8-24-2020

A Closer Look at the Chicago Fed's Activity Indexes in **Alternative Economic Indicators**

Scott A. Brave

Federal Reserve Bank of Chicago

Alternative Economic Indicators

C. James Hueng
Editor

2020

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

Copyright Page

ISBN 9780880996778 (ebook)

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

Cover design by Carol A.S. Derks.

3
A Closer Look at the Chicago Fed's Activity Indexes

Scott A. Brave
Federal Reserve Bank of Chicago

How does one go about summarizing the state of the U.S. economy? In the age of "big data," this may seem like a strange question to ask, but it is no less relevant today than it was when the National Income and Product Accounts were first developed in the early twentieth century. If anything, it may arguably be a more difficult question now than it was then, given the multitude of economic statistics produced by both government statistical agencies and private firms. While it remains common to characterize the health of the U.S. economy in terms of broad macroeconomic aggregates like gross domestic product (GDP), other measures are often used as well in order to capture the state of individual sectors of the economy or as potential indicators of the future direction of growth in GDP.

With so many indicators available to economic and financial analysts, using them effectively becomes a question of how best to make use of their common strengths while minimizing their individual weaknesses. Activity indexes are designed for just such a purpose. As an example of what is referred to as a *dense* modeling approach in statistics (Giannone, Lenza, and Primiceri 2018), these indexes aim to extract as much information on the overall state of the U.S. economy as they can, and to do it as efficiently as possible, while using all of the available data. In principle, this approach acknowledges that all of the available indicators might be important for measuring the health of the U.S. economy, despite their own individual influence potentially being small.

At the Federal Reserve Bank of Chicago (the Chicago Fed), we produce two types of activity indexes: 1) economic and 2) financial activity indexes. The former characterize business conditions in the U.S. economy at various levels of geographic detail, while the latter capture credit conditions in the financial sector, broadly considered. Both types of indexes are predicated on a common statistical framework—namely the Chamberlain and Rothschild (1983) approximate factor model, as discussed in the next section. While their estimation methods vary, both types of indexes rely on popular data-dimension reduction techniques such as principal components and dynamic factor analysis (Stock and Watson 2011).

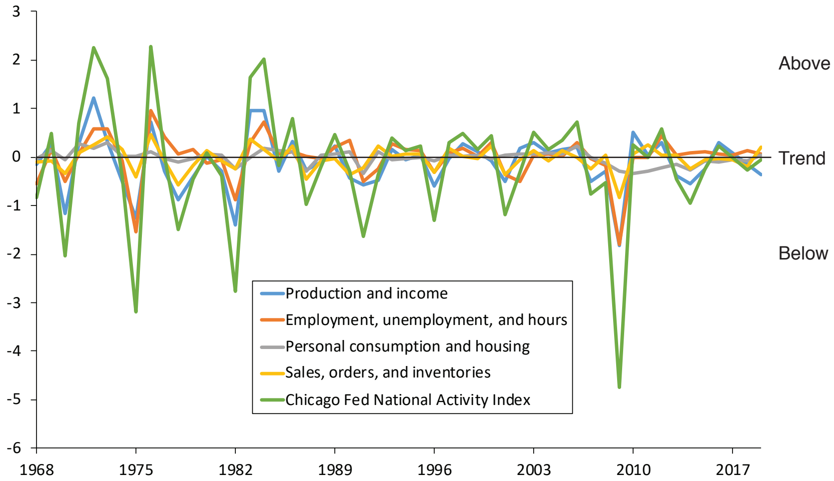
As an example of each type of index, Figures 3.1 and 3.2 plot the recent histories for the Chicago Fed National Activity Index (CFNAI) and the National Financial Conditions Index (NFCI), respectively. Based on the work of Stock and Watson (1999), the CFNAI was originally developed to help forecast inflation, but over time it has come to be viewed as a measure of the U.S. business cycle (Evans, Liu, and Pham-Kanter 2002). Positive values of the index are interpreted as representing above-trend economic growth; negative values as representing below-trend growth. The index is shown in standard deviation units based on a history extending back to early 1967. The section titled "The CFNAI" chronicles the nearly 20-year history of the production of this index as well as its offshoots and recent extensions.

The NFCI, in contrast, was developed more recently from research conducted during the global financial crisis. It aims at measuring the overall tightness of the U.S. financial system (Brave and Butters 2011). An increase in the NFCI implies an increase in *risk* or a decrease in *credit growth* or *leverage* in financial markets. Positive (negative) values denote tighter-than-average (looser-than-average) conditions in standard deviation units based on a history extending back to 1971. A separate index, the Adjusted National Financial Conditions Index (ANFCI), which rebenchmarks conditions relative to economic growth and inflation, is shown in Figure 3.2. The section titled "The NFCI" discusses some of the uses of the NFCI and ANFCI. Concluding remarks are offered in the final section.

THE APPROXIMATE FACTOR MODEL

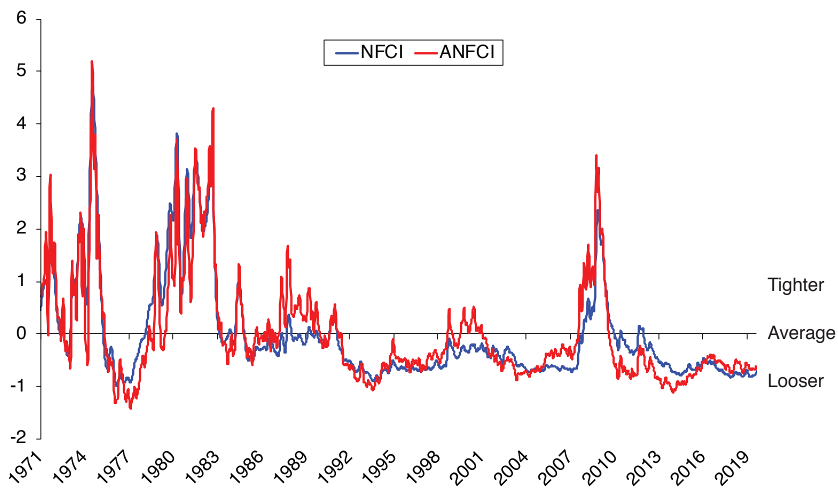
The Chamberlain and Rothschild (1983) approximate factor model has come to enjoy widespread use in economics and finance as a method

Figure 3.1 The Chicago Fed National Activity Index (CFNAI)



SOURCE: Federal Reserve Bank of Chicago (www.chicagofed.org/cfnai).

Figure 3.2 The National Financial Conditions Index (NFCI)



SOURCE: Federal Reserve Bank of Chicago (www.chicagofed.org/nfci).

to identify a small number of common components (i.e., *factors*, F_t) explaining the comovement of large panels of macroeconomic or financial time series, X_{it}. A commonly used parameterization of this model is shown in Equation 3.1,

$$(3.1) \quad \begin{aligned} X_{it} &= \Gamma_i F_t + \epsilon_{it} \\ \epsilon_{it} &\sim N(0,\sigma^2 I), \end{aligned}$$

where Γ_i are referred to as *factor loadings* for each time series *i*, and E_{it} represents the idiosyncratic variation in each time series that is uncorrelated with the factors. This framework can be used to capture, for example, sectors of the economy that vary together over the *business cycle* as well as financial markets that tend to tighten in concert over the *financial cycle*, with the single most important factor often serving as an *economic* or *financial activity index*, depending on the application.

The challenge faced by practitioners in applying this framework to construct activity indexes is that the econometrician does not typically observe the factors. Instead, latent variable estimators that can *extract* F_t up to a scale/sign rotation must be applied to X_{it}. In other words, one has to extract from the panel of time series the common *signal* in F_t from the *noise* of E_{it}. It is this feature of these estimators that was alluded to in the introduction as maximizing the common strengths of various economic and financial indicators while simultaneously minimizing their individual weaknesses in characterizing the state of the U.S. economy.

A technique commonly used for this purpose is *principal components analysis* (PCA). PCA can be viewed as a multidimensional restricted nonlinear least squares problem (Stock and Watson 2002a), e.g.,

$$(3.2) \quad \min_{\Gamma,F} \; V(\Gamma,F) = (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \Gamma_i F_t)^2 \quad s.t. \quad \frac{\Gamma'\Gamma}{N} = 1 \,.$$

Solving the error minimization problem above (in matrix form) for a single common factor produces an estimate of the activity index that is an intuitive *optimally weighted average* of large panels of time series. In other words, the index itself can be represented as a linear combination of the economic or financial time series that maximizes their *total variance explained*.

$$\text{(3.3)} \quad \textit{Activity Index:} \;\; \hat{F} = (\Gamma'\Gamma)^{-1}\Gamma' X * \frac{N}{N} = \frac{\hat{\Gamma}' X}{N} \;;$$

$$\hat{\Gamma} \equiv \text{eigenvector associated with largest eigenvalue of } (X'X)\,.$$

For large panels of time series, PCA produces consistent estimates of the factors under general conditions (Bai and Ng 2002), and given its computational ease, it has become a standard for estimating the approximate factor model.

By extending the analysis of the approximate factor model along the time dimension, some of the restrictions implied by PCA can be relaxed using an alternative estimation technique called *dynamic factor analysis*. An example is given below:

$$\text{(3.4)} \quad \begin{aligned} X_{it} &= \Gamma_i F_t + \epsilon_{it}, \\ F_t &= \Phi F_{t-1} + \eta_t, \\ \epsilon_{it} &\sim N(0, \Sigma), \;\; Cov(\epsilon_{it}, \epsilon_{jt}) = 0 \;\; i = j, \\ \eta_t &\sim N(0, 1), \end{aligned}$$

where we now specify autoregressive dynamics (in companion form) for a single factor and allow for heteroskedasticity in the idiosyncratic errors of the panel.

Estimating the activity index in this case requires signal extraction methods for normal-linear state-space models that make use of the *Kalman filter* and routines for *maximum likelihood* estimation (Durbin and Koopman 2012). While we lose some of the simplicity of interpretation of the activity index by using this method versus PCA, we also gain the ability to directly forecast anything in the panel of time series. This feature has proven to be particularly attractive to researchers interested in forecasting the current state of the U.S. economy (Giannone, Reichlin, and Small 2008). Dynamic factor models can also be easily extended to handle common data irregularities, such as unbalanced panels and mixed frequencies of observation.[1]

The treatment of mixed-frequency data sets, in particular, is a strength of the state-space methods used to estimate dynamic factor models. For example, the practice of appending frequency-matching temporal aggregation constraints to the dynamic factor model (sometimes referred to as *accumulators*, as in Harvey [1989]) has been used to construct mixed-frequency indexes of both economic and financial activity for the United States (e.g., Aruoba, Diebold, and Scotti 2009; Brave and Butters 2012b; Mariano and Murasawa 2003). While these extensions are not commonly found in standard statistical software packages, their use is becoming more widespread. For further information, see Brave, Butters, and Kelley (2019), which describes the Matlab toolbox package MFSS.

Recent research has also developed computationally efficient methods that make the estimation of dynamic factor models feasible for large panels of time series. These include quasi maximum likelihood routines such as expectation-maximization (EM) algorithms (Bańbura and Modugno 2014; Doz, Giannone, and Reichlin 2012) as well as collapsing transformations that can simplify maximum likelihood estimation. An example of the latter can be found in Bräuning and Koopman (2014). Referred to as collapsed dynamic factor analysis, their application can be viewed as a hybrid case in which principal components are construed as observations of the latent factors up to the inclusion of classical measurement errors. The Chicago Fed's activity indexes make use of both PCA and dynamic factor estimation methods. In the sections that follow, we describe these indexes and summarize some of their applications.

THE CFNAI

The Chicago Fed National Activity Index (CFNAI) is a monthly summary statistic for U.S. economic growth. Estimated by PCA, it is the first principal component of 85 monthly indicators covering four broad categories of economic activity: 1) production and income; 2) employment, unemployment, and hours; 3) personal consumption and housing; and 4) sales, orders, and inventories. Many of the most commonly cited economic indicators for the United States fall within these categories, including industrial production, payroll employment, the unemployment rate, personal consumption expenditures, housing starts, and manufacturing and trade sales.

First introduced in Evans, Liu, and Pham-Kanter (2002), the CFNAI derived largely from earlier work examining the forecasting ability of real economic activity indicators for U.S. inflation (e.g., Fisher 2000; Stock and Watson 1999). Today, however, it is primarily seen as a coincident indicator of the U.S. business cycle, as this use of the index formed much of the motivation for its initial release at the onset of the 2001 recession, as well as much of the subsequent work with the index during and after the 2007–2009 recession (e.g., Brave 2009; Brave and Lichtenstein 2012).

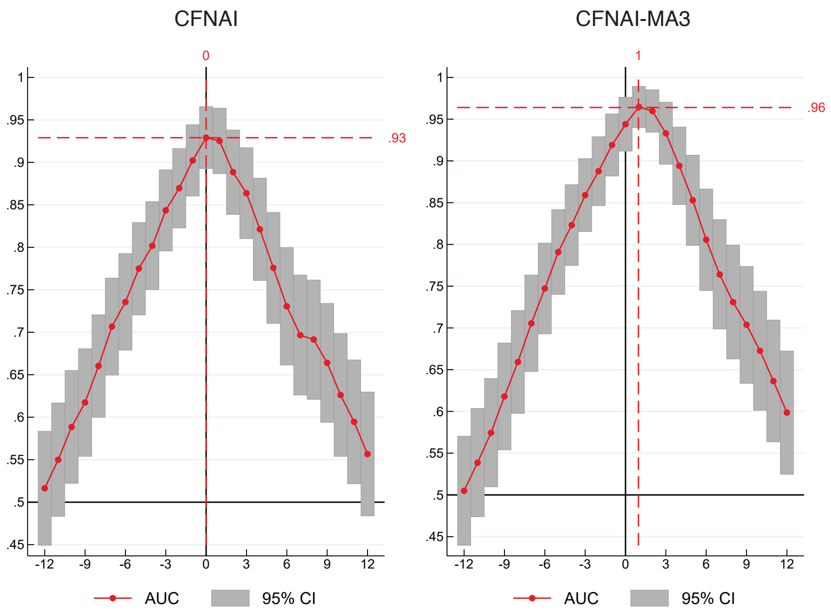
The CFNAI's performance in this regard has been quite good. For example, the index has been shown to be roughly 95 percent accurate historically in identifying U.S. recessions from expansions since 1967 based on a receiver operating characteristic (ROC) analysis of U.S. business cycles (Berge and Jordà 2011). This classification technique nonparametrically captures the trade-off between type I (false positive) and type II (false negative) errors based on the observed distribution of an indicator, C_t. To measure its accuracy for U.S. business cycles, the *ROC curve* is constructed over the range of realizations of C_t by applying the Cartesian convention $\{ROC(r), r\}$, in which $ROC(r) = TP(c)$ and $r = FP(c)$ and defining

$$
\begin{aligned}
(3.5)\quad & TP(c) = P[C_t \geq c | S_t = 1], \\
& FP(c) = P[C_t \geq c | S_t = 0],
\end{aligned}
$$

where S_t is a binary variable, with $S_t = 1$ representing a U.S. recession and $S_t = 0$ representing an expansion. The *area under the curve* (AUC) then represents C_t's accuracy in separating U.S. recessions from expansions.

Figure 3.3 depicts AUC values (red connected dots) for the CFNAI and its three-month moving average (CFNAI-MA3) at leads (negative x-axis values) and lags (positive x-axis values) in months over the U.S. business cycle. The dashed red horizontal lines in each panel correspond to the peak AUC value for each measure, while the gray bars are 95 percent confidence intervals. An AUC value statistically significant from 0.5 reflects an indicator that exhibits a significant ability to appro-

Figure 3.3 AUCs at Monthly Leads and Lags of the Business Cycle



SOURCE: Author's calculations based on data available at www.chicagofed.org/cfnai.

priately classify recessions and expansions as defined by the National Bureau of Economic Research (NBER).[2] The closer an AUC value is to 1, the more accurate the indicator. The closer an indicator's peak AUC value is to a zero monthly lag, the more coincident it is with the cycle, so that a peak value to the left of zero signifies a leading indicator and a peak value to the right of zero signifies a lagging indicator. It is clear from Figure 3.3 that both the CFNAI and CFNAI-MA3 are highly accurate coincident indicators of the U.S. business cycle, with peak AUCs of between 0.93 and 0.96 in the range of zero to one monthly lags. This result has also been borne out in practice, as the CFNAI led the NBER's dating of the 2001 and 2007–2009 recessions by 6–18 months on average in real time, according to the rules of thumb for the index used to judge the beginning and end of recessions (Brave and Butters 2010). Its success as a business-cycle measure has also led to its use in various forecasting applications for U.S. real GDP growth (Brave and Butters 2014), as well as the estimation of its trend (Brave and Butters 2013).

More recent work has expanded on the CFNAI by broadening the universe of data series and incorporating the latest advances in dynamic-factor analytic methods. For instance, Brave, Butters, and Kelley (2019) use mixed-frequency collapsed dynamic-factor analysis to summarize growth in 500 monthly real activity indicators and quarterly GDP growth to arrive at a measure of monthly GDP growth for the United States that can be decomposed into trend, cycle, and irregular components. The cycle component is then shown to be 99 percent accurate in capturing U.S. recessions and expansions and can be broken down further into leading and lagging elements that resemble the CFNAI and the Conference Board's Leading Economic Index, respectively.

The impressive résumé of the CFNAI has also spurred the development of other indexes used to measure growth in economic activity at a regional level (e.g., the Midwest Economy Index, or MEI; see Brave and Lu [2010]) and a local level (e.g., the Detroit Economic Activity Index, or DEAI; see Brave and Traub [2017]).[3] These indexes have been shown to be useful in filling gaps in our understanding of local economic conditions, given the longer publication delays and limited availability of data at state and local levels. For example, Brave and Wang (2011) used the MEI to predict gross state product growth in real time, and the DEAI was developed in order to measure the economic progress of Detroit after exiting bankruptcy. Summarizing annual, quarterly, and monthly data on city income, labor, real estate, and trade using mixed-frequency dynamic factor methods, the DEAI can also be used to estimate GDP for the city of Detroit as well as forecast its per capita income.

THE NFCI

The approximate factor model can also be applied to financial time series in order to capture periods of financial stress consistent with a *financial cycle*. Working with financial data, however, introduces additional complexities. For instance, financial time series are generally available at mixed and often higher frequencies of observation. Also, they tend to have richer correlation structures in which not all comovement can be captured in a single direction; i.e., there is generally a broader mix of procyclical and countercyclical indicators. Furthermore, if one is interested in isolating the state of financial markets from the state of the business cycle, adjustments must be made to either the data or the model to condition on this information.

All of these concerns are addressed in one form or another in the construction of the Chicago Fed's National Financial Conditions Index (NFCI). The NFCI is a weekly summary statistic for U.S. financial conditions and is estimated by mixed-frequency dynamic-factor analysis on a panel of 105 weekly, monthly, and quarterly financial time series. The index is representative of the entire U.S. financial system, containing broad coverage of money and debt and equity markets, as well as the traditional and "shadow" banking systems. It has been shown to be a useful tool in monitoring financial stability, aligning closely with historical episodes of financial stress (e.g., Brave and Butters 2011, 2012b).

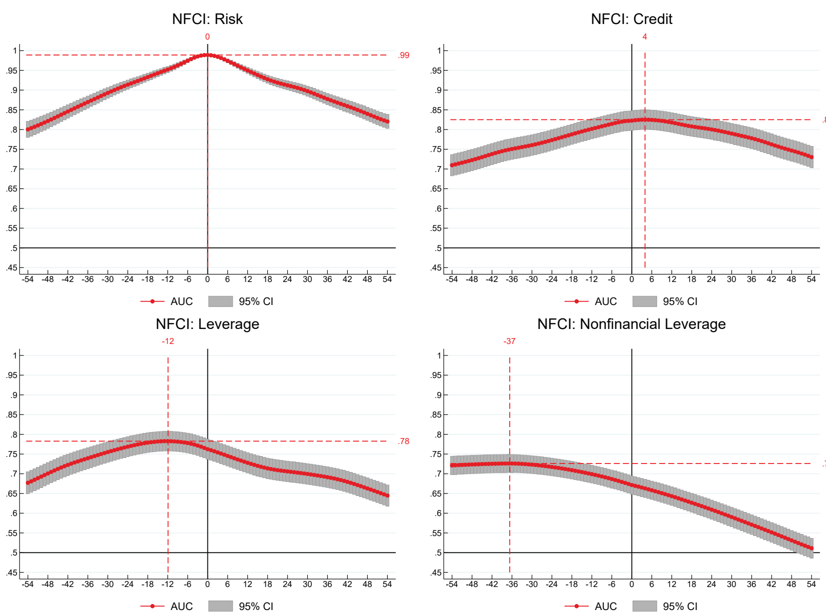
By conditioning the NFCI data on the state of the business cycle, a leading signal for financial stress can sometimes also be obtained (Brave and Butters 2011). This can be seen in Figure 3.2, which depicts the full-time series of the NFCI and its adjusted counterpart, the ANFCI. The ANFCI rebenchmarks U.S. financial conditions around a historical mean that is typical for a given level of economic growth and inflation (Brave and Kelley 2017). Positive (negative) values then denote tighter-than-average (looser-than-average) conditions on this basis. The ANFCI tends to display a slight lead on the NFCI in the run-up and aftermath of periods of financial stress. In addition, Brave and Genay (2011) find that it was also a useful predictor of Federal Reserve policy actions taken during the global financial crisis.

The indicators underlying the NFCI can be broadly classified into three types: 1) risk, 2) credit, and 3) leverage. These classifications are used in Brave and Butters (2012b) to construct subindexes of the NFCI (labeled *risk*, *credit*, and *leverage*) and highlight features of the financial cycle. Risk indicators capture volatility and funding risk in the financial sector and tend to be coincident indicators of financial stress. Credit indicators describe credit conditions in the nonfinancial sector and tend to be lagging indicators of financial stress. Finally, leverage indicators are measures of debt and equity in both sectors and tend to be leading indicators of financial stress.

In order to demonstrate these features, Figure 3.4 repeats the ROC analysis technique from the previous section on the three NFCI subindexes. For the subindexes, we classify the financial cycle based on a realization of the overall NFCI being positive or negative. Here, the x-axis values of the panels of the figure correspond to weekly leads or lags, while the y-axes continue to display AUC values. From the figure, it is clear that the risk subindex is a highly coincident indicator of financial stress (i.e., weeks where NFCI > 0), with a peak AUC value of 0.99 at a zero-week lag. On the other hand, the credit subindex tends to lag behind periods of stress by about a month, with a lower peak AUC value of 0.83, and the leverage subindex tends to lead periods of stress by about three months, with a lower peak AUC value of 0.78.

The leading signal for financial stress provided by leverage indicators can be further enhanced by isolating a subset of indicators for nonfinancial businesses and households. The resulting nonfinancial leverage

Figure 3.4 AUCs at Weekly Leads and Lags of the Financial Cycle



SOURCE: Author's calculations based on data available at www.chicagofed.org/nfci.

subindex tends to lead periods of stress by almost nine months, with a peak AUC value of 0.73, as seen in the bottom right panel of Figure 3.4. Brave and Butters (2012a) show that this particular subindex can be a useful early warning indicator, as it displays a significant lead with both the business and financial cycles and offers a superior view of potential financial imbalances in firm and household balance sheets in comparison with alternative measures like the private credit-to-GDP ratio. In addition, Brave and Lopez (2019) use this subindex to construct a probability of financial instability for the United States and then show how it can be used as a guidepost for macroprudential policymakers.

CONCLUSION

While it was not a point of focus in this chapter, it is worth mentioning that the activity index methodology can also be applied to qualitative, or survey-based, data just as easily as the quantitative government or market-based data focused on here. For example, Brave and Walstrum (2014) and Brave, Walstrum, and Berman (2015) develop an activity index methodology for quantifying survey responses collected for the Chicago Fed's *Beige Book* contribution. This work led to the introduction of the Chicago Fed Survey of Business Conditions (CFSBC).[4] Walstrum (2017) then showed how the CFSBC Activity Index could be used to forecast current-quarter GDP growth, much as with traditional activity indexes.

It is also worth noting that the development of activity indexes continues to be an active and expanding area of research, with the work of the Chicago Fed only a small part of that process. Within the Federal Reserve system, a number of indexes related to ours are also published, including various financial stress indexes and national and local business-conditions indexes.[5] Many foreign central banks and governmental agencies also produce similar indexes to ours in order to better understand fluctuations in their parts of the world. The success of these measures in capturing business and financial cycles and in aiding forecasting continues to demonstrate their value to policymakers and private-sector analysts.

Notes

Prepared for the 2018−2019 Werner Sichel Lecture Series at Western Michigan University. The views expressed herein are my own and do not necessarily represent those of the Federal Reserve Bank of Chicago or the Federal Reserve System. I would like to thank Dr. C. James Hueng and the WMU faculty and students for their hospitality; and the team of economists, research analysts, and assistants, as well as the editorial and public affairs staff, who support the production of these indexes at the Chicago Fed.

For more information on the Chicago Fed's economic and financial activity indexes, please go to chicagofed.org/research/data/index. To sign up for email notifications of any Chicago Fed index release, go to chicagofed.org/utilities/subscribe.

1. PCA can also be extended to handle some of these issues. See, for example, the alterations described in Stock and Watson (2002b).
2. As defined above, AUC values greater than 0.5 are consistent with a procyclical measure, and values less than 0.5 are consistent with a countercyclical measure. Wherever necessary, I have applied the convention of multiplying the indicator by 1 in order to assure that only AUC values greater than or equal to 0.5 are plotted. Without this sign convention, one would arrive at the overall accuracy of a countercyclical indicator by taking 1 minus its AUC value.
3. For more information on the MEI and DEAI, go to www.chicagofed.org/mei and www.chicagofed.org/deai.
4. For more information on the CFSBC, go to www.chicagofed.org/cfsbc.
5. See, for example, the metro business cycle indexes described in Arias, Gascon, and Rapach (2016) and maintained by the St. Louis Fed.

References

Arias, Maria A., Charles S. Gascon, and David E. Rapach. 2016. "Metro Business Cycles." *Journal of Urban Economics* 94(C): 90–108.

Aruoba, S. Borayğan, Francis X. Diebold, and Chiara Scotti. 2009. "Real-Time Measurement of Business Conditions." *Journal of Business and Economic Statistics* 27(4): 417–427.

Bai, Jushan, and Serena Ng. 2002. "Determining the Number of Factors in Approximate Factor Models." *Econometrica* 70(1): 191–221.

Bańbura, Marta, and Michele Modugno. 2014. "Maximum Likelihood Estimation of Factor Models on Datasets with Arbitrary Pattern of Missing Data." *Journal of Applied Econometrics* 29(1): 133–160.

Berge, Travis J., and Òscar Jordà. 2011. "Evaluating the Classification of Economic Activity into Recessions and Expansions." *American Economic Journal: Macroeconomics* 3(2): 246–277.

Bräuning, Falk, and Siem Jan Koopman. 2014. "Forecasting Macroeconomic Variables Using Collapsed Dynamic Factor Analysis." *International Journal of Forecasting* 30(3): 572–584.

Brave, Scott A. 2009. "The Chicago Fed National Activity Index and Business Cycles." Chicago Fed Letter No. 268. Chicago: Federal Reserve Bank of Chicago.

Brave, Scott A., and R. Andrew Butters. 2010. "Chicago Fed National Activity Index Turns Ten—Analyzing Its First Decade of Performance." Chicago Fed Letter No. 273. Chicago: Federal Reserve Bank of Chicago.

———. 2011. "Monitoring Financial Stability: A Financial Conditions Index Approach." *Economic Perspectives* 35(1): 22–43.

———. 2012a. "Detecting Early Signs of Financial Instability." Chicago Fed Letter No. 305. Chicago: Federal Reserve Bank of Chicago.

———. 2012b. "Diagnosing the Financial System: Financial Conditions and Financial Stress." *International Journal of Central Banking* 8(2): 191–239.

———. 2013. "Estimating the Trend Rate of Economic Growth Using the CFNAI." Chicago Fed Letter No. 311. Chicago: Federal Reserve Bank of Chicago.

———. 2014. "Nowcasting Using the Chicago Fed National Activity Index." *Economic Perspectives* 38(1): 19–37.

Brave, Scott A., R. Andrew Butters, and David Kelley. 2019. "A New 'Big Data' Index of U.S. Economic Activity." *Economic Perspectives* 43(1): 1–30.

Brave, Scott A., and Hesna Genay. 2011. "Federal Reserve Policies and Financial Market Conditions during the Crisis." FRB of Chicago Working Paper No. 2011-04. Chicago: Federal Reserve Bank of Chicago.

Brave, Scott A., and David Kelley. 2017. "Introducing the Chicago Fed's New Adjusted National Financial Conditions Index." Chicago Fed Letter No. 386. Chicago: Federal Reserve Bank of Chicago.

Brave, Scott A., and Max Lichtenstein. 2012. "A Different Way to Review the Chicago Fed National Activity Index." Chicago Fed Letter No. 298. Chicago: Federal Reserve Bank of Chicago.

Brave, Scott A., and Jose A. Lopez. 2019. "Calibrating Macroprudential Policy to Forecasts of Financial Stability." *International Journal of Central Banking* 15(1): 1–59.

Brave, Scott A., and Chenfei Lu. 2010. "A Snapshot of the Midwest Economy: Past and Present." Chicago Fed Letter No. 280. Chicago: Federal Reserve Bank of Chicago.

Brave, Scott A., and Paul Traub. 2017. "Tracking Detroit's Economic Recovery after Bankruptcy with a New Index." Chicago Fed Letter No. 376. Chicago: Federal Reserve Bank of Chicago.

Brave, Scott A., and Thomas Walstrum. 2014. "Using the Federal Reserve's *Beige Book* to Track Economic Activity." Chicago Fed Letter No. 328. Chicago: Federal Reserve Bank of Chicago.

Brave, Scott A., Thomas Walstrum, and Jacob Berman. 2015. "The Chicago Fed Survey of Business Conditions: Quantifying the Seventh District's *Beige Book* Report." *Economic Perspectives* 39(3): 77–89.

Brave, Scott A., and Norman Wang. 2011. "Predicting Gross State Product Growth with the Chicago Fed's Midwest Economy Index." Chicago Fed Letter No. 293. Chicago: Federal Reserve Bank of Chicago.

Chamberlain, Gary, and Michael Rothschild. 1983. "Arbitrage, Factor Structure, and Mean-Variance Analysis on Large Asset Markets." *Econometrica* 51(5): 1281–1304.

Doz, Catherine, Domenico Giannone, and Lucrezia Reichlin. 2012. "A Quasi-Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models." *Review of Economics and Statistics* 94(4): 1014–1024.

Durbin, James, and Siem Jan Koopman. 2012. *Time Series Analysis by State Space Methods*. 2nd ed. Oxford Statistical Science Series, No. 38. Oxford: Oxford University Press.

Evans, Charles L., Chin Te Liu, and Genevieve Pham-Kanter. 2002. "The 2001 Recession and the Chicago Fed National Index: Identifying Business Cycle Turning Points." *Economic Perspectives* 26(3): 26–43.

Fisher, Jonas D. M. 2000. "Forecasting Inflation with a Lot of Data." Chicago Fed Letter No. 151. Chicago: Federal Reserve Bank of Chicago.

Giannone, Domenico, Michele Lenza, and Giorgio E. Primiceri. 2018. *Economic Predictions with Big Data: The Illusion of Sparsity*. FRB of New York Staff Report No. 847. New York: Federal Reserve Bank of New York.

Giannone, Domenico, Lucrezia Reichlin, and David Small. 2008. "Nowcasting: The Real-Time Informational Content of Macroeconomic Data." *Journal of Monetary Economics* 55(4): 665–676.

Harvey, Andrew C. 1989. *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge: Cambridge University Press.

Mariano, Roberto S., and Yasutomo Murasawa. 2003. "A New Coincident Index of Business Cycles Based on Monthly and Quarterly Series." *Journal of Applied Econometrics* 18(4): 427–443.

Stock, James H., and Mark W. Watson. 1999. "Forecasting Inflation." *Journal of Monetary Economics* 44(2): 293–335.

———. 2002a. "Forecasting Using Principal Components from a Large Number of Predictors." *Journal of the American Statistical Association* 97(460): 1167–1179.

———. 2002b. "Macroeconomic Forecasting Using Diffusion Indexes." *Journal of Business and Economic Statistics* 20(2): 147–162.

———. 2011. “Dynamic Factor Models.” In *The Oxford Handbook of Economic Forecasting*, Michael P. Clements and David F. Hendry, eds. Oxford: Oxford University Press, pp. 35–59.

Walstrum, Thomas 2017. “Can the CFSBC Activity Index Nowcast U.S. Real GDP Growth?” Chicago Fed Letter No. 378. Chicago: Federal Reserve Bank of Chicago.