8-24-2020

Nowcasting the Great Recession in **Alternative Economic Indicators**

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Alternative Economic Indicators

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2020

W.E. Upjohn Institute for Employment Research
Kalamazoo, Michigan

Copyright Page

ISBN 9780880996778 (ebook)

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Kalamazoo, Michigan 49007-4686

Cover design by Carol A.S. Derks.

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Economists at policy institutions, trading desks, and media outlets rely on economic data produced by various statistical agencies to understand the state of the economy and predict its future path. However, the highest-quality and most comprehensive economic data are published with long delays after the periods to which they refer. Most notably, gross domestic product (GDP), the most comprehensive measure of U.S. economic activity, is first published by the Bureau of Economic Analysis (BEA) one month after the end of each reference quarter, and these initial estimates are later revised.

Faced with the challenging task of monitoring macroeconomic conditions in real time, analysts track a wide variety of data releases, distilling signal from noise in incoming data and revising their beliefs about the state of the economy when these data diverge significantly from their expectations. The Nowcasting Report of the Federal Reserve Bank of New York (the New York Fed Staff Nowcast) formalizes and automates this process through an econometric model–based approach. The platform produces *nowcasts* of economic activity—predictions for the present, recent past, and near future—which are continually updated as new data become available. The platform's nowcasts of real GDP growth can be computed before the start of the reference quarter and updated each day to incorporate the most recent information, providing useful real-time readings on the state of the economy that can be used to guide key policy and private-sector decisions.

In this chapter, we provide a brief overview of the general challenge of monitoring macroeconomic conditions in real time and the methods underlying the New York Fed Staff Nowcast. We then present two case studies that assess the ability of the New York Fed Staff Nowcast to provide accurate early estimates of GDP during important real-world situations.

First, we study the day-by-day movements in the GDP growth nowcast during two critical quarters of the 2007–2009 recession. The model is able to predict major swings in economic activity (both upward and downward) long before the publication of the first official GDP estimates, providing confidence in its ability to track business cycle fluctuations.

Second, motivated by extensive data publication delays resulting from the 2018–2019 partial shutdown of the U.S. federal government, we conduct a counterfactual exercise to evaluate the performance of the nowcast during periods of severe yet realistic disruptions to the standard flow of macroeconomic data. Even during such periods, the nowcast can predict GDP growth with an accuracy comparable to the BEA's first official estimate; in particular, it can serve as a useful substitute for the official estimate if it is not published according to schedule (as was the case in early 2019).

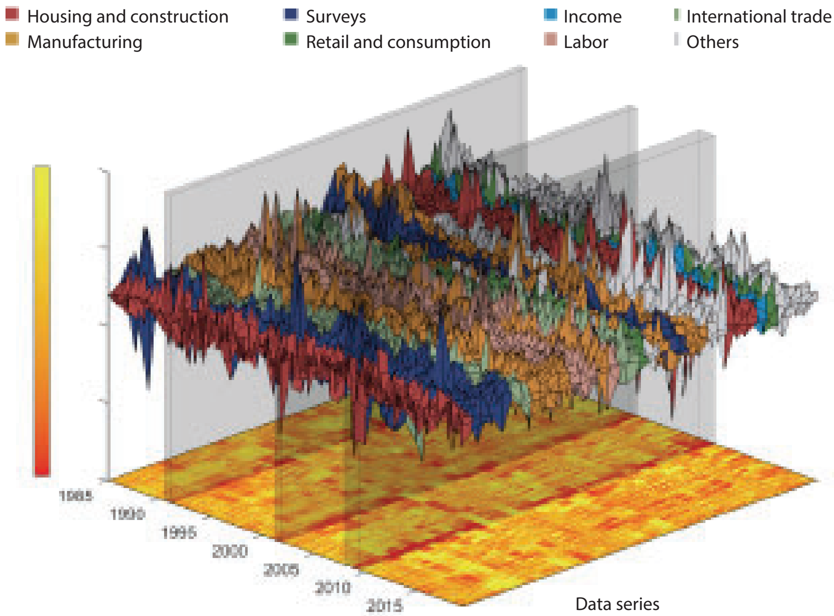
THE REAL-TIME DATA FLOW

As mentioned, in order to understand the state of the economy in real time, economists must extract signal from noise in a broad set of economic data. At any given point in time, economists face a trade-off between timeliness and quality when evaluating the most recent available data for each indicator. Business and consumer sentiment indicators—often referred to by market commentators as *soft data*—provide the first readings on economic activity during a particular reference period. Labor market indicators typically arrive next; most notably, the widely followed Employment Situation Report, released by the Bureau of Labor Statistics (BLS), provides estimates of the unemployment rate and payroll employment shortly after the end of the month to which the new data refer. Hard data on production, sales, and income begin to arrive several weeks later. Finally, the first estimate of gross domestic product—the total value of all goods and services produced in the United States over a given quarter—is published by the Bureau of Economic Analysis (BEA) roughly one month after the end of the reference quarter. Data of the highest quality and broadest coverage are thus only available well after the end of the period to which they refer.

The trade-off between timeliness and accuracy is present not only across different economic indicators, but also across different releases for the same indicator. In the case of GDP, the BEA produces benchmark estimates every five years that rely on data collected through a comprehensive economic census, covering around seven million businesses with paid employees and over 95 percent of the expenditures included in GDP. Between these benchmark estimates, annual and quarterly estimates are constructed using surveys conducted by the Census Bureau—with 150,000 and 35,000 reporting units, respectively—as well as administrative data (such as those from the Internal Revenue Service) and estimates from other sources (such as BLS employment data). In short, these benchmark revisions are the product of careful aggregation of detailed microeconomic information into national accounts. In contrast, the "advance" GDP release is the first official estimate available, with only a one-month delay. It is constructed using only half of the hard expenditure data ultimately used in the benchmark revisions and relies heavily on survey data gleaned by the Census Bureau. As a result of these unavoidable shortcuts required to produce timely estimates, these first estimates of GDP are subject to sizable revisions as higher-quality source data become available. What is gained through detailed microeconomic information is lost in timeliness.

With new data being released almost every day, and each release providing estimates for a large number of variables over a single reference period, economists face a big-data problem when attempting to monitor economic conditions. As an illustration, Figure 4.1 provides a useful visualization of the data at our disposal. The three-dimensional surface plot displays the path of 37 major economic indicators since 1985, with each data series colored according to its category.[1] The heat map on the horizontal plane presents a two-dimensional visualization of the same data: brighter yellow values indicate realizations above the sample mean for a given series, while darker red values indicate realizations well below the mean. The dark red areas are especially preva-

Figure 4.1 Big Data in Macroeconomics



NOTE: The three-dimensional surface plot displays the standardized time series for the major economic indicators since 1985, which are shaded by category as indicated in the legend. Recessions are marked by transparent gray surfaces. The heat map on the horizontal plane shows positive and negative readings of the data.
SOURCE: Authors' calculations, based on data accessed through Haver Analytics and the Federal Reserve Economic Database (FRED).

lent across many series during the recessions of the early 1990s, early 2000s, and (most notably) 2008 through 2009. In these periods, broad red strips across the heat map highlight the common downward movement across many series. However, despite the stark common movements across these series during both recessions and expansions, at any given point in time there are also individual series whose movements deviate from the others.

NOWCASTING

Nowcasting refers to the process of monitoring economic conditions by forming predictions for economic activity in the present, recent past, and near future. Nowcasting is a big-data problem, given the vast array of macroeconomic data at our disposal. The New York Fed Nowcast summarizes the rich and complex dataset depicted in Figure 4.1 using a parsimonious model motivated by the strong comovements evident among the series. The model formalizes the notion of a common business-cycle component present across all of these series and allows one to distill signal from noise by filtering out fluctuations specific to individual variables from incoming data.

The New York Fed Staff Nowcast is based upon a dynamic-factor model, which solves the "large *n*, small *T*" problem of relatively few time observations *T* compared to the large number of available data series *n*. It does this through dimension reduction: a small number of unobserved common factors are used to summarize the bulk of fluctuations in the observed variables. Forni et al. (2000) and Stock and Watson (2002a,b) presented the first applications of dynamic-factor models to large macroeconomic data sets, while Giannone, Reichlin, and Small (2008) demonstrate that these models can be used to reliably predict GDP growth in real time. Over the past decade, nowcasting models have been developed for many countries (see Bańbura et al. [2013] and Bok et al. [2018] for a survey).The dynamic-factor model can be easily cast in state space form, allowing for efficient estimation of both unknown parameters and unobserved common factors using the Kalman filter (Bańbura and Modugno 2014; Doz, Giannone, and Reichlin 2011). Moreover, the process by which the model's GDP growth forecasts are updated upon the release of new data can be interpreted in an intuitive manner that mimics market participants' processing of information. Before each data release, a new value is predicted for each variable based on previously available information. Once the new data are released, the model updates its forecast for GDP growth based on the discrepancy between predicted and realized values of all the variables; we refer to this discrepancy as *news*. If the model's predictions for each variable are exactly correct, its GDP growth forecast will remain unchanged, just as market participants would not revise their beliefs about the state of the economy in the absence of news. On the other hand, if the model's predictions are not exactly correct, its GDP growth forecast will be revised to account for the news, just as market participants who observe stronger- or weaker-than-expected data would revise their beliefs about the state of the economy accordingly.

More formally, revisions to the model's GDP growth forecasts are simply a weighted sum of news across all data releases. The sign of these weights encodes whether a higher-than-expected value for each release represents "good" or "bad" news (e.g., payroll employment versus the unemployment rate). The magnitude of the weights encodes the overall information content that the news provides on economic conditions in a particular period, taking into account factors like timeliness and the extent to which each variable is driven by common versus idiosyncratic fluctuations. The model is thus able to determine which data releases are most important for monitoring current economic conditions, just as market participants place greater emphasis on some data releases than others (as evidenced by sharp asset price movements typical upon the release of closely followed indicators like GDP).

The New York Fed Nowcast therefore provides a platform for interpreting the flow of data in real time. By determining each new observation's impact on predicted GDP growth, the model provides a "common unit" for comparing news across series like payroll employment and the unemployment rate. Additionally, the GDP growth forecasts are updated in a fully automated and judgment-free manner, allowing for continuous updates as soon as new information becomes available. And, these forecasts are available well before the publication of the first official estimate, which occurs one month after the end of each reference quarter. A detailed description of the model and the data is provided in Bok et al. (2018).

REAL-TIME ESTIMATES: TWO CASE STUDIES

We now present two case studies that illustrate the real-time performance of the New York Fed Staff Nowcast in two scenarios in which early and accurate GDP estimates serve a particularly important role in both policy and private-sector decision making. For both of these case studies, we make use of a daily real-time database that tracks the exact data available for each of the model's 37 input series on each date from October 1, 2001, to the present. By using real-time data to recursively estimate the model's parameters at the start of each quarter and update the GDP growth estimates using the new data available on each date, we are able to exactly reconstruct the estimates that forecasters would have obtained using our model in the past. Complete archives of both the reconstructed and real-time New York Fed Staff Nowcast estimates are available to the public and are described in Adams, Giannone, et al. (2019).[2]

Nowcasting the Great Recession

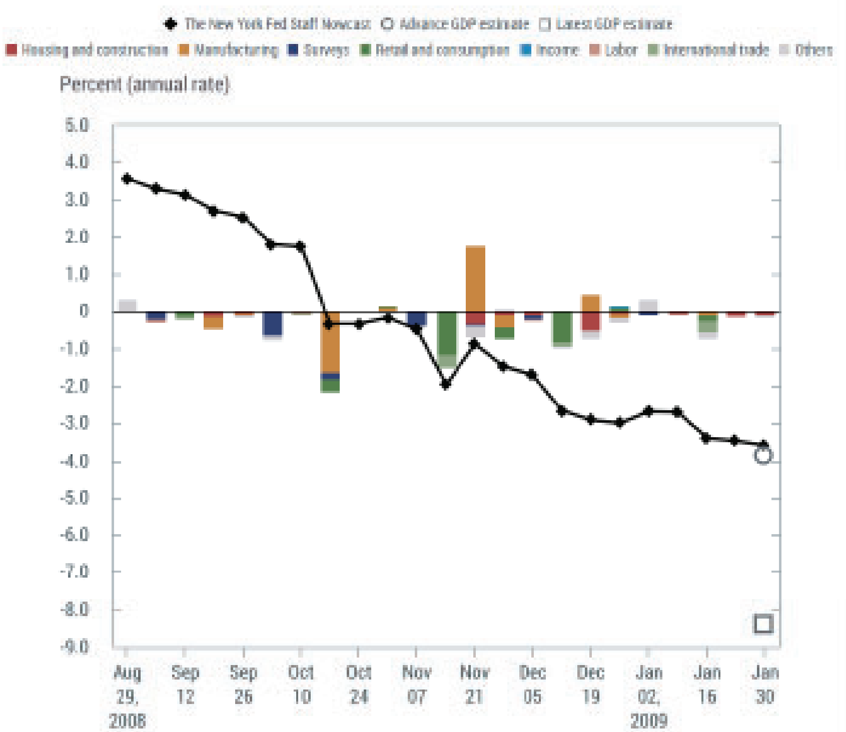
In our first case study, we track the day-by-day movements in the nowcast for GDP growth during two critical quarters of the 2007–2009 recession. The fourth quarter of 2008 saw the sharpest decline in real economic activity, while the third quarter of 2009 marked the end of the recession and the beginning of the recovery. For both quarters, we chart the progression of the GDP growth nowcast (represented by black diamonds), starting one month before the start of the quarter and ending one month after the end of the quarter after the BEA publishes the first official GDP estimate. Colored bars denote the overall contributions of data releases from different categories—surveys, retail and consumption, and more—to the weekly changes in the nowcast, based on the decompositions described in the second section. For comparison against official estimates, we also plot both the BEA's first and latest estimates for each quarter.[3]

The fourth quarter of 2008 was the worst of the recession, with real GDP contracting by 8.4 percent. On September 12, 2008 (right before the failure of Lehman Brothers was announced on September 15), our forecast for GDP growth for the fourth quarter of 2008 actually stood at a promising 3.1 percent. This estimate quickly changed as data on business sentiment, industrial production, and retail sales for the month of September became available, and our nowcast first dropped into negative territory roughly one month after Lehman Brothers' bankruptcy on October 17. The National Bureau of Economic Research (NBER) Recession Dating Committee officially announced on December 1, 2008, that the economy had been in recession for the past 12 months.

On the previous Friday, our nowcast for GDP growth in 2008:Q4 was −1.5 percent (Figure 4.2). Additional negative data releases over the next two months led to further declines in our nowcast, until our final prediction sank to −3.6 percent immediately before the advance GDP release in January 2009. Although we predicted the BEA's advance estimate almost exactly, this first estimate understated the severity of the contraction and was later revised downward substantially.

The third quarter of 2009 marked the end of the recession, as determined by the NBER Recession Dating Committee one year later. At the start of the quarter in July, our nowcast still predicted slightly negative GDP growth. However, over the next few months, a wide variety

Figure 4.2 Nowcasting the Great Recession in 2008:Q4

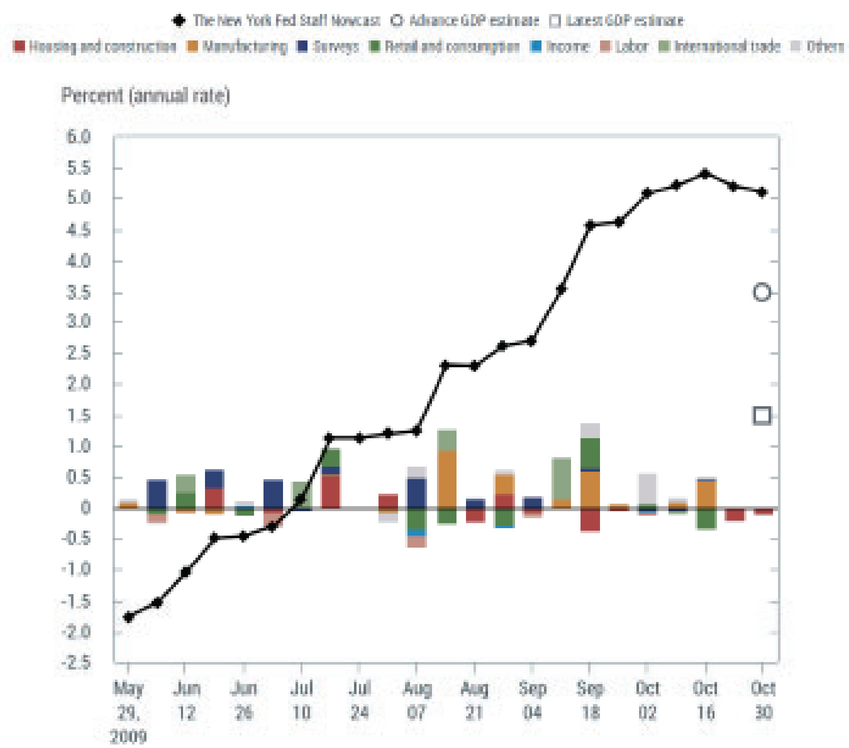


NOTE: Colored bars reflect the impact of each data release on the nowcast.
SOURCE: Authors' calculations, based on data accessed through Haver Analytics.

of better-than-expected data was released (especially for manufacturing, international trade, and business sentiment), and our nowcast for 2009:Q3 GDP growth (Figure 4.3) rose to over 5 percent by the end of the quarter. Our model successfully predicted the timing of the recovery but turned out to be overly optimistic in predicting its strength: the advance estimate of GDP growth in 2009:Q3 was 3.5 percent, but this estimate was later revised downward, as the latest available estimate reported growth of only 1.5 percent.

For both of these important quarters, the nowcast provided an early and reliable signal of the direction in which growth was headed, months before the publication of the first official estimate. These results provide

Figure 4.3 Nowcasting the Recovery in 2009:Q3



NOTE: Colored bars reflect the impact of each data release on the nowcast.
SOURCE: Authors' calculations, based on data accessed through Haver Analytics.

confidence that the New York Fed Staff Nowcast can provide useful early readings on upward and downward swings in activity by filtering through a variety of incoming data ahead of the publication of official GDP estimates. The large revisions from the first to the latest published estimates show that producing estimates with both minimal delay and high precision is a challenge even for the BEA. The contribution of the New York Fed Staff Nowcast is to extend the "accuracy timeliness" frontier in the period before official statistics are available.

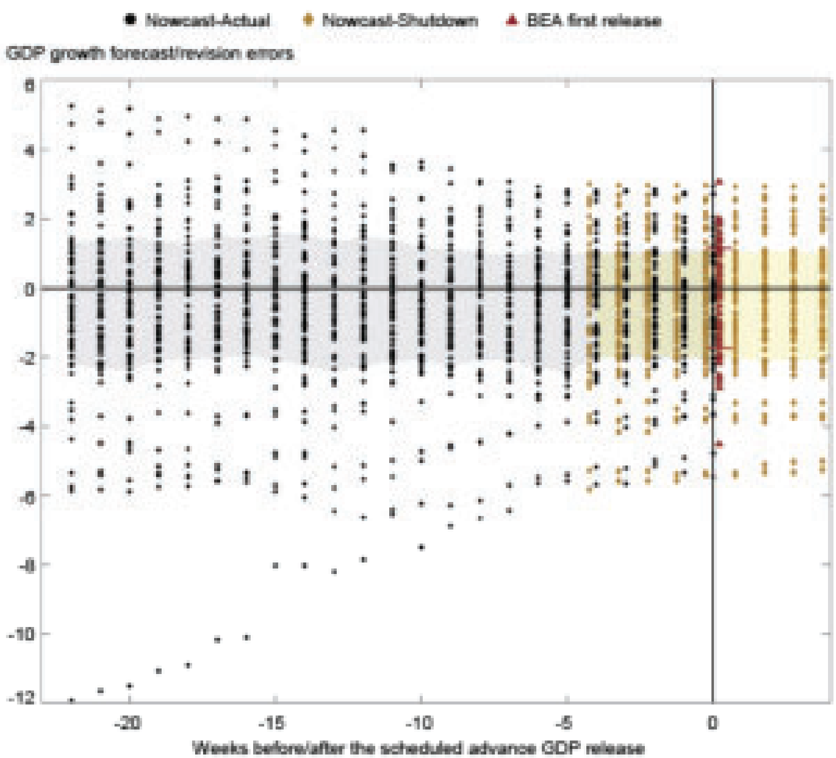
Nowcasting with Scarce Data

In our second case study, we evaluate the performance of the nowcast during periods of severe yet realistic disruptions to the standard flow of macroeconomic data. This exercise is motivated by the 2018−2019 U.S. federal government partial shutdown, during which the temporary closure of the Census Bureau and the Bureau of Economic Analysis delayed the publication of many scheduled data releases. While the most notable delayed release was the first estimate of 2018:Q4 GDP (which was postponed by one month), many other widely followed indicators of economic activity were released with substantial delays, including retail sales, home sales and construction, imports and exports, and durable goods orders.[4] However, a variety of other data sources—both hard data directly measuring activity and soft data measuring business sentiment—were published as previously scheduled.

Do such disruptions to the regular data publication schedule impair the ability of the New York Fed Staff Nowcast to accurately predict GDP growth? To answer this question, we conduct a counterfactual exercise in which we simulate similar dataflow disruptions for each quarter from 2002:Q1 to 2017:Q4, as if the Census Bureau and BEA had ceased publication of all new data releases starting one week before the end of the quarter. We assume that data previously published by these agencies remain available, and that new data published by other government agencies and private organizations become available as they are released in real time. We then evaluate the performance of our nowcasting model in this "scarce data" setting by studying the empirical distribution of its forecast errors for GDP growth, which provides a complete description of its historical forecasting performance.

Figure 4.4 plots GDP growth forecast errors for all quarters in our evaluation sample, based on the number of weeks remaining until the first GDP release at the date of each forecast (listed across the horizontal axis). The black dots represent the historical forecast errors for our nowcasting model (using the actual data available in real time),

Figure 4.4 Similar Data Delays Would Not Have Drastically Changed Past Predictions



NOTE: Points represent quarterly GDP growth forecast errors (for Nowcast-Actual and Shutdown) and revision errors (for the Bureau of Economic Analysis first release), computed with respect to the latest available estimates for the years 2002 through 2017. Shaded bands depict the 16th and 84th percentiles of the historical forecast errors, while the red lines at week 0 depict the same percentiles for revisions to the first release.

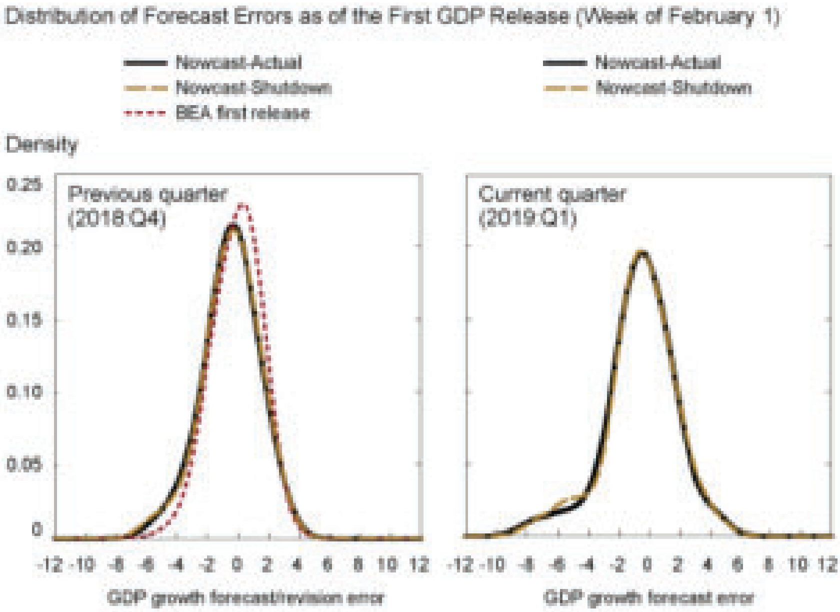
SOURCE: Authors' calculations, based on data accessed through Haver Analytics.

computed using the latest available GDP growth estimates.[5] The gold diamonds represent our model's forecast errors under the counterfactual scenario when key data releases are delayed, starting roughly four weeks before the first GDP release. The red triangles represent revision errors, from the first estimate published by the BEA for each quarter to the latest available estimates. Shaded bands depict the 16th to 84th percentile range of the errors for each forecast, while the red line on the week of the first GDP release depicts the same range for revision errors from the BEA's first to latest releases; these ranges provide an assessment of uncertainty for each of the three forecasts.

Overall, the model's forecasts for GDP growth remain accurate even when there are substantial disruptions to the usual pattern of data availability. For the weeks leading up to the first GDP release, the historical forecast error distributions represented by the black and gold markers are broadly similar, indicating that the accuracy of the nowcast is mostly unchanged when new Census Bureau and BEA data releases are not published. Moreover, under these conditions, the gold uncertainty bands reported for the nowcast are similar in width to the red bar at the week of the first GDP release, depicting uncertainty around this estimate. Therefore, the finding of Bok et al. (2018)—that uncertainty is similar around both the final nowcasts for a given quarter and the first GDP release—still holds, even when important data are not released according to their usual schedule, as was the case during the 2018–2019 federal government shutdown. Moreover, if the first release of GDP also happens to be delayed during these periods, the nowcast provides an alternative estimate of GDP growth of comparable accuracy to the first release.

Figure 4.5 presents an alternative visualization of the forecast error distributions for the nowcast (both the actual historical forecast errors and the errors under our counterfactual scenario based on the government shutdown) and first official GDP release. The left panel depicts the smoothed empirical distribution of the three sets of forecast errors plotted along the vertical line at the week of the first GDP release from the previous figure. The right panel depicts the distribution of forecast errors for current-quarter projections at the time of the previous quarter's first GDP release—e.g., the projections for 2019:Q1 GDP growth made near the end of January 2019.

Figure 4.5 Nowcast with Delayed Data Similarly Accurate to BEA First Release

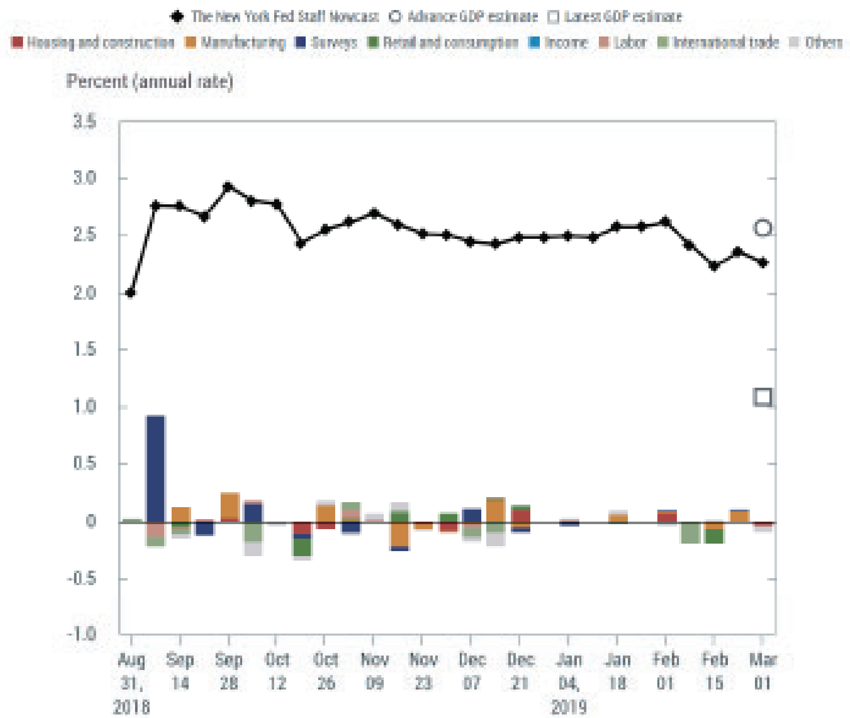


NOTE: The figures report kernel-smoother estimates of forecast error densities as of the scheduled first GDP release (week of February 1, 2019). The left panel gives error distributions for the previous quarter (2018:Q4). The right panel gives error distributions for 2019:Q1. Black lines refer to the actual nowcast errors, gold dashed lines refer to nowcast shutdown errors, and red dotted lines refer to the BEA revision errors.
SOURCE: Authors' calculations, based on data accessed through Haver Analytics.

As noted in the discussion of the previous figure, the three forecast error distributions are broadly similar, indicating that the nowcast provides estimates of GDP growth with comparable accuracy to the first official release, even under conditions of data scarcity similar to those resulting from the 2018–2019 U.S. federal government shutdown. The main differences between these distributions arise from large negative forecast errors, which are more likely to occur for the nowcast than for the BEA estimates. Moving to the right panel, both distributions for the model's longer-horizon forecast errors display greater dispersion than their shorter-horizon counterparts in the left panel, reflecting greater uncertainty when making predictions for the current (as opposed to the previous) quarter. The striking similarity of the model's actual and counterfactual forecast errors reported in the right panel illustrates that data scarcity, similar to the scarcity of data resulting from the 2018–2019 U.S. federal government shutdown, does not blunt the accuracy of early projections for the current quarter.

Finally, Figure 4.6 displays the real-time progression of the GDP growth nowcast for 2018:Q4. The effects of the shutdown-related data publication delays can be seen through the paucity of colorful bars from late December through early January. While our model's prediction was quite close to the first official estimate released in February 2019, the

Figure 4.6 Nowcasting during the Government Shutdown



NOTE: Colored bars reflect the impact of each data release on the nowcast.
SOURCE: Authors' calculations, based on data accessed through Haver Analytics.

latest available estimate is notably lower than both of these early estimates, highlighting the uncertainty about economic activity that prevails even after official statistics are initially published.

CONCLUSION

The New York Fed Staff Nowcast is able to produce accurate and early estimates of real GDP growth well before the publication of the BEA's first official estimates. We presented two case studies that evaluate the model's performance during the Great Recession and during the U.S. federal government shutdown at the beginning of 2019. We encourage interested readers to further study our model by exploring our online interactive archives, which collect both real-time forecasts for the period from 2016:Q1 to the present and reconstructed historical forecasts extending back to 2002:Q1.[6]

Notes

The views expressed in this chapter are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York, the Federal Reserve System, or the Upjohn Institute.

1. The full list of all 37 series is presented in Bok et al. (2018). Each series is appropriately transformed in order to induce stationarity, then standardized so that all variables have the same mean and variance over the sample period.
2. These archives can be explored in interactive form at the following link: https://www.newyorkfed.org/research/policy/nowcast.
3. The latest available estimates are based on data published by the BEA in July 2019.
4. For a full list of data releases delayed because of the shutdown, see Adams, Qian, et al. (2019).
5. We use the latest available estimates, since these reflect both 1) new source data that become available after the publication of the first estimate and 2) methodological changes intended to improve the quality of the estimates.
6. These archives (along with structured data files containing historical forecasts) can be found at the following link: https://www.newyorkfed.org/research/policy/nowcast.

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