ESSAYS ON HIGH-FREQUENCY MACROECONOMIC MONITORING

by

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DISSERTATION ABSTRACT

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Real-time tracking of the present state of macroeconomic activity is of great interest to firms, workers, financial market participants, and policymakers. This is particularly true for tracking recessions in real time, as these episodes have very significant costs on individuals and firms. Despite significant research focus on forecasting and nowcasting macroeconomic activity, there are still substantial delays in identifying key macroeconomic fluctuations. For example, the December 2007 peak of the Great Recession was not identified until mid-to-late 2008 by statistical tracking models in real time.

In this dissertation, the dominant theme is evaluating techniques and developing novel datasets for an improved high-frequency monitoring of the macroeconomy. The second chapter stands apart from the other chapters in its focus; however, they have some connection in methods, particularly in the use of dynamic factor models. In the second chapter, I monitor macroeconomic activity in China with a dynamic factor model and investigate asymmetries in the effects of monetary policy in the Chinese overall economy during the “high-growth” and “low-growth” phases. In the third and fourth chapters, I

shift my focus directly to the high-frequency monitoring of macroeconomic activity in the United States. In the third chapter, I develop techniques to provide an improved nowcast of U.S. business cycle phases in real time with the use of high-frequency data and leading data. In the fourth chapter, I create a novel high-frequency news-based sentiment indicator of aggregate economic conditions and investigate whether information from news articles can improve the nowcast of low-frequency macroeconomic variables.

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CHAPTER I

INTRODUCTION

Real-time tracking of the present state of macroeconomic activity is of great interest to firms, workers, financial market participants, and policymakers. This is particularly true for tracking recessions in real time, as these episodes have very significant costs on individuals and firms. Despite significant research focus on forecasting and nowcasting macroeconomic activity, there are still substantial delays in identifying key macroeconomic fluctuations. For example, the December 2007 peak of the Great Recession was not identified until mid-to-late 2008 by statistical tracking models in real time.

In this dissertation, the dominant theme is evaluating techniques and developing novel datasets for an improved high-frequency monitoring of the macroeconomy. The second chapter stands apart from the other chapters in its focus; however, they have some connection in methods, particularly in the use of dynamic factor models. In the second chapter, I focus on asymmetries in the effects of monetary policy in China. In the third and fourth chapters, I shift my focus directly to the high-frequency monitoring of macroeconomic activity in the United States.

I begin in the second chapter by studying the asymmetry in the response of the Chinese economy to monetary policy. Asymmetry is defined in terms of the effects of monetary policy in high-growth periods vs. low-growth periods. Chinese economic activity and inflation are measured using dynamic factors extracted from a large number of underlying indicators. Monetary policy shocks are identified from a factor-augmented vector autoregression as in Fernald et al. (2014). High-growth and low-growth phases are measured using a smooth transition logistic function. Finally, the response of economic activity and inflation to monetary policy shocks in high-growth periods vs. low-growth periods are estimated via the local projection method as in Tenreyro and Thwaites (2016).

I find evidence that the effects of measured monetary policy shocks on the Chinese economy are different between high-growth periods vs. low-growth periods. Monetary policy shocks have larger impacts on output growth during low-growth states; during high-growth states, monetary policy shocks have larger impacts on inflation. This evidence is consistent with a convex aggregate supply curve. This paper is the first to study asymmetric effects of monetary policy on the Chinese economy over the business cycle.

In the third chapter, I shift my attention to nowcasting U.S. business cycle phases with high-frequency data and leading data. I investigate whether the use of high-frequency data and leading data can improve the speed at which business cycle peaks and troughs can be identified in U.S. data over the existing literature that focuses primarily on low-frequency data and coincident data. This chapter aims to speed up the identification of the NBER business cycle dates in real time. First, using a dynamic factor model, I extract a coincident index of real economic activity from vintage real-time data that becomes available at high and mixed frequencies. Second, I use a supervised classification technique (Markov regime-switching) to classify the coincident index into recession and expansion regimes. Finally, I use this trained classifier to evaluate the evidence for new business cycle turning points over an out-of-sample period extending from 1979-2021.

Results show that my method replicates the National Bureau of Economic Research (NBER) peaks and troughs, with some false identifications. The timeliness of my approach outperforms those of other business cycle phases dating methods, including announcements made by the NBER's Business Cycle Dating Committee and results found in Chauvet and Hamilton (2006), Chauvet and Piger (2008), and

Giusto and Piger (2017). 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.

Finally, the fourth chapter of my dissertation is motivated by creating a new high-frequency data that contains information about macroeconomic activity in the United States. Using dictionary methods, I establish a news-based daily index of sentiment regarding economic conditions from the Wall Street Journal daily articles. I also incorporate the index in empirical studies as a complement to the more structured macroeconomic data traditionally used.

Results suggest the high-frequency news-based sentiment index has information useful for nowcasting low-frequency macroeconomic variables, including business cycle turning points and monthly variables such as initial claims, unemployment rates, the University of Michigan consumer sentiment index, and the nonfarm payroll employment. This improvement is primarily visible during recessions.

CHAPTER II

ARE THE EFFECTS OF MONETARY POLICY ASYMMETRIC IN CHINA?

II.1 Introduction

Since 2000, China's economic growth has been very strong. The reported GDP growth rate surpassed 8 percent for a decade after 2000, reaching a local peak of 14 percent in 2007. This growth has led to China becoming an increasingly important part of the world economy. It is now the second largest economic engine in the world measured by nominal GDP, and the world's largest economy by purchasing power parity, contributing 27 percent of global GDP in 2018.

Despite this importance, there has been relatively little work done on understanding the effects of Chinese monetary policy. One reason for the small amount of research is the poor quality of Chinese macroeconomic data (Wallace, 2014; Rawski, 2001; Maier, 2011; Holz, 2014). Researchers like Mehrotra and Paakkonen (2011), Fernald et al. (2015), and Clark et al. (2017) find that officially reported data has become more informative in recent decades. Meanwhile, China has experienced rapid institutional and structural changes, which may lead to changes in the Chinese monetary policy mechanism post 2000 (He et al., 2013; Fernald et al., 2014; Chen et al., 2016). In other countries, especially Western market economies, substantial attention has been paid to state-dependence, or asymmetry, in the effects of policy over the business cycle. Most papers find that monetary policy is more powerful in affecting output during recessions than during expansions (Thoma, 1994; Garcia and Schaller, 2002; Lo and Piger, 2005; Weise, 1999; Kaufmann, 2002; Peersman and Smets, 2001). However, in a recent influential paper, Tenreyro and Thwaites (2016) find an opposite result.

I investigate how monetary policy instruments affect output growth and inflation, and whether this effect is asymmetric across different states of output growth. Following Fernald et al. (2014), I measure economic activity and inflation as dynamic factors from a large number of Chinese economic indicators. To measure monetary policy, I estimate a factor-augmented vector autoregression (FAVAR) and extract monetary policy shocks using a Cholesky causal ordering with the policy variable ordered last. As in Tenreyro and Thwaites (2016), I use a smooth transition logistic function to measure high- and low-growth states in Chinese economic activity. Finally, to estimate the response of economic activity and inflation to monetary policy shocks in different growth states, I use the method of local projections first introduced by Jorda (2005).

I find evidence that the effects of measured monetary policy shocks on the Chinese economy are different between high-growth periods vs. low-growth periods. Monetary policy shocks have larger impacts on output growth in low-growth states. This is consistent with the majority of the literature studying the asymmetric effects of monetary policy shocks in Western economies. Additionally, I find that monetary policy shocks have larger effects on inflation in high-growth states. Overall, this evidence is consistent with a convex aggregate supply curve.

The remainder of this paper is structured as follows: Section 2.2 reviews the literature. Section 2.3 describes the dataset. Section 2.4 explains the empirical methods. Section 2.5 sets out the main results. Section 2.6 concludes with some thoughts for future research.

II.2 Literature Review

According to Lo and Piger (2005), the literature has focused on three types of asymmetry: (1) asymmetry related to the direction of the monetary policy action, (2) asymmetry related to the existing business cycle phase, and (3) asymmetry related to the size of the policy action. I focus on the second type of asymmetry.

As one of the earliest papers in this area, Thoma (1994) defines the business cycle, or the state of the economy, as deviations of the growth rate of output from trend. Another method to identify the unobserved state of the economy is to use a Markov regime switching model, as in Peersman and Smets (2001), Garcia and Schaller (2002), Kaufmann (2002) and Lo and Piger (2005). These papers define transition probabilities from the state of expansion to the state of recession as time-varying functions of the changes of the observed monetary policy actions. In this paper, I use a smooth transition logistic function to exploit variation in the degree of the economic activity factor of being in a regime. This Smooth transition method has been used in a number of papers to study the asymmetric effect of fiscal or monetary policy on output across expansions and recessions, such as Weise (1999), Auerbach and Gorodnichenko (2012), and Tenreyro and Thwaites (2016). [1]

Early papers measure monetary policy shocks using the first difference of a monetary policy instrument (Thoma, 1994; Peersman and Smets, 2001). Tenreyro and Thwaites (2016) estimate monetary policy shocks as residuals from a nonlinear analogue of the Romer and Romer (2004) regression. The majority of the literature has measured the monetary shock using Choleski innovations identified from the contemporaneous relationships of the variables in a standard structural VAR model, with the monetary policy tool ordered last (Weise, 1999; Peersman and Smets, 2001; Garcia

[1] I have used multiple two-state Markov regime switching models to capture the latent states. However, this family of models only fit two periods where growth rate is very fast and the single period where growth rate is very slow.

and Schaller, 2002; Lo and Piger, 2005; He et al., 2013; Fernald et al., 2014). This is the method I adopt.

Much of the recent literature has measured the effects of macroeconomic shocks, and possible asymmetry in these effects, using the Jorda (2005) method of local projections. For example, Auerbach and Gorodnichenko (2012) and Ramey and Zubairy (2014) measure the asymmetric effects of fiscal policy over the business cycle, and Tenreyro and Thwaites (2016) measure the asymmetric effects of monetary policy over the business cycle. In this paper I will also use the method of local projections to measure asymmetric effects of monetary policy in China.

Most papers that study asymmetric effects of monetary policy on output in Western market economies find that monetary policy is more powerful in affecting output during recessions than during expansions (Thoma, 1994; Garcia and Schaller, 2002; Lo and Piger, 2005; Weise, 1999; Kaufmann, 2002; Peersman and Smets, 2001). However, Tenreyro and Thwaites (2016) find an opposite result. I find evidence that Chinese monetary policy shocks have larger impacts on output growth in low-growth states, which is consistent with the majority of the literature in other countries.

For the literature that focus on Western market economies, output is measured by industrial production and GDP volume, or the logarithm and the growth rate of these indicators (Thoma, 1994; Weise, 1999; Peersman and Smets, 2001; Garcia and Schaller, 2002; Kaufmann, 2002; Tenreyro and Thwaites, 2016). I focus on asymmetric effects of monetary policy on output in China, where output cannot be measured directly with industrial production or GDP, due to the poor quality of the officially published Chinese economic data (Rawski, 2001; Maier, 2011; Wallace, 2014; Holz, 2014).

In the empirical literature that studies macroeconomics in China, there are mainly two methods to deal with the quality issue of Chinese data. The first method is to choose data that is not subject to government manipulation. Nakamura et al. (2014)

take a microeconomic perspective and use Chinese urban household survey data, which is subject to less intervention from government compared with the headline macroeconomic data. Based on the survey, the authors estimate Engle curves, and "back out" the estimate of Chinese growth and inflation. Fernald et al. (2015) use quarterly trading-partner export to China data, which is an independent measurement. They find that economic activity factors extracted from electricity consumption, rail freight, retail sales, an index of raw material supply are more informative than the officially reported GDP alone. They also find that the information content of Chinese GDP improves after 2008. Clark et al. (2017) use annual satellite nighttime lights data as an independent benchmark of Chinese economy growth. They find that the growth rate of electricity production, railroad freight, and bank loans with modified weights computed by nighttime lights data does a good job at predicting the true unobserved Chinese economy growth. Their predictor of Chinese growth shows that the rate of Chinese growth is higher than is reported in the official statistics.

The second method to evaluate Chinese economy when data is suspected to be inaccurate is to extract latent factors from a large panel of underlying time series. Mehrotra and Paakkonen (2011) use principal component analysis to evaluate China's growth from 1997 to 2009. Their estimated factor matches closely the reported GDP dynamics, especially since 2002. He et al. (2013) treat output and inflation as observed variables, measured by industrial production and consumer price index respectively. The authors extract the monetary policy factor from 15 policy variables and apply a factor-augmented vector autoregression model to study the monetary transmission mechanism in China over the period from January 1998 to February 2010. Fernald et al. (2014) also use a factor-augmented vector autoregression to estimate the effects of monetary policies on Chinese economy, over the period from January 2000 to September 2013. They treat Chinese output and inflation as unobserved latent variables, and extract an economic activity factor and an inflation factor. Their factors capture well the slowdown in China during the U.S. Great Recession and the following recovery. Dynamic factors extracted from a large number of underlying variables convey more information regarding Chinese economic activity than the reported GDP data alone. Another advantage of this method is that no prior knowledge is needed when determining which variables to include in the model, and data will speak in terms of the goodness of fit. Therefore, this is the method I use.

To my knowledge, Chen et al. (2016) is the only paper that studies asymmetric effects of monetary policy on Chinese economy. According to Chen et al. (2016), the main function of Chinese monetary policy is to control the growth rate of money supply M2 and provide support to achieve the GDP growth rate target set by the State Council, the chief administrative authority of China. In contrast to my paper, which focuses on asymmetric effects of monetary policy across high-growth and low-growth states, Chen et al. (2016) focus on the normal state when actual GDP growth meets the GDP growth rate target, and the shortfall state when actual GDP fails to meet the GDP growth rate target. Chen et al. (2016) measure monetary policy shocks as the difference between actual M2 growth and the systematic component of M2 growth, and adopts the official GDP and CPI data in their analysis. The structural VAR approach suggests that when actual GDP growth fails to meet the GDP growth target set by the government, monetary policy is more powerful in influencing the economy. Their paper presents significant evidence of the existence of asymmetric effects of Chinese monetary policy on the economy during above the target periods and below the target periods of the economy.

II.3 Data

Table II.1 lists all the variables included in this paper. All data are downloaded from the CEIC China Premium Database. As in Fernald et al. (2014), data series are divided into three groups. The first group includes fundamental series that correlate with output, from which the economic activity factor is extracted. The second group includes four price indexes, from which the inflation factor is extracted. The third group comprises the measure of monetary policy. This group has just one variable, interest rates on loans to financial institutions for less than 20 days, which is the central bank benchmark interest rate.

The release of monthly data series is affected by the two-week lunar calendar New Year holiday, of which the first day begins between late January and late February. For some indicators, the sum of January and February data is reported. [2] To get monthly values of these indicators, I redistribute values for January and February so that the growth rate from December to January equals the growth rate from January to February. Then I obtain monthly values from March to December by taking first differences.

After removing effects of the Chinese New Year, I use the Census X-12 ARIMA package to adjust for seasonality. Then I take monthly growth rates of each series, except for benchmark interest rates and price indexes. [3] Outliers of each series are identified as those data points that lie outside 10 times the interquartile range from the median. Outliers are treated as missing values and imputed as described below.

In addition to outliers, other sources of missing data include: (1) missing January and February data, which systematically stem from the lunar calendar New Year holiday; [4] (2) missing data exists at the beginning of the sample for indicators collected later than January 2000; (3) in-sample missing data; (4) missing data exists at the end of the sample for data that are no longer being released or not released in synchronicity. I adopt an iterative expectation-maximization (EM) algorithm devel-

[2] These indicators include electricity consumption, fixed assets investment, fixed assets investment in equipment purchase, fixed assets investment in new construction, real estate investment for residential buildings, and floor space started for commodity buildings.

[3] Price indexes are measured in units where the previous month's price level is fixed at 100.

[4] These indicators include retail sales of consumer goods, crude steel production, real estate climate index, electricity consumption, electricity production, natural gas production.

Table II.1
Data Summary

Time series	Sample Period
ECONOMIC ACTIVITY FACTOR	
Gross Industrial Output	2003m1 - 2012m5
Electricity Consumption	2003m1 - 2018m9
Energy Production: Electricity	2000m1 - 2018m9
Natural Gas Production	2000m1 - 2018m9
Steel: Production: Crude Steel	2001m1 - 2018m8
Real Estate Inv: Residential Building	2000m1 - 2018m9
Floor Space Started: Commodity Bldg	2000m1 - 2018m9
Real Estate Climate Index	2004m1 - 2016m12
Consumer Confidence Index	2000m1 - 2018m9
Consumer Expectation Index	2000m1 - 2018m9
Fixed Asset Investment	2000m1 - 2018m9
FAI: Equipment Purchase	2004m1 - 2017m12
FAI: New Construction	2000m1 - 2017m12
Purchasing Managers' Index: Mfg	2005m1 - 2018m9
PMI: Mfg: New Export Order	2005m1 - 2018m9
PMI: Non Mfg: Business Activity	2007m1 - 2018m9
No of Employee: Industrial Enterprise	2000m12 - 2018m8
Retail Sales of Consumer Goods	2000m1 - 2018m9
Railway: Freight Traffic	2000m1 - 2018m9
Automobile Sales: Truck	2005m1 - 2018m9
Index: CSI 300 Index	2005m4 - 2018m9
Index: Shanghai Stock Exchange: Composite	2000m1 - 2018m9
Index: Shenzhen Stock Exchange: Composite	2000m1 - 2018m9
PE Ratio: Shanghai SE: All Share	2000m1 - 2018m9
PE Ratio: Shenzhen SE: All Share	2000m1 - 2018m9
FX Rate: RMB to USD	2000m1 - 2018m9
Export FOB	2000m1 - 2018m9
Import SITC: MF: Petroleum, Petroleum Pdt and Related Material	2000m1 - 2018m8
Trade Balance	2000m1 - 2018m9
Foreign Reserves	2000m1 - 2018m9
INFLATION FACTOR	
CPI: Core (excl. Food and Energy)	2006m1 - 2018m9
CPI: Food, Tobacco and Liquor	2000m1 - 2018m9
Consumer Price Index: 36 City	2002m1 - 2018m9
Consumer Price Index	2000m1 - 2018m9
POLICY VARIABLES	
Central Bank Benchmark Interest Rate: Loan to FI Less Than 20 days	2000m1 - 2018m9

oped by McCracken and Ng (2015) to handle missing values. This EM algorithm is initialized by filling in missing data for each series with unconditional mean; then I extract factors from the demeaned and standardized dataset; then I update missing values using factors, and repeat this iterative procedure until factors converge.

After all missing values are imputed, the monthly dataset contains 224 months. I standardize the dataset to have zero mean and unit variance. Following Stock and Watson (2012), I remove a local mean from each series using a biweight kernel with a bandwidth of 100 months. The biweight kernel smoothes the series.

II.4 Methodology

II.4.1 Extracting Factors

Estimates of economic activity and inflation are measured with the first principal component of the series that measure output and price respectively. I follow Stock and Watson (2016) to set up the dynamic factor model. The dynamic factor is shown in Equations II.1 and II.2.

$$X_t = \lambda(L) f_t + e_t \tag{II.1}$$

$$f_t = \Psi(L) f_{t-1} + \eta_t \tag{II.2}$$

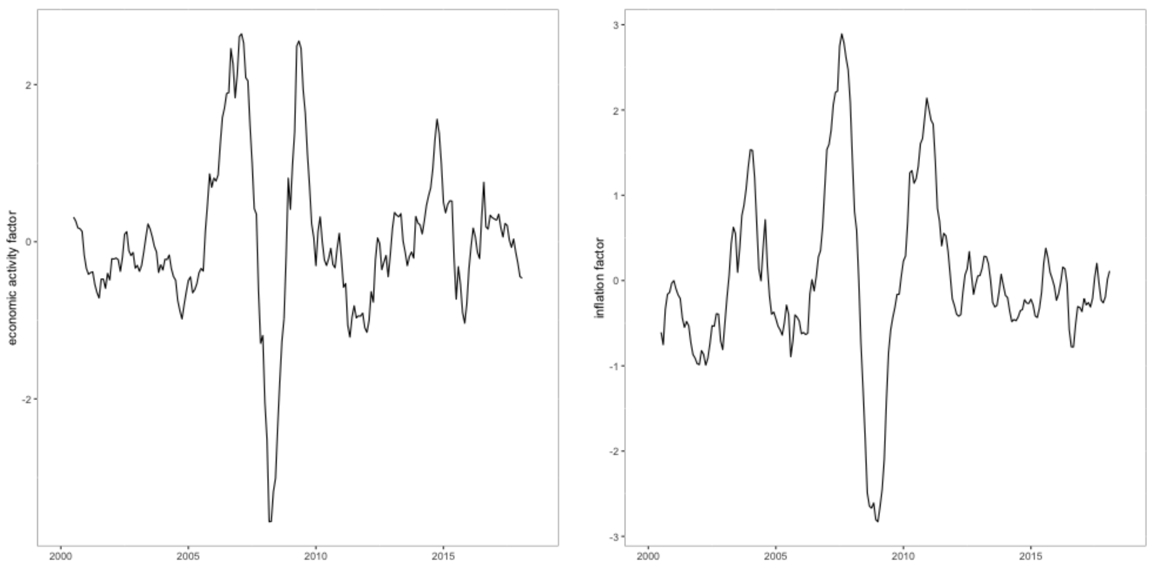
An $n \times 1$ vector of X_t contains observable underlying variables. f_t is a $k \times 1$ vector of latent common factors. The number of the observables n is assumed to be much larger than the number of factors k. I let $k = 1$ to extract one factor from series that correlate with output, and one factor from price indexes. f_t is allowed to follow an AR process. $\lambda(L)$ and $\Psi(L)$ are polynomials in the lag operator. λ is a $n \times k$ matrix and $\Psi(L)$ is a $k \times k$ matrix. $\lambda_i(L)$ is the loading of X_{it} on f_t, and $\lambda_i(L) f_t$ is the common component of the ith variable X_i. η_t is assumed to be a mean-zero $k \times 1$ vector of serially uncorrelated error term to the factors. The idiosyncratic term e_t is a $n \times 1$ vector and assumed to be uncorrelated with η_t at all leads and lags.

The principal component method is computationally simple. In addition, as long as the correlation is not too big, e_t can be assumed to be correlated across series and across observations. The standard strict factor model assumes e_t to be serially uncorrelated, while the approximate factor model relaxes this assumption. The principal component method is appropriate to find an approximate factor structure, according to Chamberlain and Rothschild (1983) and Stock and Watson (2002).

The left panel of Figure II.1 presents the economic activity factor extracted with the principal component method from variables that relate to the broad macroeconomic movement in China. The right panel presents the inflation factor extracted with the principal component method from four price indexes. Both series have been smoothed by taking the 12-month moving average and standardized to have zero mean and unit variance. In the figure, it can be seen that there are clear periods of sustained below-average growth and above-average growth. The persistent decline in the economic activity growth and inflation during the late 2008 is aligned with the U.S. Great recession and the global financial crisis.

A recession in the United States is defined by the National Bureau of Economic Research 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". In contrast to the literature that studies the asymmetric effects of monetary policy during recessions and expansions, I will avoid labeling the periods of persistent below-average growth "recessions" for the purpose of my paper. Instead, I will call those periods "low-growth states", and periods of above-average growth "high-growth states". Note that output does not necessarily decline during "low-growth states", because the trend of economic

Figure II.1
The Economic Activity Factor and The Inflation Factor



growth of China is high over these periods.

II.4.2 Measuring Monetary Policy Shocks

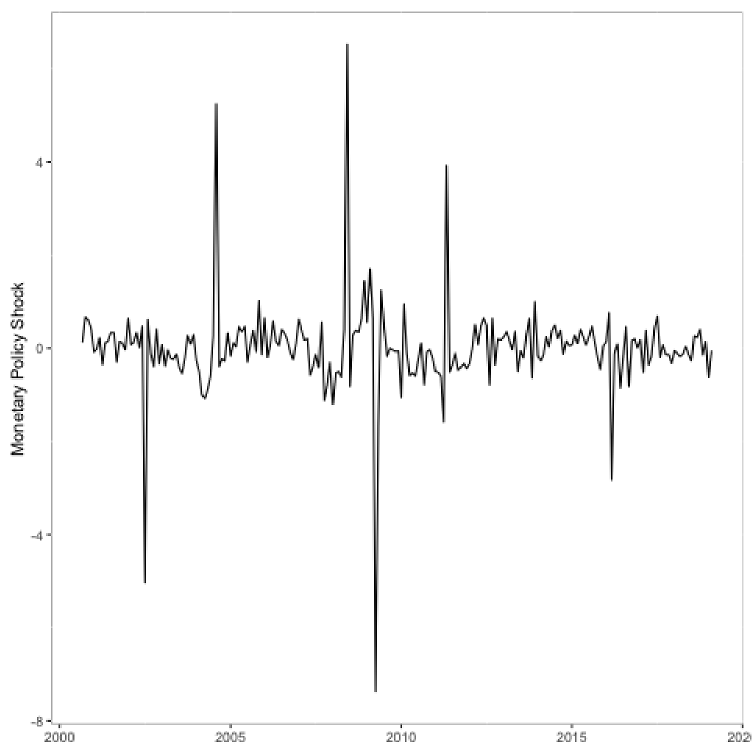
As in Fernald et al. (2014), I measure structural shocks of monetary policy using a Factor-Augmented Vector Autoregression (FAVAR) model, as in Equation II.3. Here, f_t^e denotes the standardized economic activity factor and f_t^p denotes the standardized inflation factor. y_t is the benchmark interest rate. $A(L)$ denotes polynomials in the lag operator, and I set its order to be 2.

$$\begin{bmatrix} f_t^e \\ f_t^p \\ y_t \end{bmatrix} = A(L) \begin{bmatrix} f_{t-1}^e \\ f_{t-1}^p \\ y_{t-1} \end{bmatrix} + u_t \tag{II.3}$$

$$u_t \sim i.i.d.\ N(0, \Sigma).$$

I use u_t to denote the reduced-form idiosyncratic term that is assumed to be independent and identically distributed with zero mean. I identify the structural shock through a Cholesky decomposition of Σ. This identification strategy assumes that the monetary policy variable can respond to changes in the economic activity factor and inflation factor contemporaneously, but the economic activity factor and inflation factor respond to changes in monetary policy with a lag of one month or more. This is implemented by recursively ordering the economic activity factor f_t^e and inflation factor f_t^p first, and the policy variable y_t last. Monetary policy shocks measured with the central bank benchmark interest rate are shown in Figure II.2.

Figure II.2
Monetary Policy Shocks

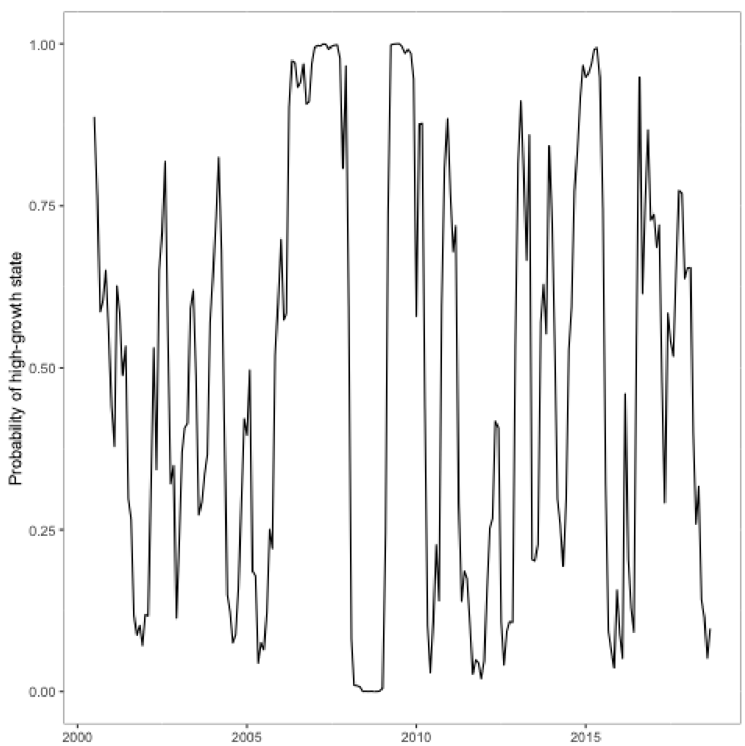


II.4.3 Identifying High and Low Growth Phases

As in Tenreyro and Thwaites (2016), probabilities of the unobservable states of the economy, "high-growth" states and "low-growth" states, are defined as a smooth increasing function, as in Equation II.4. Here, z_t is an indicator of the state of the economy, measured with 6-month one-sided moving average of the standardized economic activity factor. $F(z_t)$ measures the probability of the economy being in the high growth state. $F(z_t)$ increases as z_t increases; therefore, the economy is growing at a fast rate when $F(z_t) \approx 1$, and economy is growing at a slow rate when $F(z_t) \approx 0$. The probability that the economy is in the "high-growth" state is shown in Figure II.3. The probability that the economy is in the "low-growth" state is $1 - F(z_t)$.

$$F(z_t) = \frac{exp(\theta \frac{z_t - c}{\sigma_z})}{1 + exp(\theta \frac{z_t - c}{\sigma_z})} \tag{II.4}$$

Figure II.3
Probability of High-growth State



c is a parameter that controls the proportion of the sample the economy spend in the "slow-growth" state. The baseline specification sets $c = 0$, which indicates that the unconditional probability of the economy being in the "slow-growth" state to be equal to that in the "high-growth" state, when $z_t = 0$. σ_z is the standard deviation of z_t. θ is the parameter that controls how sharply the economy switches from the "high-growth" state to the "low-growth" state as z_t changes. As in Tenreyro and Thwaites (2016), this parameter is calibrated to 3 in the baseline specification, indicating an intermediate degree of intensity to the regime switching. The robustness of results to each of these choices is investigated below.

II.4.4 Estimating Impulse Response Functions using Local Projections

As in Tenreyro and Thwaites (2016), the baseline model specifies the impulse response of the standardized economic activity factor f^e_t, at horizon $g \in [0, G]$ in state $j \in \{h, l\}$ to a shock u_t as the coefficient β^j_g, as shown in Equation II.5. EquationII.6 presents the impulse response of the standardized inflation factor f^p_t at horizon $g \in [0, G]$ in state $j \in \{h, l\}$ to a shock u_t as the coefficient β^j_g. $j = h$ indicates the state of high growth, and $j = l$ indicates the state of slow growth. τ denotes a linear trend. α^j_g is a constant. The lag of dependent variable f^e_{t-1} and benchmark interest rate b_{t-1} are included as control variables.

$$
\begin{aligned}
f^e_{t+g} &= \tau t + F(z_t)(\alpha^h_g + \beta^h_g u_t + \gamma^h_{1,g} f^e_{t-1} + \gamma^h_{2,g} b_{t-1}) \\
&\quad + (1 - F(z_t))(\alpha^l_g + \beta^l_g u_t + \gamma^l_{3,g} f^e_{t-1} + \gamma^l_{4,g} b_{t-1}) + \nu_{t+g}
\end{aligned} \tag{II.5}
$$

$$
\begin{aligned}
f^p_{t+g} &= \tau t + F(z_t)(\alpha^h_g + \beta^h_g u_t + \gamma^h_{1,g} f^p_{t-1} + \gamma^h_{2,g} b_{t-1}) \\
&\quad + (1 - F(z_t))(\alpha^l_g + \beta^l_g u_t + \gamma^l_{3,g} f^p_{t-1} + \gamma^l_{4,g} b_{t-1}) + \nu_{t+g}.
\end{aligned} \tag{II.6}
$$

I compute impulse response functions by a local projection method: response at period g is measured by regressing the dependent variables from period $g + 1$ to the end on right-hand-side variables from period 1 to g periods from the end. According to Jorda (2005), computing impulse responses by local projections does not assume specific structure on specification and the unknown true multivariate dynamic system as required by a VAR model. With a VAR model, the impulse response function is measured by extrapolating the one-period ahead forecast, while local projections measure the impulse response function with direct multi-step forecasting.

An advantage of local projections is that it is easy to identify state-dependent asymmetry by allowing the coefficients on u_t to differ across two states, associated with the probability of being in a particular state. Hence, the impact of policy shocks on the economy in one state is separated from that in another state.

II.4.5 Inference

In order to construct confidence intervals for the impulse response functions estimated via local projections, I follow the suggestion of Jorda (2005) and construct standard errors for each local projection regression using Newey-West standard errors. The Newey-West correction is necessary as the v_{t+g} disturbance term in the local projection regression has a moving average structure. In constructing the Newey-West standard errors I follow Jorda (2005) and set the maximum lag equal to $g + 1$.

The null and alternative hypothesis of no asymmetry are given by the parametric restrictions in Equations II.7 and II.8:

$$H_0 : \beta_g^h - \beta_g^l = 0 \tag{II.7}$$

$$H_1 : \beta_g^h - \beta_g^l \neq 0 \tag{II.8}$$

In order to test the null hypothesis of no asymmetry, I follow Tenreyro and Thwaites (2016) to bootstrap the sign of $\beta_g^h - \beta_g^l$ using a block bootstrap approach. [5]

[5] Under the null hypothesis, coefficients of monetary policy shocks for high-growth periods and low-growth periods are the same, but coefficients of constant and control variables are different.

I construct 10,000 bootstrap datasets by drawing with replacement from the dataset. The block length used in generating the replicate time series is fixed at $G = 20$.

Specifically, I first generate a random date and then select from that date the next 20 observations from the original dataset, which is called the first block. I then randomly draw a new time point, select the next 20 observations as a new block, and add it to the first block. The process is repeated until the time series is equal to the length of the original time series. This is called one bootstrap dataset. In total, I have constructed 10,000 bootstrap datasets.

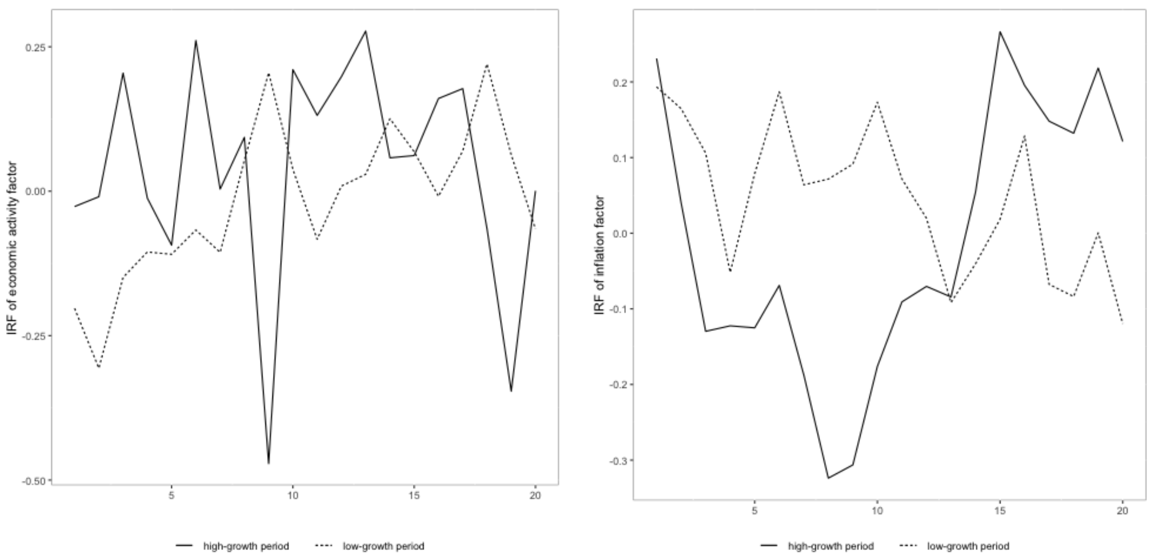
For each bootstrap dataset, I first randomly assign values of $F(z_t)$ with replacement such that the null hypothesis of no asymmetry is satisfied in population. By doing this, the actual $F(z_t)$ is randomly distributed across the data points so that there shouldn't be any relationship between $F(z_t)$ and the response of the economy at $t + h$ to shocks at time t. Then I calculate the the impulse response β_g^h and β_g^l using the local projection method. The p-value of the test is then calculated as the fraction of 10,000 cases in which the bootstrapped $\beta_g^h - \beta_g^l$ is larger than the value of $\beta_g^h - \beta_g^l$ estimated in the baseline model.

II.5 Results

II.5.1 Baseline Results

Figure II.4 presents the impulse response function of the economic activity factor and inflation factor to a one percentage point increase in the identified monetary policy shock. Horizon g is on the x-axis, and β_g^h and β_g^l are on the y-axis. The dashed curve on the left panel represents how an initial one percentage point increase in the benchmark interest rate impacts the economic activity factor over the next 20 periods during the low-growth period, and the solid curve represents how an initial one percent increase in the benchmark interest rate impacts the economic activity factor during the high-growth period. The counterpart curves on the right panel show the response of the inflation factor to an initial one percent increase in the benchmark interest rate during high-growth and low-growth periods respectively.

Figure II.4
Impulse Response Functions



The economic activity factor is extracted from a large number of growth rates of the underlying series. The negative economic activity factor during the first two months represents a decline in the level of economic activity following the monetary policy shock. Responses of economic activity during high-growth states and low-growth states are negative for the initial two months. The results are consistent with the standard theory that a tightening monetary policy leads to economic slowdown. Starting from the third month, responses of economic activity during high-growth states become positive and fluctuate around zero for the rest of the horizon, while responses of economic activity during low-growth states are negative for seven consecutive months, and then dies out over time for the rest of the periods. The evidence shows that monetary policy is more powerful in impacting economic activity during low-growth states.

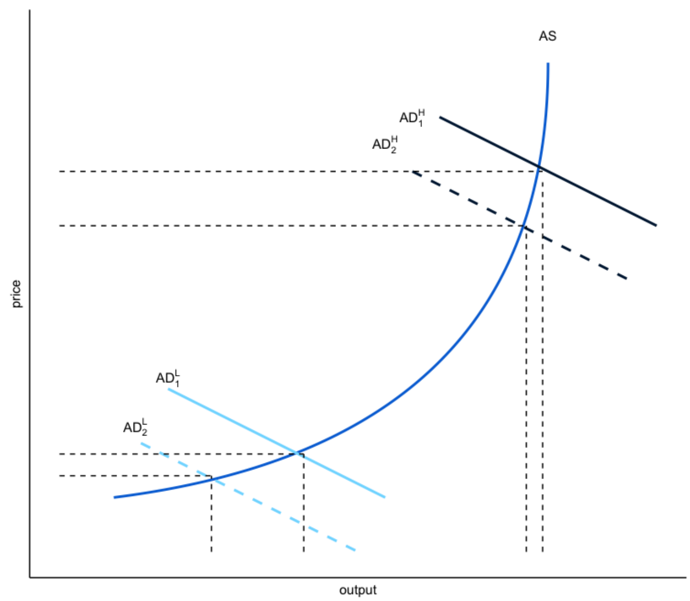
The inflation factor is extracted from growth rates of price indexes. Initial responses of the inflation factor to the monetary policy shock are positive for both states. This is similar to the price puzzle found in the effects of a policy tightening on inflation in studies of the effects of U.S. monetary policy on prices. Starting from the third month, responses of the inflation factor during high-growth states becomes negative and remains so for 13 months. This is the effect standard theory would predict - a monetary policy tightening leads to an overall reduction in the price level. Responses of the inflation factor during low-growth states fluctuate around zero for the rest of the horizon. This evidence shows that monetary policy is more powerful in impacting inflation during high-growth states.

The evidence that monetary policy shocks have larger impacts on output growth during low-growth states and larger impacts on inflation during high-growth states is consistent with a convex aggregate supply curve. As Figure II.5 shows, in such a model, during high-growth periods when the economy is more likely to be on the steep part of the aggregate supply curve, aggregate demand shifts should primarily affect prices. In contrast, during low-growth periods, when the economy is on the flat part of the aggregate supply curve, aggregate demand shifts should primarily affect output.

II.5.2 Inference

Figure II.6 shows impulse response functions with 90 percent confidence intervals. The confidence intervals are calculated with the Newey-West standard errors. There is substantial uncertainty in the impulse response function estimates. This is not surprising, as impulse response function estimates are often imprecise, and this is compounded by the short time series and noisy nature of the Chinese data. However, despite this uncertainty, there are a number of horizons for which these impulse response function estimates are significantly different from zero, suggesting that monetary policy has statistically significant effects on the Chinese economy. Note that

Figure II.5
Aggregate Supply - Aggregate Demand Analysis



the response functions are for growth rates of the factor, so that a single significant growth rate response means that there is a significant level response.

Figure II.7 shows the p-value for the null hypothesis that $\beta_g^h - \beta_g^l = 0$, using a 10 percent significance level. If the p-value is smaller than 10 percent, then the null hypothesis can be rejected. In both panels, there are a few horizons for which p-values are smaller than 0.1. At these horizons, the response of economic activity factor and inflation factor during high-growth periods is significantly different from that during low-growth periods, indicating asymmetry in the effects of monetary policy. [6]

II.5.3 Robustness Checks

The baseline specification sets $c = 0$. This indicates that the probability of the economy being in the "slow-growth" state to be equal as that in the "high-growth" state, when $z_t = 0$ on average, because the factor is standardized to have zero mean.

[6] As Figure II.7 makes clear, the p-value falls below conventional significance levels for some, but not all, horizons. The number of horizons for which the asymmetry is significant is similar to that reported in Tenreyro and Thwaites (2016) for U.S. data.

Figure II.6
Impulse Response Functions with 90 percent Confidence Interval

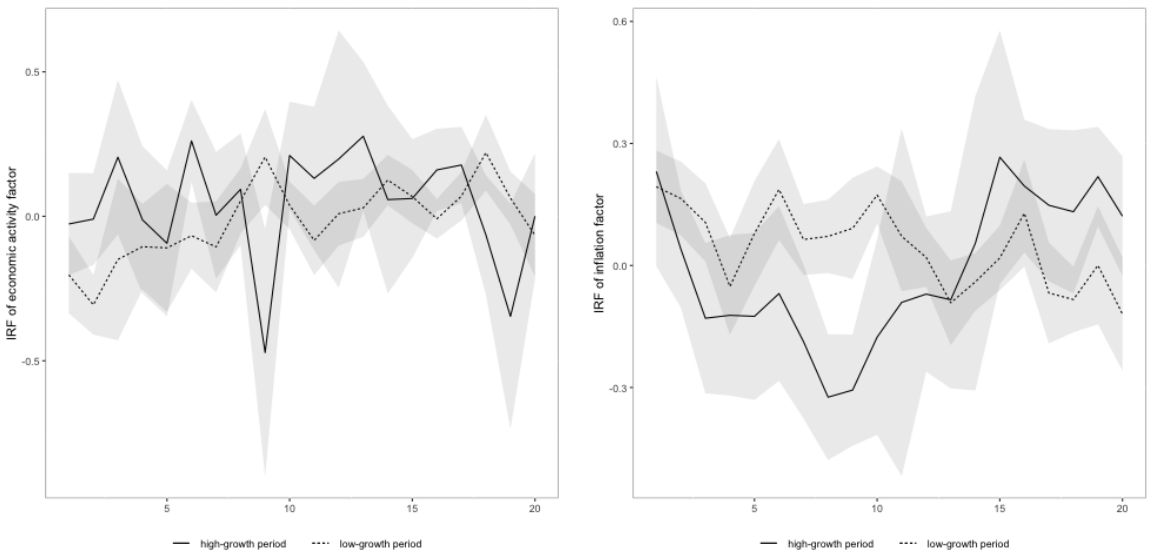
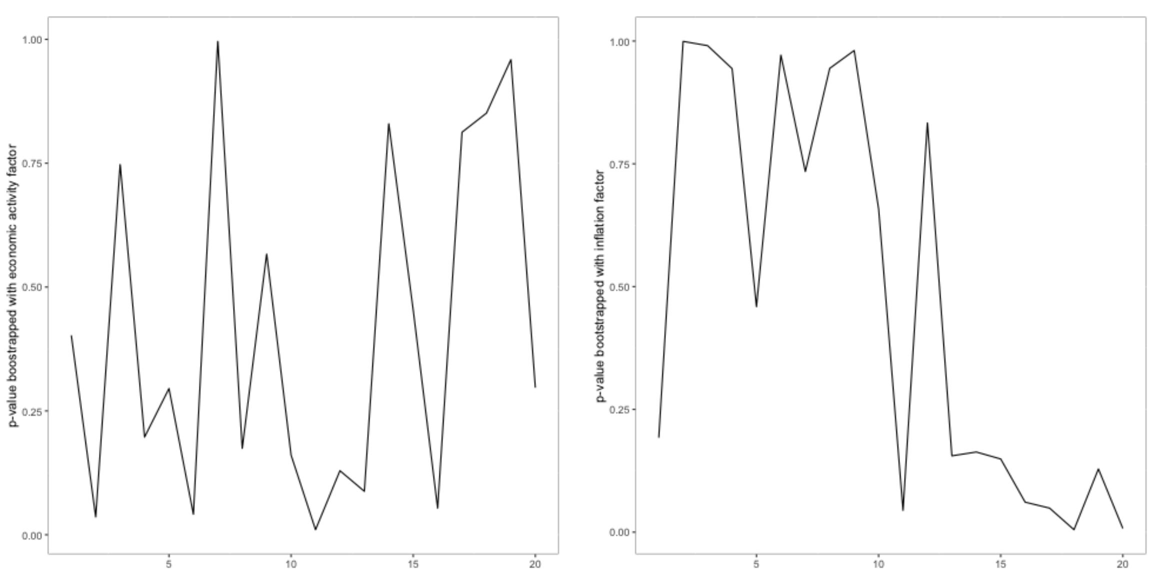
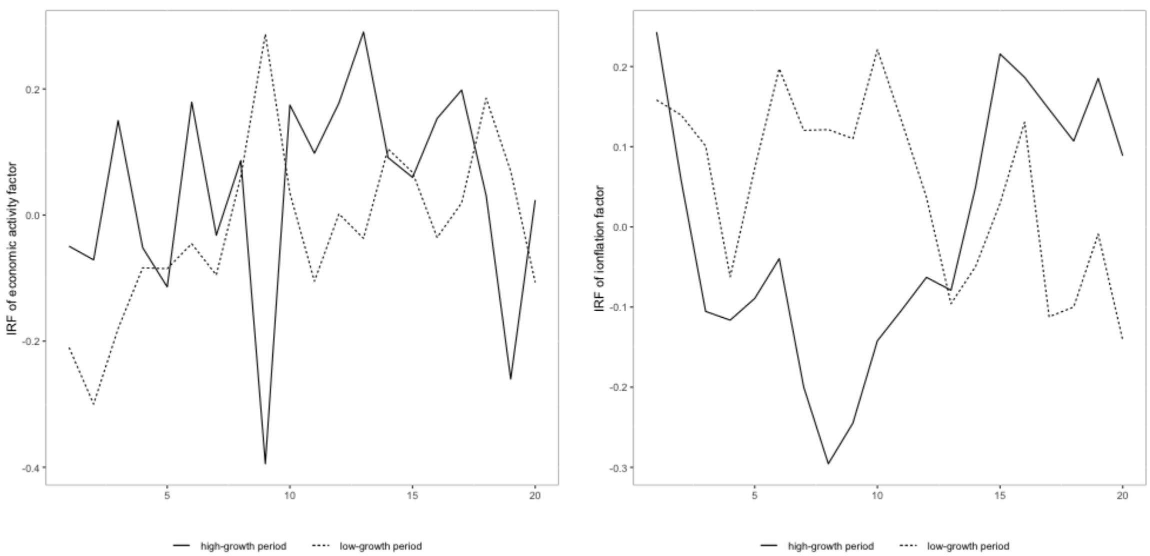


Figure II.7
Bootstrapped p-value



In the robustness checks section, c is set as -0.2, indicating the percentage of the time that $F(z_t)$ will place probability greater than fifty percent of being in the high growth regime. Figure II.8 shows the impulse response function of the economic activity factor and inflation factor to a one percentage point increase in the identified monetary policy shock when c is set to be -0.2, keeping $\theta = 3$. Main results are robust to changing c to -0.2.

Figure II.8
Impulse Response Functions with c=-0.2



The baseline specification sets $\theta = 3$. A lower θ indicates that the economy switches less sharply from "high-growth" states to "low-growth" states as z_t changes. Figure II.9 shows the impulse response function of the economic activity factor and inflation factor to a one percentage point increase in the identified monetary policy shock when θ is set to be one, keeping $c = 0$. Figure II.10 shows the results when θ is set to be five, keeping $c = 0$. The baseline result that monetary policy has asymmetric effects on Chinese economy across "slow-growth" states and "high-growth" states holds when θ is changed from one to five.

Figure II.9
Impulse Response Functions with theta=1

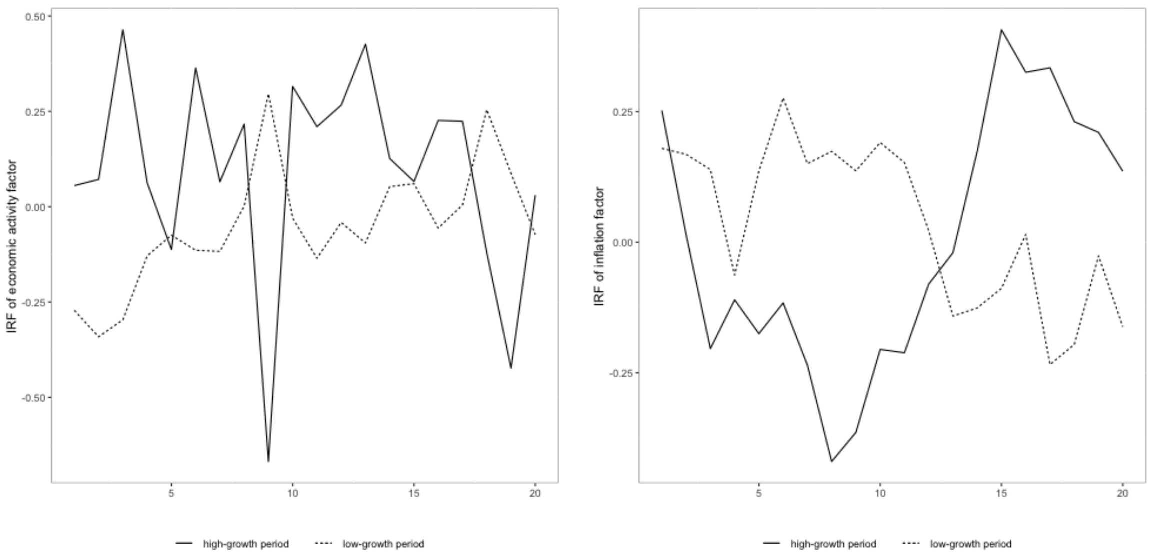
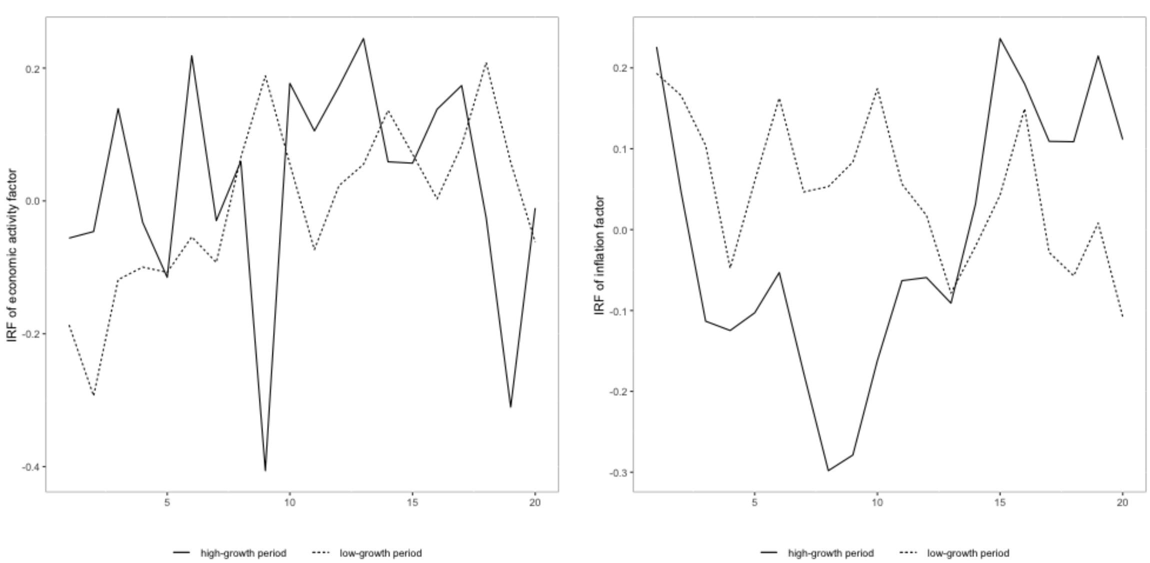


Figure II.10
Impulse Response Functions with theta=5



II.6 Conclusions

The literature that investigates asymmetries in the effects of China's monetary policy on economic activity and inflation is very limited. In this paper, I have investigated the asymmetric response of output growth and inflation to monetary policy actions during "high-growth" states and "low-growth" states. The economic activity factor and inflation factor are extracted from a large panel of underlying macroeconomic series using the principal component method. Monetary policy shocks are identified with Choleski decomposition of residuals from a factor-augmented vector autoregression. Probabilities of high-growth and low-growth phases are measured using a smooth transition logistic function. Finally, I have used a local projection method to measure the response of real economy to the identified monetary policy shocks during "high-growth" states and "low-growth" states. The evidence is consistent with monetary policy shocks having larger impacts on output growth during low-growth states and monetary policy shocks have larger impacts on inflation during high-growth states. This result is consistent with a convex aggregate supply curve.

There are periods during which the response of economic activity growth and inflation are positive following an increase in the benchmark interest rate. This indicates that economic activity and prices increase in response to a monetary policy tightening. This is counter-intuitive and may suggest potential issues with standard approaches to measure Chinese monetary policy shocks that have been used in the existing literature. According to Romer and Romer (2004), the likelihood of endogenous movements and anticipation movements can obscure the true effects of monetary policy. Romer and Romer (2004) address this problem and derive the indicator of monetary policy shocks by regressing the change in the intended policy interest rate around the Federal Reserve's internal forecast dates on these forecasts. The intended monetary policy shocks are derived using the narrative record, and the forecasts are publicly available in the "Greenbook" before each meeting of the Federal Open Market Committee.

To my knowledge, the People's Bank of China (PBC) does not publish its internal forecasts of inflation and real economic activity. Since 2009, the monetary policy committee of the PBC has been publishing reports of each of its quarterly meeting. Narrative analysis might be applicable to alleviate the endogeneity problem, which can be the focus of potential future research of this topic. Future research of this topic can also include the other two types of asymmetries: asymmetry related to the direction of the monetary policy action, and asymmetry related to the size of the policy action. This paper uses growth rates of factors to define phases of business cycle. Instead, future research can focus on the level of the factors relative to trend, and study the asymmetry of monetary policy over the cyclical component of the factors.

CHAPTER III

NOWCASTING BUSINESS CYCLE PHASES WITH HIGH-FREQUENCY DATA

III.1 Introduction

A common definition of the business cycle is alternating phases 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 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 NBER, which pro-

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

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

duces 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 and Piger (2008) and Chauvet and 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 literature studying nowcasting of U.S. business cycle phases uses coincident data at relatively low frequencies to nowcast business cycle phases, namely monthly or quarterly data that moves contemporaneously with changes in the overall economic activity. In other words, during periods of economic expansion, the coincident data increases; when the economy contracts, the data falls. 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 data at the daily or weekly frequency. There are several reasons for this expectation. First, high-frequency data would allow additional variables to be incorporated than what has typically been used in previous business cycle nowcasting literature, such as financial market variables or initial claims of unemployment insurance. Second, the use of high-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, high-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 after a full month delay.

In my paper I contribute in two primary ways to the literature studying nowcasting of U.S. business cycle turning points. First, I study whether the use of high-frequency data, namely weekly and daily 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 data at high and mixed frequencies, I propose a three-step approach. First, I use the mixed-frequency dynamic factor model as in Aruoba et al. (2009) (ADS). My model allows me to extract a coincident index of real economic activity using daily, weekly, monthly and quarterly data. Second, I train a supervised Markov regime-switching classification technique to classify the coincident index into a daily measure of recession and expansion regimes. The use of this Markov regime-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 supervised machine learning classification approaches that assume independent and identically distributed 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 my procedure for identifying new business cycle turning points in real time from January 1, 1979 to March 31, 2021 using a vintage dataset that contains the data that would have been available at each date 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.

I find that implementing these two additions - high-frequency data and leading data - significantly and consistently improves the speed at which expansions and recessions can be identified in the United States since 1979. As an example, incorporating high-frequency data and leading data, namely the yield curve term premium and initial claims, produces a call of the December 2007 business cycle peak on March 30, 2008. This is 246 days ahead of the NBER announcement, and many months ahead of the statistical procedures in the literature. 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 3.2, I describe the specification and estimation of my dynamic factor model at daily frequency. In section 3.3, I describe the construction of the vintage, real-time dataset. Section 3.4 presents out-of-sampler exercise results to identify turning point dates using the Markov regime switching classifier in real time. Section 3.5 concludes the paper.

III.2 Methodology

III.2.1 Dynamic Factor Model at Daily Frequency

In this section I lay out the model proposed in ADS and describe estimation and filtering of the daily coincident index. I follow ADS to build 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. x_t is described in Equation III.1, where e_t is a white noise innovation with variance $1 - \rho^2$.

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

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 is modeled in Equation III.2, where ζ_t is a white noise innovation with variance σ_1^2.

$$\begin{aligned} y_t^1 &= \begin{cases} \beta_1 x_t + u_t^1 \\ NA \end{cases} \\ &= \begin{cases} \beta_1 x_t + \gamma_1 u_{t-1}^1 + \zeta_t & y_t^1 \text{is observed} \\ NA & y_t^1 \text{is not observed} \end{cases} \end{aligned} \tag{III.2}$$

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 is modeled in Equation III.3, where u_t^2 is a white noise innovation with cumulated variance $7 \times \sigma_1^2$.

$$y_t^2 = \begin{cases} \beta_2 C_t^W + \gamma_2 y_{2,t-7} + u_t^2 & y_t^2 \text{is observed} \\ NA & y_t^2 \text{is not observed} \end{cases} \tag{III.3}$$

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

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

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 is modeled in Equation III.4, where u_t^3 is a white noise innovation with variance σ_1^3.

$$y_t^3 = \begin{cases} \beta_3 x_t + \gamma_3 y_{3,t-30} + u_t^3 & y_t^3 \text{is observed} \\ NA & y_t^3 \text{is not observed} \end{cases} \tag{III.4}$$

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 is modeled in Equation III.5, where u_t^4 is a white noise innovation with cumulated variance $90 \times \sigma_1^4$.

$$y_t^4 = \begin{cases} \beta_4 C_t^Q + \gamma_4 y_{4,t-90} + u_t^4 & y_t^4 \text{is observed} \\ NA & y_t^4 \text{is not observed} \end{cases} \tag{III.5}$$

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

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

The initial claims for unemployment insurance, nonfarm payroll employment and real GDP are coincident data that move with business cycle phases at the same time, whereas the yield curve term premium is a leading data that moves before business cycle phases. All y_t^i are demeaned and detrended. This completes the specification of the dynamic factor model at daily frequency. The measurement equation is cast as in Equation III.6, and the transition equation is cast as in III.7.

$$\underbrace{\begin{bmatrix} y_t^1 \\ y_t^2 \\ y_t^3 \\ y_t^4 \end{bmatrix}}_{\boldsymbol{\Upsilon_t}} = \underbrace{\begin{bmatrix} \gamma_1 & \beta_1 & 0 & 0 & 0 \\ 0 & 0 & \beta_2 & 0 & \gamma_2 \times y_{2,t-7} \\ 0 & \beta_3 & 0 & 0 & \gamma_3 \times y_{3,t-30} \\ 0 & 0 & 0 & \beta_4 & \gamma_4 \times y_{4,t-90} \end{bmatrix}}_{\boldsymbol{FF_t}} \times \underbrace{\begin{bmatrix} u_{t-1}^1 \\ x_t \\ C_t^W \\ C_t^Q \\ 1 \end{bmatrix}}_{\boldsymbol{\theta_t}} + \underbrace{\begin{bmatrix} \zeta_t \\ u_t^2 \\ u_t^3 \\ u_t^4 \end{bmatrix}}_{\boldsymbol{\nu_t}} \tag{III.6}$$

$$\underbrace{\begin{bmatrix} u^1_{t-1} \\ x_t \\ C^W_t \\ C^Q_t \\ 1 \end{bmatrix}}_{\boldsymbol{\theta_t}} = \underbrace{\begin{bmatrix} \gamma_1 & 0 & 0 & 0 & 0 \\ 0 & \rho & 0 & 0 & 0 \\ 0 & \rho & \xi^W_t & 0 & 0 \\ 0 & \rho & 0 & \xi^Q_t & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{\boldsymbol{GG_t}} \times \underbrace{\begin{bmatrix} u^1_{t-2} \\ x_{t-1} \\ C^W_{t-1} \\ C^Q_{t-1} \\ 1 \end{bmatrix}}_{\boldsymbol{\theta_{t-1}}} + \underbrace{\begin{bmatrix} \zeta_{t-1} \\ e_t \\ e_t \\ e_t \\ 0 \end{bmatrix}}_{\boldsymbol{\omega_t}} \tag{III.7}$$

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

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

The model can also be represented in time-varying state-space form as in Equations III.8 and III.9. $\boldsymbol{\Upsilon_t}$ 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.

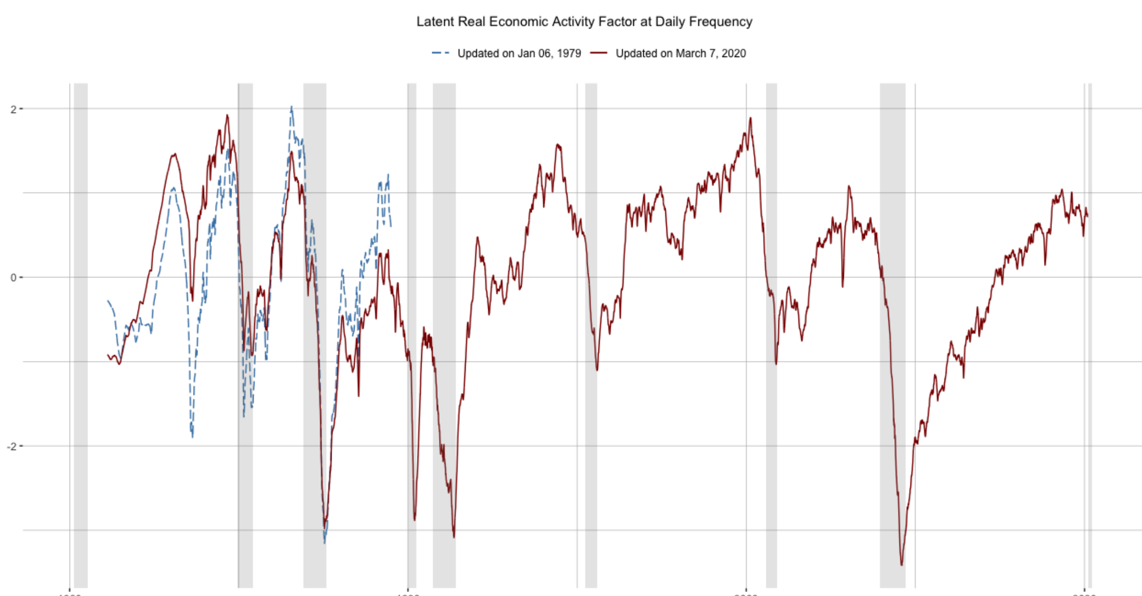
$$\boldsymbol{\Upsilon_t} = \boldsymbol{FF_t} \times \boldsymbol{\theta_t} + \boldsymbol{\nu_t} \tag{III.8}$$

$$\boldsymbol{\theta_t} = \boldsymbol{GG_t} \times \boldsymbol{\theta_{t-1}} + \boldsymbol{\omega_t} \tag{III.9}$$

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.

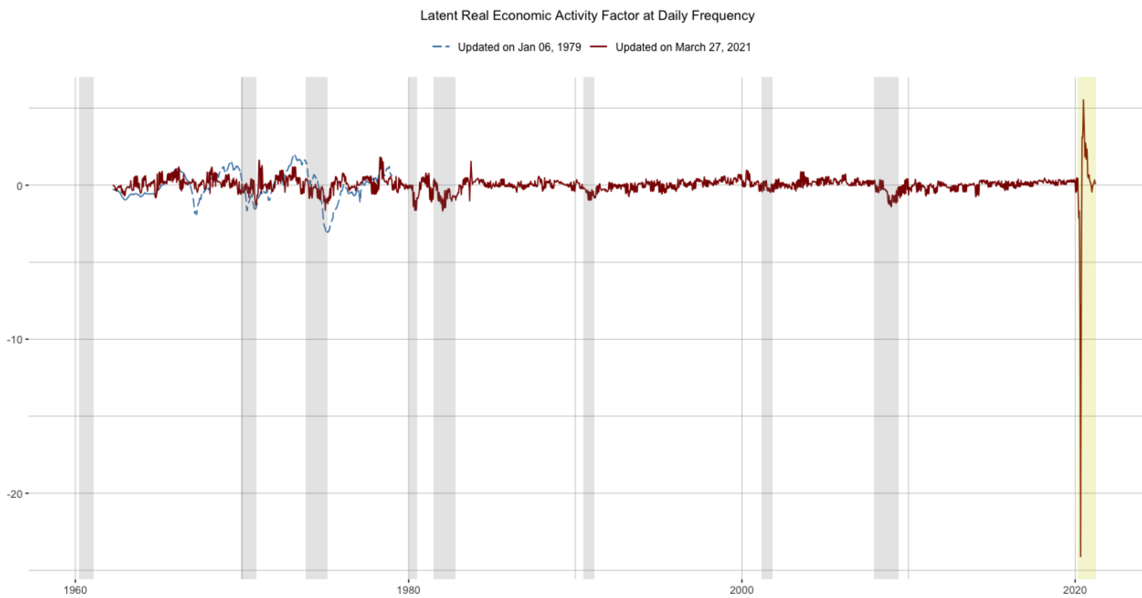
As the example, estimated factor estimated on January 6, 1979 and March 7, 2020 analysis dates are shown in Figure III.1. [3] The factor drops during recessions and drops before recessions in some cases. The sharp decline in Figure III.2 since late March 2020 presents the severe economic impact of Covid-19 pandemic. [4]

Figure III.1
Latent Real Economic Activity Factor at Daily Frequency on January 6, 1979 and March 7, 2020



[3]Shaded areas indicate U.S. recessions.
[4]The shaded area in yellow represents the most recent recession with an undecided end date.

Figure III.2
Latent Real Economic Activity Factor at Daily Frequency on January 6, 1979 and March 27, 2021



III.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 classification technique, i.e. the Markov regime-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.

The Markov regime-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 and Piger (2008) use a monthly real-time dataset and show that the dynamic factor Markov regime-switching model identifies NBER dates more accurately and identifies troughs with a larger lead than a nonparametric algorithm. Camacho et al. (2018) use a mixed-frequency dataset at monthly and quarterly frequencies, and extend the Markov regime-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}, as specified in Equation III.10. p_{ji} is the transition probability of S_t switching from regime i to regime j. Camacho et al. (2015) and Owyang et al. (2005) found that the Markov regime-switching $AR(0)$ model provided accurate and robust identification of NBER business cycle dates. As presented in Equations III.11 and III.12, I fit the first difference of the coincident index, which is denoted $\Delta\hat{x}_t$, to a univariate Markov regime-switching $AR(0)$ process with a switching mean.

$$p_{ji} = Pr(S_t = j|S_{t-1} = i) \tag{III.10}$$

$$\Delta\hat{x}_t = \beta_{S_t} + \epsilon_t \tag{III.11}$$

$$\beta_{S_t} = \beta_0 + \beta_1 \times S_t \tag{III.12}$$

$$\epsilon_t \sim N(0, \sigma^2)$$

$$\beta_1 < 0$$

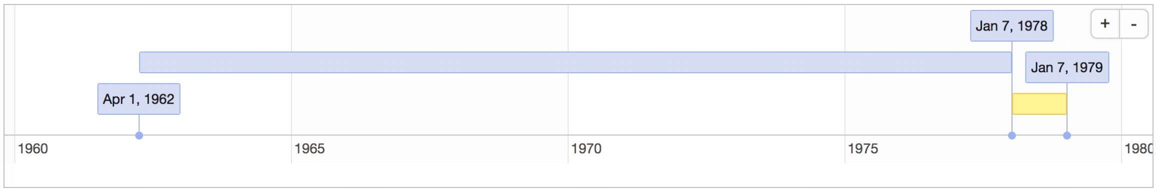
The growth rate $\Delta\hat{x}_t$ has mean β_{S_t}, and deviations from this mean growth rate are captured by the stochastic disturbance ϵ_t. The parameters of the model are $\Omega = (\beta_0, \beta_1, p_{11}, p_{22}, \sigma)'$. Let $S_t \in 0, 1$, where $S_t = 0$ indicates that day t is a expansion regime, and $S_t = 1$ indicates that day t is a recession regime. When S_t switches from 0 to 1, the mean growth rate of economic activity switches from β_0 to $\beta_0 + \beta_1$. 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 $\hat{P}(S_t = 1|\Psi_T)$.

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. I estimate transition probabilities as 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 III.3 shows the training set and testing set of the the first nowcast which occurs on 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 III.3
Training and Testing Set for the First Nowcasting



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 regime-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 $P_{00} = Pr(S_t = 0|S_{t-1} = 0)$ and $P_{11} = Pr(S_t = 1|S_{t-1} = 1)$ are very high. Over the full sample, P_{00} is 0.99962 and P_{11} is 0.99723. The Markov regime-switching based classifier captures this persistence by modeling S_t as following a Markov process.

III.2.3 Business Cycle Phases Dating Procedures

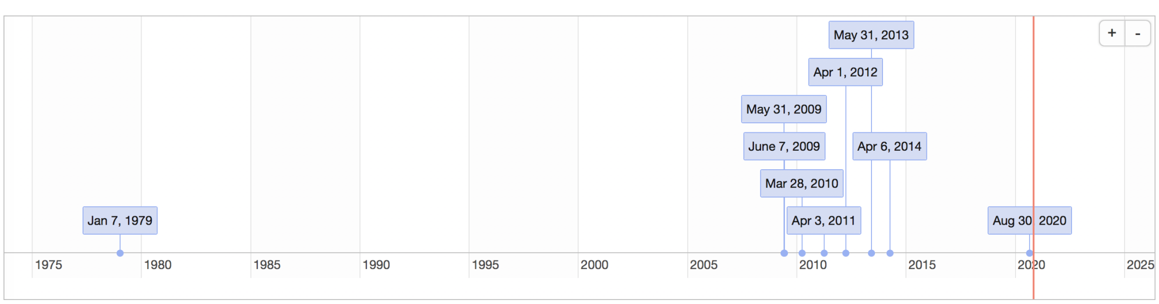
Finally, I use the classifier to evaluate the evidence for new business cycle turnings points in end-of-sample data that has not yet been classified by the NBER. In order to convert recession probabilities $\hat{P}(S_t = 1|\Psi_T)$ into a binary variable that defines whether the economy is in an expansion 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 $P(S_t = 1|\Psi_T)$ 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 $P(S_t = 1|\Psi_T)$ over the 12 weeks prior to the analysis date is below 0.2 is considered an expansion "call". This procedure mirrors that in Chauvet and 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.

III.3 Vintage Dataset

Every Sunday starting from Jan 1, 1979 to March 31, 2021 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 March 27, 2021. Figure III.4 presents a timeline of some of the analysis date that are involved in the example below.

Figure III.4
Analysis Dates



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) database maintained by the Research division of the Federal Reserve Bank of St. Louis incorporates data revisions. [5] 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 III.1 summarizes the complete revision of the value of ICSA on May 23, 2009.

Table III.1
Reported Values of ICSA on May 23, 2009

	Release	**Revise**	**Revise**	**Revise**	**Revise**	**Revise**	**Revise**
Date	2009-05-28	2009-06-04	2010-03-25	2011-03-31	2012-03-29	2013-03-28	2014-04-03
Value	623000	625000	611000	612000	608000	607000	606000

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 dates available for the data.

[5]The FRED database is available at the following website
`https://fred.stlouisfed.org/`

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 III.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.

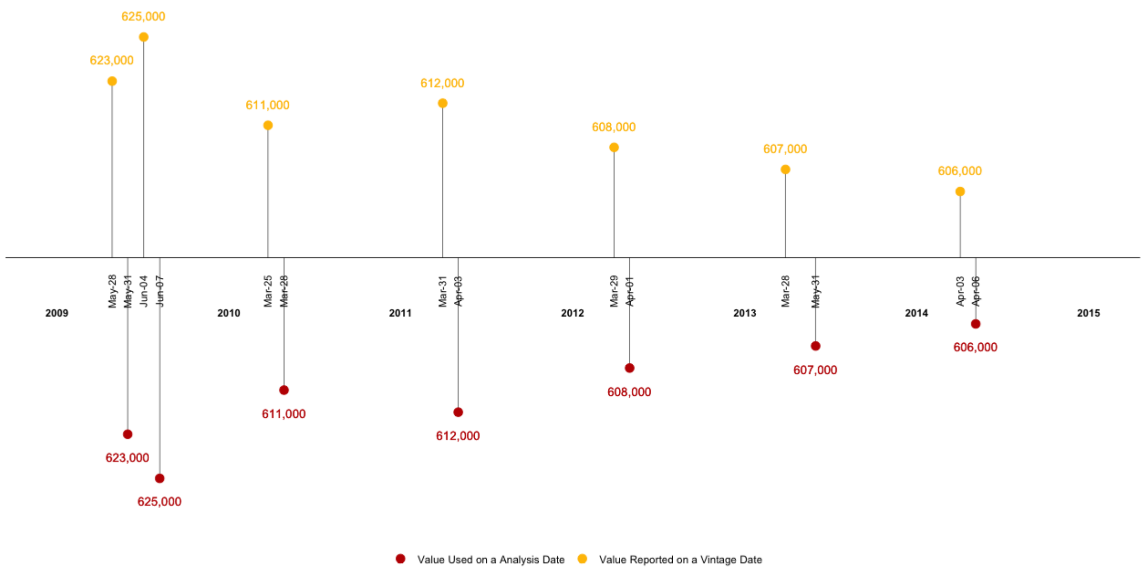
As used in ADS, I use the daily yield curve term premium defined as the difference between daily 10-year and daily 3-month U.S. Treasury yields (TY), the weekly initial claims for unemployment insurance (ICSA), the monthly nonfarm payroll employment (PAYEMS), and the quarterly real GDP (GDP) as my coincident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

Most of the fundamental series for this analysis are available on the Archive FRED (ALFRED) [6]. 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

[6] The ALFRED database is available at the following website `https://alfred.stlouisfed.org/`

Figure III.5
Values of ICSA on May 23, 2009



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 March 31, 2021.

- 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 March 31, 2021. For analysis dates before December 4, 1991, I use the vintage of the "Real Gross Domestic Product (GDPC1)" from April 1, 1962 to March 31, 2021 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 March 31, 2021.

- 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 March 31, 2021. Both series are downloaded from FRED database as of March 31, 2021.

- 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. [7]

Following ADS, 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.

[7] 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 do not 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.

III.4 Results Using a Vintage Dataset

III.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 III.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 presents the result from Chauvet and Hamilton (2006) and Chauvet and Piger (2008). While dynamic factor Markov-switching models are also the method adopted in Chauvet and Hamilton (2006) and Chauvet and Piger (2008), Chauvet and Hamilton (2006) include coincident variables at monthly and quarterly frequencies, and Chauvet and Piger (2008) focuses mainly on multiple coincident variables at the monthly frequencies. The table also compares these results to those from Giusto and 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 III.3 presents the analogous results for troughs.

The first column of the table shows the NBER turning points. [8] 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 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 values in the second column and the third column. The fifth column shows the number of days the Business Cycle Dating Committee of the NBER takes

[8] The NBER turning points are available at the following website `https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions`

to identify the turning point and to make an announcement. The remaining column shows the number of days it takes to identify the turning point in Chauvet and Hamilton (2006), Chauvet and Piger (2008), and Giusto and Piger (2017).

For example, on June 3, 1980, the Business Cycle Dating Committee of the NBER announced that a new recession started on February 1, 1980. This announcement was made 123 days after the recession occurred. The DFMSDF method made a call on April 27, 1980 and identified the recession 86 days after it started. Giusto and Piger (2017) identifies this recession 92 days after the fact, Chauvet and Hamilton (2006) identifies this recession 151 days after the fact, and Chauvet and Piger (2008) identifies this recession 181 days after the fact. [9]

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 Business Cycle Dating Committee of the NBER, Chauvet and Hamilton (2006), Chauvet and Piger (2008), and Giusto and 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 other benchmarks.

[9]Chauvet and Hamilton (2006) and Chauvet and Piger (2008) does not provide the performance of their models in the identification of the Great Recession. However, Hamilton (2011) updates the result of these methods in his survey paper.

Table III.2
Recessions Identified in Real-time

Peak as determined by NBER	First Day of Recession	Date algorithm made declaration	Algorithm declaration lead (-) or lag (+) in days	NBER declaration lead (-) or lag (+) in days	Chauvet & Hamilton (2006) declaration lead (-) or lag (+) in days	Chauvet & Piger (2008) declaration lead (-) or lag (+) in days	Giusto & Piger (2017) declaration lead (-) or lag (+) in days
Jan-1980	2/1/1980	4/27/1980	86	123	151	181	92
Jul-1981	8/1/1981	11/1/1981	92	158	184	211	126
Jul-1990	8/1/1990	8/12/1990	11	267	184	211	78
Mar-2001	4/1/2001	7/2/2000	-273	239	91	305	216
Dec-2007	1/1/2008	3/30/2008	89	335	244	397	158
Mar-2020	3/1/2020	3/22/2020	21	99	NA	NA	NA
Average			5	204	171	261	134

Dating Rule: 0.8 is used as the threshold for the average of recession probabilities over 12 weeks.

Table III.3
Expansions Identified in Real-time

Trough as determined by NBER	First Day of Expansion	Date algorithm made declaration	Algorithm declaration lead (-) or lag (+) in days	NBER declaration lead (-) or lag (+) in days	Chauvet & Hamilton (2006) declaration lead (-) or lag (+) in days	Chauvet & Piger (2008) declaration lead (-) or lag (+) in days	Giusto & Piger (2017) declaration lead (-) or lag (+) in days
Jul-1980	8/1/1980	8/10/1980	9	341	122	152	127
Nov-1982	12/1/1982	11/28/1982	-3	219	151	181	136
Mar-1991	4/1/1991	6/2/1991	62	631	122	182	443
Nov-2001	12/1/2001	8/19/2001	-104	593	182	219	308
Jun-2009	9/1/2009	5/24/2009	-38	446	122	214	157
Average			-15	446	140	190	235

Dating Rule: 0.8 is used as the threshold for the average of recession probabilities over 12 weeks.

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, Chauvet and Hamilton (2006), Chauvet and Piger (2008), and Giusto and Piger (2017) establish business cycle peaks with an average delay of 204 days, 171 days, 261 days, and 134 days respectively. The DFMSDF method established the business cycle peak on average 5 days following its beginning. All four benchmarks are slower in identifying business cycle troughs, with an average delay of 446 days, 140 days, 190 days, and 235 days respectively. 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 on June 14, 2020 and the beginning of an expansion in July 2020, as most of the states have reopened since May. On October 4, 2020, the DFMSDF model produces another recession signal. On the last analysis date, March 27, 2021, no expansions have been identified by the model. The model suggests that the economy seems to enter a double-dip recession, meaning that an economy enters recovery from a recession, but then is derailed and slides back into a recession.

The results of Tables III.2 and III.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 and Piger (2017) method based on only monthly data, and using a similar threshold, did not produce any false recessions or expansions. Table III.4 lays out these false positives and false negatives, showing seven false recessions and three false expansions detected by the DFMSDF method.

Table III.4
False Recessions and False Expansions Identified in Real-time

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		

Dating Rule: 0.8 is used as the threshold for the average of recession probabilities over 12 weeks.

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 ten 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. If the preference of policymakers is to prioritize the number of false signals over the speed of identification, one can always adopt a higher threshold when calling turning points based on recession probabilities. In the robustness check below, I show results of using 0.9 rather than 0.8 as the threshold. Indeed, one can also design a more conservative dating procedure. For example, if the new dating procedure requires the algorithm to wait for up to nine weeks before producing a recession call, then the procedure will get rid of most of false signals but still identifies turning points faster than other benchmarks.

III.4.2 Robustness Checks

Tables III.5, III.6, and III.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 III.5 and III.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 III.5
Recessions Identified in Real-time (Threshold = 0.9)

Peak as determined by NBER	First Day of Recession	Date algorithm made declaration	Algorithm declaration lead (-) or lag (+) in days	NBER declaration lead (-) or lag (+) in days	Chauvet & Hamilton (2006) declaration lead (-) or lag (+) in days	Chauvet & Piger (2008) declaration lead (-) or lag (+) in days	Giusto & Piger (2017) declaration lead (-) or lag (+) in days
Jan-1980	2/1/1980	5/18/1980	107	123	151	181	92
Jul-1981	8/1/1981	11/22/1981	113	158	184	211	126
Jul-1990	8/1/1990	7/6/1990	-381	267	184	211	78
Mar-2001	4/1/2001	7/9/2000	-266	239	91	305	216
Dec-2007	1/1/2008	7/13/2008	194	335	244	397	158
Mar-2020	3/1/2020	3/22/2020	21	99	NA	NA	NA
Average			-36	204	171	261	134

Dating Rule: 0.9 is used as the threshold for the average of recession probabilities over 12 weeks.

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

Trough as determined by NBER	First Day of Expansion	Date algorithm made declaration	Algorithm declaration lead (-) or lag (+) in days	NBER declaration lead (-) or lag (+) in days	Chauvet & Hamilton (2006) declaration lead (-) or lag (+) in days	Chauvet & Piger (2008) declaration lead (-) or lag (+) in days	Giusto & Piger (2017) declaration lead (-) or lag (+) in days
Jul-1980	8/1/1980	8/17/1980	16	341	122	152	127
Nov-1982	12/1/1982	3/7/1982	-269	219	151	181	136
Mar-1991	4/1/1991	6/9/1991	69	631	122	182	443
Nov-2001	12/1/2001	8/26/2001	-97	593	182	219	308
Jun-2009	9/1/2009	5/31/2009	-31	446	122	214	157
Average			-65	446	140	190	235

Dating Rule: 0.9 is used as the threshold for the average of recession probabilities over 12 weeks.

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

False Recessions	Duration	False Expansions	Duration
10/14/1984 - 11/04/19	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		

Dating Rule: 0.9 is used as the threshold for the average of recession probabilities over 12 weeks.

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

Tables III.8, III.9 and III.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 III.8
Recessions Identified in Real-time, with Industrial Production Included

Peak as determined by NBER	First Day of Recession	Date algorithm made declaration	Algorithm declaration lead (-) or lag (+) in days	NBER declaration lead (-) or lag (+) in days	Chauvet & Hamilton (2006) declaration lead (-) or lag (+) in days	Chauvet & Piger (2008) declaration lead (-) or lag (+) in days	Giusto & Piger (2017) declaration lead (-) or lag (+) in days
Jan-1980	2/1/1980	4/20/1980	79	123	151	181	92
Jul-1981	8/1/1981	5/3/1981	-90	158	184	211	126
Jul-1990	8/1/1990	9/9/1990	-39	267	184	211	78
Mar-2001	4/1/2001	7/9/2000	-266	239	91	305	216
Dec-2007	1/1/2008	3/23/2008	82	335	244	397	158
Mar-2020	3/1/2020	3/22/2020	21	99	NA	NA	NA
Average			-36	204	171	261	134

Dating Rule: 0.8 is used as the threshold for the average of recession probabilities over 12 weeks.

Table III.9
Expansions Identified in Real-time, with Industrial Production Included

Trough as determined by NBER	First Day of Expansion	Date algorithm made declaration	Algorithm declaration lead (-) or lag (+) in days	NBER declaration lead (-) or lag (+) in days	Chauvet & Hamilton (2006) declaration lead (-) or lag (+) in days	Chauvet & Piger (2008) declaration lead (-) or lag (+) in days	Giusto & Piger (2017) declaration lead (-) or lag (+) in days
Jul-1980	8/1/1980	8/24/1980	23	341	122	152	127
Nov-1982	12/1/1982	7/25/1982	-129	219	151	181	136
Mar-1991	4/1/1991	5/19/1991	48	631	122	182	443
Nov-2001	12/1/2001	1/20/2002	50	593	182	219	308
Jun-2009	9/1/2009	4/26/2009	-66	446	122	214	157
Average			-15	446	140	190	235

Dating Rule: 0.8 is used as the threshold for the average of recession probabilities over 12 weeks.

Table III.10
False Recessions and False Expansions Identified in Real-time, with Industrial Production Included

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		

Dating Rule: 0.8 is used as the threshold for the average of recession probabilities over 12 weeks.

III.5 Conclusion

This paper contributes to the business cycle turning point nowcasting literature by systematically investigating the ability of high-frequency data and leading data to improve upon the timeliness with which new expansions and recessions can be identified over the existing literature that primarily uses low-frequency data and coincident 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 frequencies 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 two additions - high-frequency data and leading data - 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 on March 30, 2008, 246 days ahead of the NBER announcement and many months ahead of the statistical procedures surveyed in Hamilton (2011). 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.

My approach is especially important during the Covid-19 pandemic. The NBER announced on June 8, 2020 that a new recession associated with the pandemic has started since March 2020. My approach identifies the start of this recession on March 22, 2020, 78 days ahead of the announcement from the NBER. With a more timely identification of this recession, federal and state government can make informed decisions to promote employment at a much faster pace. My approach can also be applied to timely identify new recessions and expansions in other countries that provide indicators of business cycle phases.

CHAPTER IV

A NEW HIGH-FREQUENCY, NEWS-BASED, INDICATOR OF MACROECONOMIC ACTIVITY

IV.1 Introduction

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 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 published at a relatively low frequency and for which past observation periods are revised after the fact, text such as news articles arrives daily and is not revised. These advantages make data extracted from text an appealing candidate to build more accurate and timely nowcasting models about aggregate economic activity in real time.

In this paper I propose a text-based approach to create a high-frequency News-Based Sentiment Index (NBSI) regarding aggregate economic conditions. Following dictionary methods in the Natural Language Processing literature, NBSI is established from lead paragraphs of news articles that are related to economic activity. The corpus consists of economic and financial news articles published at a daily frequency in the Wall Street Journal from April 1991 to March 2021.

In contrast to the text source and the computational approach used in the literature, my paper focuses on measuring the positive or negative feeling that traditional news media conveys to the reader using dictionary-based sentiment analysis. The news-based sentiment index picks up a wider range of information regarding economic activity compared with the survey-based consumer sentiment index. The NBSI that arrives at a daily frequency is a supplement to macroeconomic indicators available at lower frequencies. Compared with the literature, this paper demonstrates that textual data extracted from nontraditional data sources contains useful information in economics research by exploring predictive capability of news sentiment in a wider range of macroeconomic indicators, including business cycle turning points.

The remainder of this paper is organized as follows. In section 4.2 I review related literature. In section 4.3 I present a text-based approach to create the NBSI regarding aggregate economic conditions. Section 4.4 presents the NBSI and evaluates summary correlations with other variables. Section 4.5 lays out two applications that investigate the contribution of NBSI to nowcast business cycle turning points and lower-frequency data. Section 4.6 concludes.

IV.2 Literature Review

There is a growing literature that uses constructed indices from internet queries, social media, and traditional media for the purposes of forecasting and nowcasting economic activity. Google Trends search engine data is a real-time daily and weekly index of the volume of queries that users enter into Google. Choi and Varian (2012) use Google Trend data from January 2004 to July 2011 to nowcast economic indicators including initial claims for unemployment insurance and consumer confidence, and find that simple seasonal auto-regression models that include relevant Google Trends variables tend to outperform models that exclude these predictors. The authors concludes that Google Trends may help in predicting the present.

Balke et al. (2017) explore the written description of economic activity contained in the Beige Book to obtain a quantitative measure of current economic conditions. Using a dynamic factor model that consists of the Beige Book measure and traditional economic series, the authors find that the Beige Book picks up information about current economic activity that is not contained in other quantitative data. This informational advantage is relatively short-lived, lasting for three weeks.

The forecasting capability of social media data has also been explored in Lehrer et al. (2019). The authors develop a deep learning algorithm to measure sentiment within Twitter messages on an hourly basis and conduct an out of sample forecasting exercise for the consumer confidence index. Their results show that including consumer sentiment measures from Twitter improves forecast accuracy.

Kelly et al. (2019) model the inclusion and repetition of words of certain attributes at a monthly frequency in the Wall Street Journal front page news articles. The authors find out that the text from January 1990 to December 2010 documents contains additional information that is useful for forecasting monthly macroeconomic indicators beyond that of the benchmark dynamic factor model model.

Shapiro et al. (2020) derive a daily and monthly time-series sentiment from economic and financial newspaper articles from January 1980 to April 2015 with dictionary methods. The authors demonstrate that news sentiment is predictive of consumer sentiment measured using surveys. The authors also find that positive sentiment shocks increase consumption, output, and interest rates and dampen inflation.

Bybee et al. (2020) apply topic models to estimate a daily time-series of news attention to each theme. The authors use full text content of Wall Street Journal articles published from January 1984 to June 2017. The authors show that the topic-based estimates accurately track a broad range of of economic variables such as aggregate output (industrial production) and employment (non-farm payrolls). The authors also find that the estimate have incremental forecasting power above and beyond standard numerical predictors.

In contrast to Choi and Varian (2012), Balke et al. (2017), and Lehrer et al. (2019), my paper focuses on text in the traditional news media. In contrast to the computational approach used in Kelly et al. (2019) and Bybee et al. (2020), my paper focuses on measuring the positive or negative feeling that a text conveys to the reader using dictionary-based sentiment analysis. Shapiro et al. (2020) adopts the similar method to construct a high-frequency time-series sentiment from economic and financial newspaper; however, my paper explores predictive capability of news sentiment in a wider range of macroeconomic indicators, including business cycle turning points.

IV.3 Methodology to Construct NBSI

From the Factiva Database, I collect a large sample of lead paragraphs of articles published in The Wall Street Journal and The Wall Street Journal Online in the United States from April 2, 1991 to March 31, 2021 that have the following subjects: (1) News about commodity, debt, bond, equity, money and currency markets; (2) Analysts' comments or recommendations about corporations and industries; (3) Economic performance or indicators, government finance, monetary policy, trade or external payments.

The document downloaded from the database is a Rich Text Format file, which contains indexes for custom search fields, such as indexes for column name, section name, headline, author's name, word count, publication date and time, source name, lead paragraph, language code, subject code, region code, publisher name, and accession number. For the purpose of this topic, I only extract lead paragraphs and publication dates by detecting the presence of the pattern of the index in each piece of news articles. Then I match the lead paragraph with the publication date such that the text is represented at each point in time. Table IV.1 is an example of this sample.

Table IV.1
Text Example

Date	Lead Paragraph
03-28-2006	Jon Corzine, New Jersey's new Governor, isn't the first politician not to follow through on a campaign promise. But rarely is such dishonesty later presented as a virtue. The question for voters to contemplate is whether this is also an indication of what to expect if Democrats gain control of Congress in November.Mr. Corzine won the Trenton statehouse last year by running as a tax cutter who'd raise property tax rebates by 40% over four years. "I'm not considering raising taxes. It's not on my agenda. We have a very high-rate tax structure. I'm not considering it," the then-U.S. Senator had vowed in October.
03-29-2006	A growing number of homeowners, riding the crest of the real-estate boom, are getting hit by an unpleasant surprise when they sell: a hefty tax bill.This development stems from a 1997 law that Treasury Department officials said at the time would eliminate capital-gains taxes for nearly everyone selling their primary residence. Under that law, most married couples who file jointly can exclude as much as $500,000 of their gain. For most singles, the limit is $250,000.
03-29-2006	The airline most often viewed as the strongest, healthiest and best-run of the pack may be one of the weaker bets for investors hoping to profit from a budding turnaround in the industry.A strengthening market has sent some beleaguered airline stocks soaring in recent months, but shares in industry stalwart Southwest Airlines have been more sluggish. In the past year, the stock of American Airlines parent AMR Corp. has risen 168% on the New York Stock Exchange. Rival hub-and-spoke carrier Continental Airlines saw its stock price jump 142% on the Big Board during the 12-month period. But the same tide of good news has lifted Southwest's stock just 25% on the NYSE, though that gain still handily outpaced the Dow Jones Industrial Average, which was up 7% over the same period.

Before applying statistical methods, the raw text is extracted as a manageable high-dimensional numerical array using process criteria in the following order:

- Exclude lead paragraphs with less than 50 characters.

- Tokenize the text into individual words and transform it to a tidy data structure.
- Strip stopwords such as 'a', 'the', 'to', 'for' out of token lists.
- Replace words with their root such that "economic", "economics", and "economically" are all replaced by the stem "economic".
- Assign "positive" or "negative" sentiment to words based on a general-purpose "Bing" lexicon from Bing Liu and collaborators, which categorizes words in a binary fashion. [1].
- Reverse sentiment of words preceded by negation words such as no, not, never, without.
- Measure sentiment scores for each lead paragraph with $\frac{n_{pos}-n_{neg}}{n_{words}}$, where n_{pos}, n_{neg}, and n_{words} represent separately the number of positive, negative, and total words in each lead paragraph.
- Average over articles published on the same day to obtain the daily sentiment index.
- Average over the daily sentiment for the same week to obtain the weekly NBSI, denoted as $NBSI^w$.
- Average over the daily sentiment for the same month to obtain the monthly NBSI, denoted as $NBSI^m$.

[1] More details about the "Bing" lexicon are available at the following website `https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html`

IV.4 The News Based Sentiment Index

The weekly NBSI $NBSI^w$ from April 02, 1991 to March 31, 2021 is shown in Figure IV.1. [2] The index drops sharply before the start of the 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. I will explore this possibility in more detail in the applications presented in Section IV.5.1.

Figure IV.1
The Weekly News-Based Sentiment Index, April 1991 - March 2021

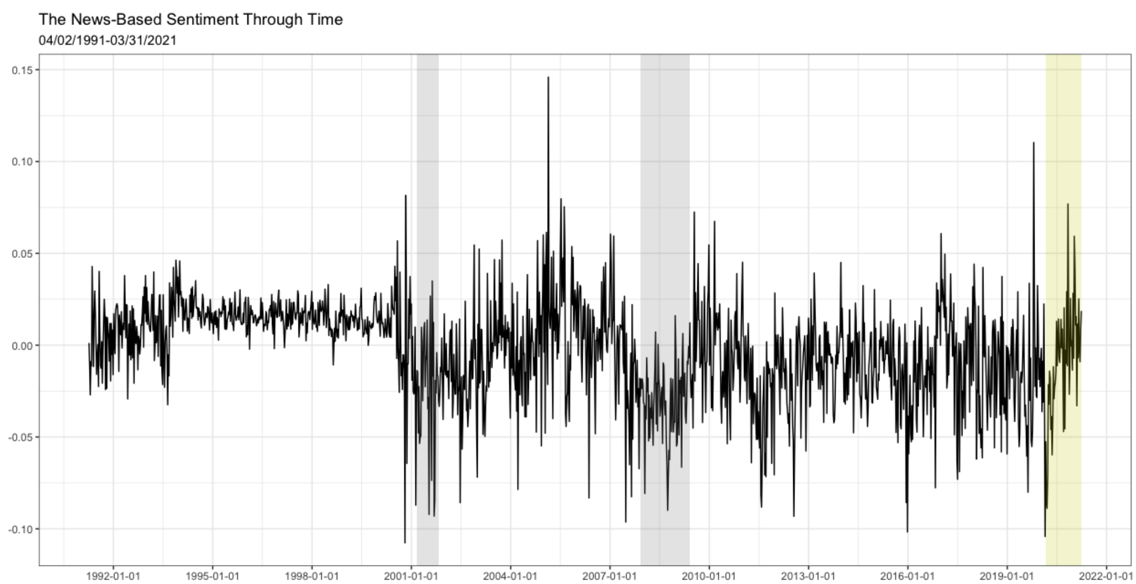
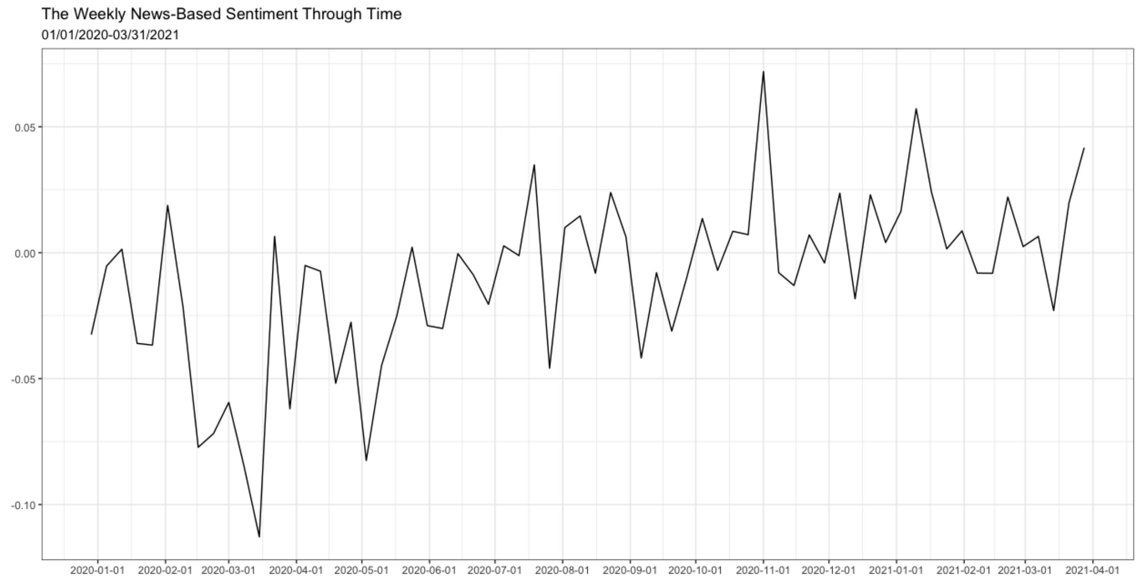


Figure IV.2 shows the weekly NBSI for January 2020 through March 2021. It presents how the NBSI tracks the economic contraction related to Covid-19 shutdowns in the United States and how NBSI picked up the bad economic outcomes in March 2020. It is also interesting that NBSI falls in February, prior to the most significant problems starting in the United States.

Next I study the correlation between the weekly NBSI and the weekly initial claims to unemployment insurance (ICSA). The left panel in Figure IV.3 shows movements

[2] Shaded areas indicate U.S. recessions. The shaded area in yellow represents the most recent recession with an undecided end date.

Figure IV.2
The Weekly News-Based Sentiment Index, January 2020 - March 2021



of NBSI and ICSA and the right panel of Figure IV.3 shows movements of NBSI and the change of ICSA. Due to the economic impact of Covid-19, ICSA has skyrocketed since late March 2020. Including these values makes the movement of NBSI and ICSA prior to late March less legible; therefore, both figures show fluctuations as of February 2020.

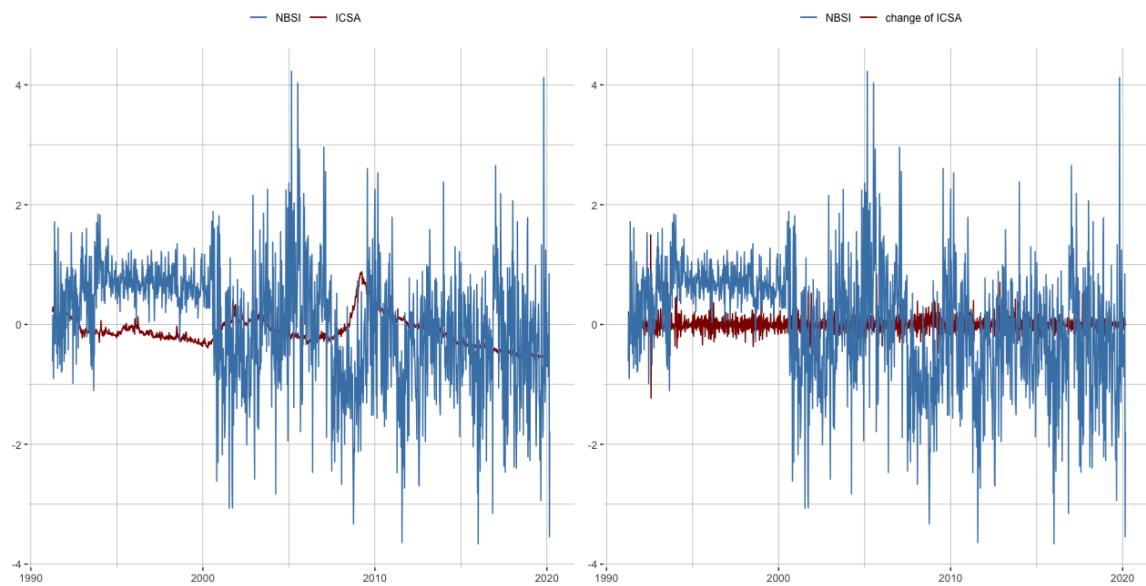
Table IV.2 shows Pearson correlations and P-values. There is sufficient evidence to conclude that there is a significant negative linear relationship between the weekly NBSI and contemporaneous ICSA at a significance level of 0.01. There is a significant negative linear relationship between NBSI and the change of ICSA at a significance level of 0.05. Both Pearson correlations have correct signs and fairly large magnitude.

Table IV.2
Contemporaneous Correlations between the Weekly NBSI and the Weekly Macroeconomic Variables

	$NBSI_t^w$
$ICSA_t$	-0.1048****
$\Delta ICSA_t$	-0.0546*

Note: $p < .0001$ ****; $p < .001$ ***, $p < .01$ **, $p < .05$ *

Figure IV.3
The Weekly News-Based Sentiment Index and the Initial Claims to Unemployment Insurance



Next, I analyze the ability of the monthly NBSI to track fluctuations in economic activity. Monthly macroeconomic variables I use include the change of unemployment rate (UNRATE), the change of University of Michigan consumer sentiment (UMCS), and the growth rate of nonfarm payroll employment (PAYEMS), which is expressed in a log-change form. It is easier to see co-movement if the scale of the graph does not have to be big enough to capture the large movements related to the Covid-19 pandemic. Hence, Figure IV.4 shows the movement between the monthly NBSI and monthly macroeconomic variables ending in February 2020.

Contemporaneous Pearson correlations and p-values between the monthly NBSI and macroeconomic variables are shown in Table IV.3. There is sufficient evidence to conclude that there is a significant negative linear relationship between the monthly NBSI and the change of unemployment rate at a significance level of 0.05. There are positive linear relationships between the monthly NBSI and other macroeconomic variables at a significance level of 0.01. All Pearson correlations have correct signs and fairly large magnitude.

Figure IV.4
The Monthly News-Based Sentiment Index and Macroeconomic Variables

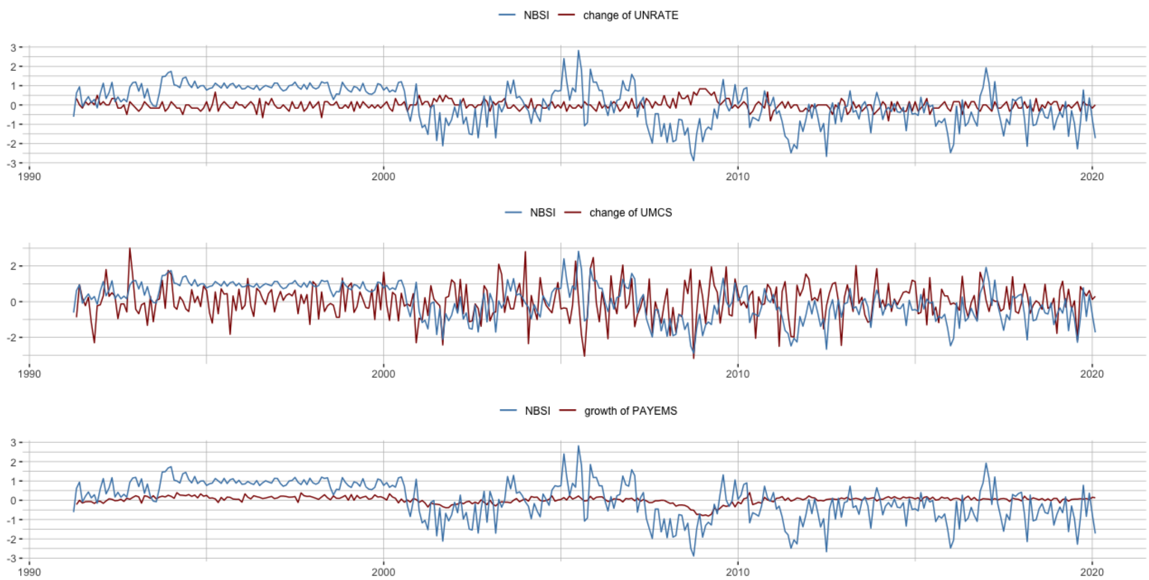


Table IV.3
Contemporaneous Correlations between the Monthly NBSI and the Monthly Macroeconomic Variables

	$NBSI_t^m$
$\Delta UNRATE_t$	-0.1092466*
$\Delta UMCS_t$	0.1955499****
$\Delta log(PAYEMS_t)$	0.1322512**

Note: $p < .0001$ ****; $p < .001$ ***, $p < .01$ **, $p < .05$ *

I have found that NBSI is correlated with various economic indicators and may be helpful for short-term economic prediction. To evaluate the ability of NBSI in predicting the present, this paper provides two applications. In the first application, I incorporate NBSI in the business cycle phases nowcasting framework developed in the third chapter, and estimate the contribution of NBSI to identify U.S. recessions in real time. In the second application, I explore the power of NBSI to nowcast monthly macroeconomic variables.

IV.5 Empirical Applications

IV.5.1 Nowcasting Business Cycle Phases

In this section I evaluate the ability of NBSI to improve turning point identification in real time over the use of the index $\hat{x}_t$ studied in the third chapter. To evaluate the nowcasting ability of the NBSI on the U.S. recessions, in the baseline model, I exclude the NBSI from the dataset and use the same estimation method and dating procedure as described in the previous chapter to declare the date of turning points. To be specific, I use the dataset that excludes NBSI from April 2, 1991 to March 31, 2021 to estimate the index $\hat{x}_t$ from the dynamic factor model as specified in Equations IV.1 and IV.2. Then, I fit the estimated $\Delta\hat{x}_t$ to a Markov regime - switching AR(0) model as specified in Equations IV.3 and IV.4. Data from April 2, 1991 to December 31, 2005 are used as the training set and remaining data from January 1, 2006 to March 31, 2021 are used as the testing set, in which recession probabilities $\hat{P}(S_t = 1|\Psi_T)$ are estimated using the Hamilton filter. Lastly, following the business cycle dating procedure proposed in the third chapter, I define day t as a recession phase if the average value of $\hat{P}(S_t = 1|\Psi_T)$ in the last 12 weeks exceeds 0.8, and define day t as an expansion phase if the average value of $\hat{P}(S_t = 1|\Psi_T)$ in the last 12 weeks is smaller than 0.2.

$$\boldsymbol{\Upsilon_t} = \boldsymbol{FF_t} \times \boldsymbol{\theta_t} + \boldsymbol{\nu_t} \tag{IV.1}$$

$$\boldsymbol{\theta_t} = \boldsymbol{GG_t} \times \boldsymbol{\theta_{t-1}} + \boldsymbol{\omega_t} \tag{IV.2}$$

$$\Delta\hat{x}_t = \beta_{S_t} + \epsilon_t \tag{IV.3}$$

$$\beta_{S_t} = \beta_0 + \beta_1 \times S_t \tag{IV.4}$$

$$\epsilon_t \sim N(0, \sigma^2)$$

$$\beta_1 < 0$$

Next, to evaluate the contribution of NBSI to identify U.S. recessions in real time, I first fit $\Delta\hat{x}_t$ and $NBSI_t$ to a bivariate version of the Markov regime-switching $AR(0)$ process with a switching mean, as specified in Equation IV.5. Then I use the same threshold 0.8 to convert recession probabilities into a binary variable that defines whether the economy is in an expansion or a recession regime. Values of NBSI are missing for weekends and holidays. I impute these missing values with the value from the previous day on which the index was recorded.

$$\begin{bmatrix} \Delta\hat{x}_t \\ NBSI_t \end{bmatrix} = \begin{bmatrix} \beta_{11} \\ \beta_{12} \end{bmatrix} + \begin{bmatrix} \beta_{12} \\ \beta_{22} \end{bmatrix} \times S_t + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \tag{IV.5}$$

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

$$\beta_{12} < 0$$

$$\beta_{22} < 0$$

Tables IV.4 and IV.5 show the identification of expansions and recessions without NBSI incorporated. To assess the contribution of NBSI, I use only $\Delta\hat{x}_t$ on the same shortened estimation window. Tables IV.6 and IV.7 show the identification of expansions and recessions with NBSI incorporated. Similar to the baseline result, the DFMSDF method predicts the occurrence of turning points faster than all other sources. Compared with the result where NBSI is not incorporated in the analysis, including NBSI accelerates the identification of the December 2007 Peak, and produces less false positives and false negatives.

Incorporating high-frequency data and leading data, namely the yield curve term premium and initial claims, produces a call of the December 2007 business cycle peak on April 6, 2008. 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.

Table IV.4
Recessions and Expansions Identified in Real-time, with NBSI Excluded

Turning points as determined by NBER	First day of business cycle phases	Date algorithm made declaration	Algorithm declaration lead (-) or lag (+) in days	NBER declaration lead (-) or lag (+) in days	Chauvet & Hamilton (2006) declaration lead (-) or lag (+) in days	Chauvet & Piger (2008) declaration lead (-) or lag (+) in days	Giusto & Piger (2017) declaration lead (-) or lag (+) in days
Dec-2007	1/1/2008	4/6/2008	96	335	244	397	158
Jun-2009	7/1/2009	5/31/2009	-31	446	122	214	157
Mar-2020	3/1/2020	3/29/2020	28	99	NA	NA	NA

Dating Rule: 0.8 is used as the threshold for the average of recession probabilities over 12 weeks.

Table IV.5
False Recessions and False Expansions Identified in Real-time, with NBSI Excluded

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

Dating Rule: 0.8 is used as the threshold for the average of recession probabilities over 12 weeks.

Table IV.6
Recessions and Expansions Identified in Real-time, with NBSI Included

Turning points as determined by NBER	First day of business cycle phases	Date algorithm made declaration	Algorithm declaration lead (-) or lag (+) in days	NBER declaration lead (-) or lag (+) in days	Chauvet & Hamilton (2006) declaration lead (-) or lag (+) in days	Chauvet & Piger (2008) declaration lead (-) or lag (+) in days	Giusto & Piger (2017) declaration lead (-) or lag (+) in days
Dec-2007	1/1/2008	12/2/2007	-30	335	244	397	158
Jun-2009	7/1/2009	6/7/2009	-24	446	122	214	157
Mar-2020	3/1/2020	3/29/2020	28	99	NA	NA	NA

Dating Rule: 0.8 is used as the threshold for the average of recession probabilities over 12 weeks.

Table IV.7
False Recessions and False Expansions Identified in Real-time, with NBSI Included

False Recessions	**Duration**	**False Expansions**	**Duration**
7/10/2011 - 11/13/2011	19 weeks		
1/10/2016 - 2/7/2016	5 weeks		
12/2/2018 - 12/9/2018	2 week		

Dating Rule: 0.8 is used as the threshold for the average of recession probabilities over 12 weeks.

IV.5.2 Nowcasting Macroeconomic Variables

In this section, I examine if NBSI, which is a real-time daily and weekly index of news-based sentiment, helps to predict the present values of economic indicators, including initial claims of unemployment benefits, unemployment rate, the University of Michigan consumer confidence, and nonfarm payroll employment. The sentiment index is available at the end of the week and is therefore available at the end of the month, but these macroeconomic variables are not released until after the end of the month. It would clearly be helpful to have more timely predictions of these economic indicators with the sentiment index. Table IV.8 presents each data series included in the nowcasting exercise.

Table IV.8
List of Variables

Series	**Frequency**	**Description**
UNRATE	Monthly	The number of unemployed as a percentage of the labor force, is typically released by the U.S. Department of Labor within a week after the reference month ends.
PAYEMS	Monthly	A measure of the number of U.S. workers in the economy that accounts for approximately 80 percent of the workers who contribute to Gross Domestic Product (GDP), is released in the same report as the UNRATE.
UMCS	Monthly	A survey-based consumer confidence index reported by the University of Michigan, which has a preliminary value and a final value. The preliminary result is usually reported in the second week of the reference month, and the final result is usually reported at the end of the reference month.
ICSA	Weekly	the number of people who filed for unemployment benefits in the week ending on a Saturday, is released by the U.S. Department of Labor on Thursday in the following week.
NBSI	Daily	The News-based sentiment index

Let y_t be the dependent variable at time t. For weekly variables, y_t is the observation in week t; for monthly variables, y_t is the observation in month t. The baseline model is an AR(1) model on the lag of the dependent variable as defined in Equation IV.6. Let x_t be NBSI at time t. The specification using NBSI at time t to predict the contemporaneous value of the dependent variable is represented in Equation IV.7.

$$y_t = \beta_1 y_{t-1} + e_t \tag{IV.6}$$

$$y_t = \beta_1 y_{t-1} + \beta_2 x_t + e_t \tag{IV.7}$$

My sentiment index is measured at a higher frequency (daily) than the macroeconomic variables (weekly and monthly). To nowcast ICSA in week t, I aggregate daily values of NBSI in week t using a simple average. To nowcast monthly variables in month t, I aggregate daily values of NBSI in month t using a simple average.

The ICSA, UNRATE, UMCS, and PAYEMS downloaded from the Fred Database are seasonally adjusted, as used by most economic forecasters. Because the dependent variables are seasonally adjusted, I also seasonally adjust the independent variable NBSI. As with Choi and Varian (2012), I use the stl command in R to decompose the sentiment index into trend, seasonality and remainder with a filtering procedure developed by Cleveland et al. (1990). Then I remove the seasonal component from the series.

Prior to including each series in this application, I perform the augmented Dickey-Fuller test. The null hypothesis is that a unit root is present in a time series. The result suggests that for all monthly variables, the level is not stationary at a significance level of 0.01. The weekly ICSA, the weekly NBSI and the monthly NBSI are stationary. To construct a stationary data series for UNRATE and UMCS, I transform the data by using the first difference; to construct a stationary PAYEMS, I transform the data by calculating the growth rate using the first difference of the logarithm. Applying the augmented Dickey-Fuller test to the transformed data, each transformed data series is stationary. The list and summary statistics of each data series in presented in Table IV.9. Table IV.10 shows regression results on the full sample which ranges from April 1991 to March 2021. For all five dependent variables, the coefficients on NBSI are statistically significant.

Table IV.9
Summary Statistics

	Minimum	**Medium**	**Mean**	**Maximum**	**Std. Dev.**
$ICSA_t$	203000	340000	384612	6149000	318367.4
$\Delta ICSA_t$	-1280000	-1000	177.1	3062000	114783
$NBSI_t^w$	-0.106	-0.0038	-0.008	0.1088	0.0268
$\Delta UNRATE_t$	-2.2	0	-0.002	10.4	0.6017
$\Delta UMCS_t$	-17.3	0	0.0086	12	3.9963
$\Delta log(PAYEMS_t)$	-0.1474	0.0013	0.0008	0.0358	0.0083
$NBSI_t^m$	-0.0684	-0.0001	-0.0029	0.0567	0.0196

Table IV.10
Regression Results (full-sample)

	Dependent variable:				
	$ICSA_t$	$\Delta ICSA_t$	$\Delta UNRATE_t$	$\Delta UMCS_t$	$\Delta log(PAYEMS_t)$
$ICSA_{t-1}$	0.933***				
	(0.009)				
$\Delta ICSA_{t-1}$		0.530***			
		(0.021)			
$NBSI_t^w$	305118.2***	187, 174.1**			
	(06,819.7)	(91,885.87)			
$\Delta UNRATE_{t-1}$			0.012		
			(0.053)		
$\Delta UMCS_{t-1}$				−0.051	
				(0.053)	
$\Delta log(PAYEMS_{t-1})$					0.006
					(0.053)
$NBSI_t^m$			3.295**	37.735***	0.056**
			(1.638)	(10.787)	(0.023)
constant	23, 408.020***	1, 408.490	−0.012	0.129	0.001**
	(4,504.352)	(2,567.985)	(0.032)	(0.211)	(0.0004)
Observations	1,564	1,563	358	358	358
R^2	0.875	0.283	0.012	0.034	0.017
Adjusted R^2	0.875	0.282	0.006	0.028	0.012
Residual Std. Error	112,701.500 (df = 1561)	97,262.450 (df = 1560)	0.601 (df = 355)	3.940 (df = 355)	0.008 (df = 355)
F Statistic	5, 459.609*** (df = 2; 1561)	308.380*** (df = 2; 1560)	2.144 (df = 2; 355)	6.208*** (df = 2; 355)	3.107** (df = 2; 355)

Stars indicate p values: *p<0.1; **p<0.05; ***p<0.01.

Next, I explore one-step-ahead out-of-sample nowcasts. I conduct the exercise on four different samples: (1) The last 30 percent of the full sample, which ranges from 2012-04-07 to 2021-03-31. (2) The period in which the 2001 recession occurred, which starts on 2001-4-1 and ends on 2001-11-30 as defined by the NBER. (3) The period when the Great Recession occurred, from 2008-1-1 to 2009-6-30 as with the NBER chronology. (4) The recession happened amid the Covid-19 pandemic, which started on 2020-3-1. The NBER has not decided the end date of this recession yet. I end this sample period on 2020-6-14, which is the date identified by the business cycle nowcasting model developed in the previous chapter. By doing this, the sample period lasts for 3.5 months.

Table IV.11 presents the percentage change of RMSE after NBSI is incorporated. On the full sample, including NBSI does not harm the nowcast of lower-frequency variables, with the only exception of the change of ICSA. There is also evidence that NBSI helps to nowcast lower-frequency variables during recessions. RMSE declines consistently during all three recessions, with the exception of the nowcast of the growth rate of PAYEMS during the 2008-2009 recession. Table IV.11 shows that NBSI, which is a real-time high-frequency data, can help predicting the present of low-frequency data, especially during recessions. Some of these improvements are large, for example, in the nowcast of the growth rate of PAYEMS during the 2001 recession, RMSE declines by 40.58% after NBSI is included in the analysis.

Table IV.11
Percentage Change in RMSE, with NBSI Included

	Full Sample	**2001 Recession**	**2008-2009 Recession**	**2020 Recession**
$ICSA_t$	-0.43	-7.23	-0.58	-0.46
$\Delta ICSA_t$	0.67	-1.69	-1.54	0.61
$\Delta UNRATE_t$	-2.92	-18.2	-10.1	-16.78
$\Delta UMCS_t$	0	-11.64	-1.08	-2.17
$\Delta log(PAYEMS_t)$	-5.38	-40.58	10.34	-5.87

IV.6 Conclusion

Applying dictionary methods, I have proposed a novel sentiment index based on economic and financial news articles published at a daily frequency by the Wall Street Journal. I have found that high-frequency news-based sentiment index can improve the nowcast of low-frequency macroeconomic variables.

In the first application, I nowcast business cycle turning points with the news-based sentiment index. Results show that incorporating the index helps to identify the 2008-2009 recession 126 days earlier than the identification without using the index. In the second application, I nowcast near-term values of economic indicators, including initial claims, unemployment rate, the University of Michigan consumer sentiment index, and nonfarm payroll employment. I have found that the simple seasonal AR models that incorporating the index tend to outperform models that exclude the index. This improvement is especially significant during recessions. [3]

[3] I have also measured sentiment scores for each lead paragraph using $n_{pos} - n_{neg}$, and have evaluated the predictive ability of the sentiment index established in this way using the two applications. For the first application, compared with Tables IV.6 and IV.7 in Section IV.5.1, including the sentiment index that does not scale over the size of the news article helps the model to identify three turning points on the same days, i.e., 12/2/2007, 6/7/2009, and 3/29/2020; however, more false signals are produced. For the second application, compared with Table IV.11 in Section IV.5.2, the improvement generated by the model that includes the new sentiment index is smaller.

CHAPTER V

DISSERTATION CONCLUSION

In this dissertation, I investigate techniques to improve high-frequency monitoring of macroeconomy. In contrast with the United States where there are alternating phases of expansion and recession, China's economic growth has been very strong and presented a sustained expansion since 2000. Instead of classifying the Chinese economic activity into phases of "expansions" and "recessions" as in the United States, in the second chapter of my dissertation, I center on the "high-growth" and "low-growth" phase in the Chinese overall economy. To monitor macroeconomic activity in China, I adopt the dynamic factor model and extract a monthly economic activity factor and a monthly inflation factor from a large panel of underlying economic indicators. I find evidence that the effects of measured monetary policy shocks on the Chinese economy are different between high-growth periods vs. low-growth periods. Monetary policy shocks have larger impacts on output growth in low-growth states; during high-growth states, monetary policy shocks have larger impacts on inflation.

In the third and the fourth chapters, I shift my focus to the high-frequency monitoring of macroeconomic activity in the United States. In the third chapter, I develop techniques to provide an improved nowcast of U.S. business cycle phases in real time. In contrast with the literature that primarily uses low-frequency data and coincident data to nowcast business cycle phases, I focus on whether the use of high-frequency data and leading data can improve the speed at which business cycle phases can be identified. Using a combination of the mixed-frequency dynamic factor model and a supervised Markov regime-switching model, I find that the addition of high-frequency data and leading data significantly and consistently improves the speed at which expansions and recessions can be identified in the United States since 1980.

In the fourth chapter, I investigate whether information from news articles can improve the nowcast of low-frequency macroeconomic variables. I create a novel high-frequency news-based sentiment indicator of aggregate economic conditions from news articles that are related to aggregate economic activity. I find that incorporating the index accelerates the nowcast of the 2008-2009 recession. I also find that incorporating the index improves the nowcast of economic indicators at lower-frequencies, and the improvement is especially significant during recessions.

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