

8-24-2020

Real-Time Measurement of Business Conditions, Macroeconomic Surprises, and Uncertainty: Is a Recession Looming? in **Alternative Economic Indicators**

Alessandro Barbarino  
Chiara Scotti

*Federal Reserve Board*

Follow this and additional works at: [https://research.upjohn.org/up\\_press](https://research.upjohn.org/up_press)



Part of the [Income Distribution Commons](#), and the [Social Welfare Commons](#)

---

Citation

Barbarino, Alessandro and Chiara Scotti. 2020. "Real-Time Measurement of Business Conditions, Macroeconomic Surprises, and Uncertainty: Is a Recession Looming?" In *Alternative Economic Indicators*, C. James Hueng, ed. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, pp. 57-80.

<https://doi.org/10.17848/9780880996778.Ch5>

This title is brought to you by the Upjohn Institute. For more information, please contact [repository@upjohn.org](mailto:repository@upjohn.org).

# **Alternative Economic Indicators**

C. James Hueng  
*Editor*

2020

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

**Copyright Page**

ISBN 9780880996778 (ebook)

© 2020

W.E. Upjohn Institute for Employment Research  
300 S. Westnedge Avenue  
Kalamazoo, Michigan 49007-4686

The facts presented in this book and the observations and viewpoints expressed are the sole responsibility of the authors. They do not necessarily represent positions of the W.E. Upjohn Institute for Employment Research.

Cover design by Carol A.S. Derks.

# 5

## Real-Time Measurement of Business Conditions, Macroeconomic Surprises, and Uncertainty

### Is a Recession Looming?

Alessandro Barbarino  
Chiara Scotti  
*Federal Reserve Board*

As pointed out by the Congressional Budget Office (CBO 2019), the current economic expansion has lasted more than nine years, becoming one of the longest expansions since 1945.<sup>1</sup> Because of such a long boom, some people think that a recession might be due soon. In January 2019, for example, the *Wall Street Journal* published a survey showing a 25 percent probability of recession in the next year, the highest level since October 2011 and twice the probability of one year ago. Similarly, the *Blue Chip Indicators* for January 2019 reported a consensus survey result for the probability of a recession in 2019 at 25 percent and the probability of a recession in 2020 at 37 percent. Reportedly, one of the reasons the Dow 30 and S&P 500 indexes both fell by more than 15 percent in December 2018 was from a concern that the economy would fall into a recession in late 2019 or 2020, prompting negative earnings growth.

This chapter focuses first on evaluating current business conditions in the United States, based on real-activity economic indicators, as well as on gauging market participants' optimism or pessimism about the economy and the uncertainty around this evaluation. Second, it evaluates some recession probability models that make use of a variety of data to pinpoint whether indeed a recession is looming.

To evaluate business conditions, we look at the Aruoba, Diebold, and Scotti (2009) business condition index (henceforth, “ADS index”) as well as the Scotti (2016) surprise and uncertainty indexes updated with the most current data. The ADS index turned negative in early 2019, suggesting worse-than-average conditions for the U.S. economy over the preceding months.<sup>2</sup> Economic surprises and uncertainty are evaluated using the Scotti (2016) indexes. The surprise index spiked early in 2019, as market participants were more pessimistic than warranted by economic releases, but then sharply collapsed following the release of the February employment report in early March. The uncertainty index steadily increased at the beginning of 2019, reaching levels last seen in late 2017.

Given this assessment, should we conclude that a recession is looming, as suggested by the CBO analysis? In order to tackle this question, we review the prediction of extant recession forecasting models by feeding them a variety of data, including the real-time indicators discussed in the first part of this chapter, a larger set of individual macro variables, and financial variables (like level, slope, curvature, corporate spreads, and so forth). When using individual data, to make sure we have entries for all the variables until the last data point, we truncate the sample in December 2018 (even if for some data series we have data until the day before we ran the estimation in March 2019) and find an increased probability of recession in mid-2019, possibly due to the big correction observed in financial markets in late 2018. When we re-estimate the recession probabilities employing only the ADS index as a summary statistic of the real indicators, which is available in real time and allows us to take care of the ragged edges of the data, the estimated probabilities significantly decrease. Our analysis also shows that, consistent with Berge (2015), real variables appear to be more powerful in signaling recessions at shorter horizons, while the term spread and some additional financial variables are valuable leading indicators at longer horizons—that is, at horizons of 6–12 months ahead and beyond.

The remainder of the chapter discusses the real-time measurement of business conditions in the next section, the real-time evaluation of optimism/pessimism and uncertainty about the state of the economy in the section after that, and the evaluation of recession probability models with a variety of data in the fourth section. The final section offers our conclusions.

## REAL-TIME MEASUREMENT OF ECONOMIC CONDITIONS

Aruoba, Diebold, and Scotti (2009) state the following:

Aggregate business conditions are of central importance in the business, finance, and policy communities, worldwide, and huge resources are devoted to the assessment of the continuously evolving state of the real economy. Literally thousands of newspapers, newsletters, television shows, and blogs, not to mention armies of employees in manufacturing and service industries, including the financial services industries, central banks, government and non-government organizations, grapple constantly with the measurement and forecasting of evolving business conditions.

Complications to this assessment include the fact that business conditions are latent, data are released at different times and therefore not always all available at the time of the evaluation, and they are at different frequencies. The latency of the business cycle means that the business cycle is not directly observed, as it is not represented by any single variable, but rather, it is derived by information contained in a number of indicators like gross domestic product (GDP), industrial production (IP), employment, and so on. In fact, the National Bureau of Economic Research (NBER) does not define a recession in terms of only one indicator of activity, such as two consecutive quarters of decline in real GDP, but as a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales.<sup>3</sup>

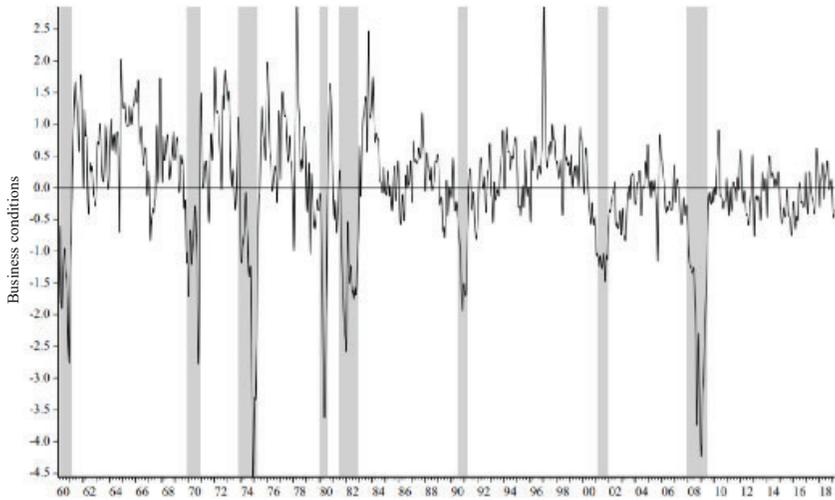
Data are released at different times. For example, nonfarm payroll is announced the first Friday of the month, and initial jobless claims are released weekly on Thursday. Assume that it is Tuesday, February 26, 2019, and we are trying to assess the current state of the economy for the first quarter of 2019. We only have partial information available relative to that quarter. The January nonfarm payroll is available, but the February job market report will not be available until the coming Friday. Likewise, as of February 26, initial jobless claims releases are available only for the first seven weeks of the year. In addition, GDP data relative to the first quarter will be released only a quarter later. This ragged-edge structure of the data complicates the evaluation of

real-time business conditions, as we need to juggle data series of different lengths.

In addition, data have different frequencies, covering various units of time. For example, GDP is quarterly, nonfarm payroll is monthly, and initial jobless claim is weekly. An assessment of business conditions needs to take this into account and be able to accommodate the different units and the aggregation that makes weekly series comparable to monthly or quarterly variables.

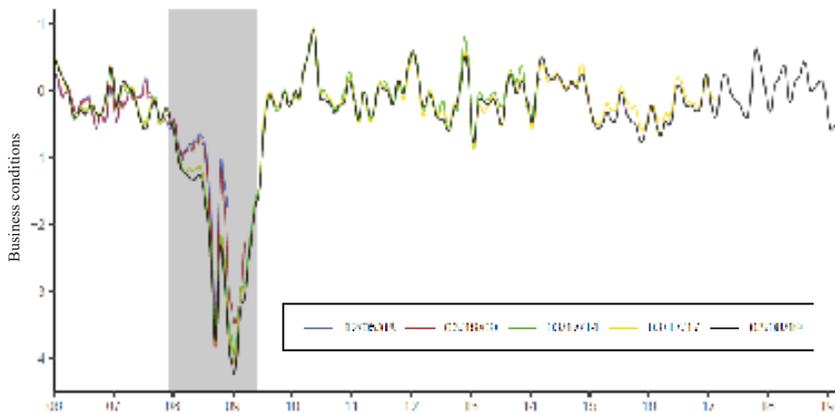
The empirical business cycle literature has dealt with these features through alternative approaches, including the dynamic factor framework, whether from the “small data” perspective, as in Aruoba, Diebold, and Scotti (2009); Chauvet (1998); Diebold and Rudebusch (1996); and Stock and Watson (1989), or the “big data” perspective, as in the seminal work of Bai and Ng (2006); Forni et al. (2000); and Stock and Watson (1991, 2002). Aruoba, Diebold, and Scotti (2009) propose a framework to measure economic activity in real time using a dynamic factor model that combines a small set of time series at different frequencies. In particular, the ADS index is designed to track real business conditions at a high frequency, combining information from (seasonally adjusted) economic indicators: weekly initial jobless claims, monthly payroll employment, monthly industrial production, monthly personal income less transfer payments, monthly manufacturing and trade sales, and quarterly real GDP. The Philadelphia Fed updates the index as soon as new data releases become available. Figure 5.1 displays the ADS index as of March 15, 2019. Of note, the average value of the index is zero, with progressively bigger positive values indicating progressively better-than-average conditions, and progressively more negative values indicating progressively worse-than-average conditions. The business condition index in Figure 5.1 is based on the information available as of March 2019. The index might look different, though, when computed on different data vintages. Figure 5.2, for example, shows the ADS index computed in real time in March 2019 and contrasts it against the index computed on different data vintages ranging from 11 to 2 years prior to March 2019. The ADS index computed on the December 2008 data vintage ends in December 2008 and, likewise, lines for the indexes computed on data vintages in 2009, 2014, 2017, and 2019 end in the respective years. Looking at the last recession, the real-time estimate of the index turned out to be overly optimistic, and it was subsequently revised downward, as shown by the wedge between the 2008 vintage (in

**Figure 5.1 Aruoba-Diebold-Scotti (ADS) Business Condition Index, 3/1/1960–3/15/2019**



NOTE: The ADS is constructed using the latest data available as of March 15, 2019. Grey shading indicates NBER-designated recessions. The limits used on the y-axis reflect the minimum and maximum values of the index over the entire history. SOURCE: Federal Reserve Bank of Philadelphia, ADS Business Conditions Index.

**Figure 5.2 ADS Index in Real Time**



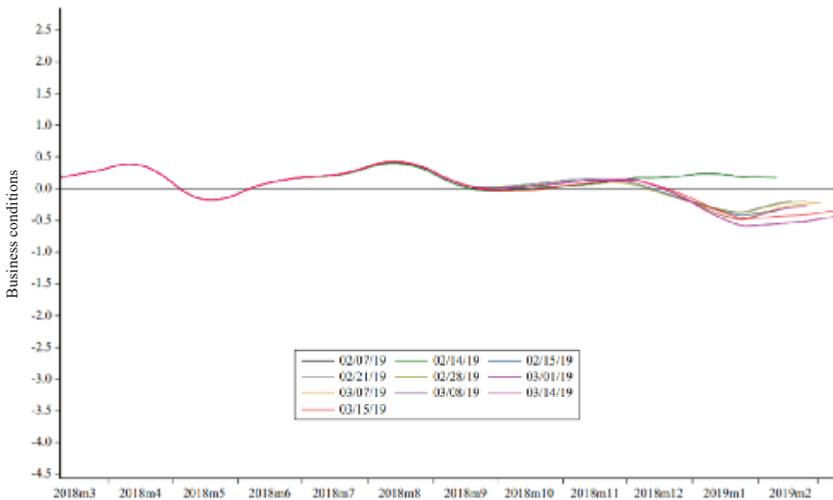
NOTE: The ADS indexes are constructed using data available up to the date indicated in the legend. SOURCE: Federal Reserve Bank of Philadelphia, ADS Business Conditions Index.

blue) and the March 2019 vintage (the black line). Focusing on recent years, Figure 5.3 shows the tentacle plot of the 10 vintages of data prior to March 2019. After a couple of positive estimates at the beginning of the year, the ADS index was subsequently revised downward into negative territory relative to estimates computed on earlier data vintages. Both the new data releases and the revisions of previous data explain the downward revision.

## REAL-TIME EVALUATION OF OPTIMISM/PESSIMISM AND UNCERTAINTY

While the ADS index measures the state of the economy and serves as a summary statistic of the information that market participants have received thus far about real activity, it is silent with respect to whether this information is in line with what market participants are expect-

**Figure 5.3 ADS Index in Real Time, Recent Vintages**



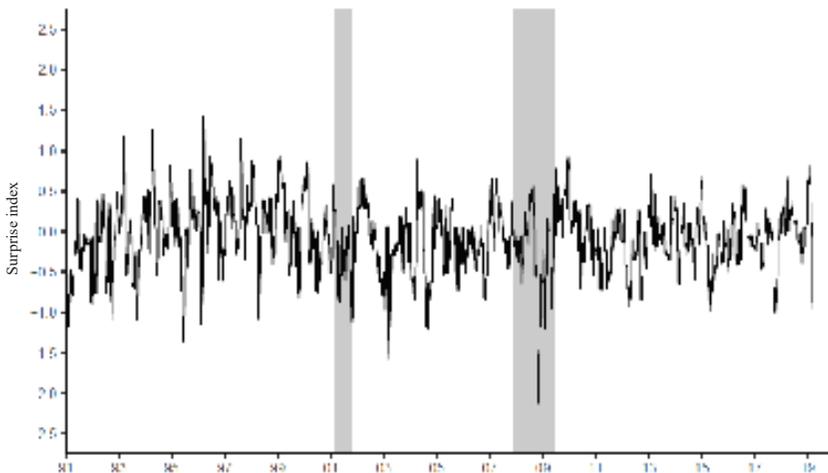
NOTE: The ADS indexes are constructed using data available up to the date indicated in the legend.

SOURCE: Federal Reserve Bank of Philadelphia, ADS Business Conditions Index.

ing and the uncertainty surrounding the data releases. The surprise and uncertainty indexes in Scotti (2016) speak to these issues. The surprise index summarizes recent economic data surprises and measures deviations from consensus expectations. A positive (negative) reading of the index indicates that agents were more pessimistic (optimistic), expecting economic data to be worse (better) than their actual realization. The uncertainty index measures the uncertainty related to the state of the economy. A greater (smaller) reading suggests that agents have, on balance, been more (less) uncertain about business conditions.

Figure 5.4 displays the surprise index computed as of March 2019. The surprise index reached its lowest value during the global financial crisis of 2008–2009, suggesting that as the crisis was unfolding, agents were less pessimistic about its possible outcome and its impact on the real economy. In contrast, the index turned positive during the beginning of 2019, indicating that agents were pessimistic about the state of the economy, harboring fairly low expectations relative to the actual

**Figure 5.4** Scotti Surprise Index



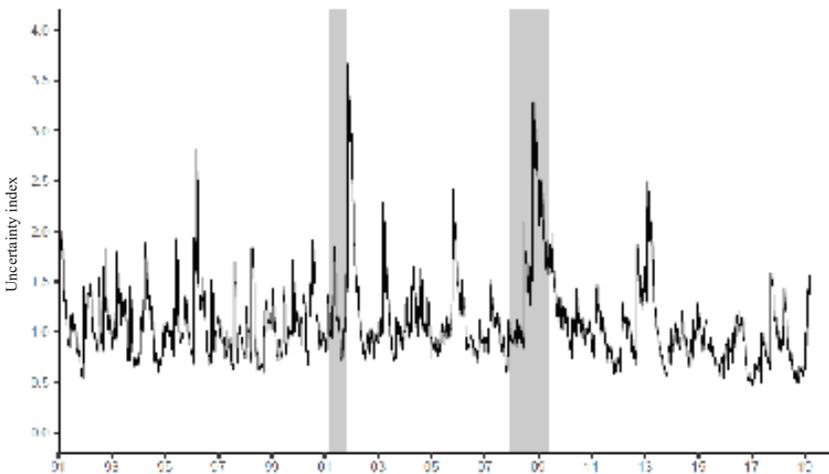
NOTE: The Scotti (2016) Surprise Index summarizes recent economic data surprises and measures deviations from consensus expectations. A positive (negative) reading of the surprise index indicates that agents were more pessimistic (optimistic), expecting economic data to be better (worse) than their actual realization.

SOURCE: Authors' calculations based on Bloomberg and NBER recession dates.

releases of GDP, IP, and nonfarm payroll. However, the index turned sharply negative in early March following the release of the February employment report.

Figure 5.5 portrays the uncertainty index, which tends to be elevated during recessions. Although there are some nonrecessionary periods in which the index spikes, it is interesting to note that the index increased in early 2019, reaching highs previously seen in 2017. This suggests that agents were less certain about the state of the economy.

**Figure 5.5 Scotti Uncertainty Index**



NOTE: The Scotti (2016) Uncertainty Index measures the uncertainty related to the state of the economy. A greater (smaller) reading suggests that agents have on balance been more (less) uncertain about business conditions.

SOURCE: Authors' calculations based on Bloomberg and NBER recession dates.

## IS A RECESSION LOOMING?

Taken together, the several indexes presented so far suggest that business conditions in the United States have turned negative in early 2019, providing fertile ground for a downturn. Does this mean that a recession is looming?

In order to address such questions, we turn to the ADS index to directly inform the probability of a recession. First off, note that forecasting a recession is a hard task, given that the NBER tends to identify recessions only after a 12- to 18-month lag. As Hamilton (2011) puts it, “If people could predict recessions, they probably would not happen. Firms would not be stuck with inventories, labor, and capital they turn out not to need, and the Federal Reserve would probably ease its policy stance earlier.” Following a long-standing academic literature on estimating recession probabilities (see, for instance, Hamilton [2011] for an enlightening literature review), we use a probit model. We estimate the probability of being in a recession in the current quarter (that is, for a forecast horizon  $h = 0$ ) only as a function of the ADS index instead of using a set of indicators. This stands as an alternative to customary estimates of recession probabilities, as can be seen from the review of relevant literature shown in Table 5.1, because we first embed in the ADS factor the information from the set of variables that constitute the ADS index, and then we feed the ADS index into the probit model. Our approach could be defined as “aggregate, then forecast,” paraphrasing the taxonomy laid out by Stock and Watson (2014).

Fossati (2016) estimates a small-scale dynamic factor model (DFM) in order to estimate a recession probability probit, but his DFM contains only monthly data (the same monthly data used in the ADS index), whereas the use of the ADS index allows us to automatically take care of mixed-frequency data and to include information on GDP.<sup>4</sup>

Figure 5.6 shows the recession probability based on the ADS index from 1960 to March 2019.<sup>5</sup> The recession probabilities computed before 2009 are based on the mid-March 2019 vintage of the ADS index, while the probabilities from 2009 to 2019 (to the right of the vertical red line) are computed in real time using the ADS vintage available at the time indicated on the x-axis. In other words, in the latter part of the sample, a probit model is recursively estimated with the new ADS index that summarizes available data up to a particular date. Generally, the model exhibits high spikes during NBER recession periods (the gray shaded areas). With an exception for the early-2000s recession, the estimated probability during all the recessions reached at least 75 percent. A word of caution on Figure 5.6: since the estimate of the probability is not in real time before 2009, looking at the estimate before the vertical red line could be deceiving if one intends to use the estimates to call recessions

**Table 5.1 Summary of Literature on Predicting Recessions**

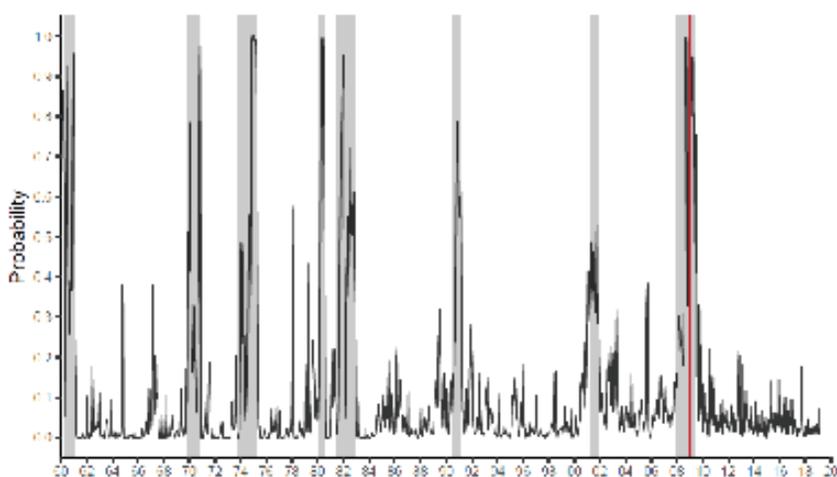
Reference	Data scale	Data type	Data freq.	Model type	Forecast type	Real-time
Stock and Watson (1989)	Small	Real financial	Monthly	Factor from UC model	Backcasting Nowcasting	No
Stock and Watson (1991)	Medium	Real financial	Monthly	Logit + factor from UC model	Backcasting Nowcasting	No
Diebold and Rudebusch (1996)	Small	Financial	Quarterly	Markov switching DFM	None	No
Chauvet (1998)	Small	Real	Monthly	Markov switching DFM	Backcasting Nowcasting	No
Chauvet and Potter (2005)	Very small	Financial	Monthly	Dynamic probit	Backcasting Nowcasting	Yes
Harding and Pagan (2006)	Large	Real	Monthly	Dating algorithm	Backcasting	No
Wright (2006)	Very small	Real	Monthly	Probit	Forecasting	Yes
Chauvet and Piger (2008)	Small	Real	Monthly	Dating algorithm Markov switching DFM	Backcasting	Yes
Kauppi and Saikkonen (2008)	Very small	Financial	Monthly	Generalized dynamic probit	Backcasting Nowcasting	Yes
Berge (2015)	Medium	Real financial	Monthly	BMA logit	Backcasting Nowcasting	Yes
Fossati (2015)	Small/ large	Real	Monthly	Dynamic probit DFM Markov switching DFM	Forecasting	Yes
Giusto and Piger (2017)	Small	Real financial	Monthly	Vector quantization	Backcasting	Yes
This study	Small/ medium	Real financial/ other	Mixed: weekly/ monthly/ quarterly	BMA logit DFM	Nowcasting	Yes

NOTE: The table presents a summary of the relevant literature on forecasting recessions at different horizons with macroeconomic and financial data. The model is formulated but not estimated. Financial data are not revised—therefore they are, by construction, real-time.

SOURCE: Authors' compilation.

in real time. That said, we verify that for the time window in which we have vintages of the ADS index, the real-time estimates are not drastically different from the estimate on the last vintage we used.

Figure 5.7 zooms in on the most recent 10 years and compares the recession probabilities estimated using the mid-March 2019 ADS vin-

**Figure 5.6 Recession Probability Based on the ADS Index**

NOTE: The recession probabilities computed based on the “Last Vintage ADS” use information as of mid-March 2019, whereas probabilities based on the “Real Time ADS” use the ADS vintages available at the time indicated on the x-axis. Grey shading indicates NBER-designated recessions.

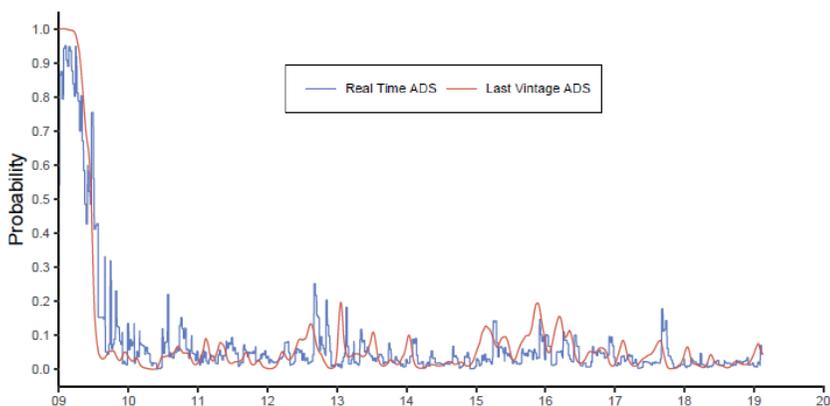
SOURCE: Authors’ calculations based on Philadelphia Fed, ADS Business Conditions Index.

tage with the estimate using the real-time ADS index available at the time indicated by the x-axis. Although the real-time recession probability is more volatile when compared to the probability computed using the last vintage of data, the real-time estimate is substantially in agreement and provides the same signal as the estimate from the last vintage that we have used.

## ADDITIONAL INDICATORS OF ECONOMIC ACTIVITY

The ADS index is a coincident indicator, and the probability computed above refers to the assessment that the economy is in recession in the corresponding month. This analysis could be expanded in two directions: 1) including alternative indicators as explanatory variables (individual macroeconomic series or financial series) and 2) forecasting

**Figure 5.7 Recession Prob. Based on the ADS Index: Real-Time Versus Last-Vintage**



NOTE: The recession probabilities computed before 2009 are based on the February 2019 vintage of the ADS index, while the probabilities from 2009 to 2019 are computed in real time using the ADS vintage available at the time indicated on the x-axis. Grey shading indicates NBER-designated recessions.

SOURCE: Authors' calculations based on Philadelphia Fed, ADS Business Conditions Index.

recession probabilities at different horizons. We investigate the second issue in the empirical analysis looking at a horizon of between 0 and 12 months. With respect to the first item, we discuss here some additional indicators that have been explored in the literature, starting from the seminal work by Stock and Watson (1989), and then we use them in conjunction with the ADS index to understand the quality of the incremental information that they provide in forecasting recessions. We find that financial indicators are very useful beyond the ADS index at longer forecast horizons.

**The term spread.** Stock and Watson (1989) introduce yield spreads—in particular the spread between 10-year and 1-year T-bonds—as useful indicators in forecasting economic activity and downturns. Estrella and Hardouvelis (1991) further explore the forecasting power of the *slope of the Treasury yield curve* as a leading indicator of downturns.<sup>6</sup> Corroborating the findings in these studies, academics and market participants point to the fact that a negative slope—a negative difference between a far-off maturity, typically 10 years, and a shorter

maturity, typically between 2 years and 3 months—generally precedes economic recessions. Accordingly, recession probability models based uniquely on the term spread generally associate declining term spreads with an elevated probability of recession in the near/medium term.<sup>7</sup> For example, in early 2019, a simple probit model based only on the term spread would have predicted a much higher probability of recession in the next 12 months. In fact, the Federal Reserve Bank of Cleveland assessed the probability of being in a recession by January 2020 at about 30 percent using information from the yield curve as of mid-March 2019.<sup>8</sup> A variety of additional financial variables closely connected with the yield curve have been tested in forecasting turning points in the economy. For instance, Wright (2006) motivates the introduction of the average of the federal funds rate over a given quarter as it provides a measure of the impetus or restraint to the economy implied by the stance of monetary policy.<sup>9</sup> In addition, Wright (2006) also finds some evidence that a measure of expected excess returns on longer-maturity bonds, the *return forecasting factor* studied by Cochrane and Piazzesi (2005), is useful in predicting recessions. In our empirical evaluation in the section titled “Real-Time Measurement of Economic Conditions,” we use both the level of the yield curve (as in Wright ([2006]) as well as slope and curvature.

**Corporate bond spreads.** Stock and Watson (1989) introduce yield spreads as useful indicators in forecasting economic activity and downturns, and they find that the spread between commercial paper and Treasury bills is a leading indicator of recessions. Several other authors have found that *corporate bond spreads*—also called *credit spreads*—are useful indicators in predicting recessions. Stock and Watson (1989) used the paper-bill spread, and Gertler and Lown (1999) studied the high-yield credit spread. Both of these spreads have predictive content on economic activity because they embed default risk, which incorporates investors’ expectations of future corporate defaults. However, recent analysis in Gilchrist and Zakrajšek (2012) tries to distill the information on future economic activity in bond credit spreads beyond default risk and calls such a component the excess bond premium (EBP). Favara et al. (2016a) use the EBP in a probit model of recessions.<sup>10</sup> We include the most recent update of the EBP in the empirical explorations in the next section.

**Other financial indicators.** Beyond credit spreads, stock market returns and other financial information such as the implied stock market volatility—as measured by the Chicago Board Options Exchange volatility index (VIX)—have been used to predict economic activity. For instance, Danielsson, Valenzuela, and Zer (2018) use the VIX in trying to explain financial crises, and Engstrom (2014) uses option pricing in trying to predict stock market crashes. We include the VIX as a regressor in the models of the section “Real-Time Management of Economic Conditions.”

## USING THE ADS INDEX WITH ADDITIONAL INDICATORS IN FORECASTING RECESSIONS

Berge (2015) finds that the term spread and some additional financial variables are valuable leading indicators, but mostly at longer horizons—that is, at horizons of 6–12 months ahead, and beyond. Conversely, at shorter horizons, real variables appear to be more powerful in signaling recessions.

We follow Berge (2015) and use a series of logit models, one for each horizon from 0 to 12 months, and a variety of real and financial explanatory variables, in order to explore the usefulness of the ADS index. Through Bayesian Model Averaging (BMA), we select the models containing the most useful indicators at each forecast horizon, reducing the dimensionality of our big system of models (with  $N$  indicators, we have  $2^N$  possible models).<sup>11</sup> The individual models are at the monthly frequency and contain a mixture of financial and real variables. Financial variables are as follows: the level, slope, and curvature of the yield curve; corporate bond spreads; the TED spread; the return on the S&P500; the trade-weighted dollar index; and the VIX. For macro indicators, we compare three different sets of variables:

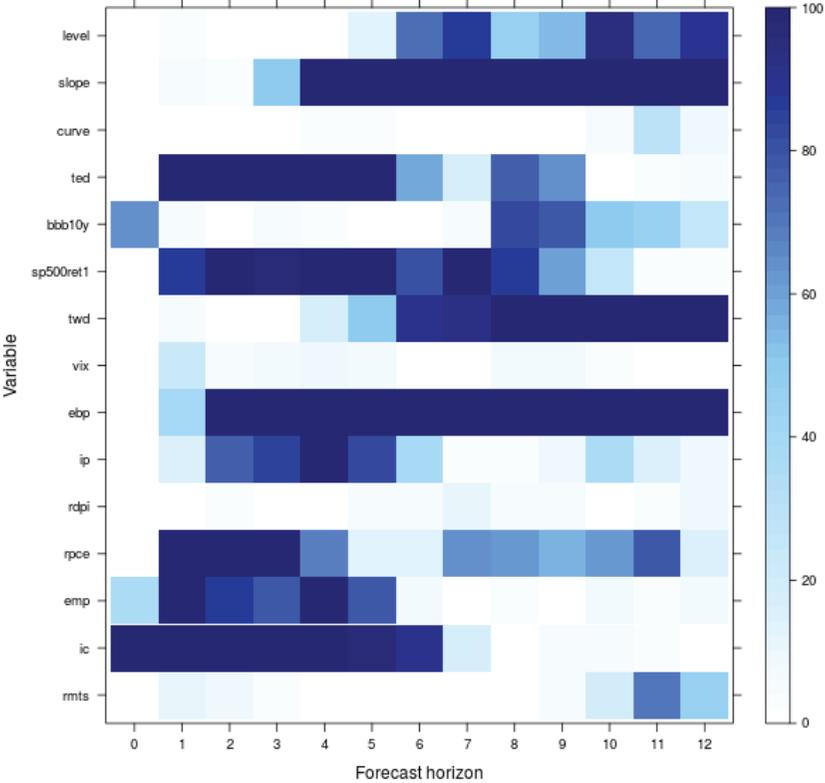
- 1) the ADS index;
- 2) the subset of real-activity variables used to compute the ADS index—specifically, nonfarm payroll, industrial production, retail sales, personal income, and a monthly average of initial jobless claims;<sup>12</sup>

- 3) a larger set of macro variables, including the variables that make up the ADS index, plus total light vehicle sales, the ISM purchasing managers' index, average weekly hours, housing permits, and the four-week moving average of unemployment claims.

Because the NBER announces turning points with a delay, and we do not want to incorrectly assume that a month in the recent past was or was not a recession (that is, assigning a 0 or 1 value to the logit dependent variable), we estimate the model up to December 2017 and use those parameter estimates in the evaluation of the recession probabilities. In this first step, our BMA approach selects the best combination of indicators at the different horizons, as shown by the heat map of the posterior inclusion probabilities in Figure 5.8. The darker color in the figure indicates a higher posterior probability that a particular variable (shown in the rows) is included in the model for that horizon (shown in the columns). We only show results for one of the models described above with financial and real variables.<sup>13</sup> It should be clear from the figure that there is a predominance of darker colors in the lower-left quadrant and in the top right, indicating that real variables have higher inclusion probabilities for shorter-horizon models, while financial variables have higher inclusion probabilities at longer horizons. An exercise in which we separate the estimation of a real-variable model and a financial-variable model highlights this finding even more, as already noted by Berge (2015). In fact, as shown in Figure 5.9, the Receiver Operating Characteristic (ROC) curves for the in-sample prediction from the 1- and 12-month-ahead models point to a superior performance of the real variables at the 1-month horizon, but a better performance of the financial indicators at the 12-month horizon.<sup>14</sup>

We then employ data up to December 2018 to forecast our indicators through December 2019, using a random walk, and compute the corresponding recession probabilities for each horizon based on the best model selected in the previous step. Figure 5.10 shows such probabilities for the three combinations of real variables outlined above. Interestingly, all three models point to an increased probability of recession in mid-2019, possibly due to the big correction observed in financial markets in late 2018. Of note, the model with the ADS index performs just as well as the model in which the underlying series enter one by one.

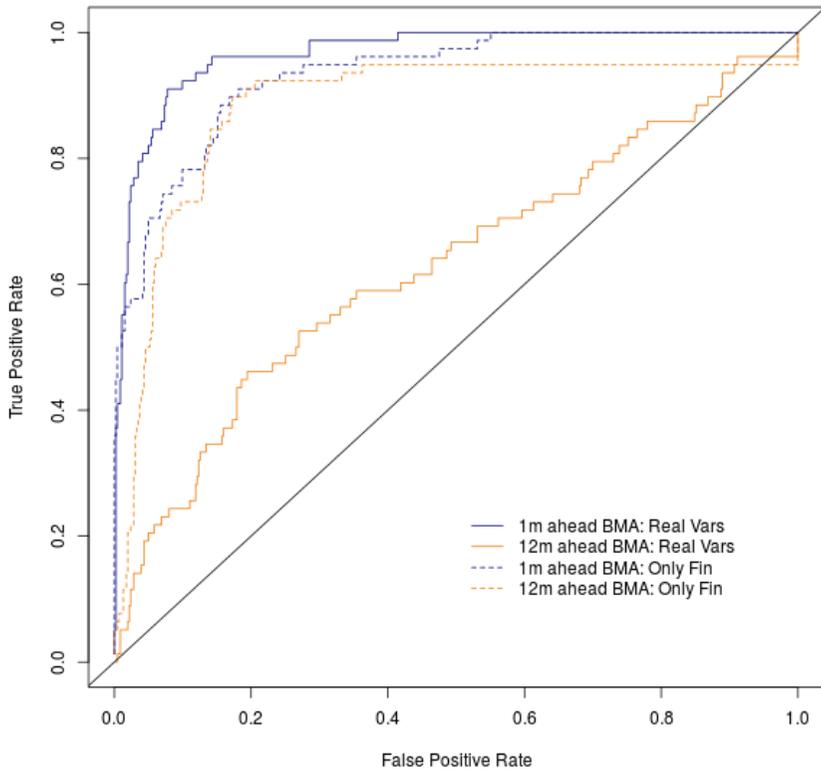
**Figure 5.8 Heat Map of Posterior Inclusion Probabilities**



NOTE: Posterior inclusion probabilities for each variable (rows) and each horizon (columns) related to the model with the ADS index and financial variables. Darker colors indicate a high inclusion probability.

SOURCE: Authors’ calculations based on NBER recession dates, BEA real disposable income.

A drawback to this forecast exercise is that it does not allow for ragged edges in the data and mixed frequency, as it needs to stop at the last point in time for which all the series are available. To overcome this issue, we reestimate the recession probabilities employing only the ADS index as a summary statistic of the real indicators plus GDP, which is available in real time. The estimated probabilities based on the ADS index and financial variables as of mid-March are shown in Figure 5.11. Based on the additional information available between

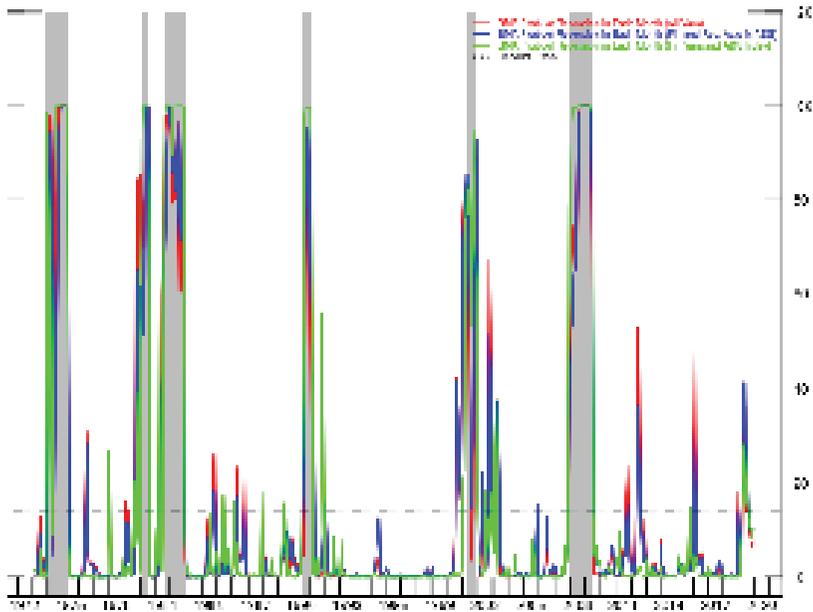
**Figure 5.9 Heat Map of Posterior Inclusion Probabilities, ROC Curves**

NOTE: ROC curves for 1- and 12-month-ahead models with real or financial indicators.  
SOURCE: Authors' calculations based on NBER recession dates, BEA real disposable income.

the end of 2018 and mid-March, the probability of the NBER declaring a recession over the next year significantly decreased, in line with the ADS-only probability from Figure 5.7.

## CONCLUSION

In this chapter, we update and evaluate a number of economic indicators as well as recession probability models. As pointed out by Berge

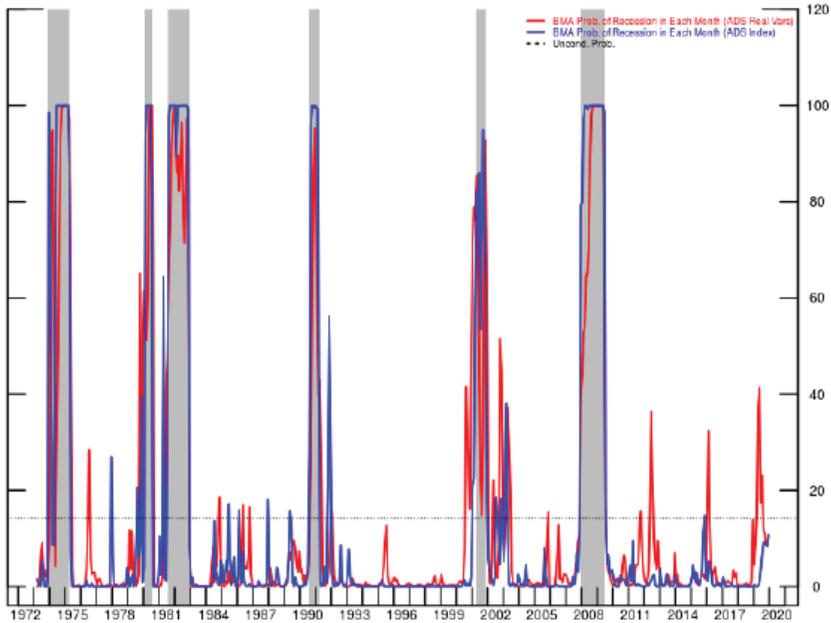
**Figure 5.10 BMA Recession Probabilities, December 2018**

NOTE: Probability that the NBER will declare a recession in a particular month based on the BMA probit model. Forecast after December 2018 based on a random walk of the various indicators. Dotted line represents the unconditional probability.

SOURCE: Authors' calculations based on NBER recession dates, BEA real disposable income.

(2015), different mixtures of real and financial variables work best at different horizons, suggesting the need to maintain a set of models that work well at different forecasting horizons. Because of the inability of probit models to account for ragged edges, a real-time indicator of real activity like the ADS index might prove useful to have more up-to-date forecasts of recession probabilities.

The analysis of this topic, however, should not be limited to what is described above. For example, other indicators might be considered among the set of explanatory variables, along the lines of Engstrom and Sharpe (2018), who further qualify the most relevant term spread to forecast recessions. They argue that the *near-term forward spread*, computed as the difference between the implied forward rate on Treas-

**Figure 5.11 BMA Recession Probabilities, Mid-March 2019**

NOTE: Probability that the NBER will declare a recession in a particular month based on the BMA probit model. Forecast after March 2019 based on a random walk of the various indicators. Dotted line represents the unconditional probability.

SOURCE: Authors' calculations based on NBER recession dates, BEA real disposable income.

surely bills six quarters ahead and the corresponding yield on a three-month Treasury bill, is a better predictor compared to more traditional term spreads. The near-term forward spread can be interpreted as a measure of the market's expectations for the trajectory of conventional near-term monetary policy. When negative, it indicates that market participants expect monetary policy to ease on net over the next several quarters, presumably because they expect monetary policymakers to respond to the threat or onset of a recession.<sup>15</sup> The superiority of using forward rates comes from the fact that, because yields are averages of the forward rates spanning the period to maturity, they tend to be a noisier signal of the expected Fed actions. They corroborate this intuition by proving that their measure outperforms in sample the term spread of the

10-year Treasury constant maturity minus two-year Treasury constant maturity spread sometimes used in the classical probit model.

The national financial condition indicator (NFCI) maintained by the Federal Reserve Bank of Chicago could also potentially be used as a financial explanatory variable, just as the ADS index is used for real variables.<sup>16</sup> The NFCI index provides a comprehensive weekly update on U.S. financial conditions in money markets, debt and equity markets, and the traditional and “shadow” banking systems. Alternatively, because U.S. economic and financial conditions tend to be highly correlated, the adjusted NFCI (ANFCI)—an index that isolates a component of financial conditions uncorrelated with economic conditions to provide an update on financial conditions relative to current economic conditions—could be considered.

Recession probabilities based on macroeconomic and financial indicators could additionally be compared to news-count measures of recession probabilities, such as the LexisNexis index of Berge and Jordà (2011) or the Google trends recession index also reported in Berge and Jordà, and used in an original way to set priors of a Bayesian DFM in Monokroussos (2015). The horizon of these news-count probabilities is, however, not clear, as articles could talk about past, current, or future recessions. Therefore, a straight comparison with the measures described above might not be so straightforward.<sup>17</sup>

## Notes

Alessandro Barbarino and Chiara Scotti are with the Federal Reserve Board, 20th and C Streets NW, Washington, DC 20551. The authors can be reached via email at [alessandro.barbarino@frb.gov](mailto:alessandro.barbarino@frb.gov) and [chiara.scotti@frb.gov](mailto:chiara.scotti@frb.gov). We thank Charles Horgan for excellent research assistance. The opinions expressed here are our own and do not necessarily reflect the views of the Board of Governors or its staff. This chapter was originally prepared for the 55th annual Werner Sichel Lecture Series in 2018–2019 on “Alternative Economic Indicators” and delivered at Western Michigan University in March 2019.

1. See CBO (2019), <https://www.cbo.gov/system/files?file=2019-01/54918-Outlook.pdf>.
2. The ADS index is maintained and updated by the Federal Reserve Bank of Philadelphia at <https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index>.
3. See <https://www.nber.org/cycles.html>.

4. Fossati (2016) also estimates the factor from a larger scale DFM modeled after Stock and Watson (2002), and he finds in his out-of-sample exercise that the factor from the large-scale DFM performs better in forecasting recessions than the factor from the small-scale DFM. In this note, we did not compare the performance of the ADS index with the performance of the factor from a larger-scale DFM.
5. How negative should the ADS be in order to signal a recession? Berge and Jordà (2011) show that the level of the ADS index that maximizes the ROC when NBER recessions are the target is about  $-0.8017$  (using the last vintage available to them and stopping the computation in December 2007).
6. See Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998) for a thorough account of the earlier literature that links the term spread and real activity. More recently, papers that focus on the predictive power of the slope of the yield curve for recessions include Benzoni, Chyruk, and Kelley (2018); Chauvet and Potter (2005); Croushore and Marsten (2016); Kauppi and Saikkonen (2008); Rudebusch and Williams (2009); and Wright (2006).
7. Notice that the slope of the yield curve does not even need to be negative to obtain considerable spikes in the estimated probability.
8. See <https://www.clevelandfed.org/our-research/indicators-and-data/yield-curve-and-gdp-growth.aspx>.
9. Wright (2006) explores both the nominal federal funds rate and the real rate (for which inflation expectations are proxied by a four-quarter backward-looking moving average of the core personal consumption expenditures [PCE] price index).
10. Updated data on the EBP can be found in Favara et al. (2016b).
11. As in Berge (2015), we use the package BMA in R by Raftery et al. (2018) in order to reduce the dimensionality of the problem.
12. We exclude quarterly GDP, as the model is monthly.
13. Heat maps for the other models are available upon request from the authors.
14. An ROC curve illustrates the trade-off associated with achieving a particular true positive rate versus the corresponding false positive rate. The area under the ROC curve (AUC) is a summary statistic measuring the classification ability of an indicator/model. The higher the AUC, the better the classification ability.
15. The only noise in this measure would be term premiums or liquidity premiums embedded in shorter-term Treasury rates.
16. See <https://www.chicagofed.org/publications/nfci/>.
17. The progressive sophistication of available dictionaries for textual analysis will make it possible to sift through finer details in texts, which will circumvent these limitations.

## References

- Aruoba, S. Borayğan, Francis X. Diebold, and Chiara Scotti. 2009. "Real-Time Measurement of Business Conditions." *Journal of Business and Economic Statistics* 27(4): 417–427.
- Bai, Jushan, and Serena Ng. 2006. "Confidence Intervals for Diffusion Index Forecasts and Inference for Factor-Augmented Regressions." *Econometrica* 74(4): 1133–1150.
- Benzoni, Luca, Olena Chyruk, and David Kelley. 2018. "Why Does the Yield-Curve Slope Predict Recessions?" Chicago Fed Letter No. 404. Chicago: Federal Reserve Bank of Chicago.
- Berge, Travis J. 2015. "Predicting Recessions with Leading Indicators: Model Averaging and Selection over the Business Cycle." *Journal of Forecasting* 34(6): 455–471.
- Berge, Travis J., and Òscar Jordà. 2011. "Evaluating the Classification of Economic Activity into Recessions and Expansions." *American Economic Journal: Macroeconomics* 3(2): 246–277.
- Chauvet, Marcelle. 1998. "An Econometric Characterization of Business Cycle Dynamics with Factor Structure and Regime Switching." *International Economic Review* 39(4): 969–996.
- Chauvet, Marcelle, and Jeremy Piger. 2008. "A Comparison of the Real-Time Performance of Business Cycle Dating Methods." *Journal of Business and Economic Statistics* 26(1): 42–49.
- Chauvet, Marcelle, and Simon Potter. 2005. "Forecasting Recessions Using the Yield Curve." *Journal of Forecasting* 24(2): 77–103.
- Cochrane, John H., and Monika Piazzesi. 2005. "Bond Risk Premia." *American Economic Review* 95(1): 138–160.
- Congressional Budget Office (CBO). 2019. *The Budget and Economic Outlook: 2019 to 2029*. Washington, DC: Congressional Budget Office.
- Croushore, Dean, and Katherine Marsten. 2016. "Reassessing the Relative Power of the Yield Spread in Forecasting Recessions." *Journal of Applied Econometrics* 31(6): 1183–1191.
- Danielsson, Jon, Marcela Valenzuela, and Ilknur Zer. 2018. "Learning from History: Volatility and Financial Crises." *Review of Financial Studies* 31(7): 2774–2805.
- Diebold, Francis X., and Glenn D. Rudebusch. 1996. "Measuring Business Cycles: A Modern Perspective." *Review of Economics and Statistics* 78(1): 67–77.
- Engstrom, Eric. 2014. "Forecasting Stock Market Crashes Is Hard—Especially Future Ones: Can Option Prices Help?" *FEDS Notes*, May 7.
- Engstrom, Eric, and Steve Sharpe. 2018. "The Near-Term Forward Yield

- Spread as a Leading Indicator: A Less Distorted Mirror.” Finance and Economics Discussion Series 2018-055. Washington, DC: Board of Governors of the Federal Reserve System.
- Estrella, Arturo, and Gikas A. Hardouvelis. 1991. “The Term Structure as a Predictor of Real Economic Activity.” *Journal of Finance* 46(2): 555–576.
- Estrella, Arturo, and Frederic S. Mishkin. 1998. “Predicting U.S. Recessions: Financial Variables as Leading Indicators.” *Review of Economics and Statistics* 80(1): 45–61.
- Favara, Giovanni, Simon Gilchrist, Kurt F. Lewis, and Egon Zakrajšek. 2016a. “Recession Risk and the Excess Bond Premium.” *FEDS Notes*, April 8. Washington, DC: Board of Governors of the Federal Reserve System.
- . 2016b. “Updating the Recession Risk and the Excess Bond Premium.” *FEDS Notes*, October 6. Washington, DC: Board of Governors of the Federal Reserve System.
- Forni, Mario, Marc Hallin, Marco Lippi, and Lucrezia Reichlin. 2000. “The Generalized Dynamic-Factor Model: Identification and Estimation.” *Review of Economics and Statistics* 82(4): 540–554.
- Fossati, Sebastian. 2015. “Forecasting U.S. Recessions with Macro Factors.” *Applied Economics* 47(53): 5726–5738.
- . 2016. “Dating U.S. Business Cycles with Macro Factors.” *Studies in Nonlinear Dynamics and Econometrics* 20(5): 529–547.
- Gertler, Mark, and Cara S. Lown. 1999. “The Information in the High-Yield Bond Spread for the Business Cycle: Evidence and Some Implications.” *Oxford Review of Economic Policy* 15(3): 132–150.
- Gilchrist, Simon, and Egon Zakrajšek. 2012. “Credit Spreads and Business Cycle Fluctuations.” *American Economic Review* 102(4): 1692–1720.
- Giusto, Andrea, and Jeremy Piger. 2017. “Identifying Business Cycle Turning Points in Real Time with Vector Quantization.” *International Journal of Forecasting* 33(1): 174–184.
- Hamilton, James D. 2011. “Calling Recessions in Real Time.” *International Journal of Forecasting* 27(4):1006–1026.
- Harding, Don, and Adrian Pagan. 2006. “Synchronization of Cycles.” *Journal of Econometrics* 132(1): 59–79.
- Kauppi, Heikki, and Pentti Saikkonen. 2008. “Predicting U.S. Recessions with Dynamic Binary Response Models.” *Review of Economics and Statistics* 90(4): 777–791.
- Monokroussos, George. 2015. “Nowcasting in Real Time Using Popularity Priors.” MPRA Paper No. 68594. University Library of Munich, Germany.
- Raftery, Adrian, Jennifer Hoeting, Chris Volinsky, Ian Painter, and Ka Yee Yeung. 2018. “Bayesian Model Averaging (BMA) R Package.” Seattle: University of Washington.

- Rudebusch, Glenn D., and John C. Williams. 2009. "Forecasting Recessions: The Puzzle of the Enduring Power of the Yield Curve." *Journal of Business and Economic Statistics* 27(4): 492–503.
- Scotti, Chiara. 2016. "Surprise and Uncertainty Indexes: Real-Time Aggregation of Real-Activity Macro-Surprises." *Journal of Monetary Economics* 82(C): 1–19.
- Stock, James H., and Mark W. Watson. 1989. "New Indexes of Coincident and Leading Economic Indicators." In *NBER Macroeconomics Annual*, Vol. 4, Olivier Jean Blanchard and Stanley Fischer, eds. Cambridge, MA: MIT Press, pp. 351–409.
- . 1991. "A Probability Model of the Coincident Economic Indicators." In *Leading Economic Indicators: New Approaches and Forecasting Records*, Kajal Lahiri and Geoffrey H. Moore, eds. Cambridge: Cambridge University Press, pp. 63–89.
- . 2002. "Macroeconomic Forecasting Using Diffusion Indexes." *Journal of Business and Economic Statistics* 20(2): 147–162.
- . 2014. "Estimating Turning Points Using Large Data Sets." *Journal of Econometrics* 178(P2): 368–381.
- Wright, Jonathan H. 2006. "The Yield Curve and Predicting Recessions." Working paper, Finance and Economics Discussion Series. Washington, DC: Board of Governors of the Federal Reserve System.