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Macroeconomic Nowcasting and Forecasting with Big Data

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Abstract

Data, data, data ... Economists know their importance well, especially when it comes to monitoring macroeconomic conditions—the basis for making informed economic and policy decisions. Handling large and complex data sets was a challenge that macroeconomists engaged in real-time analysis faced long before "big data" became pervasive in other disciplines. We review how methods for tracking economic conditions using big data have evolved over time and explain how econometric techniques have advanced to mimic and automate best practices of forecasters on trading desks, at central banks, and in other market-monitoring roles. We present in detail the methodology underlying the New York Fed Staff Nowcast, which employs these innovative techniques to produce early estimates of GDP growth, synthesizing a wide range of macroeconomic data as they become available.

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"[O]nly by analyzing numerous time series, each of restricted significance, can business cycles be made to reveal themselves definitely enough to permit close observation."

Burns & Mitchell (1946), *Measuring Business Cycles* (p.11)

1 Introduction

For more than a century, government agencies and private institutions have been collecting and organizing information on many facets of the economy, and over time the scope of data collection has grown and the quality of data has improved. Today, data are released to the public on a regular schedule: almost every day new data become available and are analyzed, commented, and interpreted. Real-time monitoring of macroeconomic conditions has become the full-time job of dedicated economists at central banks, at government agencies, and in the corporate world, who sift through big and complex data to distill all relevant information. Releases that come out as surprises move markets, sometimes significantly, as investors reassess their expectations about the state of the economy.

Although the term "big data" typically conjures up the image of data collected via the Internet about individual habits on consumption and social media, big data presented a challenge to macroeconomists well before the collection of more granular data became pervasive in other disciplines. From the pioneering search for patterns and regularities in the data that led Burns and Mitchell to identify the business cycle and the parallel effort of Kuznets to build the National Income and Product Accounts, to the vast array of expert data collection and analysis done today, macroeconomists have embraced the big data challenge, pushing the frontier of statistical methods and refined measurement.

New methodologies in time-series econometrics developed over the past two decades have made possible the construction of automated platforms for monitoring macroeconomic conditions in real time. Giannone, Reichlin & Small (2008) built the first formal and internally consistent statistical framework of this kind by combining models for big data and filtering techniques. Because of the emphasis on the present, they dubbed it "nowcasting," a term originally used in meteorology for forecasting the weather within the next few hours.

As an illustration of nowcasting with big data, this paper describes in some detail the New York Fed Staff Nowcast. This platform was introduced to the public in April 2016 (Aarons et al., 2016). Its estimates of GDP growth for the current and subsequent quarter based on data released over the course of each week are made available every Friday at 11:15 a.m. on the New York Fed's public website. This nowcasting model extracts the latent factors that drive movements in the data and produces a forecast of each economic series that it tracks: when the actual release for that series differs from the model's forecast, this 'news' impacts the nowcast of GDP growth. This approach formalizes key features of how market participants and policymakers have traditionally produced forecasts, a process that involves monitoring many data releases, forming expectations about them, and then revising the assessment of the state of the economy whenever facts differ from those expectations. The model combines in a unified framework a variety of approaches developed over time for monitoring economic conditions.

Figure 1, whose detailed explanation we defer to Section 5, illustrates the evolution of the nowcast of annualized real GDP growth for 2016:Q4.

[Insert Figure 1 here.]

The black diamonds represent the weekly updates of the nowcast, i.e., the predictions of the model based on the information available at the dates indicated on the horizontal axis. Their progression reflects how the news in the data released each week changes the nowcast for that week. The impact on the nowcast of news from a week's data releases is visualized by the colored bar of that week, where the colors identify the categories of the data releases as indicated in the legend. For example, on November 11, the nowcast of real GDP growth for the fourth quarter of 2016 was 1.6 percent; a string of positive surprises during the following week, primarily from consumption data (represented by the green segment of that week's bar) and housing market data (the red segment), only partially offset by negative surprises from manufacturing data (the orange segment), increased the nowcast to 2.4 percent.

Before moving to a detailed description of the nowcasting model employed at the New York Fed, in the next section (2) we review the variety of methods developed over time to monitor macroeconomic conditions. We then discuss issues of data collection and measurement, with an emphasis on the nature of macroeconomic time-series data and their real-time flow (Section 3). In Section 4 we present the econometric framework for nowcasting with a large data set, focusing on the parsimonious aspect of the dynamic factor model methodology. In Section 5 we dig into the specifics of the New York Fed Staff Nowcast. Section 6 concludes.

2 Monitoring economic conditions

Every day economists parse the trove of economic data released by statistical agencies, private and public surveys, and other sources to assess the health of the economy. Separating meaningful signals from noise is not an easy task, and several approaches have been developed and applied over time to tackle it. These range from detecting business cycle turning points and constructing indexes of economic activity to forecasting comprehensive measures of the state of the economy with formal models and judgment.

The first systematic analysis of economic fluctuations dates back to Arthur Burns and Wesley Mitchell, the economists who pioneered business cycle analysis at the National Bureau of Economic Research (NBER) in the late 1930s. Faced with the complexity of the economic system, Burns and Mitchell attacked their investigation as a big data problem: they scrutinized hundreds of data series in search for patterns and regularities.[1] What they uncovered was a systematic co-movement among the series and a pervasiveness of fluctuations across different sectors and different kinds of economic activities. This led them to

[1]Burns and Mitchell classified 71 out of the original 487 economic time series as the most trustworthy indicators of business cycle revivals: "[...] we have drawn up a list of statistical series differing widely in other respects but alike in that each has in the past proved to be a fairly consistent indicator of cyclical movements in general business. We regard this list not as a 'forecasting' machine, but rather as a registering device that may be useful to those who are trying to interpret the general drift of current fluctuations in different types of business activity," (Mitchell & Burns, 1938, p. 1).

identify the broad recurrence of two states in the economy: expansions and recessions. And so they defined the business cycle as the "type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions," (p. 3).[2] What makes Burns and Mitchell's work so important and innovative is the fact that the pattern they were looking for was unknown—in modern language we would call it "unsupervised classification." We could argue that their careful screening for pattern recognition is what many decades later became machine learning.

Pervasiveness in the movement of various indicators (across sectors and activities) remains central to the definition of business cycles currently used by the NBER Business Cycle Dating Committee: "During a recession, a significant decline in economic activity spreads across the economy and can last from a few months to more than a year. Similarly, during an expansion, economic activity rises substantially, spreads across the economy, and usually lasts for several years."[3]

In a modern context, determining business cycle turning points from a variety of series can be seen as a two-step process: first identifying turning points in each of the large variety of data and then constructing reference turning points based on the distribution of the individual series' turning points. The first step was initially based on judgment, and was later automated by Bry & Boschan (1971). The identification of clusters of turning points to determine aggregate turning points has been formalized by Harding & Pagan (2006, 2016) and Stock & Watson (2010, 2014).

The 'dating' of the business cycle represents one of the most common and robust summaries of the economy, widely understood not only by experts, but also by the public at large. The NBER dating committee today continues the work of Burns and Mitchell, determining the official turning points in the U.S. economy. It examines and compares the behavior of a variety of broad and comprehensive economic activity measures, primarily real gross domestic product (GDP) and most recently real gross domestic income (GDI), employment, and industrial production, together with other less broad but highly informative indicators, to determine when a recession starts and when it ends.

Monitoring a large number of different variables can enhance timeliness and accuracy in assessing the health of the economy: it not only enables one to exploit different sampling frequencies and different timing of macroeconomic data releases but also mitigates the risk of overweighting idiosyncratic fluctuations as well as measurement errors. However, since many indicators move together over the cycle, the behavior of multiple series providing a similar signal can be well summarized with low-dimensional indexes, which can be broadly considered as indexes of business cycles.

Indexes of economic activity such as the leading, coincident, and lagging indicator indexes for the U.S. economy constructed by the Conference Board are in this tradition. The OECD also publishes a composite leading indicator (CLI) index for 21 member countries and three zone aggregates (OECD, 2012), and for the euro area the Conference Board publishes coincident and leading indicators.[4] More recently, indexes of economic indicators have been

[2]The most well-known research of Burns and Mitchell is collected in the 1946 NBER Volume "Measuring Business Cycles."

[3]See www.nber.org/cycles/recessions.html.

[4]For a survey of indexes of economic indicators, see Marcellino (2006).

constructed using dynamic factor models, which, as we will argue at length in Section 4, amounts essentially to using model-based aggregation schemes. The use of factor models for the construction of business cycle indexes was pioneered by Stock & Watson (1989).

From an econometric perspective, the use of factor models to monitor macroeconomic conditions stems from the basic insight that information about different aspects and sectors of the economy can be considered as imperfect measures of a latent common business cycle factor. A robust finding of this literature is that a few common factors can capture the salient features of business cycle fluctuations. First documented by Sargent & Sims (1977), this result has more recently been confirmed with high-dimensional macroeconomic data, as shown by Giannone et al. (2004) and Watson (2004).

Vector autoregression (VAR) models are also widely used in macroeconomics to jointly model the dynamics of economic variables. In these very general linear models every variable depends on its own past and on the past of each of the other variables, and the pattern of correlation of the forecast errors in different variables is left unconstrained. In Bayesian VARs (BVARs), this high level of complexity is combined with a naive prior model that assumes that all the variables are independent white noise or random walks. Bayesian VARs have been advocated by the earliest proponents of VAR models in economics (Sims, 1980; Doan et al., 1984). Recent research has shown that they are strictly connected with factor models and are suitable for the analysis of big data (De Mol et al., 2008; Bańbura et al., 2010).

Economists also focus on some key and comprehensive indicators of economic activity, such as real GDP growth. Indeed, the business cycle turns out, ex post, to be very close to the peaks and troughs of this single comprehensive measure of economic activity.[5] Moreover, the journalistic definition of a recession as two consecutive quarters of negative real GDP growth is a popularized version of algorithms derived to identify business cycle turning points. This bridges business cycle analysis with the careful work dedicated to the construction of GDP data in the National Income and Product Accounts, as we will discuss in Section 3. However, since comprehensive measures are available only with a delay, it is customary to make predictions for the official figures while waiting for their release, pooling information from a variety of economic series.

Forecasting is essential to central banks in informing their policy decisions and communicating their economic outlook to the public. Central bank staff typically use a suite of models and a fair amount of expert judgment to arrive at their forecasts.[6] Businesses and consumers, lacking individual expertise, also rely on forecasts by professional economists to inform their spending and investment decisions.

The collection of expert forecasts has a long tradition. The oldest quarterly survey of macroeconomic forecasts is the Survey of Professional Forecasters (SPF), which began in 1968 and is currently conducted by the Federal Reserve Bank of Philadelphia.[7] Forecasters provide quarterly projections of U.S. GDP growth and measures of inflation, unemployment,

[5]See, for example, Hamilton (1989) and Harding & Pagan (2002).

[6]Sims (2002) provides an insightful review and assessment of the forecasting activity at several major central banks.

[7]The survey was initially conducted by the American Statistical Association (ASA) and the NBER, known as the ASA-NBER Survey. See Zarnowitz (1969). The New ASA-NBER Survey of Forecasts by Economic Statisticians. The survey was taken over by the Federal Reserve Bank of Philadelphia in 1990.

and payroll employment for the current quarter and subsequent four quarters as well as annual projections for the current and following year.[8]

Professional forecasters typically use a combination of approaches for forecasting. A special survey conducted by the Real-Time Data Research Center at the Philadelphia Fed in 2009 revealed that the majority of the SPF panelists use mathematical models to form their projections, but also apply subjective adjustments to their model-generated forecasts. Interestingly, the use of models is predominant for short-horizon forecasts, less so for long-horizon projections. However, not all forecasters monitor economic conditions at high frequency: only 5 out of 25 respondents seem to update their forecasts at higher than monthly frequency.

Alongside professional forecasters, market analysts also strive to understand where the economy currently is and to forecast in which direction it is going. They track major data releases to detect early signals: news in the data, relative to their expectations, leads them to update their projections. Market forecasts are also collected in surveys, of which a popular example is the one conducted by Bloomberg. When releases come out as surprises they move markets (Gürkaynak et al., 2005; Bartolini et al., 2008; Gürkaynak & Wright, 2013). In fact, macroeconomic surprises explain a large part of asset price fluctuations.[9] This evidence suggests that investors continuously update and reassess their expectations about the future path of the economy and the policy reaction based on macroeconomic news.

How successful are professional forecasts? Apparently, there is little predictability of real GDP growth beyond the current and next quarter, as shown in Table 1, which reports the SPF forecast error statistics alongside those of a naive statistical model: the big gain of SPF forecasts is at horizon 0 (forecast of current quarter). For reference, the table also includes the root-mean-square error of the BEA's advance GDP release assessed relative to its most recent revised value.

[Insert Table 1 here.]

Forecasts appear most helpful when one wants to understand where the economy is now, but predicting the present requires tracking a large and complex set of data as it becomes available continuously in real time. Traditionally, this was achieved using a combination of data scrutiny, a variety of simple models, and expert judgment. As discussed in the introduction, in the last two decades new methodologies in time-series econometrics have made possible the development of platforms for real-time forecasting that combine formal models for big data and filtering into nowcasting. The model we decribe in this paper is one such platform, which we would argue unifies several analytical approaches for monitoring current economic conditions that are typically used independently. As indexes of coincident

[8] Another old survey is the Livingston Survey, started in 1946 and currently run by the Federal Reserve Bank of Philadelphia. This survey is semi-annual and consists of forecasts of 18 different quarterly and monthly variables describing national output, prices, unemployment, and other macroeconomic data. Also, since 1999 the ECB runs a Survey of Professional Forecasters similar to the U.S. survey that collects expectations for the rates of inflation, real GDP growth, and unemployment in the euro area for several horizons, together with a quantitative assessment of the uncertainty surrounding them. In addition to other private surveys, such as Blue Chip and Consensus Economics, several institutions such as the OECD and the IMF communicate and summarize their economic outlook by publishing forecasts.

[9] Altavilla et al. (2017) show that these surprises explain up to one third of the quarter-to-quarter fluctuations in government bond yields.

and leading indicators do, our model characterizes current economic activity by condensing the information into a few factors that summarize business cycle conditions. The model mimics the behavior of market participants and professional forecasters, by tracking all relevant measures of economic activity, making predictions that are constantly updated in response to unexpected developments in economic releases. The general finding is that these automated forecasts are as accurate as, and highly correlated with, the forecasts produced by institutions and experts.

Unlike professional forecasters, who combine a variety of unrelated models and apply some form of judgment, using a single formal model allows for a transparent and internally coherent analysis of the real-time data flow. The model, in essence, codifies within an econometric framework the best practice and expert knowledge in business cycle analysis. This is a significant change in paradigm that is well summarized by Stock & Watson (2017).[10]

3 Big data and the real-time information flow

Parallel to the development of various ways of monitoring economic conditions just described is the advancement of measurement. The effort to collect a very large and complex set of measurements on the economy and to organize and synthesize them in a system of coherent aggregates—the national accounts—was first undertaken during the Great Depression, at the same time that macroeconomics emerged as an independent discipline. If macroeconomics was the answer to the challenges posed to economics by the events of the Great Depression, national accounting was its counterpart in the realm of economic measurement. In the United States, Simon Kuznets developed the National Income and Product Accounts (NIPAs) to provide a comprehensive picture of what was happening in the economy during that time of crisis, as well as to monitor the effect of the many policies put in place by President Roosevelt to fight the Depression. Subsequently, the NIPAs became a crucial tool in the efforts to transform the economy in support of the war effort.[11]

Nowadays, academic analysis largely focuses on a few macroeconomic aggregates that comprise the national accounts, such as GDP, consumption, or investment. These time series result from a complex and systematic effort to measure all the economic activity taking place in the U.S. economy within a formalized and coherent framework. Conceptually, this framework is based on accounting principles, rather than on statistical or economic models, but it too is a formalized answer to a big data challenge: how to describe and track over time the evolution of a complex and continually evolving system like the U.S. economy.

For GDP, the most representative and cited of all macroeconomic variables, the Bureau

[10] "Twenty years ago, economists who monitored the economy in real time used indexes of economic indicators and regression models for updating expectations of individual releases [...], combined with a large dose of judgment based on a narrative of where the economy was headed. While this approach uses data, it is not scientific in the sense of being replicable, using well-understood methods, quantifying uncertainty, or being amenable to later evaluation. Moreover, this method runs the risk of putting too much weight on the most recent but noisy data releases, putting too little weight on other data, and being internally inconsistent because each series is handled separately. [...] The current suite of tools for handling large series and complicated data flows [...] using a single model to evaluate these releases—rather than a suite of small models or judgment—provides a scientific way to use the real-time data flow" (p. 71).

[11] See Landefeld et al. (2008) for more details.

of Economic Analysis (BEA) produces every five years benchmark estimates based on an economic census that covers virtually all the roughly seven million businesses with paid employees in the United States and over 95 percent of the expenditures included in GDP. Economic data hardly get any bigger than this! Between these benchmark estimates, which provide an accurate, comprehensive, and detailed snapshot of the U.S. economy, annual and quarterly estimates are based on surveys also conducted by the Census Bureau, with about 150,000 and 35,000 reporting units, respectively, as well as on administrative data (for instance, from the Internal Revenue Service) and by extrapolations based on past patterns or other source data (for instance, employment, hours, and earnings from the Bureau of Labor Statistics). This process, whereby very detailed microeconomic information is aggregated into a coherent set of national accounts, produces a regular stream of GDP estimates and subsequent revisions. After the first, or advance, quarterly print, released about one month after the end of the quarter in question, a second and a third quarterly estimate are released in the subsequent months, and comprehensive revisions ultimately follow, which incorporate methodological advances that update the accounts to reflect changes in the economy.

One of the primary considerations in the design of this release schedule, and of the data collection efforts that underpin it, is the trade-off between accuracy on the one hand and timeliness and frequency of the estimates on the other. Maximum accuracy is achieved with the benchmark releases, since they are based on a census, but this is only carried out every five years. At the other extreme, the advance release is available every quarter and with less than a month's delay, but only about half of the included expenditures data reflect survey-based information for all three months of the quarter. The rest is based on information for two months and on extrapolations. As a result of these statistical "shortcuts," which are the inevitable cost of a timely release, the initial estimates are subject to potentially sizable revisions as more comprehensive and reliable information is folded into the accounts.

The statistical imprecision inherent in the quarterly GDP estimates, together with the fact that even the first estimate is available with a delay of nearly a month, poses a significant challenge to policymakers and other observers with an interest in monitoring the state of the economy in real time. As a result, as we discussed in the previous section (2), most of these observers rely on alternative indicators of the health of the economy that become available over the course of the quarter to form a real-time view of economic developments. Table 2 contains a list of the releases by both government agencies and the private sector that contain the most widely followed of these indicators. These releases are followed closely not just by economists, but by market participants, people in business, and the media. The bars in the first column of the table provide a measure of the relevance of each release based on the percentage of Bloomberg users who subscribe to related alerts.

[Insert Table 2 here.]

Perhaps the most prominent among these releases is the Bureau of Labor Statistics' Employment Situation report, which is issued on the first Friday of every month, as described in the third column of Table 2. This report, which includes data on payroll employment, unemployment, earnings, and many other aspects of the labor market, is of independent interest because it provides an in-depth picture of a particular segment of the economy that is not covered in as much detail in the national accounts. Yet, the nature of business cycles, in which most sectors of the economy tend to move together, implies that good news for the labor market—or for manufacturing, construction, retail trade, and so on—usually reflects good news for the economy as a whole. Therefore, the information in the Employment Report, along with that contained in all the other releases listed in Table 2, can be used to extract a signal on the current overall level of economic activity well before the first GDP estimate is available.

Of course, this exercise is subject to a trade-off between accuracy and timeliness, similar to the one we discussed above in relation to the successive GDP releases. None of the releases listed in Table 2 is quite as comprehensive in its coverage of economic activity as the NIPAs. Moreover, the surveys underlying the releases vary widely in size and hence in their statistical reliability. In general, indicators released closer to their reference period are bound to be less accurate. Therefore, no one indicator can be a silver bullet that solves the problem of accurately tracking the evolution of the economy in real time. A more promising approach is instead combining the information contained in the many available releases. Given the number of these releases, and the hundreds of statistics they often include, designing such an approach is once again a big data challenge, essentially the same one faced by Kuznets in developing the national accounts: how to synthesize the complexity of the U.S. economy through one summary statistic. GDP provides an answer to this question based on accounting principles. Nowcasting addresses the same challenge through statistical modeling, as we will discuss in detail in Sections 4 and 5.

In principle, the nowcasting solution to this problem is straightforward. The data are summarized through a few common factors whose evolution is tracked in real time through filtering techniques. In practice, however, the implementation of this idea is complicated by the intricate nature of the information being tracked. As shown in Table 2, economic indicators are released on a nearly continuous basis over the course of a quarter. This trickling of information over time is often referred to as the data flow, but it is actually less smooth than the term might suggest, although it does follow an entirely predictable calendar. The earliest available information for the national economy on any given quarter is provided by the ISM manufacturing report for the first month of that quarter, which is released on the first business day of the following month (second row in Table 2). On that same day, the Census Bureau's Construction Spending report is also made available (first row of Table 2) but, unlike the ISM report, it refers to two months prior. Therefore, it does not carry relevant information for the current quarter until the third month of the quarter. Similar considerations hold for the international trade and manufacturers' shipments report. Next are two closely followed reports on the labor market. The most important is the already mentioned Employment Situation Report by the BLS, which is released on the first Friday of every month. Since 2006, this report has been preceded on Wednesday by the ADP National Employment Report. ADP is a large private payroll processing company that has assembled a nationally representative sample of firms among its clients, which allows it to estimate total payroll employment. From its relatively short track record, the ADP payroll estimate appears to be noisier than that produced by the BLS. However, the fact that it is available two days earlier makes it a potentially useful input in any effort to track the economy in real time; it offers a nice illustration of the trade-off between accuracy and timeliness that we discussed above.

Given the richness of the available macroeconomic information, what might be the role for the ever-growing alternative sources of big data such as Internet search queries, electronic payments, or online prices in monitoring the economy? Choi & Varian (2012) and Askitas (2015) highlight the potential of such data in predicting current economic activity. They show that Google Trends data can improve the forecasting of timely economic indicators such as auto sales and initial claims when compared to a univariate autoregressive model. However, Li (2016) and Gil, Pérez, Sánchez & Urtasun (2017) show that Google search queries and other alternative data have limited marginal information content once one takes into account the range of economic data already available, such as that shown in Table 2.

Moreover, these alternative sources of information are also subject to a trade-off between timeliness and quality. Although they have the potential to allow monitoring the economy closer to real time, since they do not need to be processed by statistical agencies, this is also a shortcoming. Indeed Li (2016) and Lazer et al. (2014) caution about measurement problems that have not yet been fully addressed for these new data sources. By contrast, most economic indicators are processed to eliminate problems such as bias, non-representativeness, and seasonality: these adjustments take time, and this is the reason why official statistics are not quite as timely.[12]

Nevertheless, there are cases in which alternative data can prove very useful. The Billion Prices Project (Cavallo & Rigobon, 2016) is a good example of the successful use of this type of big data in the absence of accurate information from official statistical agencies. At its inception, the project collected daily prices from large online retailers in Argentina that were able to provide reliable and timely measures of inflation at a time when the official numbers were being manipulated for political reasons. Alternative sources of big data could also be useful to monitor aspects of the economy that are less covered by official statistics, such as the service sector and sectors in the digital economy that are not yet well captured in the national accounts (Nakamura et al., 2017). Finally, this type of big data can be useful to monitor very local economic developments in a timely manner. For example, Aladangady et al. (2016) use electronic transactions data to analyze the effect of hurricanes on consumption in the areas directly affected.

For the purpose of nowcasting the U.S. economy, we currently restrict ourselves to the use of "traditional" macroeconomic releases. These sources of information have been developed and used reliably over the last century, thanks to their careful measurement and well-understood connection with economic activity. The promise of alternative sources of big data in monitoring economic activity in real-time is exciting. However, given the richness and reliability of traditional economic indicators, the contribution from these new data sources currently appears to be minimal, at least during normal times.

Table 2 provides a qualitative snapshot of the richness and complexity of the regularly available data tracked by economists and other observers, and that are accordingly used as an input in the New York Fed model. Figure 2 provides a complementary, more quantitative perspective on these same data, by plotting their joint evolution over time. The heat map on the horizontal plane highlights the degree of co-movement in the series, with more intense red denoting realizations further below the mean and brighter yellow realizations further above the mean. The red 'ridges' in the early 1990s, early 2000s, and most notably in 2008 and

[12] As an example, the UK Office of National Statistics (ONS) is postponing by two weeks the release of the first estimate of GDP because of large errors in the recent period (ONS, 2017).

2009 emphasize quite clearly the three recessions in the sample. This visualization captures in a simple, unstructured way not only the co-movement that drives the data flow over the business cycle, but also the extent to which idiosyncratic factors drive each series in different directions at any given point in time. Nowcasting is essentially a structured, formal, and efficient way of extracting the business cycle signal and discarding the idiosyncratic "noise" from this rich and complex set of data. Section 4 introduces the econometric theory behind this exercise, while Section 5 presents more details on how these ideas are implemented in the New York Fed Staff Nowcast.

[Insert Figure 2 here.]

4 Dealing with big data: econometric models

As discussed extensively in the previous sections, monitoring macroeconomic conditions in real time is inherently a big data problem. It crucially relies on the availability and the exploitation of a large amount of complex data. Increasing complexity of the data leads to increasing complexity in the models, with a growing number of parameters to estimate. Indeed, dealing with large data sets using overly simplified models may lead to misspecification since important features are omitted. On the other hand, modeling the interaction among a large number of variables leads to a proliferation of parameters: that implies large estimation uncertainty, which makes the results from traditional tools unreliable and unstable. This fact is often referred to as the "curse of dimensionality": the modeler faces a trade-off between excessive simplicity (leading to misspecification) and excessive complexity (leading to instabilities). The econometrics of big data aims to turn the curse of dimensionality into a blessing by capturing in a parsimonious manner the salient features of the interactions among many series.

From an econometric perspective, estimation is challenging whenever the number of parameters is large relative to the number of observations. This is known in statistics as the "large p, small n" paradigm, where p stands for the number of variables and n indicates the number of observations. Given their long tradition in handling a large amount of heterogeneous and complex data with a short time span, it is not surprising that macroeconomists have pioneered the statistical analysis of big data. At the root of the recent statistical developments is the key insight of Burns and Mitchell that we discussed: the pervasiveness of common fluctuations across different sectors of the economy implies strong cross-sectional correlations, suggesting that the bulk of fluctuations is essentially driven by a few common sources. Dynamic factor models (DFMs) build on this basic fact to provide a parsimonious and yet suitable representation for the macroeconomic series; they are one of the main tools that macroeconomists today use to handle big data.

A dynamic factor model assumes that many observed variables $(y_{1,t}, \ldots, y_{n,t})$ are driven by a few unobserved dynamic factors $(f_{1,t}, \ldots, f_{r,t})$, while the features that are specific to individual series, such as measurement errors, are captured by idiosyncratic errors $(e_{1,t}, \ldots, e_{n,t})$. The empirical model can be summarized in the following equation:

$$y_{i,t} = \mu_i + \lambda_{i,1} f_{1,t} + \cdots + \lambda_{i,r} f_{r,t} + e_{i,t}, \text{ for } i = 1, \ldots, n \tag{1}$$

which relates the data $y_{i,t}$ to the r latent common factors $f_{1,t}, \ldots, f_{r,t}$ through the factor loadings $\lambda_{i,1}, \ldots, \lambda_{i,r}$. The idiosyncratic component $e_{i,t}$ captures the movements specific to each variable i.

As discussed in Section 2, factor models have a long tradition in the statistical and econometric literature. However, the application to big data is relatively recent. The earliest contributions are Forni et al. (2000) and Stock & Watson (2002a,b), who introduced principal components estimators for large dynamic factor models in economics. Also associated with these developments were the earliest occurrences of the term big data in the academic context.[13] Simultaneously, West (2003) pioneered Bayesian inference with large factor models in statistics and introduced the "large p, small n" paradigm, which translates into "large n, small T" in our context, where T is the sample size. These pioneering papers have led to many further advances in this research field; these advances have been recently surveyed by Stock & Watson (2016).

As initially pointed out by Giannone et al. (2008), dynamic factor models are particularly suitable for nowcasting and monitoring macroeconomic conditions in real time. This is because these models are naturally cast in a state-space form, and hence, inference can be performed using Kalman filtering techniques, which in turn provide a convenient and natural framework for handling the irregularities of the data in real time (i.e., mixed frequencies and non-synchronicity of the data releases) and updating the predictions. Indeed, the Kalman filter digests incoming data in a coherent and intuitive way: it updates the predictions of the model recursively by weighting the innovation components of incoming data on the basis of their timeliness and their quality. Moreover, as the model produces forecasts for all variables simultaneously, the analysis of the flow of data does not require piecing together many separate, unrelated models.

To illustrate the versatility of the DFM framework, consider how it allows the user to handle mixed-frequency data. The idea is to write the state-space system at the highest available data frequency (or even higher) and treat the lower-frequency data as a filtered version of latent high-frequency data that are periodically missing. In our case the highest frequency is monthly and the lowest frequency is quarterly, so, for instance, the quarterly growth rate of GDP can be reconstructed through a filter applied to a latent monthly growth rate.[14] The same idea can be easily applied to higher-frequency data; for example, Bańbura et al. (2010) mix daily, weekly, monthly, and quarterly frequencies. Until recently, however, the literature resorted to approximations to this idea based on regression models owing to computational constraints and the lack of a complete understanding of the properties of large dimensional models estimated with Kalman filtering techniques. Examples of these approximations are ridge regressions (Parigi & Schlitzer, 1995; Golinelli & Parigi, 2007), MIDAS models (Ghysels et al., 2007; Andreou et al., 2013), simple dimension reduction techniques such as principal components (Marcellino & Schumacher, 2010), or averaging of many small models (Kitchen & Monaco, 2003).

Heuristic solutions to handle the non-synchronicity of data releases essentially consist of artificially shifting and realigning the data set at every update. The drawback of these approaches is that they make it difficult to interpret why and how incoming data affect the

[13] See Diebold (2012) for an interesting discussion on the origin(s) of the term "big data."

[14] See Mariano & Murasawa (2003) for the computational details of this frequency aggregation.

predictions. The reason is that these models only predict a single target variable, without a model for the predictors. But in the absence of a prediction for each series, they do not allow the computation of the news component of each release, which in turn is the key to the clear interpretation of the impact of new data releases. In addition, because of realignments and other approximations, the partial model changes at every update and the meaning of the parameters changes. In contrast, by jointly modeling all variables, our approach enforces internal consistency and allows one to interpret the impact of incoming releases in terms of news. The non-synchronicity of the data does not affect the model because the Kalman filter allows the user to handle all possible features of the data available within the same invariant model. This is a desirable feature because the model depends only on the properties of the data and not on how and when they are released.

To conduct inference in DFMs using likelihood-based methods and Kalman filtering techniques, the common factors and the idiosyncratic components are modeled as Gaussian autoregressive processes, which account for their serial correlation and persistence.

$$f_{j,t} = a_j f_{j,t-1} + u_{j,t}, \quad u_{j,t} \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2_{u_j}) \quad \text{for } j = 1, \ldots, r \tag{2}$$

$$e_{i,t} = \rho_i e_{i,t-1} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2_{\varepsilon_i}) \quad \text{for } i = 1, \ldots, n \tag{3}$$

Equations 1, 2, and 3 form a state-space model where the common factors and the idiosyncratic components are unobserved states. Equation 1 is known as the measurement equation and links the data to the unobserved states. Equations 2 and 3, known as the transition equations, describe the dynamics of the system. In order to avoid the proliferation of parameters it is typical to maintain a parsimonious empirical specification for the idiosyncratic components and assume that they are cross-sectionally orthogonal.

A model of this kind was first used by Stock & Watson (1989) to extract a single common factor ($r = 1$) from a small set of monthly core indicators, including employment, industrial production, sales, and income ($n = 4$). Mariano & Murasawa (2003) extended it to include GDP growth ($n = 5$) and Aruoba et al. (2009) to include weekly unemployment claims ($n = 6$). This framework also encompasses simpler approaches to the construction of business cycle indexes. In particular, the extracted common factor corresponds to the principal components if the empirical model is constrained to be static, i.e., assuming serially uncorrelated factors ($a_1 = \cdots = a_r = 0$) and idiosyncratic components ($\rho_1 = \cdots = \rho_n = 0$), and with homogeneous signal-to-noise ratio ($\sigma^2_{\varepsilon_1} = ... = \sigma^2_{\varepsilon_n}$). If there is only one factor ($r = 1$) loaded homogeneously by all variables ($\lambda_{1,1} = ... = \lambda_{n,1}$), the extracted common factor corresponds to cross-sectional averages.

The use of likelihood-based methods for factor models with big data was advocated by Doz et al. (2012), who established the viability of the approach. It was shown that if the factor structure is strong, maximum likelihood estimates are not only consistent when the sample size T and the cross-sectional dimension n are large, but also robust to cross-sectional misspecification, time-series correlation of the idiosyncratic components, and non-Gaussianity. In this respect, this is a quasi-maximum likelihood estimator in the sense of White (1982). Importantly, no constraint is required on the number of series n that can be handled for a given sample size T, which ensures that the approach is suitable for the large n, small T paradigm.

In practice, the estimates can be conveniently computed iteratively using the Kalman smoother and the EM algorithm. The algorithm is initialized by computing principal components, and the model parameters are estimated by OLS regression, treating the principal components as if they were the true common factors. This is a good initialization, especially with a large data set, given that principal components are reliable estimates of the common factors. In the second step, given the estimated parameters, an updated estimate of the common factors is obtained using the Kalman smoother. Stopping at the second step gives the two-step estimate of the common factors used in Giannone et al. (2008) and studied by Doz et al. (2011). Maximum likelihood estimation is obtained by iterating the two steps until convergence, taking into account at each step the uncertainty related to the fact that factors are estimated.[15]

The model described above is the one we use for the New York Fed Staff Nowcast, which we illustrate in Section 5. We kept it as simple as possible in order to minimize pre-testing and specification choices, but it can be easily extended to include more lags in the autoregressive process and allow for dynamic interactions among common factors. Other extensions can be useful to further improve accuracy. D'Agostino et al. (2016) extended the model to accommodate heterogeneity in the lead-lag relationships of different indicators along the business cycles; Kim & Nelson (2001) introduced time-varying parameters in the form of Markow switching; Antolin-Diaz et al. (2017) introduced time variation in the intercept; and Marcellino et al. (2016) introduced time-varying volatility. It is worth emphasizing that in spite of, and indeed thanks to, its simplicity, this basic model has been successfully applied to nowcasting in many economies with very different characteristics. These include large developed economies and small open economies, as well as emerging-market and developing economies.[16]

We focus here on factor models, since they summarize the state of the economy in a lower dimension, and hence provide a direct link to business cycle analysis.[17] But, as pointed out in Section 2, vector autoregressive (VAR) models offer an alternative approach to monitoring the economy in real time, since they share many advantages of the DFM. They also provide a joint model of all variables, are internally coherent, and can be cast in a state-space form, allowing the economist to handle missing data via filtering techniques and update forecasts with each new data release.

Earlier applications of VAR models with mixed-frequency data include Zadrozny (1990)

[15]For details on the EM algorithm for the estimation of large factor models see Doz et al. (2012). Bańbura & Modugno (2014) show how to perform the parameter estimation step in the presence of arbitrary patterns of missing data.

[16]For instance, see Giannone et al. (2008), Bańbura et al. (2013), Lahiri & Monokroussos (2013), and Liebermann (2014) for nowcasting the United States; Angelini et al. (2011) and Bańbura et al. (2011) for the aggregate euro area economy alongside Runstler et al. (2009) for individual member countries; and Bragoli (2017) for Japan. See Chernis & Sekkel (2017) for Canada; Aastveit & Trovik (2012) and Luciani & Ricci (2014) for Norway; Matheson (2010) for New Zealand; and Anesti et al. (2017) for the UK. See Dahlhaus et al. (2017) for the BRIC countries and Mexico; Bragoli et al. (2015) for Brazil; Bragoli & Fosten (2017) for India; Yiu & Chow (2010) for China; Caruso (2015) for Mexico; Luciani et al. (2015) for Indonesia; and Kabundi et al. (2016) for South Africa. For an extensive survey, see Bańbura et al. (2011, 2013) and Luciani (2017).

[17]Giannone, Monti & Reichlin (2010, 2016) perform the same analysis with a linearized DSGE model: this is straightforward, since the model has a state-space form.

and Mittnik & Zadrozny (2005). A systematic treatment of the models is provided by Anderson et al. (2016a,b). Until recently these models were not used for nowcasting, since they are richly parameterized and hence can only handle a small number of data series.[18] Recent research has shown, however, that Bayesian shrinkage makes VAR models suitable for high-dimensional problems (see Bańbura, Giannone & Reichlin, 2010; Koop, 2012; Giannone, Lenza & Primiceri, 2015). The basic idea consists of addressing the curse of dimensionality by using a parsimonious naive prior to discipline the estimation of a very flexible, densely parameterized, and complex model. This is an important line of research, since Bayesian inference provides a coherent probabilistic framework that can be exploited to greatly reduce the number and importance of subjective choices, such as data transformations or selection of the priors (see Giannone et al., 2015; Carriero et al., 2015). Recent applications of mixed frequency Bayesian VARs include Brave et al. (2016), Schorfheide & Song (2015), Eraker et al. (2015), and McCracken et al. (2015).[19]

5 Nowcasting in practice

In this section, we describe the platform used at the Federal Reserve Bank of New York to track U.S. real GDP growth.[20]

The New York Fed Staff Nowcast is based on the dynamic factor model described in Section 4 and incorporates all the releases listed in Table 2. As described in Section 3, these are the releases most widely followed by market participants. While our nowcasting model is parsimonious and can accommodate many data series, we include only the headlines of each release, those that "move" markets and make front-page news. We do not include disaggregated data since there are no substantial gains in prediction from including them, although they can be useful for interpretation.[21] Therefore, for example, from the Employment Situation report, the model incorporates the unemployment rate and non-farm payrolls, but does not include information on employment by age or industry; similarly, the model includes only total indexes for industrial production and capacity utilization, disregarding sectoral disaggregation. We should note that financial variables are not included in the model: although they provide timely information, they tend to be quite volatile and have a limited role in nowcasting GDP growth once a rich set of macroeconomic variables has been included (see Bańbura et al., 2013; Knotek & Zaman, 2017). However, going beyond the prediction of the central tendency, financial conditions can provide valuable information, especially for monitoring downside risks (Adrian et al., 2016).

All variables are listed in the first column of Table 3. The colored box next to the series' name indicates the category to which the series is assigned. Each series enters the model in

[18] For example, Giannone et al. (2009) apply this type of model to nowcast euro area GDP with a handful of monthly indicators.

[19] For a recent survey of Bayesian vector autoregressive models, see Karlsson (2013) and Koop (2017).

[20] A similar platform is used at the Atlanta Fed for nowcasting U.S. GDP growth, called GDPNow (Higgins, 2014). That model also builds on Giannone et al. (2008); however, it combines the components' forecasts with an "accounting" step that mimics the key elements of the GDP construction process followed by the BEA, as discussed in Section 3. Partly as a result of this modeling choice, GDPNow is especially focused on predicting the advance estimate of GDP growth.

[21] For a detailed discussion see Bańbura et al. (2011, 2013).

stationary form: in most cases this requires simply including the series as it is tracked by financial market participants (i.e., as reported in Bloomberg).[22] The last column of Table 3 indicates the units in which each series enters the model.

We specify the model by assuming that a single common factor, the global factor (G), affects all variables.[23] In addition, we include a few local blocks to control for idiosyncrasies in particular subgroups of series; this can improve inference even though estimation is robust to the presence of local correlations among idiosyncratic components. Specifically, to model the local correlations in survey data, we include the soft block (S), on which only variables representing economic agents' perceptions and sentiments load. Two additional local blocks are included for real (R) and for labor (L) variables; the structure of factor loadings is given in the second column of Table 3.

[Insert Table 3 here.]

Figure 3 below reports the standardized data (dotted colored lines) along with the global factor (solid black line) estimated from the model specification of Table 3. It is clear that the common (global) factor captures the bulk of the covariation between the variables.

[Insert Figure 3 here.]

The New York Fed Staff Nowcast is updated daily at 10 a.m. whenever new data releases are issued. This daily updating allows users to read the real-time data flow and quantify how each data release contributes to updates in the forecasts of all other variables. The factors, and, hence, the nowcast, change if either the data changes or the model parameters are re-estimated. The data change constantly, not only because new data are released, but also because data are revised. Model parameters are re-estimated at the beginning of every quarter using the most recent 15 years of data. In the nowcast detail table, 'parameter revisions' are changes to the nowcast due to the re-estimation, while 'data revisions' reflect changes in previously released data; both are classified within the 'other' (gray) category.

Figure 4 reports the evolution of the nowcast of real GDP growth in 2016:Q4. This is the same figure reported in the introduction, to which we add shades to provide information about forecasting uncertainty. In particular, the shaded area represents the 68 percent probability interval constructed using the empirical distribution of the forecast errors. We will discuss forecasting performance in more detail later, but it should be noticed here that the bands narrow as the quarter progresses and information accumulates. This suggests that the data contain useful information that the model is able to exploit in real time. Notice too the substantial uncertainty also present in the official release of GDP, as illustrated in the figure by the error bar around the release, which reflects data revisions. This uncertainty is similar in magnitude to that of the last model forecast, suggesting that the model predictions

[22]There are a few exceptions, though. Housing starts, for instance, are typically tracked in levels by market participants, but because of evident trends this series enters the model in monthly changes.

[23]While in general the single factor model has been proven quite robust, it is possible to use selection criteria and tests in order to select the number of factors. For a discussion of these methods in the context of large n, large T see Stock & Watson (2016). For an extension of these criteria in the context of quasi maximum likelihood estimators of large dynamic factor models see Coroneo et al. (2016).

are roughly as accurate as the first release in predicting the latest available estimates of GDP growth.

The solid black line in the figure shows the progression of the nowcast throughout the period of updates, which starts one month before the reference quarter and comprises the three months of the reference quarter and one month after the reference quarter, until the BEA publishes the advance GDP release; after this release, the nowcast for that quarter is no longer updated. Each black diamond on the line is the nowcast for the particular week indicated on the x-axis; the colored bar corresponding to that diamond represents the contribution of the surprises in the releases of that week to the change in the nowcast. Each bar has potentially many segments of different colors, which represent the net contributions of different categories of data. Accompanying this plot is a table that breaks down the colored bars into the contribution of the news in individual series. In the figure, we report the details pertaining to the week ending on September 16, 2016. For each series, the table reports the day and time of the release (first column), reference period (third column), as well as the units in which the series is reported (fourth column). In the next four columns the table reports, respectively, the model prediction for the series [a], the actual value of the series in the release [b], the weight [c] that the model assigns to the surprise (or news) [$(b-a)$] in the nowcast of GDP growth, and the impact [$c(b-a)$]: how this surprise changes the nowcast.

[Insert Figure 4 here.]

Reading Figure 4, one sees that the initial model prediction for 2016:Q4 GDP growth on August 19, 2016 was around 2.0 percent. After an initial fall to a low of 1.2 percent due largely to negative surprises from survey, manufacturing, and retail and consumption data, the nowcast steadily increased until, in the middle of the quarter, in the week of November 18th, it jumped up almost one full percentage point to 2.6 percent, due to positive surprises from housing data and retail and consumption data. This increase was partially reverted just a few weeks later, on December 16, due to negative news from manufacturing and housing data. The nowcast moved slightly upward in the following six weeks and was last recorded at 2.0 percent on January 27, just before the advance GDP release. By comparison, the BEA advance estimate of real GDP growth was 1.9 percent (circle in Figure 4), and the latest official estimate was 2.1 percent (square).

We performed a comprehensive backtesting to evaluate the real-time performance of the model. We computed the nowcast recursively on real-time vintages of data reconstructed to replicate the data exactly as they were available at the time. The nowcast for any given week is therefore precisely what would have been computed by a forecaster running the model at that time. Backtesting was conducted over the period from January 2000 through January 2017. The incoming data were automatically incorporated at the end of any given week. As we do currently, the parameters were estimated recursively at the beginning of every quarter.

The dots in Figure 5 report the errors of the real-time nowcast, relative to the most recent GDP data, for all quarters in the evaluation sample. For comparison, we also report in the figure the errors of the SPF forecast for real GDP growth in the current quarter (these are the squares that appear in the middle of the nowcasting period) and the revision error of the advance GDP release (the dots at horizon zero). Considering the universe of the nowcast errors, we uncovered a preponderance of negative errors, i.e., an upward bias in the nowcast. This pattern is related to the much discussed issue of residual seasonality in first quarter real GDP growth.[24] We therefore partitioned the error distribution into first quarter errors (blue dots) and errors for all quarters except first quarters (black dots). We report the interval between the 16th and 84th percentiles separately for first quarters (blue shaded area) and for all others quarters (gray shaded area). These are the bands superimposed on the nowcast progression plot in order to provide a measure of forecast uncertainty. Similarly, we report 68 percent probability intervals for the revision errors of advance GDP and the prediction errors of the SPF consensus forecast, separately for first quarters (blue error bar) and for all others quarters (black error bar).

Inspecting the shaded bands reveals that much of the upward bias comes from first quarter nowcasts, in line with the issue of residual seasonality just discussed. The asymmetry is evident not only in the nowcasts but also in the revision errors of advance GDP estimates as well as the median SPF forecast errors.

Beyond issues pertaining to residual seasonality, the error distributions clearly show the attributes of a good forecast. Contrary to the first quarters, in which the errors exhibit significant downward bias, the errors for the other quarters are generally distributed symmetrically around zero. Furthermore, the bands get narrower as time goes on, indicating on average a more accurate prediction of GDP growth over the nowcasting period as more information about the economy is released. Finally, at the end of the nowcast updating period, the bands are similar to the error bars for the advance GDP release, indicating that the uncertainty surrounding the final nowcast made for each quarter is similar to that of the BEA's first estimate in predicting the true value of aggregate output growth in the economy. Moreover, the error bars for the SPF align closely with, but lie within the nowcast error bands at the same horizon, indicating that professional forecasters are slightly more accurate than the nowcasting model. Model accuracy tends to improve as time progresses and is in line with that of the SPF benchmark near the end of the reference quarter.

[Insert Figure 5 here.]

[Insert Figure 6 here.]

We conclude this analysis by asking: what are the most important variables driving the nowcast, when, and why? Figure 7 reports the average (absolute) weekly impact of each series, grouped by category, computed in real-time over the evaluation sample 2000 to 2016. From this figure three features are evident. First, the most prominent colors are blue, green, orange, and red, indicating that survey, consumption, manufacturing, and housing data are the main contributors to changes in the nowcast. Second, the bell shape of the plot indicates that the most useful information for the nowcast arrives in the middle of the nowcasting period, when data for the reference period first become available. Conversely,

[24] The BEA reported its findings on residual seasonality and its plan to publish a not seasonally adjusted (NSA) GDP series in Moulton & Cowan (2016). See also Gilbert et al. (2015), Stark (2015), Rudebusch et al. (2015), Groen & Russo (2015), Phillips & Wang (2016), Kliesen (2017), Lunsford (2017), and Barigozzi & Luciani (2018).

surprises move the nowcast less both at the beginning and at the end of the period: at the beginning, because, at that time, signals for GDP growth are still too weak, and at the end because, by then, most useful information has become available and there is little room for improvement. Third, we see from the contribution of surveys that soft data have a large impact at the beginning of each nowcasting timeframe. Later, as more information accumulates, their impact diminishes and hard data become more important. This confirms that timeliness is just as important as the quality of the data.

Overall, each of the series tracked by the nowcast provides relevant information at various updating horizons. The combined information allows us to track the economy during each quarter and interpret the changes in the nowcast with increasing precision, highlighting the importance of closely monitoring and continuously updating the outlook of the economy via the real-time data flow.

[Insert Figure 7 here.]

6 Conclusion

In this paper, we illustrate the application of recent statistical techniques for the construction of an automated platform to process the real-time data flow—nowcasting, which we place in the context of various approaches developed over time to monitor and measure economic conditions. Nowcasting is a relatively new field in time-series econometrics, and it is likely to continue to be developed on many fronts.

First, jointly modeling macroeconomic and financial conditions would provide an interface between finance and the macroeconomy. This would present a coherent framework to study the mechanisms through which macroeconomic news is transmitted to financial markets. Furthermore, it would allow us to go beyond the prediction of the central tendency toward nowcasting vulnerabilities and risks to the outlook, along the line of Adrian et al. (2016).

Second, nowcasting can be developed in a structural environment. Giannone et al. (2016) proposed a nowcasting framework for a dynamic stochastic general equilibrium model. A benefit of this analysis is that it would allow researchers to compute real-time estimates of model-based variables that are not directly observable, such as the output gap (which captures the difference between actual GDP and its potential value) and the natural rate of interest. Reading the data flow through the lens of a structural model would also make it possible to identify meaningful shocks to the economy in real time.

Third, while our model makes use of big data with the "traditional" data sets that macroeconomists have analyzed for a long time, new sources of big data, such as web searches, electronic transactions, and textual analyses offer a timely glimpse into economic activity. The value of such data has been demonstrated in monitoring the economy in the absence of reliable data from statistical agencies, as well as in providing early estimates of economic indicators in particular sectors and geographic regions. However, further studies are needed to determine whether these alternative data could be integrated with the current array of economic data for the purpose of macroeconomic nowcasting.

Finally, it is important to continue to refine the communication and sharing of nowcasting, a step we have taken by publishing weekly updates of this model on the New York Fed's public website. This will foster interaction with other analysts and forecasters and help maintain the development of the model attuned to changes in market practices.

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Table 1: Forecast errors for GDP at different horizons

	Root-mean square error (RMSE)					
horizon (quarters ahead)	-1	0	1	2	3	4
BEA	1.61					
Naive AR model		2.43	2.46	2.55	2.55	2.55
SPF		1.94***	2.21**	2.40	2.47	2.52

Root mean square errors (RMSEs) for GDP forecasts at horizons 0 (i.e. nowcast) to 4 quarters ahead. Errors are computed on the evaluation sample 1985 to 2014 as the difference between the latest available GDP estimate and three types of GDP "projections": BEA refers to the first official (also known as advance) estimate published by the Bureau of Economic Analysis at the end of the month following the quarter under consideration. Therefore this is a "projection" produced with a one month delay, as indicated by the -1 in the column heading. Naive AR model refers to iterative forecasts from an autoregressive model calculated by the Federal Reserve Bank of Philaldelphia. SPF is based on the median forecasts from the Survey of Professional Forecasters (see "Forecast Error Statistics for the Survey of Professional Forecasters" on the Philadelphia Fed's website for more details).
*** and ** indicate SPF forecasts that are significantly more accurate than those of the Naive AR model at the 1% and 5% levels, respectively, based on Diebold-Mariano tests with a quadratic loss function.
Sources: Authors' calculations, Bureau of Economic Analysis, Federal Reserve Bank of Philadelphia.

Table 2: Macroeconomic data releases

Release	Publication Timing, Reference Period	Delay (days)	Source
Construction Spending	first business day of the month, two months prior	33	Census Bureau
ISM Manufacturing Report on Business	first business day of the month, one month prior	3	ISM
ISM Non-Manufacturing Report on Business	third business day of the month, one month prior	5	ISM
U.S. International Trade in Goods and Services	first full week of the month, two months prior	35	BEA, Census Bureau
Manufacturers' Shipments, Inventories, and Orders	first week of the month, two months prior	35	Census Bureau
ADP National Employment Report	first Wednesday of the month, one month prior	5	ADP
Employment Situation	first Friday of the month, one month prior	7	BLS
Manufacturing and Trade Inventories	first full week of the month, two months prior	44	Census Bureau
Job Openings and Labor Turnover	second week of the month, two months prior	42	BLS
U.S. Import and Export Price Indexes	middle of the month, one month prior	13	BLS
Retail Trade	ninth business day of the month, one month prior	14	Census Bureau
Producer Price Index	middle of the month, one month prior	14	BLS
Wholesale Trade	middle of the month, two months prior	37	Census Bureau
Empire State Manufacturing Survey	15th of the month, current month	-14	New York Fed
Manufacturing Business Outlook Survey	third Thursday of the month, current month	-11	Philadelphia Fed
Industrial Production and Capacity Utilization	middle of the month, one month prior	17	Federal Reserve Board
Consumer Price Index	middle of the month, one month prior	18	BLS
New Residential Construction	12th business day of the month, one month prior	16	Census Bureau
Advance Economic Indicators	last week of the month, one month prior	28	Census Bureau
New Residential Sales	17th business day of the month, one month prior	26	Census Bureau
Advance Durable Goods	third week of the month, one month prior	26	Census Bureau
Personal Income and Outlays	last week of the month, one month prior	30	BEA
Gross Domestic Product	last week of the month, prior quarter	28	BEA
Productivity and Costs	first week of the month, prior quarter	34	BLS

This is a list of all the macroeconomic data releases used in the New York Fed Staff Nowcast. Releases are ordered based on their time of publication within the calendar month. The delay of each release in the third column is computed relative to the end of the reference period based on the 2017 calendar. The bar graphs indicate the importance of each release according to the Bloomberg relevance index.
Source: Bloomberg.

Table 3: Data Series that enter the New York Fed Staff Nowcast

Data Series	Block G S R L	Units
All employees: Total nonfarm	■□□■	Level change (thousands)
Real gross domestic product	■□■□	QoQ % change (annual rate)
ISM mfg.: PMI composite index	■■□□	Index
CPI-U: All items	■□□□	MoM % change
Manufacturers new orders: Durable goods	■□■□	MoM % change
Retail sales and food services	■□■□	MoM % change
New single family houses sold	■□■□	MoM % change
Housing starts	■□■□	MoM % change
Civilian unemployment rate	■□□■	Ppt. change
Industrial production index	■□■□	MoM % change
PPI: Final demand	■□□□	MoM % change
ADP nonfarm private payroll employment	■□□■	Level change (thousands)
Empire State Mfg. Survey: General business conditions	■■□□	Index
Merchant wholesalers: Inventories: Total	■□■□	MoM % change
Value of construction put in place	■□■□	MoM % change
Philly Fed Mfg. business outlook: Current activity	■■□□	Index
Import price index	■□□□	MoM % change
ISM nonmanufacturing: NMI composite index	■■□□	Index
ISM mfg.: Prices index	■■□□	Index
Building permits	■□■□	Level change (thousands)
Capacity utilization	■□■□	Ppt. change
PCE less food and energy: Chain price index	■□□□	MoM % change
CPI-U: All items less food and energy	■□□□	MoM % change
Inventories: Total business	■□■□	MoM % change
Nonfarm business sector: Unit labor cost	■□□■	QoQ % change (annual rate)
JOLTS: Job openings: Total	■□□■	Level change (thousands)
Real personal consumption expenditures	■□■□	MoM % change
PCE: Chain price index	■□□□	MoM % change
ISM mfg.: Employment index	■■□□	Index
Export price index	■□□□	MoM % change
Manufacturers shipments: Durable goods	■□■□	MoM % change
Mfrs. unfilled orders: All manufacturing industries	■□■□	MoM % change
Manufacturers inventories: Durable goods	■□■□	MoM % change
Real gross domestic income	■□■□	QoQ % change (annual rate)
Real disposable personal income	■□■□	MoM % change
Exports: Goods and services	■□■□	MoM % change
Imports: Goods and services	■□■□	MoM % change

Housing and construction · Manufacturing · Surveys · Retail and consumption · Income · Labor · International trade · Others

This is a list of all the data series that enter the New York Fed Staff Nowcast. The color-coded squares refer to the category to which each series belongs, as detailed in the legend. Blocks are the factors on which each data series loads in the dynamic factor model, as indicated by the filled-in squares: G, S, R, and L indicate the global, soft, real, and labor factors, respectively.

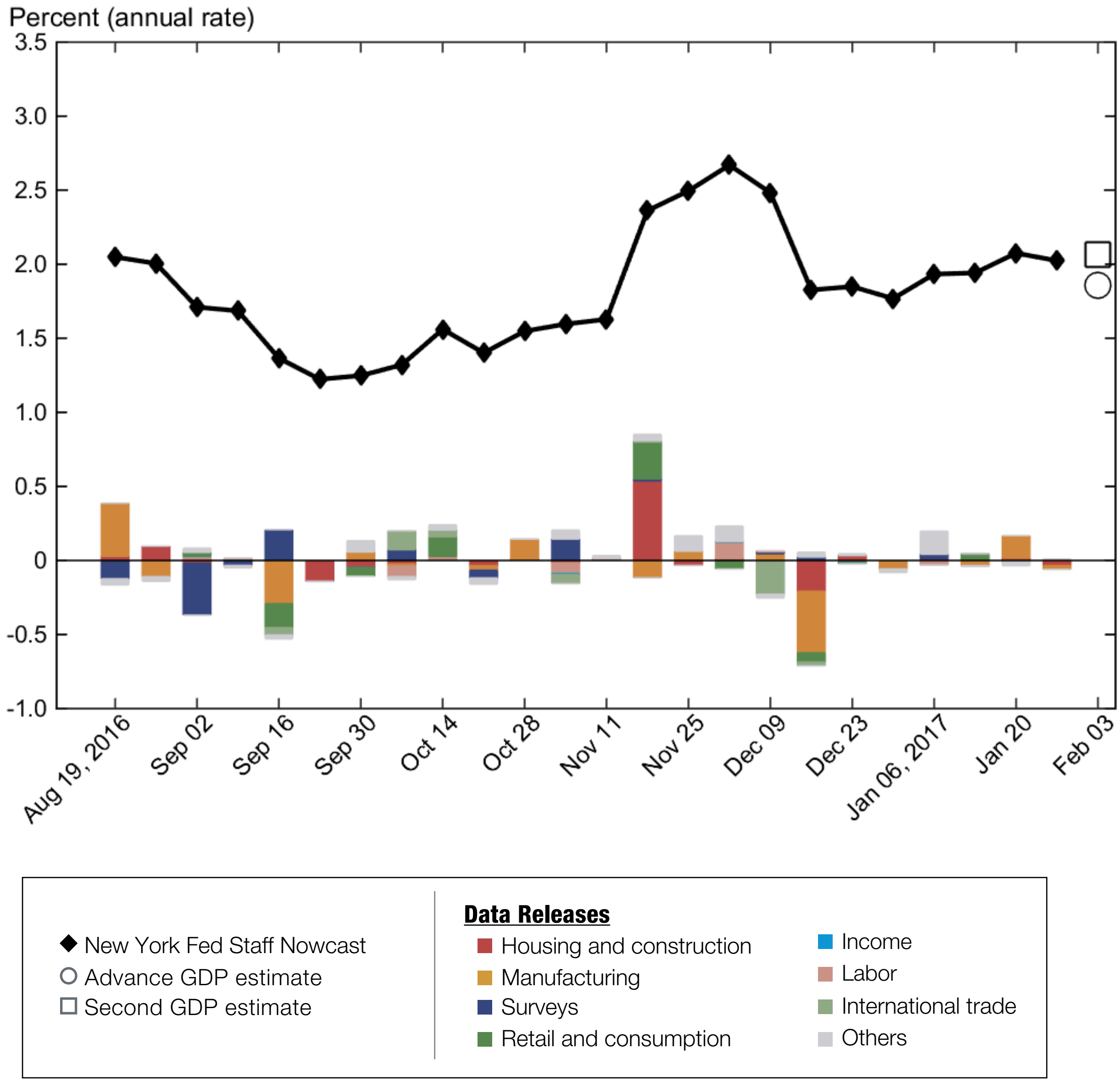


Figure 1: The New York Fed Staff Nowcast for 2016:Q4. See Figure 4 for details. Source: Federal Reserve Bank of New York "Nowcasting Report" March 3, 2017. www.newyorkfed.org/research/policy/nowcast

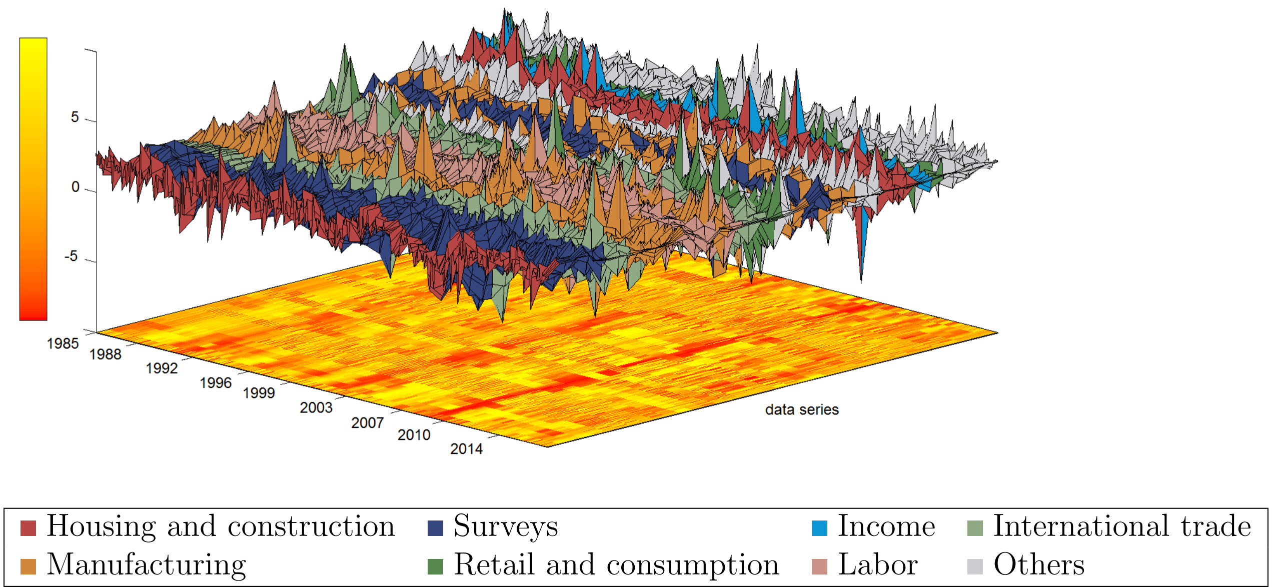


Figure 2: Big data in macroeconomics. The three-dimensional surface plot displays the standardized time series for the economic indicators used in the New York Fed nowcasting model, colored by category as indicated in the legend.
The heat map on the horizontal plane shows observations above (yellow) and below (red) the mean; the intensity of the color is a function of the size of the deviation.
Source: Authors' calculations, Haver Analytics.

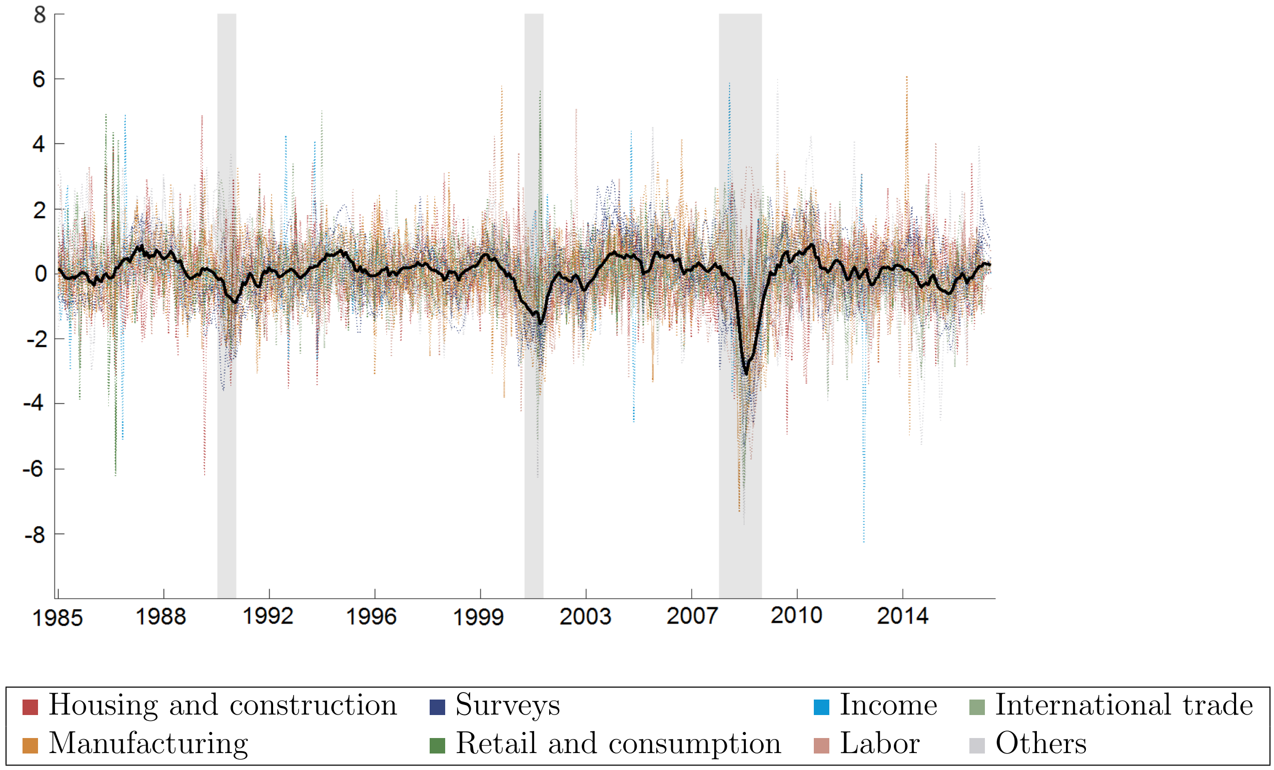
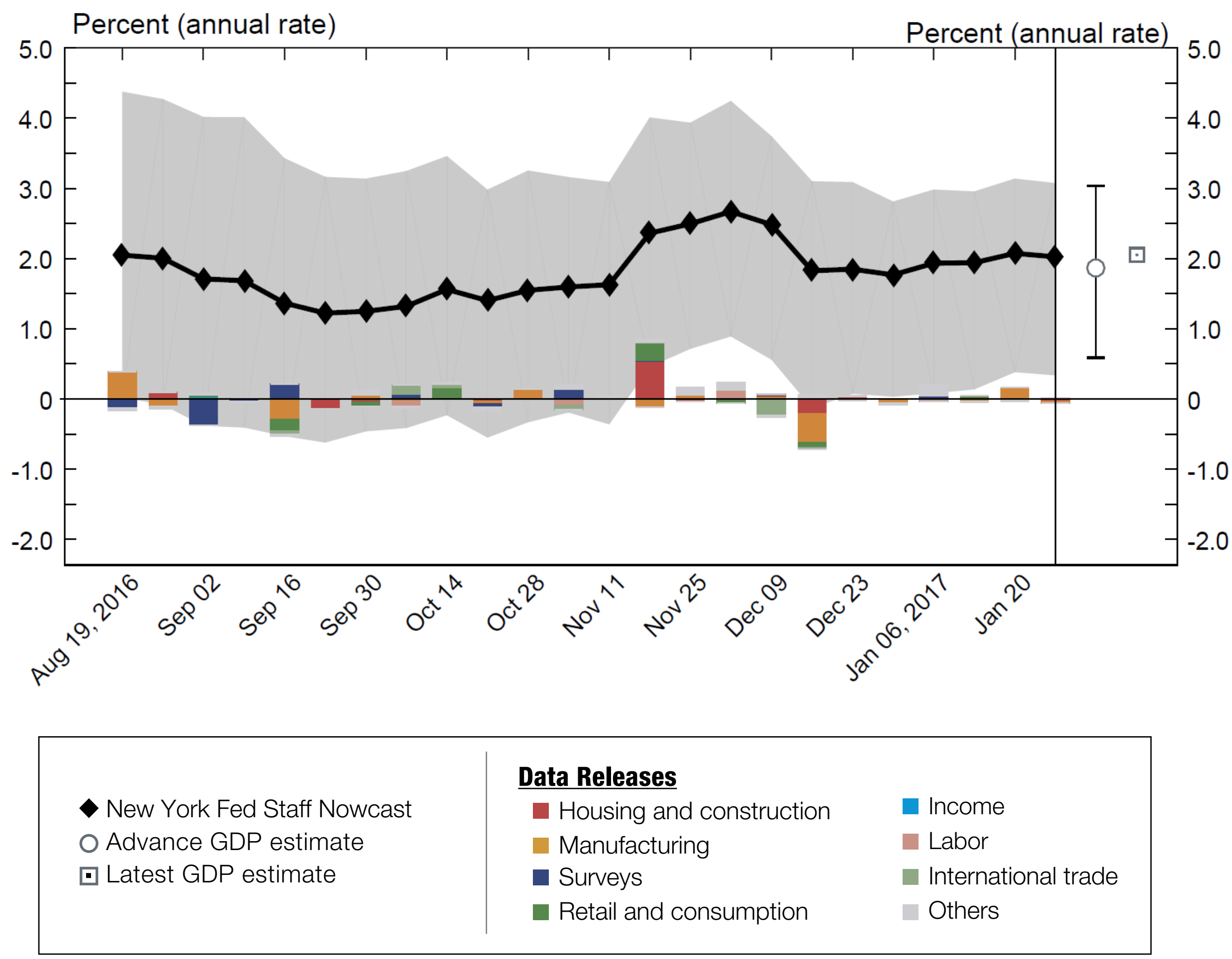


Figure 3: Estimated global factor. The dotted lines are all the data series that enter the New York Fed nowcasting model, in standard deviations from their mean and colored by category as indicated in the legend. The solid black line is the global factor estimated from the dynamic factor model. Shaded areas indicate NBER recessions.
Source: Authors' calculations, Haver Analytics, National Bureau of Economic Research.



Update	Release Date	Data Series	Reference Period	Units	Forecast	Actual	Weight	Impact	Nowcast GDP Growth
					[a]	[b]	[c]	[$c(b-a)$]	
Sep 09									**1.69**
	8:30AM Sep 14	Import price index	Aug	MoM % chg.	-0.119	-0.248	0.029	-0.004	
	8:30AM Sep 14	Export price index	Aug	MoM % chg.	0.058	-0.826	0.053	-0.047	
	8:30AM Sep 15	Retail sales and food services	Aug	MoM % chg.	0.489	-0.295	0.206	-0.161	
	8:30AM Sep 15	PPI: Final demand	Aug	MoM % chg.	-0.021	0.000	0.040	0.001	
	8:30AM Sep 15	Empire State Mfg. Survey	Sep	Index	-0.583	-1.99	0.014	-0.019	
	8:30AM Sep 15	Philadelphia Fed Mfg. Business Outlook	Sep	Index	-1.50	12.8	0.016	0.228	
	9:20AM Sep 15	Industrial production index	Aug	MoM % chg.	-0.051	-0.433	0.415	-0.158	
	9:20AM Sep 15	Capacity utilization	Aug	Ppt. chg.	-0.100	-0.357	0.520	-0.134	
	8:30AM Sep 16	CPI-U: All items	Aug	MoM % chg.	0.048	0.199	0.062	0.009	
	8:30AM Sep 16	CPI-U: All items less food and energy	Aug	MoM % chg.	0.142	0.252	0.021	0.002	
		Data revisions						-0.037	
Sep 16									**1.37**

Figure 4: The New York Fed Staff Nowcast for 2016:Q4. The solid black line is the progression of the nowcast of annualized real GDP growth for 2016:Q4. The diamonds mark the weekly public updates. The circle and square at the right of the chart are the first and latest official GDP estimates, respectively. Colored bars represent the contributions of data releases over the course of each week to changes in the nowcast, grouped by categories as indicated in the legend. Details on the impact of each data release over the course of the week of September 9 are reported in the table below the legend as an illustration. The gray shading around the nowcast progression represents the interval between the 16th and 84th percentile of the empirical distribution of the forecast errors; the whisker around the circle represents the same 68 percent probability interval of historical revision errors from the first estimate of GDP to the latest. Both intervals are based on real-time prediction errors over the 2000 to 2016 sample, as detailed in Figure 5.
Source: Authors' calculations, Federal Reserve Bank of New York "Nowcasting Report."

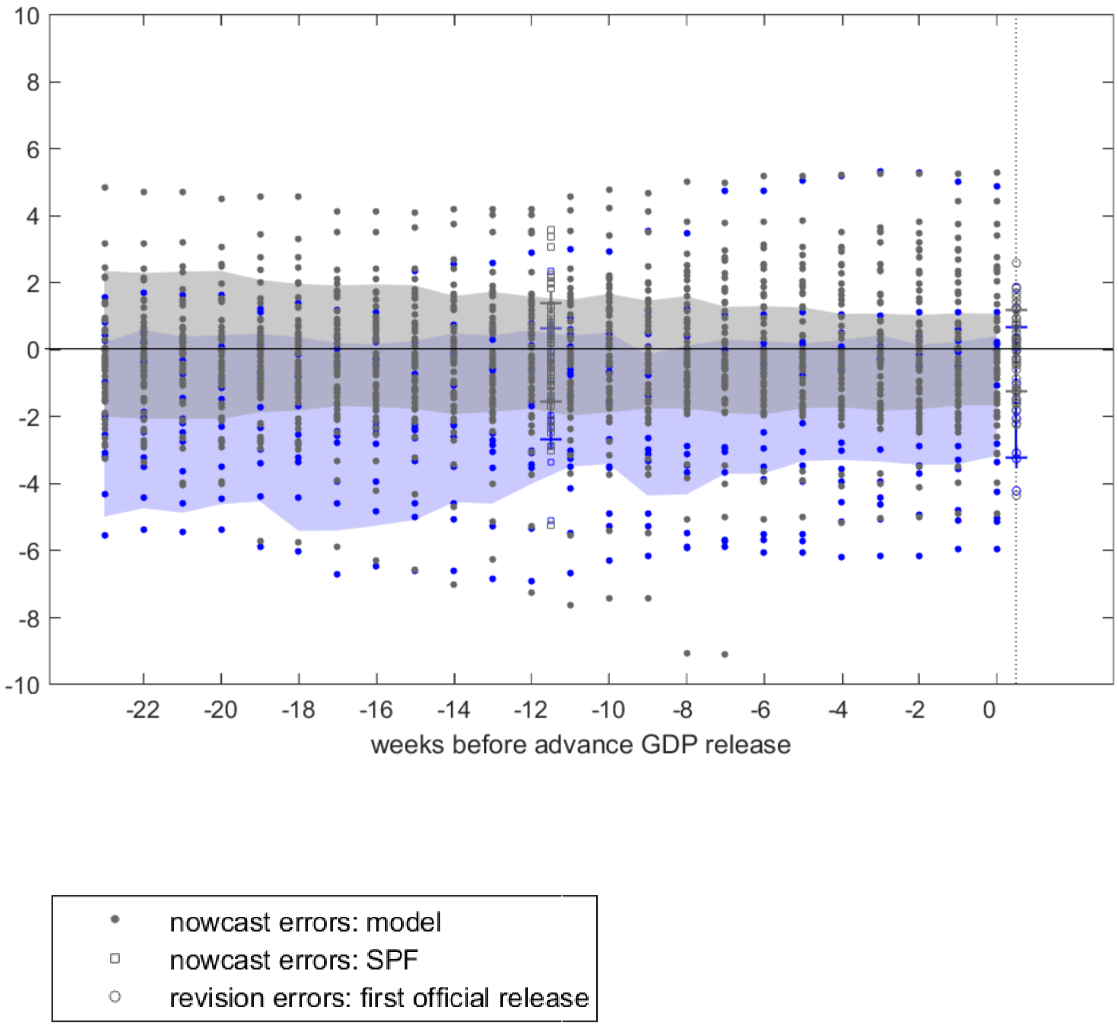


Figure 5: Empirical nowcast error distribution. Nowcast errors are computed as the difference between the real-time nowcast and the latest official GDP estimate. The x-axis indicates the point in the quarter when the nowcasts were made, measured in terms of weeks before the first official GDP release. The dots are the model nowcast errors for individual quarters over the evaluation sample 2000 to 2016. Errors are partitioned in two groups: blue represents errors for first quarters; gray represents errors for all other quarters. Shaded areas represent the interval between the 16th and 84th percentile of the empirical distribution of the forecast errors in the respective partitions. The squares in the middle of the quarter represent the nowcast errors for the median of SPF projections. The circles at the end of the quarter are the revision errors for the first GDP release. The overlapping whiskers on top of the circles and squares represent the 68 percent probability intervals based on their empirical distribution.
Source: Authors' calculations.

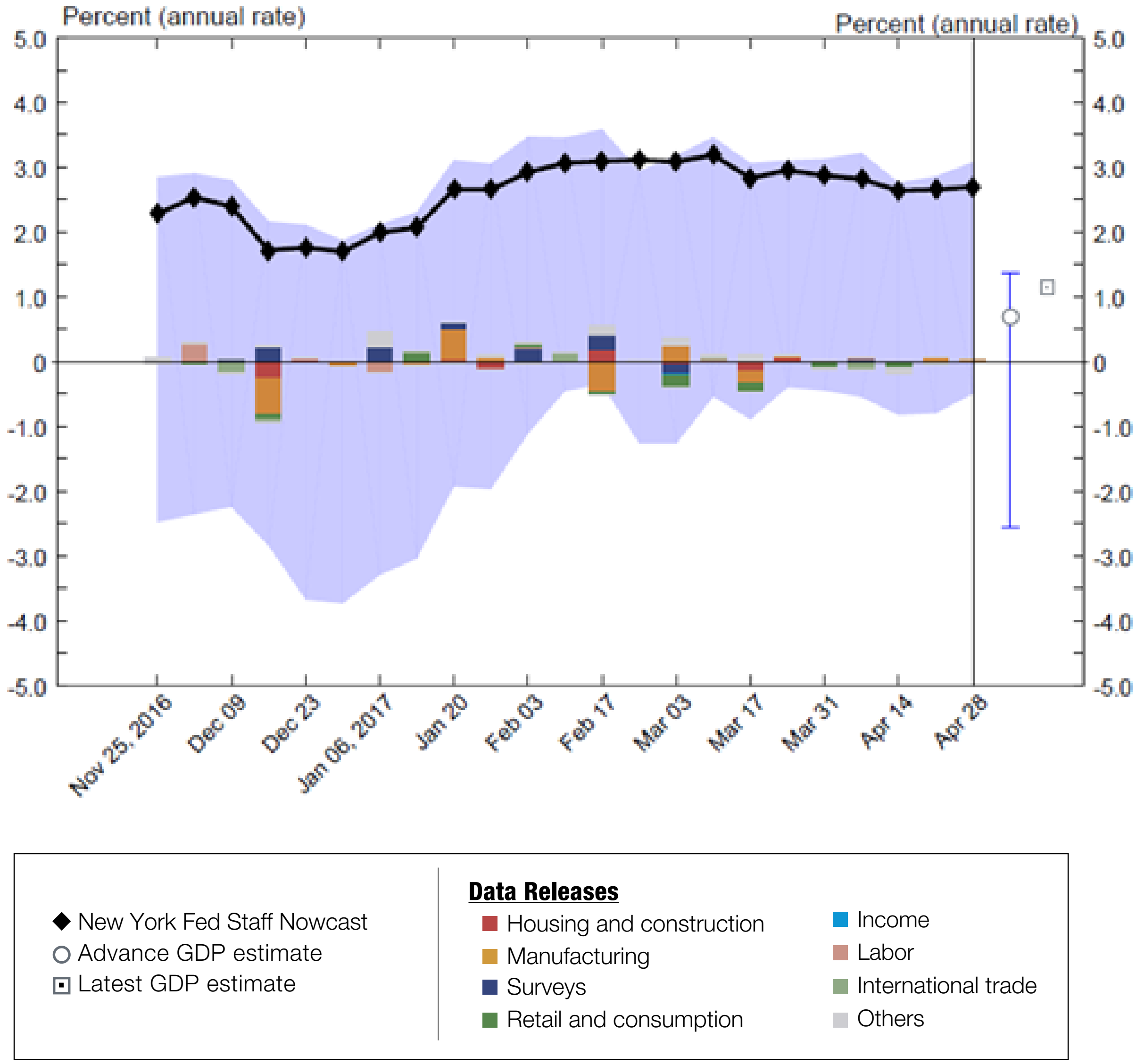


Figure 6: The New York Fed Staff Nowcast for 2017:Q1. The solid black line is the progression of the nowcast of annualized real GDP growth for 2017:Q1. The circle and square at the right of the chart are the first and latest official GDP estimates respectively. Colored bars represent the contributions of data releases over the course of each week to changes in the nowcast, grouped by categories as indicated in the legend. The blue shading around the nowcast progression represents the interval between the 16th and 84th percentile of the empirical distribution of the forecast errors; the whisker around the circle represents the same 68 percent probability interval of historical revision errors from the first estimate of GDP to the latest. Both intervals are based on real-time prediction errors over the 2000 to 2016 sample, as illustrated in Figure 5.
Source: Authors' calculations, Federal Reserve Bank of New York "Nowcasting Report."

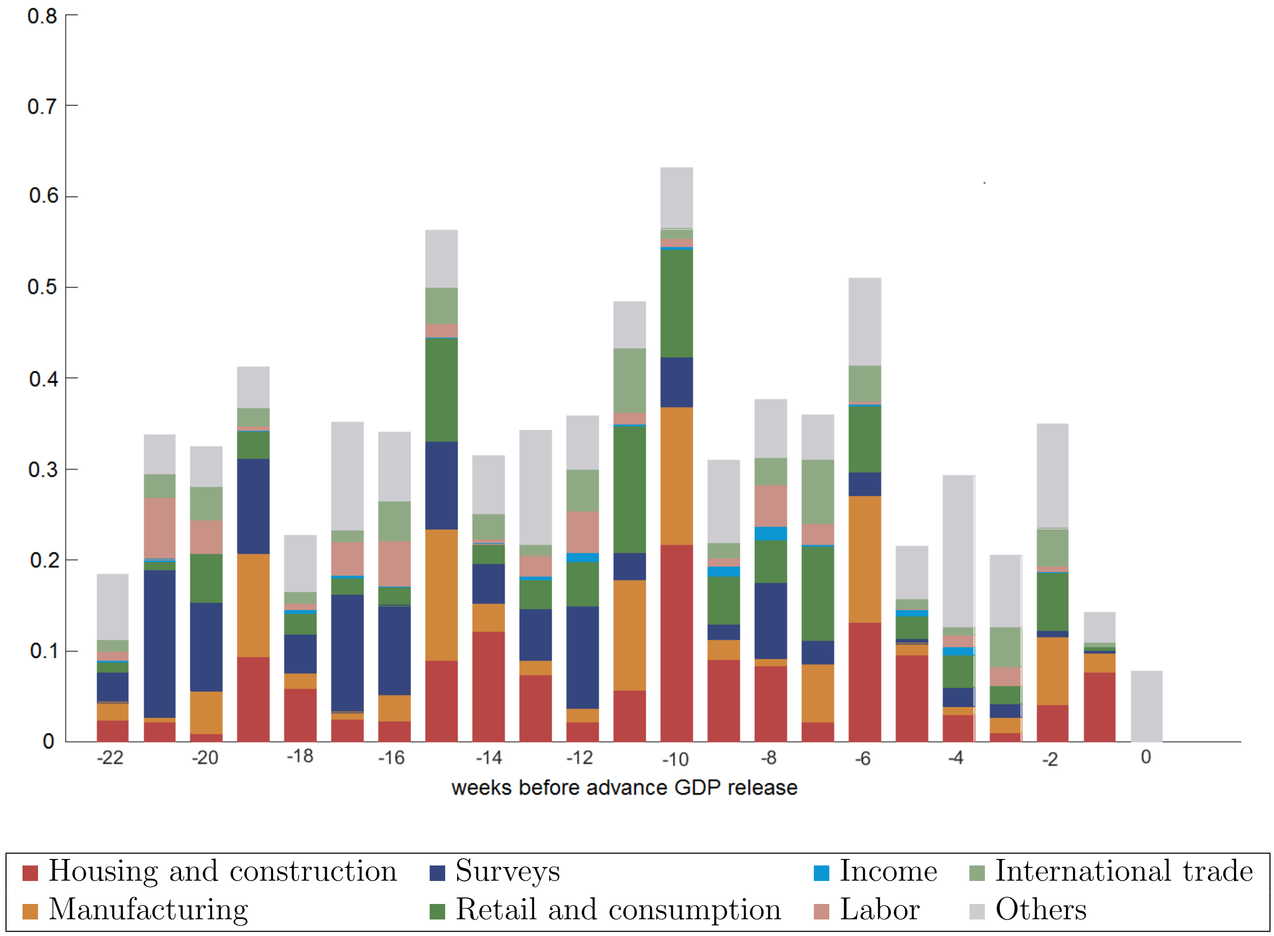


Figure 7: Impact of data releases on the nowcast. The bars indicate the average absolute impact of each data series on the nowcast computed in real time over the evaluation sample 2000 to 2016. The series are grouped by category as indicated in the legend. The x-axis indicates the point in the quarter when the nowcasts were made, measured in terms of weeks before the first official GDP release.
Source: Authors' calculations.