Nowcasting Business Cycle Phases with High and Mixed Frequency Data

by

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Abstract: This paper is the first to systematically evaluate the ability of high frequency data to improve upon the timeliness with which new expansions and recessions can be identified. Using a mixed frequency dynamic factor model combined with a Markov-switching model, I find that the use of higher frequency data significantly and consistently improves the speed at which expansions and recessions can be identified in the United States since 1980. As representative examples, my model identifies the start of the Great Recession on March 30, 2008, months ahead of other statistical models surveyed in Hamilton (2011). During the Covid-19 pandemic, my model identified the start of the recession on March 22, 2020, 78 days ahead of the announcement from the National Bureau of Economic Research.

1 Introduction

A common definition of the business cycle is of alternating periods of expansion and recession, where an expansion is a period of widespread, persistent, economic growth, and a recession is a period of widespread, persistent, economic contraction. The existence of new turning points between these phases, commonly called peaks and troughs, are of substantial interest to real-time economic decision makers, including firms, policymakers, and individual consumers. Given this, a large literature has developed that attempts to forecast business cycle turning points, and business cycle peaks in particular, with some limited success.[1] However, it is widely recognized that there are many examples of recessions that were not predicted with any substantial lead time, which leaves us trying to identify new recessions and expansions in a window of time just prior to or, often, after the turning point occurs. Such an endeavor, which is commonly called "nowcasting" of business cycle turning points, has received significant recent attention in the literature.[2]

For the United States, one source of nowcasts is provided by the National Bureau of Economic Research (NBER), which produces dates of new business cycle turning points in real time. However, the NBER's goal is to provide an accurate historical record of turning points, not speed of detection, and as a result their calls of new turning points often occur long after the fact. For example, the December 2007 peak of the Great Recession was not announced by the NBER until December 1, 2008. More recently, the NBER announced on June 8, 2020 that a new recession associated with the COVID-19 pandemic started in March 2020. As shown by Chauvet & Piger (2008) and Chauvet & Hamilton (2006), statistical models are able to improve significantly on the speed of detection of new turning points over the NBER. However, these models still produce new turning points with a substantial lag time. For example, Hamilton (2011) surveys a range of statistical models in use during 2008 and finds they would not have identified the December 2007 peak in economic activity until late 2008.

Nearly all of the nowcasting literature uses relatively low frequency data to nowcast turning

[1]For recent contributions to this literature, see Berge (2015), Chauvet & Potter (2005), Kauppi & Saikkonen (2008), Ng (2014), and Rudebusch & Williams (2009).

[2]See for example, Chauvet & Piger (2008), Chauvet & Hamilton (2006), Fossati (2016), and Giusto & Piger (2017).

points, namely monthly or quarterly data. It seems reasonable to expect that significant gains in the speed with which turning points dates can be identified might be achieved by also incorporating higher frequency data at the daily or weekly frequency. There are several reasons for this expectation. First, higher frequency data would allow additional variables to be incorporated than what has typically been used in the business cycle nowcasting literature, such as financial variables or initial claims of unemployment insurance. Second, the use of higher frequency data would allow for more frequent updating of the model, since most monthly or quarterly variables relevant for tracking the business cycle are released in a cluster around the end of the month. Third, higher frequency variables generally have much shorter reporting lags. For example, initial claims on unemployment insurance for a given week are available only a few days after the week ends, whereas many monthly series, such as personal income, are released only after a full month delay.

In this paper I contribute in three primary ways to the literature studying nowcasting of U.S. business cycle turning points. First, I study whether the use of higher frequency data can improve the speed at which business cycle peaks and troughs post 1980 can be identified in U.S. data over the existing literature that focuses primarily on monthly and quarterly data. To identify turning points with high and mixed frequency data, I propose a three-step approach. First, I use the mixed frequency dynamic factor model of Aruoba, Diebold, & Scotti (2009) (ADS) to extract a coincident index of real economic activity using daily, weekly, monthly and quarterly data. Second, I use a supervised Markov-switching classification technique to classify the coincident index into a daily measure of recession and expansion regimes. The use of this Markov-switching model, which contains a mechanism for capturing the very high persistence of the daily business cycle phase indicator, performs significantly better than other commonly used classification approaches that assume i.i.d. classes. Finally, I use the trained classifier to evaluate the evidence for new business cycle turning points in end-of-sample data that has not yet been classified by the NBER. I evaluate the out-of-sample performance of this procedure for identifying new business cycle turning points in real-time from January 1, 1979 to August 30, 2020 using a vintage real-time dataset containing the data that would have been available at each daily vintage over this period.

The second contribution is to incorporate a mix of both leading variables and coincident variables for the purpose of nowcasting business cycle turning points. The existing literature focused on forecasting turning points has used only leading variables, while the literature focused on nowcasting turning points has used only coincident variables. Here I use a dataset containing a significant number of standard coincident variables used in the literature and by the NBER, which ensures that the model will be able to eventually capture new business cycle turning points. However, I also use a leading variable in the analysis, namely a yield curve premium, which has been shown to have significant forecasting power for recessions. This leading variable can help reinforce signals coming from coincident variables in the time periods prior to and after recessions begin, and thus potentially speed up the identification of new business cycle turning points.

The third contribution of my paper is to evaluate the ability of a new daily news-based index of economic sentiment constructed in Li (2020) for nowcasting business cycle turning points. Information encoded in text has been recently used in empirical economics research as a complement to the more structured macroeconomic and financial data traditionally used (Gentzkow, Kelly, & Taddy (2019)). Text selected from news, social media, reports and speeches contains "soft" information missing in more quantifiable variables. Unlike most of the headline macroeconomic data that are published at a relatively low frequency and for which past observation periods are revised as more accurate estimates become available, text such as news articles arrives daily and is not revised. These advantages make data extracted from text an ideal candidate to nowcast business cycle turning points.

I find that implementing these three additions - high frequency data, leading data, and information from news articles - significantly and consistently improves the speed at which expansions and recessions can be identified in the United States since 1980. As an example, incorporating daily and weekly frequency data, where the daily variable is the yield curve premium, produces a call of the December 2007 business cycle peak on March 30, 2008. This is 256 days ahead of the NBER announcement, and many months ahead of the statistical procedures surveyed in Hamilton (2011). When I further incorporate information from the news-based sentiment index in Li (2020), I am able to identify the December 2007 business cycle peak even earlier, on December 2, 2007. In several cases, business cycle turning points are called prior to their occurring, which demonstrates the value-added of incorporating leading data into the analysis.

The remainder of this paper is organized as follows. In section 2 I describe the specification and estimation of the dynamic factor model at daily frequency. In section 3 I describe the construction of the vintage dataset. Section 4 presents results of the out-of-sampler exercise to identify turning point dates using the Markov regime switching classifier. Section 5 concludes the paper.

2 Methodology

2.1 Dynamic Factor Model at Daily Frequency

I follow Aruoba et al. (2009) to propose a dynamic factor model at daily frequency to extract a coincident index of real economic activity using weekly, monthly and quarterly data. Let x_t denote the underlying real economic activity at day t, which is assumed to evolve daily with $AR(1)$ dynamics described as follows,

$$x_t = \rho x_{t-1} + e_t$$

where e_t is a white noise innovation with variance $1 - \rho^2$.

I use the yield curve term premium for the daily variable y_t^1, defined as the difference between 10-year and 3-month U.S. Treasury yields. Because the term premium is a stock variable, there are no aggregation issues. y_t^1 depends linearly on x_t and contemporaneously and serially uncorrelated innovations u_t. Because the term premium is reported every weekday, its persistence is modeled at the daily frequency with a u_t^1 term that follows $AR(1)$ dynamics,

$$y_t^1 = \begin{cases} \beta_1 x_t + u_t^1 \\ \\ NA \end{cases}$$

$$= \begin{cases} \beta_1 x_t + \gamma_1 u_{t-1}^1 + \zeta_t & y_t^1 \text{is observed} \\ \\ NA & y_t^1 \text{is not observed} \end{cases}$$

where ξ_t is a white noise innovation with variance σ_1^2.

I use initial claims for unemployment insurance for the weekly variable y_t^2. Because it is a flow variable reported on every Saturday covering the seven-day period from Sunday to Saturday, y_t^2 on Saturday is set to the sum of the previous seven daily values, constructed with a weekly cumulator variable C_t^W. To model persistence at the daily frequency, y_t^2 is set to depend on its previous observed value with one-week lag. Theoretically the persistence can be modeled with multiple lags of the u_t^2 term; however, the number of parameters need to be estimated will be unnecessarily large.

$$y_t^2 = \begin{cases} \beta_2 C_t^W + \gamma_2 y_{2,t-7} + u_t^2 & y_t^2 \text{is observed} \\ \\ NA & y_t^2 \text{is not observed} \end{cases}$$

$$C_t^W = \xi_t^W C_{t-1}^W + x_t = \xi_t^W C_{t-1}^W + \rho x_{t-1} + e_t$$

$$\xi_t^W = \begin{cases} 0 & \text{if t is the first day of a week} \\ \\ 1 & \text{otherwise} \end{cases}$$

where u_t^2 is a white noise innovation with cumulated variance $7 \times \sigma_1^2$.

I use nonfarm payroll employment for the monthly variable y_t^3. Because it is a monthly stock variable, the end-of-month value is set to the end-of-month daily value. Persistence is modeled with its observed value with one-month lag. The number of days in each month is assumed to be 30 for simplicity.

$$
y_t^3 = \begin{cases} \beta_3 x_t + \gamma_3 y_{3,t-30} + u_t^3 & y_t^3 \text{is observed} \\ \\ NA & y_t^3 \text{is not observed} \end{cases}
$$

where u_t^3 is a white noise innovation with variance σ_1^3.

I use real GDP for the quarterly variable y_t^4. Because it is a flow variable, the end-of-quarter value is set to the sum of daily values within the quarter with a quarterly cumulator variable C_t^Q. Persistence is modeled with its observed value with one-quarter lag. The number of days in each quarter is assumed to be 90 for simplicity.

$$
y_t^4 = \begin{cases} \beta_4 C_t^Q + \gamma_4 y_{4,t-90} + u_t^4 & y_t^4 \text{is observed} \\ \\ NA & y_t^4 \text{is not observed} \end{cases}
$$

$$
C_t^Q = \xi_t^Q C_{t-1}^Q + x_t = \xi_t^Q C_{t-1}^Q + \rho x_{t-1} + e_t
$$

$$
\xi_t^Q = \begin{cases} 0 & \text{if t is the first day of a quarter} \\ \\ 1 & \text{otherwise} \end{cases}
$$

where u_t^4 is a white noise innovation with cumulated variance $90 \times \sigma_1^4$.

All y_t^i are demeaned and detrended. This completes the specification of the model. The dynamic factor model at daily frequency model is cast as follows.

$$
\underbrace{\begin{bmatrix} y_t^1 \\ y_t^2 \\ y_t^3 \\ y_t^4 \end{bmatrix}}_{\boldsymbol{\Upsilon_t}} = \underbrace{\begin{bmatrix} \gamma_1 & \beta_1 & 0 & 0 & 0 \\ 0 & 0 & \beta_2 & 0 & \gamma_2 \times y_{2,t-7} \\ 0 & \beta_3 & 0 & 0 & \gamma_3 \times y_{3,t-30} \\ 0 & 0 & 0 & \beta_4 & \gamma_4 \times y_{4,t-90} \end{bmatrix}}_{\boldsymbol{FF_t}} \times \underbrace{\begin{bmatrix} u_{t-1}^1 \\ x_t \\ C_t^W \\ C_t^Q \\ 1 \end{bmatrix}}_{\boldsymbol{\theta_t}} + \underbrace{\begin{bmatrix} \zeta_t \\ u_t^2 \\ u_t^3 \\ u_t^4 \end{bmatrix}}_{\boldsymbol{\nu_t}} \tag{1}
$$

$$
\underbrace{\begin{bmatrix} u^1_{t-1} \\ x_t \\ C^W_t \\ C^Q_t \\ 1 \end{bmatrix}}_{\boldsymbol{\theta_t}} = \underbrace{\begin{bmatrix} \gamma_1 & 0 & 0 & 0 & 0 \\ 0 & \rho & 0 & 0 & 0 \\ 0 & \rho & \xi^W_t & 0 & 0 \\ 0 & \rho & 0 & \xi^Q_t & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{\boldsymbol{GG_t}} \times \underbrace{\begin{bmatrix} u^1_{t-2} \\ x_{t-1} \\ C^W_{t-1} \\ C^Q_{t-1} \\ 1 \end{bmatrix}}_{\boldsymbol{\theta_{t-1}}} + \underbrace{\begin{bmatrix} \zeta_{t-1} \\ e_t \\ e_t \\ e_t \\ 0 \end{bmatrix}}_{\boldsymbol{\omega_t}} \tag{2}
$$

$$
\underbrace{\begin{bmatrix} \zeta_t \\ u^2_t \\ u^3_t \\ u^4_t \end{bmatrix}}_{\boldsymbol{\nu_t}} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \underbrace{\begin{bmatrix} {\sigma_1}^2 & 0 & 0 & 0 \\ 0 & 7 \times {\sigma_2}^2 & 0 & 0 \\ 0 & 0 & {\sigma_3}^2 & 0 \\ 0 & 0 & 0 & 90 \times {\sigma_4}^2 \end{bmatrix}}_{\boldsymbol{V_t}} \right) \tag{3}
$$

$$
\underbrace{\begin{bmatrix} \zeta_{t-1} \\ e_t \\ e_t \\ e_t \\ 0 \end{bmatrix}}_{\boldsymbol{\omega_t}} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \underbrace{\begin{bmatrix} {\sigma_1}^2 & 0 & 0 & 0 & 0 \\ 0 & 1-\rho^2 & 0 & 0 & 0 \\ 0 & 0 & 1-\rho^2 & 0 & 0 \\ 0 & 0 & 0 & 1-\rho^2 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}}_{\boldsymbol{W_t}} \right) \tag{4}
$$

The model can be represented in time-varying state-space form as

$$
\boldsymbol{\Upsilon_t} = \boldsymbol{FF_t} \times \boldsymbol{\theta_t} + \boldsymbol{\nu_t} \tag{5}
$$

$$
\boldsymbol{\theta_t} = \boldsymbol{GG_t} \times \boldsymbol{\theta_{t-1}} + \boldsymbol{\omega_t} \tag{6}
$$

where $\boldsymbol{\Upsilon_t}$ is a vector of variables that are subject to missing values, $\boldsymbol{\theta_t}$ is a vector of state variables, $\boldsymbol{\nu_t}$ and $\boldsymbol{\omega_t}$ are vectors of measurement and transition shocks.

Following ADS, I use the Kalman filter and smoother to obtain optimal extractions of the latent state of real economic activity. At each analysis date, parameters are re-estimated. As is standard for classical estimation, I initialize the Kalman filter using the unconditional mean and covariance matrix of the state vector. Parameters are estimated with maximum likelihood methods.

As the example, estimated factor estimated on January 6, 1979 and March 7, 2020 analysis dates are shown in Figure 1. Shaded areas indicate U.S. recessions. The factor drops during recessions and drops before recessions in some cases. The sharp decline in Figure 2 since late March 2020 presents the severe economic impact of COVID-19 pandemic.

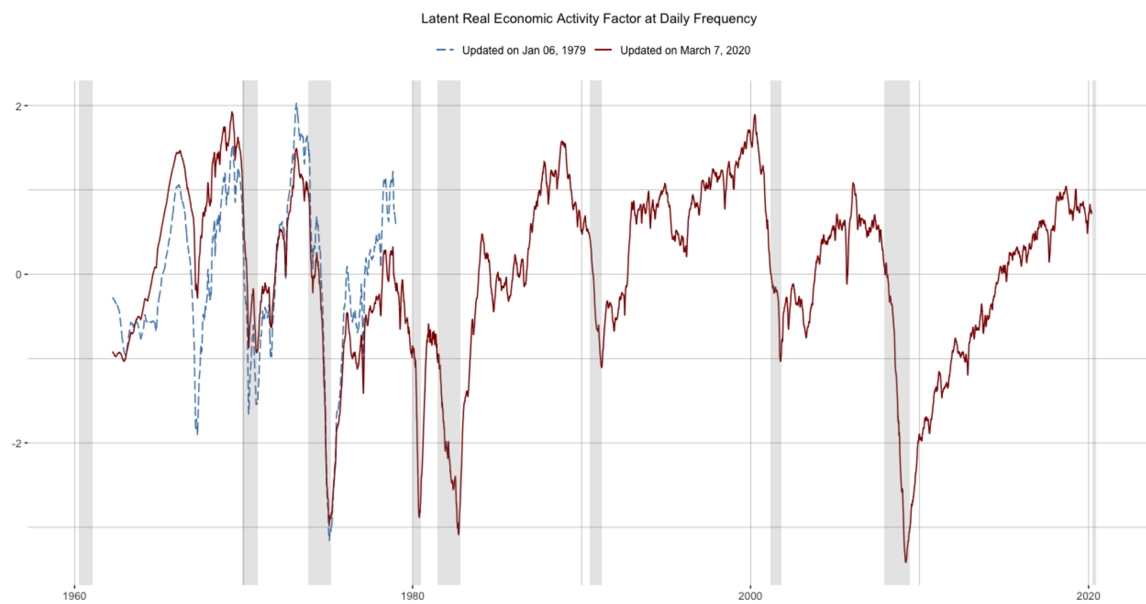

Figure 1: Latent Real Economic Activity Factor at Daily Frequency on January 6, 1979 and March 3, 2020

2.2 Supervised Markov Regime-Switching Classifications

$\hat{x_t}$ is the coincident index of real economic activity at day t extracted from the dynamic factor model with mixed frequencies, using linear optimal procedures as described in the previous step. The second step is to nowcast the recession and expansion regimes of $\hat{x_t}$ at day t. I train a supervised

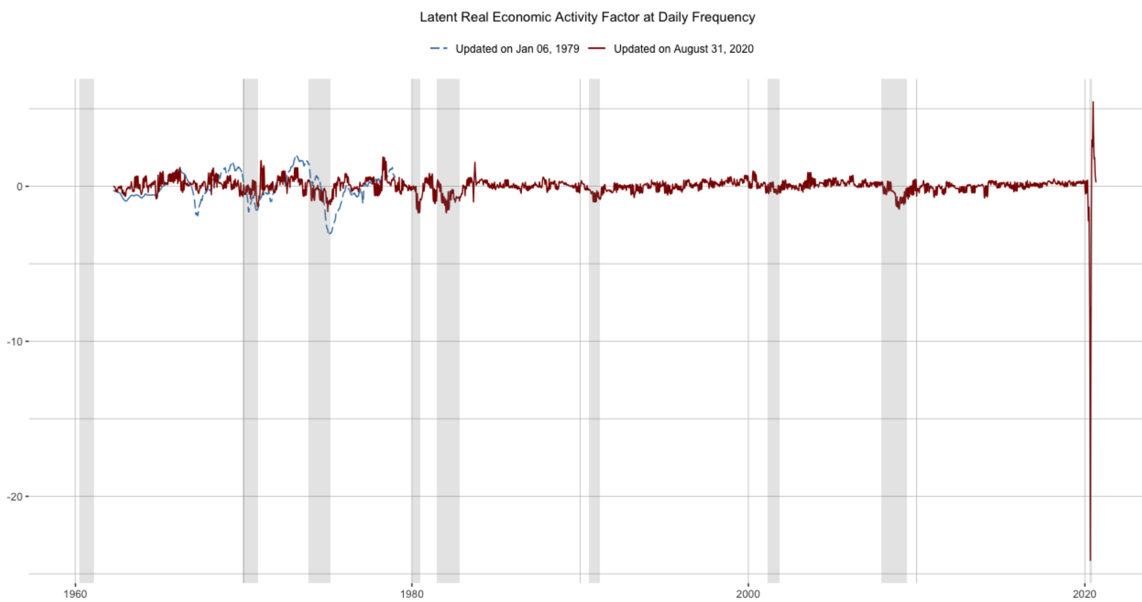

Figure 2: Latent Real Economic Activity Factor at Daily Frequency on January 6, 1979 and August 31, 2020

classification technique, i.e. the Markov-switching model to classify the coincident index into recession and expansion regimes. In this case, supervised classification techniques require NBER turning point dates to be known. The NBER turning point dates are therefore taken as given that it correctly classify the unobservable state of the economy into either regime. In the following section, I describe details of each classification method.

The Markov-switching classification technique models the differences between regimes using a mixture of normal distributions. A significant literature has emphasized that expansions and recessions are probabilistically different, and out-of-sample real-time dating used by this approach has turned out to be promising. Chauvet & Piger (2008) use a monthly real-time dataset and show that the dynamic factor Markov-switching model identifies NBER dates more accurately and identifies troughs with a larger lead than a nonparametric algorithm. Camacho, Perez, & Poncela (2018) use a mixed-frequency dataset at monthly and quarterly frequencies, and extend the Markov-switching dynamic factor model to monitor economic activity on a monthly basis. Compared with a balanced panel of indicators, Camacho et al. (2018) obtain substantial improvements in producing real-time business cycle probabilities.

The transition between regimes is driven by a Markov process with $p_{ji} = Pr(S_t = j|S_{t-1} = i)$, which is the transition probability of S_t switching from regime i to regime j. Camacho, Perez, & Poncela (2015) and Owyang, Piger, & Wall (2005) found that the Markov-switching $AR(0)$ model provided accurate and robust identification of NBER business cycle dates. Following Owyang et al. (2005), I fit the first difference of the coincident index, which is denoted $\Delta\hat{x}_t$, to a univariate Markov-switching $AR(0)$ process with a switching mean.

$$\Delta\hat{x}_t = \beta_{S_t} + \epsilon_t \tag{7}$$

$$\epsilon_t \sim N(0, \sigma^2) \tag{8}$$

$$\beta_{S_t} = \beta_0 + \beta_1 \times S_t \tag{9}$$

$$\beta_1 < 0 \tag{10}$$

The growth rate $\Delta\hat{x}_t$ has mean β_{S_t}, and deviations from this mean growth rate are captured by the stochastic disturbance ϵ_t. The parameters of the model are $\Omega = (\beta_0, \beta_1, p_{11}, p_{22}, \sigma)'$. Let $S_t \in 1, 2$, where $S_t = 1$ indicates that day t is a expansion regime, and $S_t = 2$ indicates that day t is a recession regime. When S_t switches from 1 to 2, the mean growth rate of economic activity switches from $\beta_0 + \beta_1$ to $\beta_0 + 2 \times \beta_1$. This implies that when the growth rate of economic activity switches from an expansion regime which has higher growth to a recession regime which has lower growth, $\beta_1 < 0$ ensures that the mean growth rate of economic activity declines. The model estimates probabilities of a recession regime on day t conditional on data available on day T, denoted $\hat{P}(S_t = 2|\Psi_T)$.

I estimate the Markov regime switching model using a non-parametric technique. It directly ties the estimates to the NBER regimes, which is what I am trying to nowcast. I estimate β_0 and β_1 as the mean of $\Delta\hat{x}_t$ in each NBER regime, and the estimated transition probabilities are the mean of the transitions using the NBER regimes. The variance of the disturbance terms are estimated from the residuals of this regression.

Because NBER recession and expansion dates are known only with a substantial lag, I do not use the NBER indicator that classifies the regime through the end of the relevant sample to estimate parameters at each analysis date. Instead I adopt a conservative approach and estimate model parameters on data ending one year prior to the analysis date. Then, given the estimates, the filter developed in Hamilton (1989) is run through to the end of the data available at the analysis date in order to get the recession probabilities.

For example, Figure 3 shows the training set and testing set of the the first analysis date, January 7, 1979. The blue bar represents the training set ranging from April 1, 1962 to January 6, 1978, on which the parameters are estimated. The yellow bar represents the testing set ranging from January 7, 1978 to January 7, 1979, on which the regime for the first analysis date is predicted using the Hamilton filter.

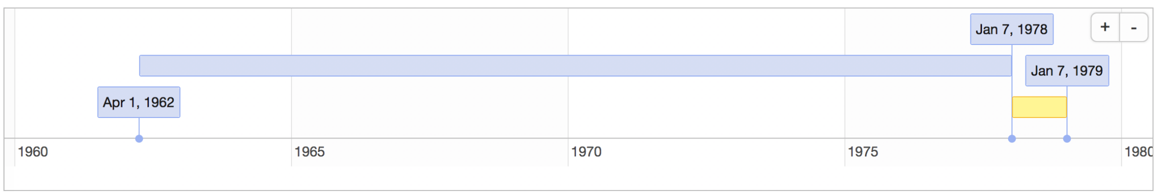

Figure 3: Training and Testing Set for the First Analysis Date

In a recent paper, Piger (2020) compares the timely performance of a wide range of classifiers to nowcasting the U.S. expansion and recession phases at monthly frequency, and finds that the k-nearest neighbor classifier and the random forest classifier are quick to identify turning points while producing no false positives for a narrow data set. I have trained a variety of supervised classification techniques to classify the coincident index into recession and expansion regimes, including the k-nearest neighbor classifier, the random forest classifier, and the Naive Bayes classifier. However, these classifiers failed to identify a large number of recessions, and overall their performance was dominated by the Markov-switching classifier.

One explanation for the poor performance of these classifiers is that they do not have a mechanism to capture the very high level of persistence of the daily regime variable, the NBER indicator S_t. In other words, they assume S_t is Independent and identically distributed. At a daily frequency, the estimated values of $P_{11} = Pr(S_t = 1|S_{t-1} = 1)$ and $P_{22} = Pr(S_t = 2|S_{t-1} = 2)$ are very high. Over the full sample, P_{11} is 0.99962 and P_{22} is 0.99723. The Markov-switching based classifier captures this persistence by modeling S_t as following a Markov process.

2.3 Business Cycle Phases Dating Procedures

Finally, I use the classifier to evaluate the evidence for new business cycle turnings points in end-of-sample data that has not yet been classified by the NBER. In order to convert recession probabilities $\hat{P}(S_t = 2|\Psi_T)$ into a binary variable that defines whether the economy is in an expansion or a recession regime on day t, and whether a new peak or trough can be confirmed to occur on day t, I use a simple procedure.

Specifically, suppose that the last NBER turning point date that was announced is a business cycle trough, followed by periods of known expansions. Then the earliest analysis date of all analysis dates for which the average value of $P(S_t = 2|\Psi_T)$ over the 12 weeks prior to the analysis date exceeds 0.8 is considered a recession "call". Alternatively, suppose that the last NBER turning point date that was announced is a business cycle peak, followed by periods of known recessions. Then the the earliest analysis date of all analysis dates for which the average value of $P(S_t = 2|\Psi_T)$ over the 12 weeks prior to the analysis date is below 0.2 is considered an expansion "call". This procedure mirrors that in Chauvet & Piger (2008) for monthly data. Having elements of my model specification be consistent with existing literature is useful to compare my results to this literature. I also produce results for an alternative threshold of 0.9 as a robustness check.

3 Vintage Dataset

Every Sunday starting from Jan 1, 1979 to August 31, 2020 is defined as the "analysis date" for the purpose of my paper. It is the date to conduct the nowcasting exercise. The first analysis date is January 7, 1979 and the last analysis date is August 30, 2020. Figure 4 presents a timeline of some of the analysis date that are involved in the example below.

In general, economic data for past observation periods are revised as more accurate estimates become available. The data set that was obtained from the Federal Reserve Economic Data (FRED)

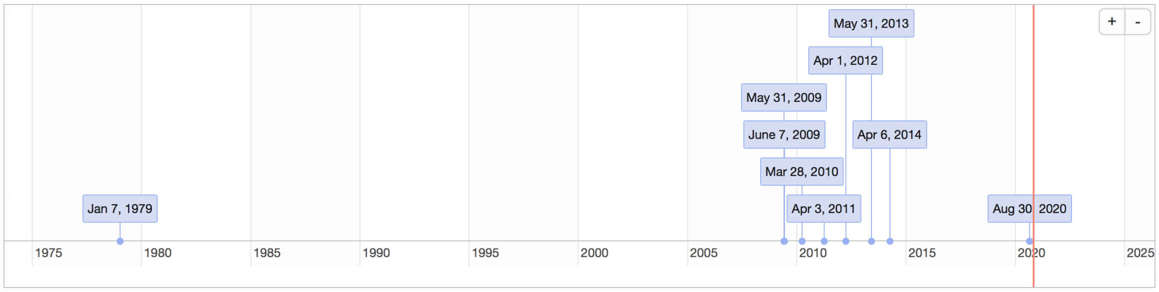

Figure 4: Analysis Dates

database maintained by the Research division of the Federal Reserve Bank of St. Louis[3] on August, 31 2020 incorporates data revisions. The value obtained from the FRED database today might be different from what a researcher could get access to on a specific date in history.

For example, the value of the initial claims for unemployment insurance (ICSA) on May 23, 2009 became available on May 28, 2009, and the value was reported to be 623,000. However, this value was later revised. The first revision occurred on June 4, 2009. The value of ICSA on May 23, 2009 reported on June 4, 2009 became 625,000. The last revision occurred on April 3, 2014. The value was reported to be 606,000 and has remained to be not revised since then. The pseudo value of ICSA on May 23, 2009 downloaded from the FRED database on August 31, 2020 is 606,000, which is not available for a researcher on the analysis date of May 28, 2009. On May 28, 2009, the researcher could only use the value of 623,000 to conduct nowcasting exercises. Table 1 summarizes the complete revision of the value of ICSA on May 23, 2009.

Table 1: Reported Values of ICSA on May 23, 2009

	Announcement	Revision	Revision	Revision	Revision	Revision	Revision
Date	2009-05-28	2009-06-04	2010-03-25	2011-03-31	2012-03-29	2013-03-28	2014-04-03
Value	623,000	625,000	611,000	612,000	608,000	607,000	606,000

Vintage data enables researchers to reproduce research and build more accurate forecasting models using the data available at the time. To conduct the nowcasting exercise on analysis dates, I compile the data into a vintage dataset that would have been available on each analysis date. For each analysis date, I use the data that was available at that time based on the most recent vintage

[3] https://fred.stlouisfed.org/

dates available for the data. By using the vintage dataset, I search for new business cycles turning points as if I were an analyst on each analysis date beginning on Jan 1, 1979.

As a representative example, Figure 5 presents a timeline that shows the evolution of the value of ICSA on May 23, 2009 used in the analysis over time, represented by the red dot. On May 31, 2009, 623,000 is used as the value of ICSA on May 23, 2009. On June 7, 2009, the revised value 625,000 is used as the value of ICSA on May 23, 2009. Since then, 625,000 has been used to be the value of ICSA on May 23, 2009 for all analysis dates until March 28, 2010, on which the revised value 611,000 is used to be the value of ICSA on May 23, 2009. I have used 611,000 as the value of ICSA on May 23, 2009 for all analysis dates until April 3, 2011, on which the revised value 612,000 is used instead. 612,000 has then been used as the value of ICSA on May 23, 2009 for all analysis dates until April 1, 2012, on which the revised value 608,000 is used. The value of ICSA on May 23, 2009 has remained to be 608,000 until May 31, 2013, on which the revised value 607,000 is put. The value of ICSA on May 23, 2009 has remained to be 607,000 until April 6, 2014, on which the revised value 606,000 is chosen instead. Since then, 606,000 is used as the value of ICSA on May 23, 2009 until the last analysis date.

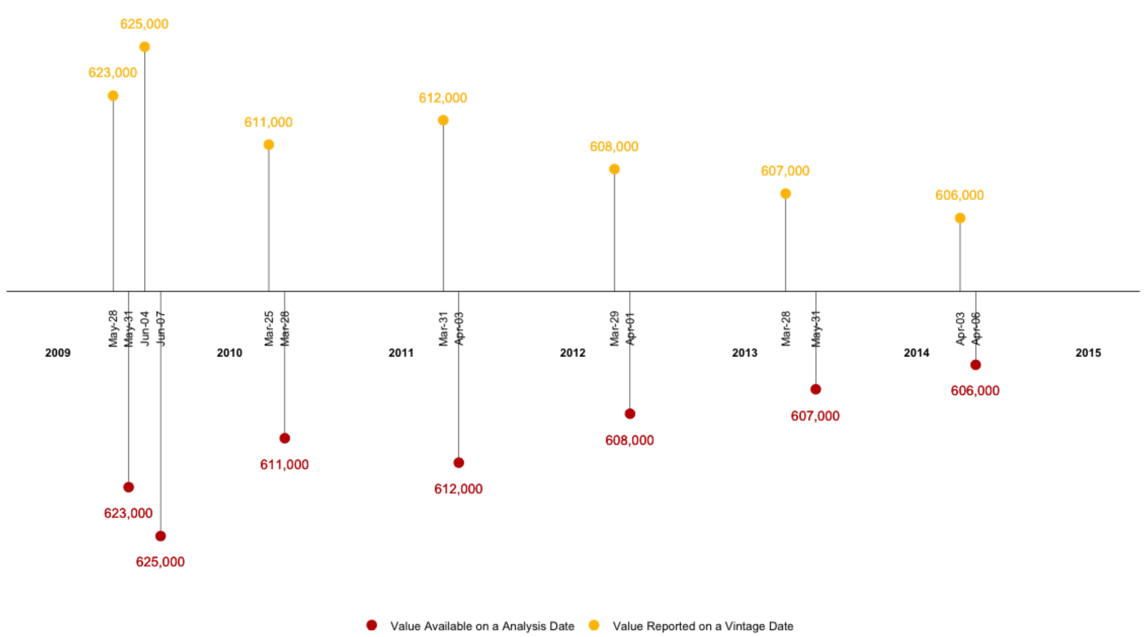

Figure 5: Values of ICSA on May 23, 2009

As used in Aruoba et al. (2009), I use the daily yield curve term premium defined as the difference between daily 10-year and daily 3-month U.S. Treasury yields (TY), the weekly initial claims for unemployment insurance (ICSA), the monthly nonfarm payroll employment (PAYEMS), and the quarterly real GDP (GDP) as my coincident variables.

Most of the fundamental series for this analysis are available on the Archive FRED (ALFRED).[4] ALFRED is a database that allows to retrieve vintage versions of economic data that were available on specific dates in history. The following procedure describes how I compile the vintage dataset.

- The furthest vintage back for the monthly PAYEMS is prior to the first analysis date, January 7, 1979. Hence I downloaded all vintages of "All Employees, Total Nonfarm (PAYEMS)" from the first available vintage post the first analysis date to the first vintage post the last analysis date to construct the real-time series of PAYEMS from April 1, 1962 to August 31, 2020.

- The furthest vintage back for the quarterly real GDP is December 4, 1991, post the first analysis date, January 7, 1979. The Gross National Product was the preferred measure of quarterly gross output produced by the Bureau of Economic Analysis for the United States prior to 1991. On ALFRED, the furthest vintage back for the Gross National Product is prior to the first analysis date, January 7, 1979. Therefore, for analysis dates before December 4, 1991, I use the vintage of the "Real Gross National Product (GNPC96)" from April 1, 1962 to August 31, 2020. For analysis dates before December 4, 1991, I use the vintage of the "Real Gross Domestic Product (GDPC1)" from April 1, 1962 to August 31, 2020 from ALFRED.

- The furthest vintage back for ICSA is May 28, 2009. For analysis dates prior to May 28, 2009, I use the May 28, 2009 vintage of "Initial Claims (ICSA)" downloaded from ALFRED database to construct a pseudo real-time series. This vintage reported on May 28, 2009 contains the value of ICSA from January 7, 1967, the start of the observation of ICSA, up to May 23, 2009. For analysis dates after May 28, 2009, I use vintages of ICSA downloaded from ALFRED database to construct the "real" real-time vintage series from January 7, 1967 to August 31, 2020.

[4] https://alfred.stlouisfed.org/

- The daily yield curve term premium isn't revised, so I use the difference between daily 10-year and daily 3-month U.S. Treasury yields from April 1, 1962 to August 31, 2020. Both series are downloaded from FRED database as of August 31, 2020.

- I take the logarithm of ICSA, PAYEMS, and GDP. For each analysis date, I strip TY, ICSA, and PAYEMS of a linear and a quadratic trend, and standardized the residuals. I then strip GDP data of a linear, a quadratic and a cubic trend, and standardized the residuals.

- I also include data lagged one period of ICSA, PAYEMS, and GDP into the vintage dataset.[5]

Following Aruoba et al. (2009), I use simple first-order dynamics throughout the framework to reduce the number of parameters to be estimated. As shown below, the simple $AR(1)$ dynamics produces promising results.

4 Results Using a Vintage Dataset

4.1 Baseline Results

Using the vintage dataset, I evaluate the ability of my approach to identify new business cycle peaks and troughs in the United States since 1980. Table 2 compares the real-time performance of the Dynamic Factor Markov Switching Model at Daily Frequency (DFMSDF) for detecting business cycle peaks in real time. The table also compares these results to those from Giusto & Piger (2017), which proposes a learning vector quantization approach to nowcast U.S. recessions in real time using only monthly data and was shown to improve on other leading approaches in the literature. Table 3 presents the analogous results for troughs.

The first column of the table shows the NBER turning points, which are available from www.nber.org. Taking the NBER turning points as given, the second column shows the first day of the business cycles phases, which is defined as the first day of the month following the month

[5] There are data entry mistakes to the vintage date downloaded from ALFRED. For example, for real GDP release, the GDPC1_19991028 vintage and the GDPC1_20031210 vintage don't contain any new information, and should be deleted. For ICSA release, the ICSA_20181121 vintage should be deleted because it looks like this is an earlier than usual release and is replaced two days later by another release. For the ICSA_20190703 vintage, there is a data entry error to the ICSA value for June 8, 2019. I filled in this value from the value from the previous release - 222000, because it looks almost certainly like this is what the value should have been.

of the NBER turning point. The third column shows analysis dates when turning points are called using the DFMSDF method. The fourth column shows the number of days the DFMSDF method takes to identify the turning point, which is the number of days between the second column and the third column. The fifth column shows the number of days the Business Cycle Dating Committee of the NBER takes to identify the turning point and to make an announcement. The sixth column shows the number of days Giusto & Piger (2017) takes to identify the turning point using a learning vector quantization method. For example, on June 3, 1980, the Business Cycle Dating Committee of the NBER announced that a peak started in January 1980. Taken this as given, the associated recession occurred on February 1, 1980, the first day after the peak month. The DFMSDF method made a peak call on April 27, 1980 and identified the recession 86 days after the recession started. The announcement was made by the Committee 123 days after the recession started. Giusto & Piger (2017) identifies this recession 92 days after the fact.

Table 2: Recessions Identified in Real-time (Threshold=0.8)

NBER Peak Date	First Day of Recession	Date Recession Call Available - DFMSDF	DFMSDF Lag	Business Cycle Dating Committee Lag	Giusto & Piger (2017) Lag
Jan-1980	2/1/1980	4/27/1980	86	123	92
Jul-1981	8/1/1981	11/1/1981	92	158	126
Jul-1990	8/1/1990	8/12/1990	11	267	78
Mar-2001	4/1/2001	7/2/2000	-273	239	216
Dec-2007	1/1/2008	3/30/2008	89	335	158
Mar-2020	3/1/2020	3/22/2020	21	99	NA
Average			**5**	**204**	**134**

Table 3: Expansions Identified in Real-time (Threshold=0.8)

NBER Trough Date	First Day of Expansion	Date Expansion Call Available - DFMSDF	DFMSDF Lag	Business Cycle Dating Committee Lag	Giusto & Piger (2017) Lag
Jul-1980	8/1/1980	8/10/1980	9	341	127
Nov-1982	12/1/1982	11/28/1982	-3	219	136
Mar-1991	4/1/1991	6/2/1991	62	631	443
Nov-2001	12/1/2001	8/19/2001	-104	593	308
Jun-2009	7/1/2009	5/24/2009	-38	446	157
Average			**-15**	**446**	**235**
		6/14/2020		NA	NA

The tables shows that the DFMSDF method identifies all NBER peaks and troughs over the out of sample period. All of the NBER turning points dates in the first column are identified by the DFMSDF method in the third column. The tables also suggest that the DFMSDF method is very fast in identifying NBER turning points dates. The fifth and sixth column show that the Business Cycle Dating Committee of the NBER and Giusto & Piger (2017) produce NBER turning points dates with a significant delay. The fourth columns shows that the peak and trough calls made by the DFMSDF approach are quicker than those by the Business Cycle Dating Committee and by Giusto & Piger (2017).

In the cases of the March 2001 peak, the November 1982 trough, the November 2001 trough, and the June 2009 trough, the DFMSDF method identifies business cycle phases prior to their starting dates. This striking result shows the value-added for some turning points of incorporating leading data in concert with coincident data in the analysis, as the existing nowcasting literature based only on coincident data does not detect new turning points until after they occur. On the other hand, for the other turning points, the coincident data allows the model to still detect the business cycle turning point relatively quickly after the recession begins, a fact that is not true for models in the literature based only on leading data. Thus, it seems valuable to incorporate both leading and coincident data for nowcasting turning points.

On average, the Business Cycle Dating Committee and Giusto & Piger (2017) establish business cycle peaks with delay of 204 and 134 days respectively; however, the DFMSDF method established the business cycle peak on average 5 days prior to its beginning. Both the Business Cycle Dating Committee and Giusto & Piger (2017) are slower in identifying business cycle troughs, with an average delay of 446 and 235 days respectively, while the DFMSDF method identifies the business cycle trough with an average lead of 15 days.

During the COVID-19 pandemic, the NBER announced on June 8, 2020, that a new recession started in the U.S. in March 2020. The DFMSDF model identified the start of this recession on March 22, 2020, 78 days ahead of the NBER announcement. While a new expansion has not been classified by the NBER, the DFMSDF model identified the end of this recession and the beginning of a new expansion on June 14, 2020, as most of the states have reopened since May.

The results of Tables 2 and 3 suggest that using high frequency and leading data can provide a significant improvement in the speed with which turning points are detected over existing methods that are based only on monthly data. This improvement in speed is not entirely without drawbacks however, in that the procedure based on daily data produces several false positives and false negatives, whereas the Giusto & Piger (2017) method based on only monthly data, and using a similar threshold, did not produce any false recessions or expansions. Table 4 lays out these false positives and false negatives, showing seven false recessions and three false expansions detected by the DFMSDF method.

While these false signals should be acknowledged, it is also true that most of these signals were only produced for a relatively short amount of time, with six of the 10 signals lasting for four weeks or less. As macroeconomic policy takes time to be implemented, it is unlikely that policy mistakes predicated on these signals would have been large. Further, two of the false peaks are in a period of time prior to the start of a recession, such as 1988 and 1989, or during periods of significant weakness in the economy, such as 2003. Thus, rather than being false positives, these events may be better interpreted as early warning of economic recessions, or a period of recession-like behavior in the economy.

Table 4: False Recessions and False Expansions Identified in Real-time (Threshold=0.8)

False Recessions	Duration	False Expansions	Duration
10/7/1984 - 11/11/1984	6 weeks	2/21/1982 - 7/25/1982	23 weeks
5/4/1986 - 5/18/1986	3 weeks	6/15/2008 - 7/6/2008	4 weeks
1/24/1988 - 2/7/1988	3 weeks	7/27/2008 - 8/17/2008	4 weeks
7/9/1989 - 8/6/1989	5 weeks		
4/23/1995 - 6/18/1995	9 weeks		
4/13/2003 - 5/4/2003	4 weeks		
5/14/2006 - 5/21/2006	2 weeks		

4.2 Robustness Checks

Tables 5, 6 and 7 show the results using the threshold of 0.9 as a robustness check. The results are qualitatively similar to those for the 0.8 threshold, although significant less false expansions and false recessions are identified in this case. This is to be expected, as the higher threshold should lead to less turning points detected, and thus less false turning points.

One would also expect that a more stringent threshold should reduce the speed with which turning points are identified. As Tables 5, 6 make clear, this is true for several of the turning points. However, this is not true in all cases - for example the July 1990 peak and the November 1982 trough are identified more quickly using the higher threshold. The reason for this counter-intuitive result is that under the 0.8 threshold, a false peak followed by a trough is identified in 1989, prior to the start of the 1990 recession. Under the 0.8 threshold, this is characterized as a false recession. However, under the 0.9 threshold, no trough is detected after the peak found in 1989 but prior to the beginning of the 1990 recession, and so this 1989 peak is used as a very early detection of the 1990 recession. This again reinforces that some of the false positives using the 0.8 threshold might be better characterized as early warnings of subsequent recessions.

Table 5: Recessions Identified in Real-time (Threshold=0.9)

NBER Peak Date	First Day of Recession	Date Recession Call Available - DFMSDF	DFMSDF Lag	Business Cycle Dating Committee Lag	Giusto & Piger (2017) Lag
Jan-1980	2/1/1980	5/18/1980	107	123	92
Jul-1981	8/1/1981	11/22/1981	113	158	126
Jul-1990	8/1/1990	7/6/1989	-381	267	78
Mar-2001	4/1/2001	7/9/2000	-266	239	216
Dec-2007	1/1/2008	7/13/2008	194	335	158
Mar-2020	3/1/2020	3/22/2020	21	99	NA
Average			**-36**	**204**	**134**

Table 6: Expansions Identified in Real-time (Threshold=0.9)

NBER Trough Date	First Day of Expansion	Date Expansion Call Available - DFMSDF	DFMSDF Lag	Business Cycle Dating Committee Lag	Giusto & Piger (2017) Lag
Jul-1980	8/1/1980	8/17/1980	16	341	127
Nov-1982	12/1/1982	3/7/1982	-269	219	136
Mar-1991	4/1/1991	6/9/1991	69	631	443
Nov-2001	12/1/2001	8/26/2001	-97	593	308
Jun-2009	7/1/2009	5/31/2009	-31	446	157
Average			**-65**	**446**	**235**
		6/21/2009		NA	NA

As another robustness check, I look at what happens if additional monthly variables are considered.

Table 7: False Recessions and False Expansions Identified in Real-time (Threshold=0.9)

False Recessions	Duration	False Expansions	Duration
10/14/1984 - 11/04/1984	4 weeks	7/27/2008 - 8/3/2008	2 weeks
4/30/1995 - 6/11/1995	7 weeks		
4/20/2003 - 4/27/2003	2 weeks		

Specifically, I incorporate Industrial production (INDPRO), which is a monthly variable, into the analysis. The furthest vintage back for the monthly INDPRO series is prior to the first analysis date, January 7, 1979. Hence I downloaded all vintages of "Industrial Production Index (INDPRO)" from the first available vintage post the first analysis date to the first vintage post the last analysis date to construct the real-time series of INDPRO from April 1, 1962 to August 31, 2020. I take a logarithm of INDPRO. Then it is stripped of a linear and quadratic trend, and the residual is standardized. I also include data lagged one period of INDPRO into the dataset.

Table 8, Table 9 and Table 10 show the result using the vintage dataset. To compare with the baseline result, the threshold used here is 0.8. The addition of industrial production helps identify many turning points more quickly, but at the cost of generating more false positives and false negatives.

Table 8: Recessions Identified in Real-time, with Industrial Production Included (Threshold=0.8)

NBER Peak Date	First Day of Recession	Date Recession Call Available - DFMSDF	DFMSDF Lag	Business Cycle Dating Committee Lag	Giusto & Piger (2017) Lag
Jan-1980	2/1/1980	4/20/1980	79	123	92
Jul-1981	8/1/1981	5/3/1981	-90	158	126
Jul-1990	8/1/1990	9/9/1990	-39	267	78
Mar-2001	4/1/2001	7/9/2000	-266	239	216
Dec-2007	1/1/2008	3/23/2008	82	335	158
Mar-2020	3/1/2020	3/22/2020	21	99	NA
Average			**-36**	**204**	**134**

5 A News-Based Index of Macroeconomic Activity

The information encoded in text has been recently used in empirical economics research as a complement to the more structured macroeconomic and financial data traditionally used (Gentzkow

Table 9: Expansions Identified in Real-time, with Industrial Production Included (Threshold=0.8)

NBER Trough Date	First Day of Expansion	Date Expansion Call Available - DFMSDF	DFMSDF Lag	Business Cycle Dating Committee Lag	Giusto & Piger (2017) Lag
Jul-1980	8/1/1980	8/24/1980	23	341	127
Nov-1982	12/1/1982	7/25/1982	-129	219	136
Mar-1991	4/1/1991	5/19/1991	48	631	443
Nov-2001	12/1/2001	1/20/2002	50	593	308
Jun-2009	7/1/2009	4/26/2009	-66	446	157
Average			**-15**	**446**	**235**
		6/28/2020		NA	NA

Table 10: False Recessions and False Expansions Identified in Real-time, with Industrial Production Included (Threshold=0.8)

False Recessions	Duration	False Expansions	Duration
10/14/1984 - 10/28/1984	3 weeks	11/12/2000	1 week
4/20/1986	1 week	3/4/2001 - 3/18/2001	3 weeks
5/7/1989 - 7/23/1989	12 weeks	6/22/2008 - 9/7/2008	12 weeks
4/9/1995 - 6/25/1995	12 weeks	12/28/2008	1 week
4/19/1998 - 5/24/1998	6 weeks		
8/9/1998 - 8/23/1998	3 weeks		
12/1/2002 - 12/8/2002	2 weeks		
8/1/2004 - 8/22/2004	4 weeks		
8/15/2010 - 10/10/2010	9 weeks		
4/12/2015 - 4/19/2015	2 weeks		

et al. (2019)). Text selected from news, social media, reports and speeches contains "soft" information missing in more quantifiable variables. Unlike most of the headline macroeconomic data that are published at a relatively low frequency and for which past observation periods are revised as more accurate estimates become available, text such as news articles arrives daily and is not revised. These advantages make data extracted from text an ideal candidate to build more accurate nowcasting models about aggregate economic activity in real time.

Following dictionary methods in the natural language processing literature, I establish a text-based approach to create a high-frequency news-based sentiment indicator (NBSI) regarding aggregate economic conditions from lead paragraphs of news articles that are related to economic activity. The corpus consists of 412,197 economic and financial news articles published at a daily frequency in the Wall Street Journal from April 2, 1991 to August 31, 2020. Details of construction of NBSI can be referred to my other paper Li (2020). In this section I evaluate the ability of this indicator to improve turning point identification in real time over the use of the index $\hat{x}_t$ studied in previous sections.

The NBSI from April 02, 1991 to August 31, 2020 is shown in Figure 6. Shaded areas indicate U.S. recessions. The index drops sharply before the start of the two recessions in the sample period. This suggests that the index might be a leading indicator with respect to recessions and might be used to nowcast or even forecast recessions. Figure 7 shows the standardized NBSI for January through August in 2020, and shows how the NBSI tracks the economic contraction related to COVID-19 shutdowns in the United States. It presents how NBSI picked up the bad economic outcomes in March 2020. It is also interesting that NBSI falls in February, prior to the most significant problems starting in the United States.

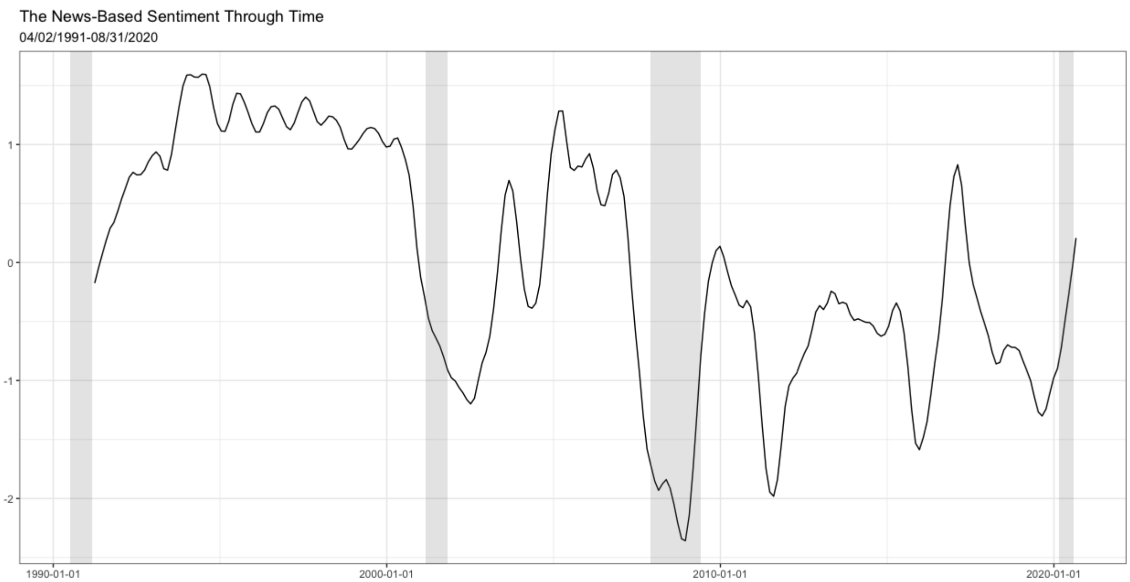

Figure 6: The News-Based Sentiment Index (April 1991- April 2020)

To evaluate the nowcasting ability of the NBSI on the U.S. recessions from April 2, 1991 to August 31, 2020, I incorporate NBSI in the business cycle phase nowcasting models developed in previous sections, and evaluate the contribution of NBSI to identify U.S. recessions in real time. Values of NBSI are missing for weekends and holidays, and I impute these missing values with the value from the previous day on which the index was recorded. I fit $\Delta\hat{x}_t$ and $NBSI_t$ to a bivariate version of the Markov regime-switching $AR(0)$ process with a switching mean in equations (11-15).

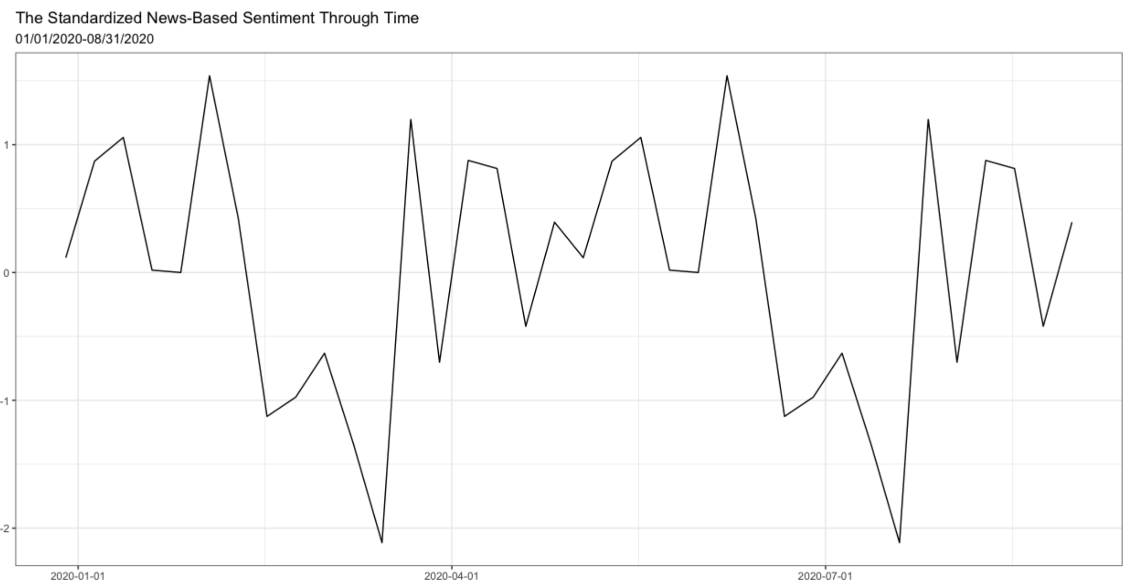

Figure 7: The News-Based Sentiment Index in 2020

$$\begin{bmatrix} \Delta\hat{x}_t \\ NBSI_t \end{bmatrix} = \begin{bmatrix} \beta_{11} \\ \beta_{12} \end{bmatrix} + \begin{bmatrix} \beta_{12} \\ \beta_{22} \end{bmatrix} \times S_t + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \tag{11}$$

$$\begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{bmatrix} \right) \tag{12}$$

$$\beta_1 < 0 \tag{13}$$

$$\beta_2 < 0 \tag{14}$$

For the out-of-sample prediction, I pick January 1, 2006 as the first analysis date. I use the same estimation method and dating procedure as described in the previous sections. Using 0.8 as the threshold, Tables 11, 12 and 13 show the result. Similar to the baseline result, the DFMSDF method predicts the occurrence of turning points faster than the Business Cycle Dating Committee and Giusto & Piger (2017).

To assess the contribution of NBSI, I use only $\Delta\hat{x}_t$ on the same shortened estimation window, Results are shown in Tables 14, 15 and 16. Compared with the result where NBSI is incorporated

Table 11: Recessions Identified in Real-time, with NBSI Included (Threshold=0.8)

NBER Peak Date	First Day of Recession	Date Recession Call Available - DFMSDF	DFMSDF Lag	Business Cycle Dating Committee Lag	Giusto & Piger (2017) Lag
Dec-2007	1/1/2008	12/2/2007	-30	335	158
Mar-2020	3/1/2020	3/29/2020	28	99	NA

Table 12: Expansions Identified in Real-time, with NBSI Included (Threshold=0.8)

NBER Trough Date	First Day of Expansion	Date Expansion Call Available - DFMSDF	DFMSDF Lag	Business Cycle Dating Committee Lag	Giusto & Piger (2017) Lag
Jun-2009	7/1/2009	6/7/2009	-24	446	235
		6/21/2020			

Table 13: False Recessions and False Expansions Identified in Real-time, with NBSI Included (Threshold=0.8)

False Recessions	Duration	False Expansions	Duration
7/10/2011 - 11/13/2011	19 weeks		
12/2/2018 - 12/9/2018	2 weeks		

Table 14: Recessions Identified in Real-time, with NBSI Excluded (Threshold=0.8)

NBER Peak Date	First Day of Recession	Date Recession Call Available - DFMSDF	DFMSDF Lag	Business Cycle Dating Committee Lag	Giusto & Piger (2017) Lag
Dec-2007	1/1/2008	4/6/2008	96	335	158
Mar-2020	3/1/2020	3/29/2020	28	99	NA

Table 15: Expansions Identified in Real-time, with NBSI Excluded (Threshold=0.8)

NBER Trough Date	First Day of Expansion	Date Expansion Call Available - DFMSDF	DFMSDF Lag	Business Cycle Dating Committee Lag	Giusto & Piger (2017) Lag
Jun-2009	7/1/2009	5/31/2009	-31	446	235
		6/21/2020			

in the analysis, excluding NBSI slows the identification of the December 2007 Peak, and produces more false identifications. Incorporating daily and weekly frequency data, where the daily variable is the yield curve premium, produces a call of the December 2007 business cycle peak on March

Table 16: False Recessions and False Expansions Identified in Real-time, with NBSI Excluded (Threshold=0.8)

False Recessions	Duration	False Expansions	Duration
5/21/2006 - 5/28/2006	2 weeks	6/8/2008	1 week
1/24/2016	1 week	6/22/2008 - 7/13/2008	4 weeks
12/9/2018	1 week	8/3/2008 - 8/24/2008	4 weeks

30, 2008, as shown in Table 2. When information from the news-based sentiment index is further incorporated, the December 2007 business cycle peak is identified even earlier, on December 2, 2007. The contribution of the news-based sentiment index is promising but more data is needed before concluding that the index helps to identify recessions in real time over the use of the coincident index $\Delta\hat{x}_t$ alone.

6 Conclusion

This paper contributes to the business cycle turning point nowcasting literature by systematically investigating the ability of high frequency and leading data to improve upon the timeliness with which new expansions and recessions can be identified over the existing literature that primarily uses coincident and low frequency data. I have proposed a three-step approach, known as the Dynamic Factor Markov Switching Model at Daily Frequency (DFMSDF), for the purpose of classifying macroeconomic data at mixed and high frequency into expansion and recession regimes. As part of this paper, I compile the data into a vintage dataset that would have been available on each analysis date.

I evaluate the real-time performance of the approach for identifying business cycle turning points in the United States since 1980. I find that implementing these three additions - high frequency data, leading data, and information from news articles - significantly and consistently improves the speed at which expansions and recessions can be identified in the United States since 1980. For example, with high frequency and leading data included into the analysis, the model identifies the start of the Great Recession 256 days ahead of the NBER announcement and many months ahead of the statistical procedures surveyed in Hamilton (2011). When I further incorporate information from the news-based sentiment index in Li (2020), I am able to identify the December 2007 business cycle peak even earlier, on December 2, 2007. In several cases, business cycle turning points are called prior to their occurring, which demonstrates the value-added of incorporating leading data into the analysis.

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7 References

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