

Massive Job Losses

COVID-19 has hit the labor market to an unprecedented extent.



Note: Nonfarm payroll employment, month-over-month change, seasonally adjusted, in thousands, 2010–2020

Source: Bureau of Labor Statistics.

Tracking U.S. Real GDP Growth During the Pandemic

COVID-19 has wreaked economic havoc with remarkable speed, which is why it's so important for policymakers to know what's happening to the economy in real time.

BY JONAS ARIAS AND MINCHUL SHIN

COVID-19 has caused a public health and economic crisis across the globe. As scientists fervently search for an effective treatment and a vaccine, policymakers are implementing policies to dampen the economic hardship experienced by households and firms.

Such policies are more likely to succeed if their design reflects current economic conditions, but policymakers often find it difficult to learn about the economy in real time—even more so when a new and unpredictable disease has caused nearly all economic indicators to shatter long-standing records. For example, in April alone the U.S. economy lost as many jobs as had been gained during the previous decade. The labor market perked up in May and June, but it's still too soon to accurately estimate when employment will return to pre-COVID-19 levels.

Earlier this year, professional forecasters agreed that real gross domestic product (GDP) would shrink in the second quarter, but by how much? Answering this question precisely in real time is challenging, but it is feasible to produce estimates based on econometric analysis.¹

Policymakers have three types of state-of-the-art measures of current economic conditions. First, there are real-time estimates

of the pace at which real GDP is increasing or decreasing, such as the Atlanta Fed GDPNow and the New York Fed Staff Nowcast. Second, real-time business conditions indicators provide a signal of the underlying state of the economy, including the Chicago Fed National Activity Index, the Philadelphia Fed Business Conditions Index, and the recently developed New York Fed Weekly Economic Index. And third, there are survey-based estimates of current and future economic activity. Blue Chip Economic Indicators and the Survey of Professional Forecasters both have a long history of conducting and summarizing survey-based forecasts of U.S. economic growth.

Methodology

Although all three types are useful, we adopt the first approach to estimate in real time the pace at which real GDP is increasing or decreasing during the pandemic. This approach offers a simple procedure for quantifying the economic consequences of COVID-19 in real time. Indices of economic activity typically abstract from reporting estimates of real GDP growth, and surveys are generally more expensive to conduct and update in real time.

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The backbone of our analysis is a traditional dynamic factor model approach.² Recent extensions of this framework deal with flows of information at different frequencies, turning sparse signals into one aggregate summary statistic at each point in time.³

Our model is similar to the one used by the Philadelphia Fed for its Aruoba-Diebold-Scotti Business Conditions Index.⁴ Accordingly, it includes data on these variables: initial jobless claims, nonfarm payroll employment, real manufacturing and trade industries sales, real personal income excluding current transfer receipts, the industrial production index, and real GDP.⁵ However, we also add raw steel production in order to take into account COVID-19's sudden effect on the production side of the economy. Although we could have incorporated other weekly economic indicators,⁶ we decided to preserve the parsimonious spirit of Aruoba, Diebold, and Scotti's original research.

Using the data and the dynamic factor model, we extract an unobserved factor characterizing the underlying state of the

economy (also known as latent business conditions), and we translate this factor into a real-time estimate of the current pace of real GDP growth. This is commonly referred to as real-time tracking of real GDP growth.⁷

Tracking Real GDP Growth During the First Quarter

Our real-time estimate for the first quarter of 2020 evolved as new information was released from January 30 through April 29. We selected these dates so that our model always provided an estimate of real GDP growth in association with the next release of the Bureau of Economic Analysis (BEA). More specifically, the BEA releases the advance estimate of real GDP in the final week of the month following the end of the quarter for which real GDP is being estimated. For example, on January 30 the BEA released the advance estimate of real GDP growth in the fourth quarter of 2019, and on April 29 it released the advance estimate of real GDP growth in the first quarter of 2020.

Figure 1 shows the evolution of our real-time estimate of real GDP growth in the first quarter of 2020. According to the model, during the first two months of

the first quarter, real GDP was increasing at a pace slightly above 2 percent—similar to the trend growth rate of many forecasters.⁸

On March 19, as the COVID-19 pandemic worsened, California issued the first stay-at-home order in the U.S., and almost all states eventually followed suit. A week later, on March 26, the Bureau of Labor Statistics (BLS) provided a first look at COVID-19's whopping economic impact when it reported that nearly 3.3 million people filed for unemployment insurance during the week ending March 21. Our model translated this bleak picture of the labor market into a 2.9 percentage point decline in the real-time estimate for the annual rate of real GDP growth in the first quarter of 2020.

The data on raw steel production released on March 30 confirmed that the decline in economic activity signaled by the labor market was also being felt across industries that rely on steel and iron as inputs. The model interpreted these data as further signaling a decline in the pace of economic activity, so the real-time estimate dropped to an annualized rate of -0.9 percent.

Three days later, the BLS reported that the number of initial jobless claims filed for the week ending March 28 had reached

See [Real-Time Tracking of Real GDP Growth and A Brief Literature Review](#).



Real-Time Tracking of Real GDP Growth

We use the term *real-time tracking of real GDP growth* to refer to economic predictions of the near past, present, or immediate future.¹³ We will also use the term to refer to the system of methods developed to generate such predictions. This methodological approach is particularly important because economic data are often released with a lag. For example, given how hard it is to summarize and combine economic information from different economic sectors, it takes roughly a month for the BEA to release the initial official estimate (known as the advance estimate) of the rate at which GDP contracted or expanded in the preceding quarter.¹⁴

Any model for tracking real GDP growth in real time is a function that inputs from the vast and continuously evolving economic data and outputs the current estimate of a variable, such as inflation or real GDP growth. In our study, the function is the small-data dynamic factor model and the inputs are the seven variables we previously described. Consider a hypothetical example in which the goal is to estimate real GDP growth during period $[t_0, t_1]$ using information from $t_0 + \Delta_0$ until $t_1 + \Delta_1$.¹⁵ As new data become available for each of the input variables at any given point during the period $[t_0 + \Delta_0, t_1 + \Delta_1]$, we feed it into a function that returns the best guess of the target variable; that is, the estimate that minimizes the expected prediction errors associated with our tracking estimates. Hence, real-time tracking of real GDP growth is a sequential process.

A Brief Literature Review

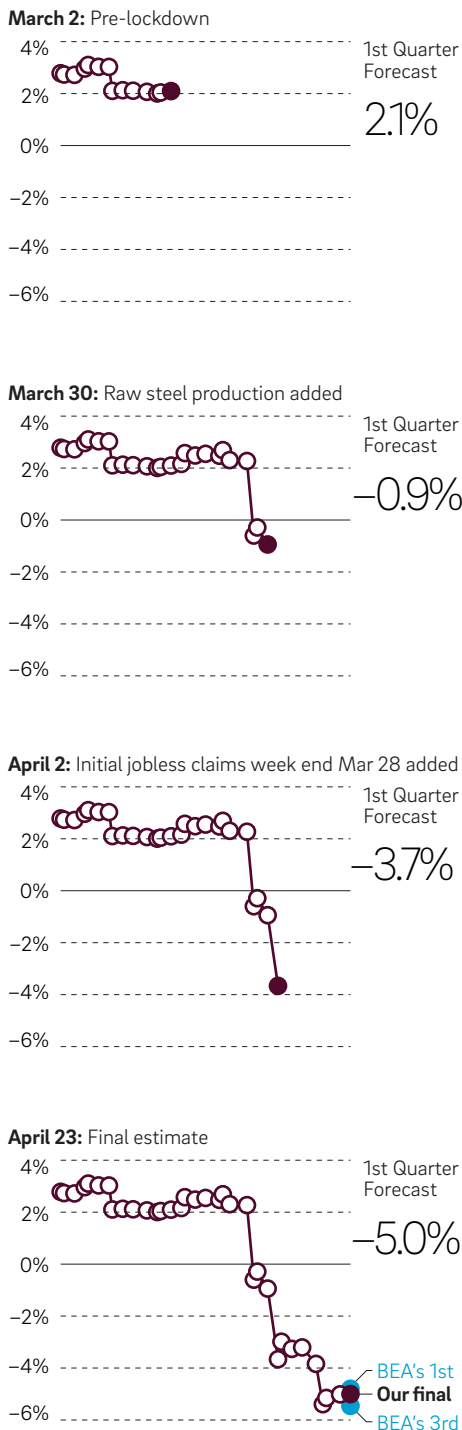
How can we improve the quality of our real-time estimate for the current level of the nation's output growth using mixed-frequency data? The Federal Reserve System has taken the lead in addressing this important question. Early examples include Corrado and Greene (1988), Trehan (1989), Fitzgerald and Miller (1989), and Zdrozny (1990). Economists use two classes of econometric models to track real GDP growth.¹⁶ The first class is called partial modeling; the second, full modeling. Partial modeling focuses on how the set of predictors affects the target variable. Full modeling characterizes a complete joint relationship among the variables under consideration.¹⁷ The former is computationally simpler and robust to a model misspecification, as it considers a minimal set of relationships among variables to generate an estimate for the target variable. However, because it does not use the full relationship among variables, the former can be less efficient than the latter.¹⁸ Economists disagree regarding which approach is consistently superior.

FIGURE 1

Evolution of Real-Time Estimate of Real GDP Growth in 1Q2020

As new information became available, model's estimate approached BEA advance estimate.

Estimated percent change in GDP at an annual rate, 1Q2020



Source: All data from FRED, Federal Reserve Bank of St. Louis (<https://fred.stlouisfed.org/>), except raw steel production (from American Iron and Steel Institute), downloaded from Haver Analytics.

an all-time high of 6.6 million. We fed these data into our model, and our estimate for the annualized rate of real GDP growth in the first quarter of 2020 declined 2.7 percentage points to -3.7 percent.

As new data became available, our estimate hovered between -3 and -4 percent—until the April 15 release of industrial production data for March 2020, which lowered our estimate to -5.4 percent. Thereafter, new data pushed the real-time estimate of real GDP growth up, not down.

Our final estimate using data as of April 23 was -5.0 percent. This is remarkably close to the BEA's advance estimate of -4.8 percent (on April 29) and third estimate of -5.0 percent (on June 25), but more analysis is needed before we can draw conclusions about the predictive performance of our parsimonious model.

Regardless, as new information became available, our model's estimate approached the BEA advance estimate. This is a typical feature of models tracking real GDP growth: As the information set increases, the estimates become more accurate, on average.⁹ To see this more clearly, we computed the prediction errors (that is, the absolute value of the difference between the estimate and the realized value of real GDP growth in the first quarter of 2020), and report them in Figure 2. For ease of exposition, we focus on the prediction errors associated with

the economic releases starting on March 16 and until our final estimate on April 23. Clearly, the most accurate estimate is associated with the final date shown in the chart.¹⁰

Tracking Real GDP Growth During the Second Quarter

Figure 3 tracks the evolution of the real-time estimate for the annual rate of real GDP growth in the second quarter of 2020, starting on April 29—that is, starting on the day the BEA released the advance estimate of real GDP growth in the first quarter of 2020. The initial estimate for real GDP growth in the second quarter was a seasonally adjusted annual rate (SAAR) of -7.6 percent. During subsequent days, we updated the model with initial jobless claims for the weeks ending April 25 and May 2, raw steel production for the week ending May 2, and real personal income and real manufacturing and trade industries sales for March. None of these releases had a significant impact on the initial estimate for the second quarter: On May 7—the eve of the release of the much-anticipated April labor report—the prediction was the same as when we began tracking the second quarter.

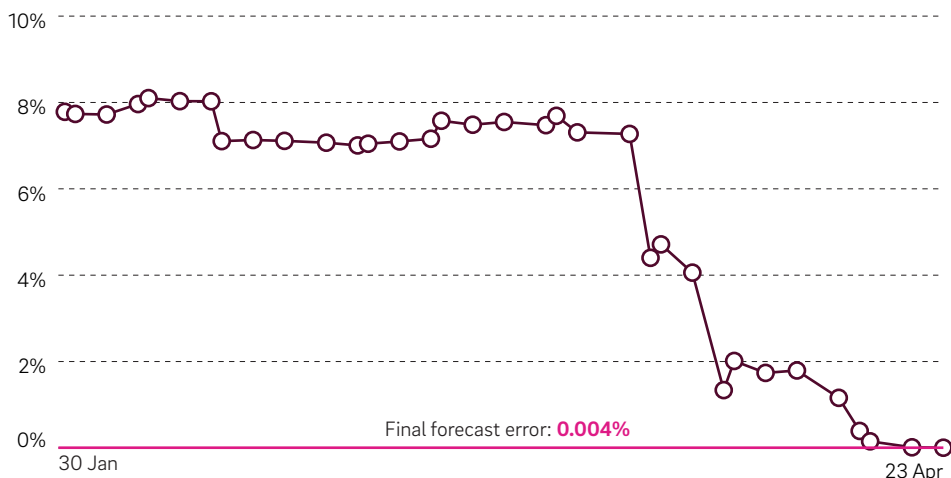
During the second week of May, the estimate plunged due to the dreary

FIGURE 2

Prediction Errors of Real-Time Estimate of Real GDP Growth in 1Q2020

Forecast error shrinks to near 0 by end of quarter.

Absolute value of the difference between estimate and realized value of real GDP growth at an annual rate in 1Q2020

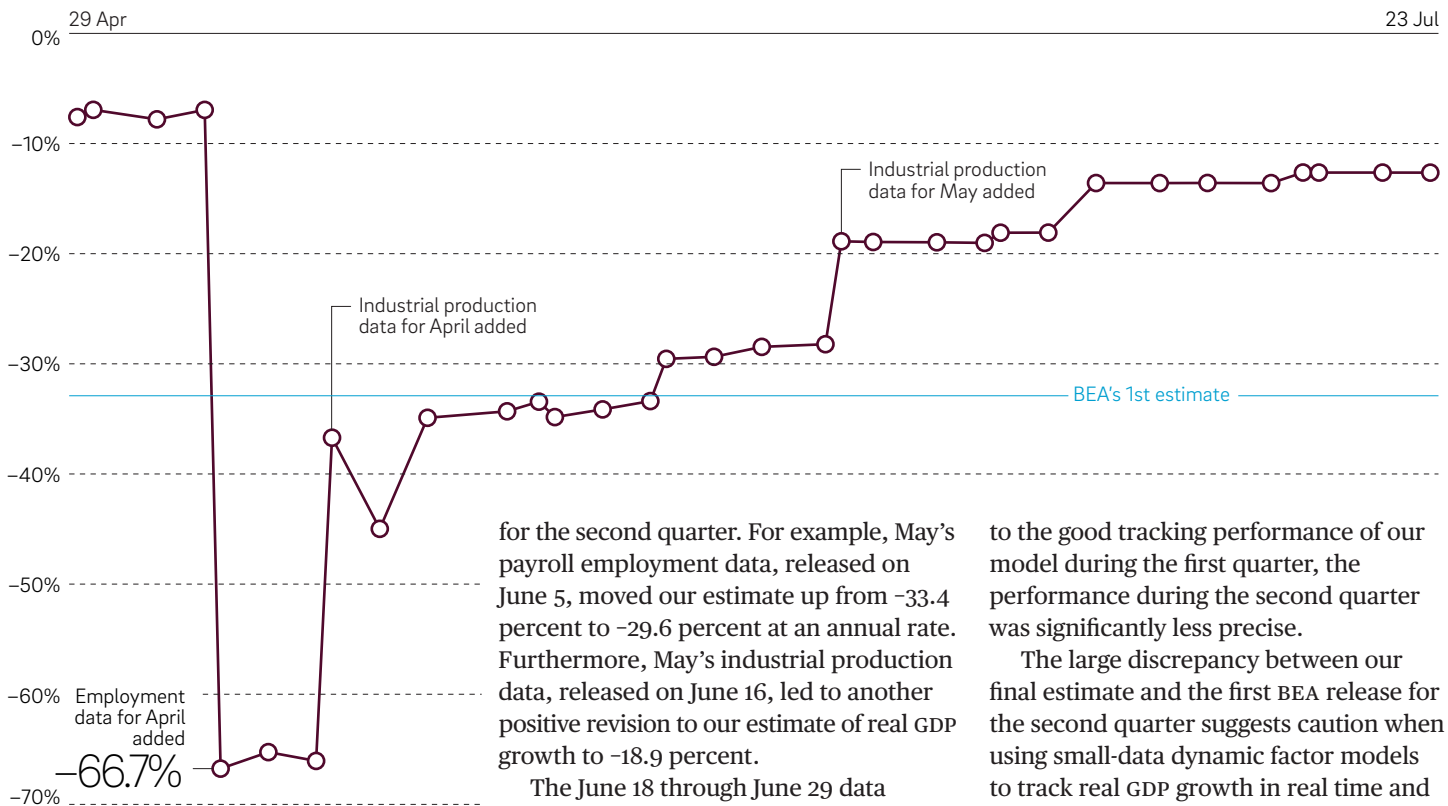


Source: FRED, Federal Reserve Bank of St. Louis (<https://fred.stlouisfed.org/>); authors' calculations.

FIGURE 3

Evolution of Real-Time Estimate of Real GDP Growth in 2Q2020

Changes in estimate reflect addition of labor and production data.
Estimated percent change in GDP at an annual rate, 2Q2020



Source: FRED, Federal Reserve Bank of St. Louis (<https://fred.stlouisfed.org/>); authors' calculations.

employment data: The employment situation summary released by the BLS on May 8 showed an unprecedented decline in nonfarm payroll employment, proof that the COVID-19 crisis had erased all the job gains since the Great Recession.

In the face of such a stunning decline in the growth rate of payroll employment, and in the absence of other monthly indicators to put the labor market data into perspective, the real-time estimate declined to an annual growth rate of -66.8 percent. Weekly data on raw steel production and initial jobless claims did not change this dramatic estimate.

The May 15 release of industrial production for April 2020 offered a less gloomy picture of the economy than the monthly labor market data. As a result, the model upwardly revised our estimate to -36.7 percent at an annual rate. Subsequent data releases from May 18 through June 5 induced further upward revisions in the estimated growth rate of real GDP

for the second quarter. For example, May's payroll employment data, released on June 5, moved our estimate up from -33.4 percent to -29.6 percent at an annual rate. Furthermore, May's industrial production data, released on June 16, led to another positive revision to our estimate of real GDP growth to -18.9 percent.

The June 18 through June 29 data releases of initial claims, raw steel production, real manufacturing and trade sales (for April), and real personal income excluding transfers (for May) did not induce significant revisions to our estimates of real GDP growth. This is because such data releases were in line with the predictions of the model. In contrast, the positive June payroll employment report (released on July 2) was a surprise for the model, leading to a positive revision of our estimate of real GDP growth of nearly 5 percentage points.

Subsequent data releases from July 6 until July 23 continued to indicate (through the lens of our model) that the decline in real GDP during the second quarter was not likely to be as dramatic as our tracking estimates of the second week of May (i.e., about -67 percent at an annual rate).

In sum, our model's final estimate of real GDP growth during the second quarter of 2020 was -12.6 percent at an annual rate, about 20 percentage points more optimistic than the first estimate of real GDP growth for the second quarter released by the BEA on July 30. In contrast

to the good tracking performance of our model during the first quarter, the performance during the second quarter was significantly less precise.

The large discrepancy between our final estimate and the first BEA release for the second quarter suggests caution when using small-data dynamic factor models to track real GDP growth in real time and at high frequency during a pandemic. In particular, our conjecture is that the model puts more weight on recent data and hence the bad April data are downplayed relative to the good May and June data. We believe that this may be a feature of other types of econometric models relying on dynamic factors or vector autoregressions with mixed-frequency data. Consequently, we view our results as calling for further scrutiny of the ability of econometric models with mixed-frequency data to track real GDP growth at times of high economic uncertainty.


Conclusion

In addition to the large prediction error for the second quarter, our real-time estimates of real GDP growth were subject to large changes within the quarter. These swings could be interpreted as another undesirable consequence of tracking real GDP growth using small-data dynamic factor models. In particular, given that the model takes a signal about the state of the economy from each of the seven input variables, an unusually large variation in

one variable could cause the model to significantly change the assessment of current macroeconomic conditions. Including additional variables should shrink each variable's average contribution. For example, the model used for the New York Fed Nowcasting Report includes 37 variables.¹¹ Even so, the case against small-data approaches is not yet settled. Using more predictors doesn't necessarily lead to better forecasting.¹² Furthermore, estimates tend to stabilize as more information becomes available.

If the estimates are subject to large variations at the beginning of the quarter, when can policymakers start relying on them with confidence? Several researchers have been trying to answer this question by evaluating the out-of-sample performance of estimates generated by their models. For example, Giannone, Reichlin, and Small (2008) show that their model performs better than a no-change (random walk) forecast starting on the beginning of the second month, and it clearly has a 20 percent smaller root mean square forecast error from the middle of the second month.

Whether these results apply to our model is a question for future research, but the discussion above highlights the fact that policymakers may face an important trade-off: Either they can swiftly respond with policies conditional on a less-accurate estimate of the state of the economy, or they can delay taking action until the current state of the economy becomes clearer.

Last, the actions of policymakers affect real GDP growth. Hence, at least part of the swings in the real-time estimates of the pace at which the economy is growing is due to policy responses to shocks. Determining which fraction of the final value of real GDP growth in a given quarter is due to economic shocks and which is due to policy responses to such shocks is an active research area in economics. 

Notes

1 The term “econometrics” as we know it today was coined by Ragnar Frisch, who shared the first Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel with Jan Tinbergen in 1969. In Frisch’s words: “Intermediate between mathematics, statistics, and economics, we find a new discipline which for lack of a better name, may be called econometrics.” See Bjerkholt (1995) for additional details about the term.

2 Dynamic factor models (DFMs) are econometric models whose distinctive premise is that a few unobserved (latent) variables can explain the comovement of a larger number of observed variables. See Geweke (1977), Sargent and Sims (1977), and Stock and Watson (1989).

3 See Aruoba, Diebold, and Scotti (2009), Modugno (2013), and Bańbura et al. (2013).

4 For more on this small-data dynamic factor model, see Aruoba, Diebold, and Scotti (2009).

5 All input variables except for initial jobless claims and raw steel production enter the model in log first differences. We normalize initial jobless claims by a weekly estimate of the population, and take the natural logarithm to the resulting threshold. Finally, raw steel

production enters the model in levels. Both types of variables (that is, those that are transformed and those that enter in levels) are standardized before entering the model. All data are from FRED at the Federal Reserve Bank of St. Louis, except for raw steel production (from the American Iron and Steel Institute), which we downloaded from Haver Analytics.

6 See the list of variables used by the New York Fed Weekly Economic Index.

7 We decompose the growth rate of the quarterly flow variables into the quarterly sum of daily differences of latent quarterly growth rates. An alternative option is to approximate the growth rate of the quarterly flow variables with the quarterly sum of daily log difference, following Mariano and Murasawa (2003). Such a modelling approach delivers more negative real-time estimates for the sample period under consideration.

8 See, for example, the first-quarter 2020 Survey of Professional Forecasters.

9 See Giannone, Reichlin, and Small (2008).

10 This is in line with Giannone, Reichlin, and Small (2008), whose finding is based on the

root mean squared prediction error computed using the evaluation sample from the first quarter of 1995 to the first quarter of 2005. Our Figure 3 is based on the absolute value of prediction errors computed using one evaluation sample point.

11 See Bok et al. (2018).

12 See Boivin and Ng (2006) and Bai and Ng (2008).

13 See Bańbura et al (2013).

14 For example, the BEA didn't release GDP data for the first quarter of 2020 until April 29, 2020.

15 For example, in our application for the first quarter of 2020, t_0 refers to January 1, t_1 refers to March 31, $t_0 + \Delta_0$ refers to January 30, and $t_1 + \Delta_1$ refers to April 23.

16 See Bańbura et al. (2013).

17 Examples of partial modeling include bridge equation regressions (e.g., Trehan [1989]) and mixed data sampling (MIDAS) regressions (e.g., Ghysels, Santa-Clara, and Valkanov [2004], Clements and Galvão [2008], and Marcellino and Schumacher [2010]). Full modeling

approaches include mixed-frequency vector autoregression (e.g., Zdrozny [1990], Eraker et al. [2015], and Schorfheide and Song [2015]) and a mixed-frequency dynamic factor model (e.g., Liu and Hall [2001], Mariano and Murasawa [2003], and Giannone, Reichlin, and Small [2008]). Economists have authored many academic papers on real-time tracking of real GDP growth based on those models. Here, we list just a few early papers on the topic. For a complete list of papers, see, for example, Bańbura et al. (2013).

18 See Bai, Ghysels, and Wright (2013).

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