NY Fed Models



Note: Dates correspond to releases of the Federal Reserve Bank of New York's tracking estimates.
Sources: Federal Reserve Bank of New York and authors' calculations.

component of GDP growth, which can be approximated by growth in private domestic final sales. Indeed, the estimates of private domestic final sales from the KC Fed's accounting-based model (not shown) fairly closely follow the New York Fed's GDP tracking estimates.

Comparing the KC Fed model's tracking estimates with those from other Reserve Bank models suggests that the real-time tracking of GDP is fairly robust to implementation details. The main difference in each model's estimates is which aspect of GDP the models target. If policymakers are more interested in tracking the systematic component of GDP that may persist in the future, a factor model may be more useful to the extent that it smooths out idiosyncratic variations in high-frequency data. However, if policymakers are more interested in understanding current macroeconomic conditions as accurately as possible, information from an accounting-based model may be more appealing. Ultimately, these two approaches are complementary; the KC Fed model allows us to combine estimates from the factor model and accounting-based model, resulting in better predictions of GDP.

Conclusion

Understanding how data releases influence current macroeconomic conditions in real time is important for monetary policymakers who set policy in a data-dependent way. The Federal Reserve Bank of Kansas City has developed a model to track GDP in real time using high-frequency indicators and recent developments in time series econometrics. Specifically, the KC Fed model combines estimates from two different models—an accounting-based model and a factor model—to produce estimates of current-quarter GDP that adjust in response to new data.

We compare estimates from the KC Fed model to estimates from two other real-time tracking models and find that all three models produce relatively consistent estimates provided they share the same target variable (for example, the official estimate of GDP or the underlying trend of GDP more relevant for predicting future macroeconomic conditions). By combining estimates from models with different target variables, the KC Fed model can provide a useful source for understanding both current and future macroeconomic conditions.

Endnotes

[1]In the euro area, the official estimate of quarterly GDP is released six to seven weeks after the end of the quarter. Although GDP is measured on a quarterly basis in the United States and euro area, unofficial estimates of GDP at higher frequencies are available from the private sector (for example, the Monthly GDP series produced by Macroeconomic Advisers in the United States). In addition, some public institutions provide alternative estimates of real activity measures at higher frequencies (for example, the monthly Chicago Fed National Activity Index (CFNAI).

[2]For example, some indicators are released in the first month of the quarter, while others are released in the second month of the quarter.

[3]The KC Fed model does not represent the official view of the Federal Reserve Bank of Kansas City. The model is one input that is included in staff discussion on the current state of the economy.

[4]The nine subcomponents are personal consumption expenditures, business investment in nonresidential structures, business investment in equipment, business investment in intellectual property, residential investment, government spending, exports, imports, and changes in inventories.

[5]The four methods are a moving average from horizons of three to 12 months, exponential smoothing with a smoothing factor between 0.1 and 0.5, a univariate regression with one to 12 lags using the last 24 months of data, and a univariate regression with one to 12 lags using the last 120 months of data.

[6]The BEA's accounting framework used to calculate GDP is available at https://www.bea.gov/resources/methodologies/nipa-handbook, and the KC Fed's accounting-based model follows these guidelines as much as possible.

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