The 2001 recession and the Chicago Fed National Activity Index: Identifying business cycle turning points

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Introduction and summary

On March 5, 2001, the Federal Reserve Bank of Chicago first released publicly the Chicago Fed National Activity Index (CFNAI), a single, summary measure of real economic activity that is based on a weighted average of 85 economic indicators. This inaugural CFNAI release explicitly mentioned the possibility that the U.S. economy had begun to slip into a recession. On November 26, 2001, the National Bureau of Economic Research's (NBER) Business Cycle Dating Committee "determined that a peak in business activity had in fact occurred in the U.S. economy in March 2001 (NBER, 2001)." As the eight-months lag of the NBER report indicates, business cycle turning points are typically only recognized many months after the event; thus, the ability of the CFNAI to identify the recession in approximately real time is important—since early recognition of business cycle turning points will enable more timely monetary policy responses.

Although one of the first uses of the CFNAI was to gauge inflationary pressures (Fisher, 2000), there is a strong statistical relationship between this index of economic activity and business cycle movements. We can see this in figure 1, which displays the three-month moving average index (CFNAI-MA3) from 1986 through 2001. Whenever the three-month moving average of this index falls into the range of –0.70 to –1.00, there is an increasing probability that the U.S. economy is in a recession. The substantial fall in the index to –1.50 in late 1990 corresponds to the 1990–91 recession. Similarly, the 2001 recession (see figures 2 and 3) is clearly evident as the index fell below –1.00. Prior to the current recession, there were five recessions over the 1967–2000 period. In six cases, the CFNAI-MA3 fell below –0.70, after having previously been above zero when the economy was expanding. On five of these occasions, the U.S. economy had just entered a recession as determined later by the NBER. Taken at face value, this is an 83 percent success rate for the CFNAI.

To further our understanding of the CFNAI and its role as a business cycle indicator, we address two main questions in this article. First, what is the general relationship between the CFNAI and economic recessions? While economic downturns are clearly evident in the sharp reductions in the CFNAI, how much more information do we gain beyond what we would learn by simply focusing on single indicator measures of economic activity like industrial production, personal consumption expenditures, and others? We offer a graphical analysis of the data to answer this question. Second, what probabilistic statements about economic performance can we attach to specific values of the CFNAI-MA3? When the CFNAI-MA3 plunges to values below –0.70, what is the probability that the U.S. economy has entered a recession? We adopt a statistical approach to modeling the dynamic evolution of the 85 economic indicators in order to answer this question.

To summarize our findings, our graphical analysis indicates that individual economic indicators appear to predict the onset of economic recessions almost as well as the CFNAI-MA3. Indeed, many business cycle analysts prefer a relatively small number of economic indicators to guide their analysis. For example, the NBER November 2001 committee report makes clear the importance of four monthly coincident economic indicators of real activity: payroll employment, industrial production, real personal income less

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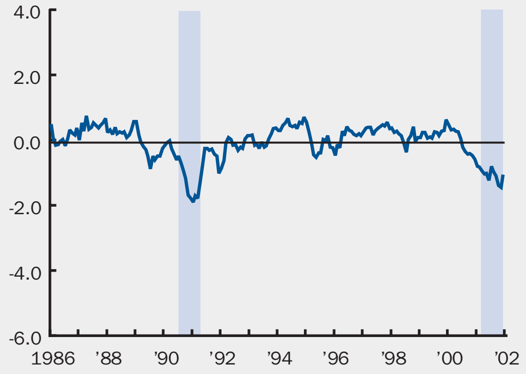
transfer payments, and manufacturing and trade sales in real terms.[1] However, while all of the economic indicators were signaling that the real economy was growing well below trend throughout this period, they conveyed different information about the timing of the business cycle peak. Essentially, the NBER selected the business peak based upon a peak in one very important indicator, total payroll employment. Visual inspection of the co-movements between industrial production, employment, and the CFNAI-MA3 suggests that perhaps the gain in computing the index of 85 indicators is fairly small.

However, the small number of economic recessions since 1967 makes this assessment misleading. Using Monte Carlo simulations, a more careful evaluation of the statistical properties suggests substantial improvements from using the CFNAI-MA3 over individual indicators. For example, when the CFNAI-MA3 falls to –0.70, the probability that the economy has entered a recession is around 70 percent. When similarly normalized three-month moving average indexes of industrial production and personal consumption expenditures fall below –0.70, the probabilities are 50 percent and 35 percent, respectively. This quantitative analysis indicates that the CFNAI-MA3 is useful for detecting the onset of economic recessions.

In the following sections, we explain the development and construction of the CFNAI. Then, we examine how quickly and how well the index has historically identified business cycle turning points. We examine whether it is possible to accurately reflect the economy with fewer indicators or whether more than 85 indicators may be necessary to average out the idiosyncratic noise from the underlying economic signals. Finally, we use a statistical technique, Monte Carlo simulations, to analyze the index's performance. This statistical approach provides us with a far greater number of observations than the five recessions that have actually occurred since 1967. In particular, we focus on the index's ability to correctly identify the onset of recession in the simulated economy.

FIGURE 1

CFNAI-MA3
(1986–2001)



Note: Shaded areas indicate NBER recessions.

Origins of the CFNAI

The Chicago Fed National Activity Index is based upon an index designed by James Stock and Mark Watson in their *Journal of Monetary Economics* article on "Forecasting Inflation" (Stock and Watson, 1999a). Stock and Watson's Activity Index summarizes the information of 85 data series in a single index value. This is accomplished using the well-known method of principal component analysis (see box 1 for an explanation). The current version of the CFNAI attempts to implement their monthly data selections as closely as possible in real time. The CFNAI is the first principal component of these data series, accounting for the largest independent variation among the economic indicators in the data set. Equivalently, the CFNAI is a weighted average of the 85 economic indicators. For example, a principal component index y based on three series can be expressed as $y_t = w_1 \times x_{1t} + w_2 \times x_{2t} + w_3 \times x_{3t}$, where x_1, x_2, and x_3 are the three original series, and w_1, w_2, and w_3 are the weights assigned to the data series. In practice, the weights measure the relative importance of each series in the index.

An index like the CFNAI can be used in several ways. One approach is to use the index as an explanatory variable in estimating linear relationships. By computing a single index value for a large data set, the gains from data reduction allow the analyst to specify parsimonious forecasting relationships. This approach has been used by Stock and Watson (1999a, 1999b), Fisher, Liu, and Zhou (2002), and Bernanke and Boivin (2002). Another approach is to use the index to identify non-linear regime switches. For example, Fisher (2000) describes how movements in the activity index relate to broad accelerations in inflation during certain time periods. In this article, we focus on non-linear regime switches from economic expansions to recessions, as in Hamilton (1989) and Diebold and Rudebusch (1996).

Constructing the CFNAI

One of Stock and Watson's (1999a) findings is that the first principal component of our 85-variable dataset captures aggregate real activity in the United States. When we double the dataset by including various inflation rates, monetary aggregates, interest

BOX 1

Construction of the CFNAI

Data transformations and the principal components method

The CFNAI is the first principal component of a dataset consisting of 85 economic indicators. Background on the method of principal components may be found in most advanced statistics and econometrics books. Henri Theil's (1971) classic text *Principles of Econometrics* provides an excellent overview of this method; we use Theil's exposition and notation in the following discussion.

Let x_t denote the 1 x 85 row vector consisting of observations at time t of the 85 data series. Let X_T denote the $T \times 85$ stacked matrix of data vectors, that is,

$$X_T = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{bmatrix}, \text{ where } T \text{ is the total number of observations.}$$

By this construction, each column of X_T contains T observations of an individual economic indicator.

Each of the 85 raw series used to compute the CFNAI has already been inflation adjusted and, if necessary, seasonally adjusted by the original data provider. After obtaining these raw data series from HaverAnalytics, we first assess each series for its stationarity properties. If a series is determined to be non-stationary, we apply an appropriate transformation to render the series stationary. In most instances, the data are log-differenced so that the indicator series are transformed into growth rates. This is the case, for example, with employment and industrial production data. In some cases, such as the Institute for Supply Management's Purchasing Managers Indexes, the data require no transformation.

Second, each stationary series is adjusted for outlying observations. We define an outlier to be an observation whose distance away from the median is greater than six times the interquartile range of the series. That is, x_{it}—the observation at time t of series i—is an outlier if $\left| x_{it} - x_i^{50} \right| > 6(x_i^{75} - x_i^{25})$, where x_i^{25}, x_i^{50}, and x_i^{75} are the 25th, 50th, and 75th percentiles of series x_i. An outlier that is above the median has its original value replaced with $x_i^{50} + 6(x_i^{75} - x_i^{25})$, while an outlier that is below the median has its original value replaced with $x_i^{50} - 6(x_i^{75} - x_i^{25})$.

Finally, we rescale each series to have a mean of zero and standard deviation of one. These standardized series are the indicator series used in X_T for the principal component calculation.

In general, a principal component of X_T is determined by a specific eigenvalue of the second-moment matrix $X_T'X_T$. Computing the *first* principal component of X_T requires calculating the eigenvector associated with the *largest* eigenvalue of $X_T'X_T$. Consequently, since the CFNAI is the first principal component of X_T, it is simply a particular weighted average of the 85 economic indicators. In particular, $CFNAI_t = x_t a$, where a is an 85 x 1 vector of weights. Although the weights in the vector a correspond to the elements of the eigenvector associated with the largest eigenvalue of $X_T'X_T$, the vector a is re-scaled such the resulting CFNAI has a mean of zero and standard deviation of one. Since we estimate a single set of weights over the entire sample period, this vector of weights remains fixed for a given set of data X_T.

Revisions to the CFNAI

There are two main sources of revisions in the CFNAI. Firstly, because the CFNAI is designed to be released in a timely way and because indicator data are released at different times, not all of the indicators are available in time for a particular month's CFNAI release. For example, employment data are usually available within one week of a month's end, but inflation-adjusted retail inventory data are typically not available until another five weeks have elapsed.

For any given CFNAI release in 2001, approximately one-third of the indicators will have had their latest monthly values forecast. In other words, the reported CFNAI is based on the latest observed values for two-thirds of the 85 series and based on forecast values for the remaining one-third. In the following month's CFNAI release, the data for the "lagging" series will have become available, and the previous month's CFNAI value will be revised based on this data. In this way, forecast error is a source of revision in the CFNAI.

Secondly, throughout the calendar year, the 85 monthly series are systematically revised by the original reporting institutions. These revisions will alter the underlying monthly data, resulting in a change in the value of CFNAI. Although both sources of revision will also result in a change in the weighting vector a, we expect this and the re-normalization of the underlying data to have a negligible effect on the index.

rates, commodity prices, and equities, the first principal component is essentially unchanged. That is, a measure of real activity continues to account for the largest independent, common variation in each of the data series. So using 166 indicators rather than our 85 would lead to negligible changes in our threshold analysis below. Consequently, we focus on real economic indicators in computing our index.

The CFNAI is constructed from 85 coincident economic series that are drawn from five categories of economic activity. Table A3 in the appendix lists all 85 series. The five categories are:

1. Production and income—These data include industrial production growth for several industries and product classifications; component indexes from the Institute for Supply Management's (ISM) Purchasing Managers Index (PMI); capacity utilization measures; and real income growth measures (21 series).
2. Employment, unemployment, and labor hours—These data include employment growth rates for several industries from the Payroll Survey; the employment component of the PMI; changes in unemployment rates for several demographic groups from the Household Survey; initial claims for state unemployment insurance; growth rates of production hours; and changes in help-wanted measures (24 series).
3. Personal consumption and housing—These data include the growth rate of real personal consumption expenditures for several categories; housing starts nationally and by region; building permits for new housing units; and shipments of mobile homes (13 series).
4. Manufacturing and trade sales—These data include growth rates of real sales measures for manufacturing industries; several categories of wholesale trade sales; and several categories of retail trade sales (11 series).
5. Inventories and orders—These data include components of the PMI related to new orders and vendor performance; the growth rate of inventories and inventory–sales ratios by manufacturing and trade categories; and the growth rate of new orders for durable goods manufacturing and nondefense capital goods (16 series).

Prior to constructing the activity index, the individual data series are transformed to be stationary as denoted in table A3. In practice, this means that trending variables are often measured as growth rates, while variables without trends are often left untransformed. These transformed data are then each de-meaned and standardized to have a unit variance. We then compute the CFNAI as the first principal component of the 85 data series. Box 1 presents the formal details of the methodology used to construct the index.

Basic properties of the CFNAI

Figure 2 displays the monthly CFNAI from 1967 through 2001. By construction, the monthly index has an average value of zero and a standard deviation of one. Since many data series are deviations of growth rates from their sample average, the monthly index can be interpreted as the deviation of national activity growth from its trend rate. Consequently, an index value of zero is associated with trend rates of growth. Another reaction to figure 2 is that the index is quite volatile from month to month. Although index values above zero tend to stay above zero for a period of time, there are many reversals of sharp spikes from month to month. The monthly index, therefore, appears to track broad movements in the economy, but contains transitory noise. Consequently, taking a moving average of the monthly series would average out the transient noise while leaving the underlying signal in place.

Figure 3 displays the trailing three-month moving average of the monthly index. We refer to this moving average as the CFNAI-MA3. Clearly, much of the transient noise in the monthly index has been filtered out. Now it is easier to see the persistent movements of the index over time. Since the index is a weighted average of 85 economic indicators, movements in each of the components contribute to movements in the CFNAI-MA3. Large positive or negative index values tend to arise when most of the individual indicators are moving together. This is especially evident during periods of economic contraction. In figure 3, sharply negative values of the CFNAI-MA3 correspond to official NBER recessions. From 1967 through 2000, the moving average index fell below –0.70 after having

FIGURE 2

CFNAI, monthly index
(1967–2001)

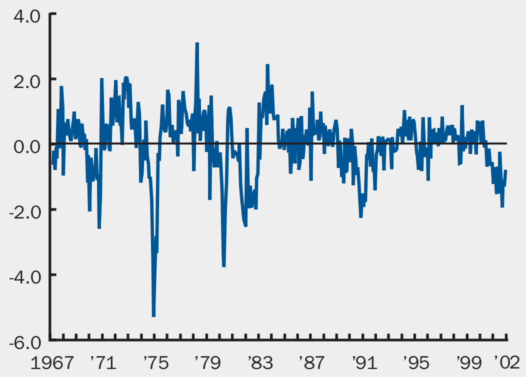
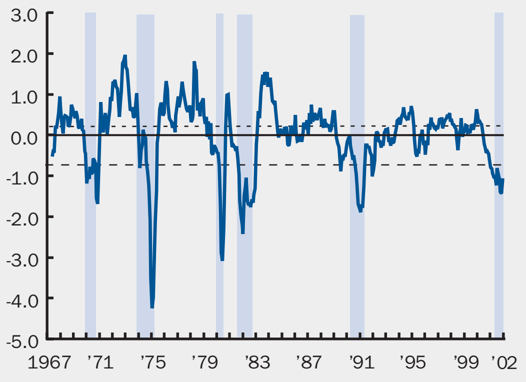


FIGURE 3

CFNAI-MA3 and business cycles
(1967–2001)



Note: Shaded areas indicate NBER recessions.

previously been above zero on six occasions, and five of those were associated with recession.

Perhaps it should not be surprising that a basket of economic indicators can provide a useful guide to the state of aggregate economic activity. In financial markets, individual stock prices reflect both market and company-specific risk. A portfolio of stocks, like the Standard & Poor's 500, provides diversification of the idiosyncratic risks for individual stocks, leaving in place the undiversifiable market risk. Movements in the stock index provide indications of how the stock market is evolving. Similarly, the CFNAI-MA3 is a portfolio of economic indicators. Thus, movements in the CFNAI-MA3 are reflective of how the economy is evolving. Over the period 1967 to 2000, the CFNAI-MA3 fell substantially whenever the U.S. economy was in a recession.

Identifying business cycle turning points with the CFNAI

The construction of the CFNAI highlights its properties as a coincident indicator of economic expansions and contractions. There are many ways to evaluate an indicator. Fisher, Liu, and Zhou (2002) examine how the CFNAI contributes to the out-of-sample explanatory power in linear models for forecasting inflation over the last 15 years. In this article, we focus on how quickly and how well the CFNAI aids in identifying business cycle turning points. Applying a simple threshold criterion, we examine how accurately the historically constructed CFNAI would have identified past recessions and recoveries.

Identifying recessions

During the period 1967–2000, there were five economic recessions, as identified by the NBER; these occurred in 1970, 1973–75, 1980, 1981–82, and 1990–91.[2] Figure 3 shows the movements in the CFNAI-MA3 in the context of the NBER recession episodes, which are the shaded regions. As we mentioned earlier, figure 3 suggests that the CFNAI-MA3 may be a useful guide for identifying whether the economy has slipped into and out of a recession. Specifically, note that, in each of the five recessions, the smoothed CFNAI-MA3 fell below –0.70 (the dashed negative horizontal line) very near the onset of the recession. If we designate –0.70 as our recession threshold, we see that during the 1970, 1981–82, and 1990–91 recessions, the index first fell below the threshold during the first month of the recession. During the 1973–75 and 1980 recessions, the index first fell below the –0.70 threshold during the third and second months of the recessions, respectively. Thus, during the period 1967–2000, the CFNAI-MA3, using the –0.70 threshold, gave a signal of the economy being in a recession within the first three months of the recession.

The –0.70 recession threshold generated one false alarm during the 1967–2000 period. Specifically, in July 1989, the CFNAI-MA3 fell to –0.94, but no recession materialized. One explanation for the significant dip in the CFNAI-MA3 is that, from mid-1988 through spring 1989, the Federal Open Market Committee pursued a contractionary monetary policy in an attempt to reduce inflation. This tight policy was reflected in an increase in the federal funds rate to 9.75 percent. During this time, the smoothed CFNAI exhibited a steady decline, reaching its low level in July 1989, before returning above the –0.70 threshold.

This brief analysis highlights some problems with using the CFNAI-MA3 and a simple threshold rule to identify recessions. In particular, having a threshold low enough to prevent false signals of recessions will delay the date at which a true recession can be identified. The threshold value of –0.70 identified all five of the true recessions, but falsely signaled a sixth recession. Using a lower recession threshold of –1.50 would have eliminated the false alarm, but the true recessions would not have been identified until many months into the recession. Indeed, the 1970 recession would not have been identified until its twelfth month—the last month of this recession.

Identifying historical recoveries

The tension between identifying turning points early and minimizing the number of false signals also arises when we try to determine when the economy has successfully pulled out of a recession. In this case, we start with the rule that, when the CFNAI-MA3 first crosses the +0.20 threshold level from below, the recession has ended; this threshold is indicated in figure 3 by the dashed positive horizontal line.

We see that, for four of the last five recessions, the CFNAI-MA3 crossed +0.20 from below within five months of the NBER-identified trough (official end of the recession). Following the 1970 recession, the smoothed index exceeded +0.20 two months after the trough. For the 1973–75, 1980, and 1981–82 recessions, the threshold was crossed in the fifth, third, and fourth months, respectively, following the official trough.

For the 1990–91 recession, however, the smoothed CFNAI did not provide an early indication of the recession's end. Specifically, the CFNAI-MA3 crossed +0.20 in November 1993, even though the trough was retrospectively identified by the NBER as March 1991. In part, high levels of corporate debt and financial institutions' reduced ability to extend new financing slowed the recovery from the 1990–91 recession. To mitigate the effects of these financial headwinds, the monetary policy response was to keep the federal funds rate at 3 percent until February 1994. The CFNAI signal was further delayed by the choppy nature of the recovery. The halting movements of the activity index, seen in figure 3, are consistent with contemporaneous economists' accounts of double- and triple-dips in economic activity during this period. Indeed, this recovery was so difficult to discern that the NBER only declared an end to this recession almost two years after the trough had passed.

A more lax recovery threshold of +0.00, or return to trend growth, would have identified the end of the 1990–91 recession earlier. Had this threshold been in effect, the recovery would have been signaled in April 1992, or 19 months prior to the +0.20 threshold date. On the other hand, the weaker recovery threshold would also have generated false signals. In particular, a +0.00 threshold would have prematurely (by 11 months) signaled the end of the 1973–74 recession.

Overall, then, the CFNAI-MA3 with a recovery threshold of +0.20 was able to identify all of the recoveries, signaling four out of the five recoveries within the first five months. Its identification of the erratic 1990–91 recovery, however, did not come until 32 months after the actual trough.

The CFNAI during the 2001 recession

Up until the 2001 recession, the evidence in favor of using the CFNAI as a barometer for detecting the onset of recessions was all historical. But with the inaugural publication of the January 2001 CFNAI on March 5, 2001, the evaluation process moved from the sterile laboratory setting of a computer to a field test using real-time data.

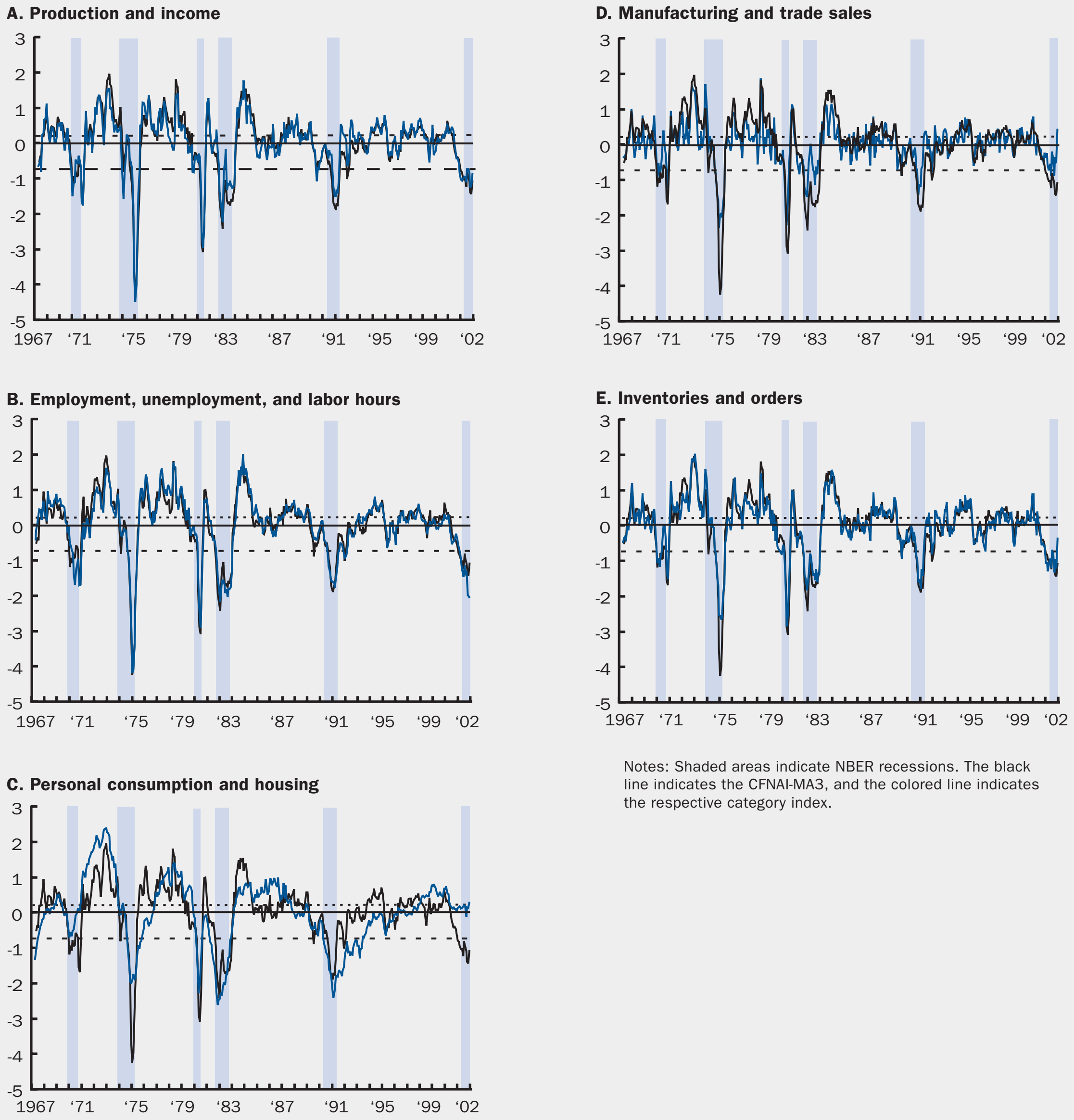
In the spring of 2000, the U.S. economy was continuing to expand at a rate that was above its potential growth rate. Second-quarter real gross domestic product (GDP) growth was 5.7 percent. Monetary policy had shifted to a relatively tight stance. The federal funds rate began its initial increase in June 1999 from 4.75 percent to 6.50 percent in May 2000. By the summer of 2000, business analysts' were expecting the economy to begin a transition from above-trend growth to a period of below-trend growth. Growth rates of industrial production turned negative beginning in July 2000, while other indicators began to cool noticeably. The January 2001 release of the CFNAI reported that the CFNAI-MA3 had fallen below zero in July 2000. As zero represents the economy growing at trend, the index captured the transition that business analysts in the press had been discussing.

Much of the initial drop in the CFNAI-MA3 comes from industrial production and the ISM Purchasing Managers Index data. These components provided strongly negative weight to the other index components that were more evenly spread around trend growth behavior. Figure 4 displays category indexes representing each of the five data categories of the CFNAI from 1986 through 2001. The category indexes are constructed by summing only the weighted series in each respective category. Each category index is then re-scaled to have a standard deviation of one. With this transformation, if any of the category indexes captured all of the movements of the CFNAI, the two would lie on top of each other in figure 4.

The production/income (panel A), employment (panel B), and inventory/orders (panel E) categories track the initial decline in economic activity pretty well for the second half of 2000. Manufacturing/trade (panel D) captured some of this decline, while the consumer (panel C) category did not fall below zero at all in 2000. Once the recession began in March 2001, according to the NBER business cycle dating committee, the categories began to diverge to a greater extent. The production/income and inventory/orders categories moved with the total CFNAI-MA3 during this period. The employment category, however, fell much more sharply, particularly beginning in March 2001. This latter observation is not surprising in the context of the NBER's announcements regarding the selection of March 2001 as the most recent business cycle peak. The dating committee mentioned that movements in payroll employment were decisive in

FIGURE 4

CFNAI category indexes—MA3 and business cycles (1967–2001)



Notes: Shaded areas indicate NBER recessions. The black line indicates the CFNAI-MA3, and the colored line indicates the respective category index.

picking the date, and very important in the overall determination that the economy had entered recession.

Within the full index, figure 4 displays some degree of heterogeneity among the category indexes during the recession of 2001. Manufacturing/trade fell less than the overall index. And the consumer category hardly registered any negative values. Simply using the consumer category as a proxy for the CFNAI would clearly result in different inferences. The production and employment categories move much more strongly with the full index, although there are periodic differences in magnitude.

Is there value in diversifying the basket of economic indicators?

The previous discussion raises the issue: How many indicators are necessary to provide an accurate description of the state of economic activity? Does it take a large number of economic indicators to filter out the idiosyncratic noise, or can a single, favorite indicator do the trick? Most analysts' first approach to answering this question would involve producing large numbers of graphs and staring. Figure 5 (on page 34) provides an abbreviated tour of the data.

Figure 5 displays graphs of several baskets of economic indicators, as well as individual indicators. Each panel graphs a three-month moving average of the indicator against the CFNAI-MA3. We consider two questions here: 1) How does the individual indicator compare with the CFNAI-MA3?; and 2) How well does the individual indicator perform at detecting recessions and expansions using thresholds like –0.70 and +0.20?

Are 85 real indicators enough? The CFNAI contains only 85 indicators. Perhaps worse still, none of these are financial indicators that have a proven track record of periodically signaling turning points. An alternative approach would construct an economic index using a larger set of data that include financial, monetary, and price variables. Figure 5, panel A displays an analogous index employing 166 economic, financial, monetary, and price indicators. The striking feature of panel A is that the two measures are nearly identical. Apparently, the first principal component of this larger dataset is essentially an activity index. This observation was originally made by Stock and Watson (1999a).

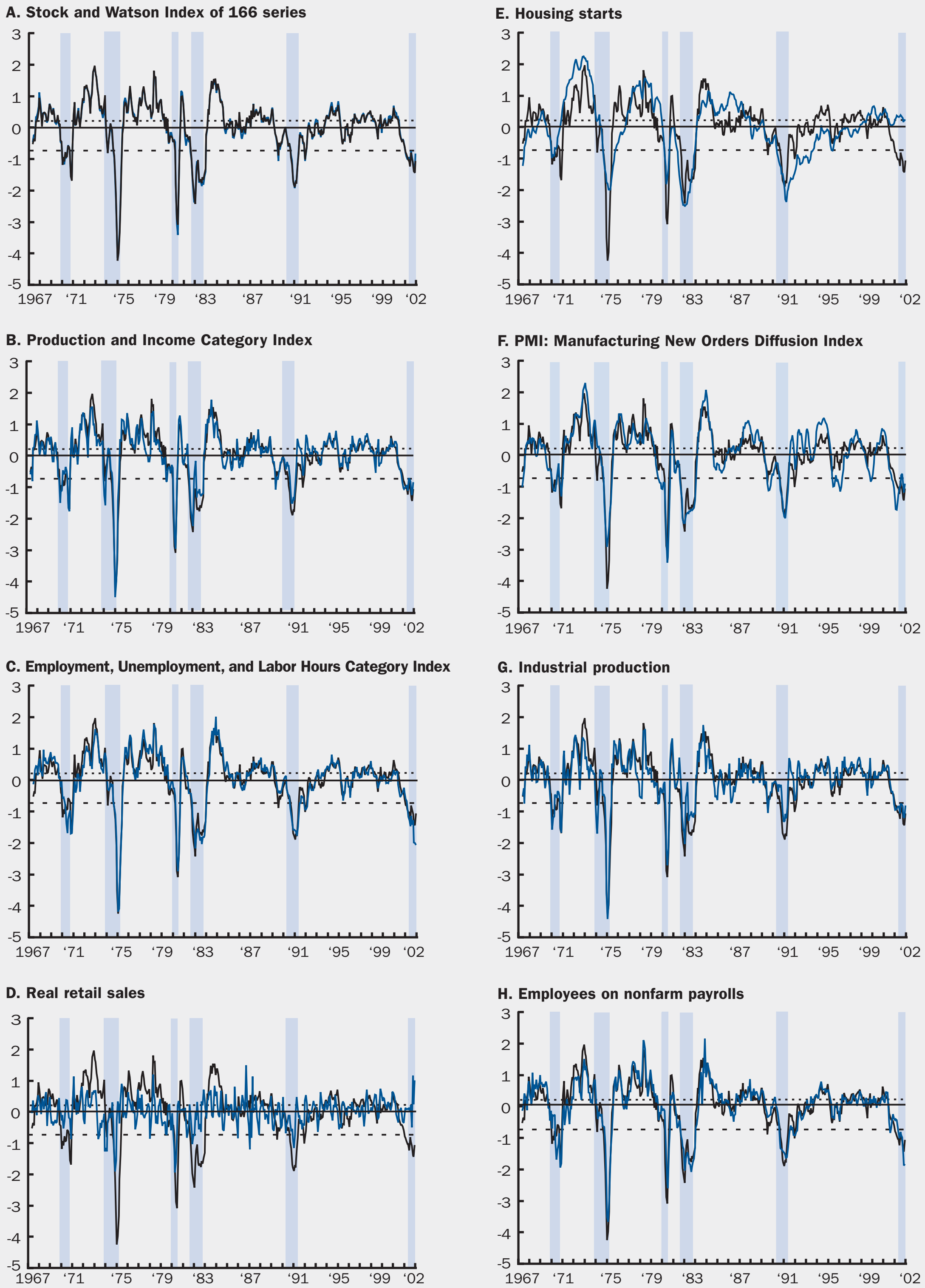
Do we really need 85 indicators? In our earlier analysis of the 2001 recession, we found that subcomponents of the CFNAI performed reasonably well in tracking the economic downturn. Perhaps a smaller index performs just as well as the CFNAI. Figure 5, panels B and C display the production and employment category indexes, respectively. The production index follows the CFNAI-MA3 quite closely, and there appear to be few differences in inference about business cycle turning points. Both suffer from the false recession signal in July 1989. The production index has an additional false positive prior to the onset of the 1980 recession. The CFNAI-MA3 was in negative territory in 1979 prior to the recession, but it did not cross the –0.70 threshold until 1980. Following the 1990–91 recession, the production index signals the end of the recession much sooner than the full index. However, the slow expansion in 1991–92 makes this virtue a bit hollow. In 1991, the production index has a close brush with calling a second recession. The CFNAI-MA3 moved lower in 1991 than the production index; but since the index had not determined the end of the recession, it would not be a second recession. In both cases, the 1990–92 period is a difficult one. The employment component in figure 5, panel C also performs reasonably well. On the plus side, this component did not falsely signal a recession in July 1989. On the downside, it did not capture the 1973–75 recession until late 1974, almost at its end. In summary, smaller component indexes may perform about as well as the CFNAI, but more experience is required to sort this out.

Many individual indicators provide false signals. As the focus narrows to individual economic indicators, it is not surprising that many series provide false readings on the state of the aggregate economy. The discussion of the consumption and manufacturing/trade categories of the CFNAI suggests that many of these data are poor candidates by themselves. Figure 5, panels D, E, and F display real retail sales growth, housing starts, and the PMI New Orders Index, respectively. Each series has been transformed to be mean zero and unit standard deviation and is a three-month moving average. Retail sales growth is quite volatile and often falls below the –0.70 threshold when the economy is not in recession. Housing starts tend to be low during most recessions. The slow recoveries following the 1973–75 and 1990–91 recessions suggest that this indicator does not provide a quick indication of economic recovery. In addition, there were false recession warnings in 1967 and 1996; and the 2001 recession has been missed completely. Similarly, the PMI New Orders Index captures the five recessions prior to 2001, as well as the current one. However, there are several false warnings: 1967, 1996, and 1998. Many single economic indicators contain transient fluctuations that are not related to the state of the economy.

Some individual indicators do pretty well. Because the CFNAI gives substantial weight to data on industrial production and employment, it may be the case that single indicators in this category provide similar information to the CFNAI. Figure 5, panels G and H display growth rates of industrial production and private payroll employment. Similar to the CFNAI category measures, these indicators do pretty well. For both of them, recessions are periods when industrial production and employment are low and below –1.00. Using a recession threshold of –0.70 for industrial production admits a couple of false recession warnings, but the performance improves if the lower threshold is decreased further to –1.00. Employment seems to do better than industrial production. This may be because the NBER has tended to focus the recession determination on employment data more than on industrial production, at least in recent years.

FIGURE 5

CFNAI-MA3 versus select economic indicators, three-month moving average (1967–2001)



Note: Shaded areas indicate NBER recessions. The black line indicates the CFNAI-MA3, and the colored line indicates the respective economic indicator.

Summary of analysis

To sum up, our visual inspection of individual data series suggests that the CFNAI-MA3 does not perform appreciably better than the workhorse NBER coincident economic indicators like industrial production and private payroll employment. But an essential question is: How much of this has been the result of data-mining from the small number of recessions under examination? The idiosyncratic statistical noise in individual data series may have simply been small enough over this period to make a couple of data series work. In pooling 85 economic indicators for the CFNAI, the method is purchasing an insurance policy against statistical noise. And just like a home insurance policy, the mere fact that a house hasn't burned down in the ten years that it has been insured does not mean that the insurance was unnecessary. To address this issue over a longer period, we now turn to simulation results of an empirically relevant statistical model.

Statistical approach and Monte Carlo simulations

The preceding historical analysis provides only a limited assessment of the CFNAI because the five-recession sample during the 1967–2000 period is small in statistical terms. For this reason, we have developed and analyzed Monte Carlo simulations of a business cycle index, 85 economic indicators, and the activity index to assess patterns based on a larger number of simulated observations.

The challenge is to estimate an empirically relevant set of business cycles and 85 equations for the economic indicators. For the business cycle indicator, we adopt a nonlinear Markov-switching process developed by Hamilton (1989). This model states that real activity transitions exogenously between expansionary and contractionary rates of growth, while capturing the historical average duration of business cycle expansions and recessions. Diebold and Rudebusch (1996) have also studied a system like this. For the economic indicator equations, we follow the unobserved component model studied by Stock and Watson (1989). This specification states that each indicator is related to the business cycle index but also is contaminated by independent statistical noise. This captures the idea that each of the indicators has an idiosyncratic component that is not related to aggregate activity. Precise details on these specifications and the estimation strategy are reported in the appendix.

Given estimates of our statistical model from the 1967–2000 period, we conduct Monte Carlo simulations for the economy over a period of approximately 2,000 years. During this period, the nonlinear Markov-switching model generates 404 recessions. We can use the simulated data for the 85 economic indicators to compute a CFNAI index over the 2,000-year period. With these data, we can repeat the exercise of using the CFNAI to decide if the economy has entered a recession. Specifically, for any given recession threshold of $-r$, we calculate whether the CFNAI-MA3 indicates the economy is in recession. The procedure works as follows.

1. Begin with the economy in an expansionary state.
2. If the CFNAI-MA3 falls below $-r$ from above, then the economy is in a "CFNAI recession."
3. The CFNAI recession continues until the CFNAI-MA3 rises above +0.20, and then the economy is in a "CFNAI expansion."

Repeating steps 1 through 3 until the data sample is exhausted provides a long time-series of business cycle dates according to the CFNAI-MA3 criterion.

The advantage of the laboratory environment is that the experimental design allows us to know at any date whether the true state of the simulated economy is expansion or contraction. We can tabulate what percentage of the time a CFNAI recession is in fact a true recession, and also what percentage of recessions are missed by the CFNAI using a threshold of $-r$. For example, using a threshold of –0.70, the CFNAI-MA3 criterion determined that 394 recessions occurred during the 2,000 years of simulations. On the date that the recession call occurred, the true state of the business cycle was a recession in only 285 of the 394 recession calls. At this threshold, the frequency of success in calling a recession was 72 percent. This frequency can also be thought of as the *probability that a "recession call" is correct.* Notice that 119 recessions were missed (404 true recession minus 285 correct recessions). Therefore, the frequency of failing to call a recession was 29 percent when the threshold criterion insisted that the moving average index fall below –0.70.[3] These are cases where the true economy was in recession, but the severity of the downturn was relatively modest.[4]

Before turning to the overall simulation results, notice that we can also compute the success of other indicators in calling recessions. We consider three additional gauges. First, given the visual success of the industrial production three-month moving index, we have tabulated the success frequencies for a measure we call IP3. Second, given the visual failure for consumption measures, we tabulated success frequencies based upon a real personal consumption expenditure measure, referred to as CON3. Third, in order to assess the overall accuracy of the CFNAI-MA3 measure, we tabulated a success frequency for an unobserved measure of the business cycle that is common to all 85 economic indicators. By construction, this measure has no indicator-specific idiosyncratic noise. In some sense, this is a virtually ideal indicator of the business cycle. We refer to this as ZSIM3, and it corresponds to observing z directly (as defined in the appendix).

Table 1 reports the simulation frequency results for all four moving average indexes, using thresholds from –0.70 to –2.20. Recall that during the 2,000-year period of the exercise, the simulated business cycle generates 404 "true" recessions.

First, consider the results for the CFNAI-MA3. As we mentioned above, with a threshold of –0.70, the probability that the economy has moved into recession is 0.72. A practical application of this can be seen from the March 2001 release of the CFNAI. As reported on May 31, 2001, the March 2001 CFNAI-MA3 was –0.80. According to the simulation results here, that corresponds to approximately a 75 percent probability that the economy was in recession. In fact, the NBER reported in November that the economy entered a recession in March, but the Business Cycle Dating Committee also mentioned that without the terrorist attacks of September 11, the economy might not have gone into recession. Our calculations indicate a relatively high likelihood, three out of four chances, that the economy was in recession prior to the terrorist attacks. Next, notice that as the threshold for calling a recession becomes more stringent, the probability of making a false recession call becomes less likely. The CFNAI releases during 2001 pointed out that every economic recession since 1967 had breached the –1.50 level, and most had declined much more. The Monte Carlo simulations attach a 0.95 probability to a threshold of –1.50, which seems consistent with these observations. Not surprisingly, this increased reliability comes at a higher cost. As the threshold tightens, more true recessions are missed because they are not sufficiently deep. Taken to an extreme, a very large, negative threshold would likely guarantee that recessions as deep as the Great Depression would be captured, but perhaps at the cost of missing large recessions such as 1973–75 or 1981–82.

The simulation results indicate that the CFNAI-MA3 filters out almost all of the idiosyncratic noise from the individual 85 economic indicators. Specifically, if the aggregate indicator z were directly observable, then the ZSIM3 measure could be constructed. At a threshold of –0.70, whenever ZSIM3 crossed this threshold, there would be a 74 percent probability that the economy was in recession, compared with the CFNAI-MA3 probability of 72 percent. Across the range of thresholds considered, these differences are essentially negligible.

Looking at the performance of IP3, however, the differences appear to be more substantial at first

TABLE 1

Simulation frequency results for all four moving average indexes

	Probability that recession call is correct				Probability that recession is missed			
Threshold	**ZSIM3**	**CFNAI–MA3**	**IP3**	**CON3**	**ZSIM3**	**CFNAI–MA3**	**IP3**	**CON3**
–0.70	0.74	0.72	0.51	0.35	0.27	0.29	0.23	0.26
–0.80	0.78	0.76	0.58	0.38	0.27	0.30	0.25	0.37
–0.90	0.83	0.81	0.67	0.44	0.27	0.30	0.25	0.48
–1.00	0.86	0.85	0.70	0.46	0.28	0.29	0.29	0.57
–1.10	0.89	0.88	0.73	0.55	0.30	0.30	0.34	0.67
–1.20	0.92	0.92	0.77	0.57	0.33	0.33	0.39	0.77
–1.30	0.93	0.94	0.81	0.57	0.37	0.36	0.45	0.85
–1.40	0.94	0.94	0.84	0.57	0.40	0.40	0.53	0.90
–1.50	0.96	0.95	0.89	0.65	0.43	0.45	0.57	0.93
–1.60	0.97	0.96	0.94	0.70	0.49	0.50	0.65	0.96
–1.70	0.98	0.97	0.96	0.67	0.56	0.54	0.71	0.98
–1.80	0.99	0.99	0.98	0.62	0.60	0.60	0.78	0.99
–1.90	0.99	0.99	0.99	N/A	0.66	0.65	0.83	N/A
–2.00	0.99	0.99	0.98	N/A	0.72	0.71	0.87	N/A
–2.10	0.99	0.99	0.97	N/A	0.78	0.76	0.92	N/A
–2.20	0.99	0.99	0.96	N/A	0.81	0.80	0.94	N/A

Note: N/A indicates not applicable.

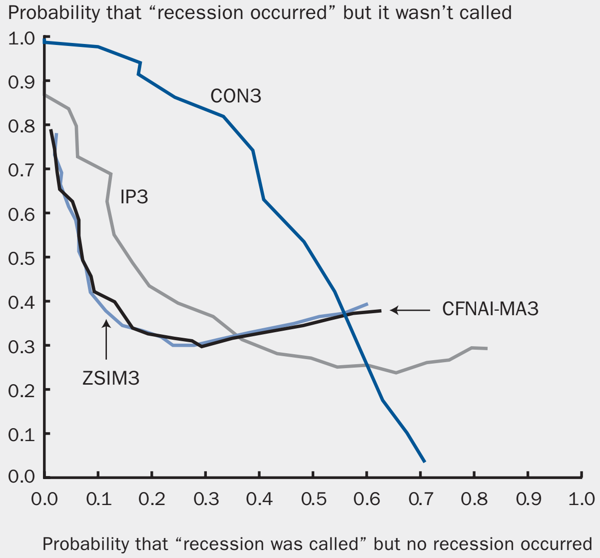
glance. At a threshold of –0.70, the IP3 measure has a recession success probability of only 51 percent. However, industrial production exhibits deeper reductions during recessions, so a lower threshold may be more accurate. In fact, at –1.00, the IP3 success rate is 70 percent, with only a missed probability of 29 percent. This is essentially the same performance as the CFNAI-MA3 at the –0.70 threshold.

A cleaner comparison of these performances is to graph the probability trade-offs for each indicator on the same graph. For each indicators' threshold, figure 6 plots a pair of probabilities: the probability that "a recession was called" when no recession occurred versus the probability that "a recession occurred" but wasn't called. The most efficient indicators will minimize both of these probabilities and exhibit a probability frontier, which is concentrated in the southwest portion of the figure.

Figure 6 clearly displays two useful properties of the CFNAI-MA3 as a business cycle indicator. First, the performance of CFNAI-MA3 closely follows the performance of the unobservable index ZSIM3. By using the CFNAI to filter out idiosyncratic noise in the 85 economic indicators, we lose little by not observing the z indicator. Second, the IP3 indicator only performs better than the CFNAI-MA3 at levels of false positives that most analysts would deem unacceptable. As long as the probability of *successfully calling a recession* exceeds 65 percent, the CFNAI-MA3 and ZSIM3 provide lower rates of *failing to call a recession* than the IP3 index. Finally, focusing on consumption indicators alone is unlikely to provide useful indicators of business cycle turning points. The CON3 frontier is dominated by the other indicators for all reasonable probabilities. This is not really surprising, considering that household spending indicators do not always turn down dramatically during recessions. During the 2001 recession, which is not included in the simulated business cycle analysis here, the economy continued to experience strong growth in consumer spending during much of the downturn.

FIGURE 6

Risk trade-offs in deciding to call a recession



Conclusion

The Chicago Fed National Activity Index was launched on March 5, 2001, and was promptly tested by the deceleration of U.S. economic growth that began in the summer of 2000. Throughout this period, the CFNAI release discussed how the low index values below –0.70 had previously been associated with economic recessions, and each successive month in 2001 was showing an increasing probability that the economy was already in recession. The NBER later declared that the economy officially entered recession in March 2001. The statistical analysis presented in this article indicates that the March 2001 CFNAI-MA3 of –0.80 was associated with a 75 percent probability that the economy was in recession at that time. The March CFNAI was released on May 2, 2001, compared with the NBER report in November 2001. Consequently, the real-time experience with the index and the statistical analysis here seem consistent with the view that the Chicago Fed National Activity Index is a good early warning indicator of current economic conditions.

NOTES

[1]See NBER (2001).

[2]More specifically, the NBER recession periods were December 1969–November 1970, November 1973–March 1975, January 1980–July 1980, July 1981–November 1982, and July 1990–March 1991. According to the NBER definition of contraction (recession), the first date of each recession period indicates the peak of a business cycle, and the second date indicates the subsequent trough of the cycle.

[3]Notice that given knowledge of the total number of true recessions, 404, the two percentages are sufficient to recover the number of "recessions called," "correctly called recessions," and "recessions not called."

[4]The Monte Carlo simulations of the Hamilton–Markov switching process include a restriction that recessions and expansions can be no shorter than six months. The stochastic process described in the appendix has the property that the economy could shift to recession for a single month. Although this is not likely, short recessions do occur over a 2,000-year simulation. In the simulations, if the economy shifted from one state to another before six months had elapsed, we assumed that the shift happened at the six-month mark. This had no noticeable effect on the average duration of recessions in the simulations.

APPENDIX: MONTE CARLO SIMULATION METHODS

The Monte Carlo simulation consists of four parts. First, we specify two models: a model of the business cycle index and a model of the relationship between the (unobserved) business cycle index and the observable parts of the economy. Second, we estimate the parameters required for the models using data from historical indicators. Third, using the estimated parameters, we simulate the unobservable business cycle index and the 85 observable series. Finally, we compute the simulated CFNAI index as a weighted average of these 85 simulated series, and we evaluate the ability of the activity index to signal turning points in the simulated business cycle index.

Model of the business cycle and observable series

Heuristically, a single index of the business cycle indicates whether the aggregate economy is expanding or contracting. Because of the complexities of large, dynamic, and decentralized economies, individual economic indicators will be correlated with this latent index of the business cycle, but are measured with idiosyncratic noise.

We use the Hamilton regime-switching model (Hamilton, 1989, and Diebold and Rudebusch, 1996) to formalize the behavior of the business cycle index. In particular, we express unobservable real activity as:

1) $$z_t = \mu_{exp} + \mu_{recess} S_t + \tilde{z}_t,$$

where

z_t is the (unobservable) growth in economic activity;

μ_{exp} is the growth of economic activity during expansions;

$\mu_{recess} + \mu_{exp}$ is the growth of economic activity during recessions;

$S_t \in \{0,1\}$ is the binary random variable identifying the state/regime, where $S_t = 0$ designates an expansion and $S_t = 1$ designates a recession, and the switching between expansion and recession states is determined by Markov transition probabilities; and

$\tilde{z}_t$ is a noise term that follows an AR(1) process, namely

2) $$\tilde{z}_t = \varphi \tilde{z}_{t-1} + v_t,$$

where

$v_t \sim N(0, \sigma_v^2)$, is independent and identically distributed (i.i.d.). $\tilde{z}_t$ is a deviation of current growth from trend growth, which is independent of the business cycle state S.

In this way, latent economic activity is modeled as a non-linear process with cyclical noise.

We model the observable variables x to be noisy measures of z_t. In particular, we specify that each of the 85 observable variables is determined by:

3) $$x_{it} = \gamma_i z_t + u_{it},$$

where

x_{it} is the observable indicator, where $1 \leq i \leq 85$, and

u_{it} is a noise term that follows an AR(1) process:

4) $$u_{it} = d_i u_{it-1} + \varepsilon_{it}, \text{ where } \varepsilon_{it} \sim N(0,\ )\ \sigma_{\varepsilon_i}^2 \text{ is i.i.d.}$$

Similar specifications have been studied in many aggregate time series studies; see Stock and Watson (1989) for an extended example and additional references. Combining equations 1 and 3, we have:

5) $$x_{it} = \gamma_i (\mu_{\exp} + \mu_{recess} S_t) + w_{it},$$

where

TABLE A1	
Estimated business cycle parameters	
$\hat{\mu}_{\exp} = 4.4\%$	$\Pr\{S_t = 0 \mid S_{t-1} = 0\} = 0.98$
$\hat{\mu}_{recess} = -1.6\%$	$\Pr\{S_t = 1 \mid S_{t-1} = 1\} = 0.91$
$\hat{\varphi} = 0.94$	$\hat{\sigma}^2_v = 0.653$

$$6)\quad w_{it} = \gamma_i \, \tilde{z}_t + u_{it}.$$

It is important to recognize that S, $\tilde{z}$, and u are mutually independent. Similar assumptions are typically employed in the empirical literature, as in Hamilton (1989), Diebold and Rudebusch (1996), and Stock and Watson (1989).

Estimation of parameters

To provide empirically interesting simulation experiments, we need estimates of the model parameters μ_{exp}, μ_{recess}, the Markov transition probabilities, φ, σ^2_v, γ_i, d_i, and σ^2_v for each indicator x_i.

We estimate μ_{exp} and μ_{recess} from the growth rates of real GDP from 1947 to 2000. Specifically, we compute the growth rate of real GDP during each expansionary period and each recessionary period (as identified by the NBER). We then set the parameter μ_{exp} equal to the average GDP growth rate over all expansions, and $\mu_{recess} + \mu_{exp}$ equal to the average growth rate over all recessions. Table A1 lists the estimated values of these parameters.

The transition probabilities are calibrated so that they correspond to the average length of historical expansions and recessions. In particular, we use the relations that the duration of an expansion = 1/(1 – probability of remaining in an expansion), and the duration of a recession = 1/(1– probability of remaining in a recession). That is, the mean duration of an expansion $= 1/(1 - \Pr\{S_t = 0 \mid S_{t-1} = 0\})$, and the mean duration of a recession $= 1/(1 - \Pr\{S_t = 1 \mid S_{t-1} = 1\})$. Based upon the NBER business cycle dates for 1947–2000, the mean duration of an expansion has been 50 months and the mean duration of a recession has been 12 months. The transition probabilities based on these calculations are also shown in table A1.

To find estimates of γ_i, we regress each of the 85 actual indicators on $\hat{\mu}_{\exp} + \hat{\mu}_{recess} S_t$ for the period 1967–2000, where S is the binary variable indicating expansionary and recessionary periods. This regression is well specified, given the independence of S, $\tilde{z}$, and u. For values of S, we note that Hamilton (1989) finds that his Kalman-smoothed inferences of the latent business cycle index correspond reasonably closely with the NBER business cycle dates. Let $S = 0$ during expansion months and $S = 1$ during recession months.[1] According to equation 5, this regression gives us $\hat{\gamma}_i$ and $\hat{w}_i$ for each of the i indicators.

To estimate the remaining parameters, we make an additional assumption that allows us to use a simple method of moments estimator. The additional assumption is that there are two "instrument" indicators that reflect the business cycle to the same degree. Specifically, let x_1 and x_2 be as follows:

$$7)\quad x_{1t} = \gamma_1 z_t + u_{1t} = \gamma_1(\mu_{\exp} + \mu_{recess} S_t) + w_{1t},$$

and

$$8)\quad x_{2t} = \gamma_2 z_t + u_{2t} = \gamma_2(\mu_{\exp} + \mu_{recess} S_t) + w_{2t},$$

with the restriction that

$$9)\quad \gamma_1 = \gamma_2 = \gamma.$$

As noted earlier, the disturbance terms w_1 and w_2 are independently distributed. This restriction is most likely to be satisfied when two indicators attempt to measure the same economic phenomenon but are from different source data. An example of this is in Prescott (1986), when he proposes a probability model of measured employment hours based upon the establishment survey and the household survey. Another example is where the two indicators have a similar relationship to the business cycle index, but are measured with different levels of precision. For example, equation 9 might hold even when one indicator was a measure of output and another was a measure of input. In any event, the two instrument indicators used in this study are Private Payroll Employment growth from the BLS and the Institute for Supply Management's Purchasing Managers Index of New Orders. The source data for these two series are clearly independent. In addition, the restriction in equation 9 is not rejected by the parameter estimates for these two indicators.

We use the restriction in equation 9 to estimate φ and σ^2_v, and (for each indicator) d_i and $\sigma^2_{\varepsilon_i}$. Using equation 6, we first note that:

$$10)\quad w_{it} - \frac{\gamma_i}{\gamma_2} w_{2t} = u_{it} - \frac{\gamma_i}{\gamma_2} u_{2t}.$$

To find an estimate of d_i, we use equations 4, 6, and 10 and find that:

$$11)\quad E[(w_{it} - \frac{\gamma_i}{\gamma_2} w_{2t}) w_{it}] = E[u^2_{it}] = \sigma^2_{u_i};$$

TABLE A2

Estimated parameters of selected indicator equations

Indicator	$\hat{\gamma}_i$	$\hat{d}_i$	$\hat{\sigma}^2_{\varepsilon_i}$	R^2
PMI, new orders	0.282	0.715	0.399	0.673
Employment, private	0.272	0.297	0.578	0.636
Employment, nonagriculture	0.268	–0.244	0.601	0.619
Employment, goods industry	0.278	–0.190	0.566	0.670
Unemployment rate	–0.232	–0.436	0.686	0.426
Help-wanted ads	0.197	–0.431	0.731	0.341
PMI, production	0.288	0.724	0.372	0.709
Industrial production	0.229	–0.184	0.725	0.458
IP, manufacturing	0.236	–0.243	0.701	0.479
Capacity utilization, manufacturing	0.221	–0.195	0.726	0.451
Personal income, transfers	0.197	–0.128	0.837	0.296
Housing permits	0.256	0.915	0.273	0.542
Housing starts, Midwest	0.213	0.765	0.500	0.403
Housing starts, West	0.253	0.839	0.383	0.494
Manufacturing and trade sales	0.153	–0.392	0.841	0.169
Retail sales (real)	0.081	–0.271	0.949	0.036
Personal consumption expenditures	0.092	–0.312	0.930	0.050
New orders, construction, and materials	0.130	–0.250	0.909	0.128
Manufacturing and trade, inventory/sales	–0.117	–0.238	0.933	0.083

Note: The variables being measured in this table are derived from equation 3—$x_{it} = \gamma_i z_t + u_{it}$—and equation 4—$u_{it} = d_i u_{it-1} + \varepsilon_{it}$—where $\varepsilon_{it} \sim N(0, \sigma^2_{\varepsilon_i})$.

12) $$E[(w_{it} - \frac{\gamma_i}{\gamma_2} w_{2t})w_{it-1}] = d_i E[u^2_{it-1}] = d_i \sigma^2_{u_i} .$$

From equations 11 and 12, it is clear that:

13) $$d_i = \frac{E[(w_{it} - \frac{\gamma_i}{\gamma_2} w_{2t})w_{it-1}]}{E[(w_{it} - \frac{\gamma_i}{\gamma_2} w_{2t})w_{it}]} .$$

Because we have estimates of γ_i and w_i, we can use equation 13 to find $\hat{d}_i$.

To find estimates of $\sigma^2_{\varepsilon_i}$, we note that equation 4 implies the following relationship between the variances of ε_i and u_i:

14) $$\sigma^2_{\varepsilon_i} = (1 - d^2_i)\sigma^2_{u_i} .$$

Since $\sigma^2_{u_i}$ can be estimated using equation 11, we can easily obtain estimates of $\sigma^2_{\varepsilon_i}$ using equation 14. Similarly, we obtain an estimate of φ by noting that equations 2 and 6 imply:

15) $$E[w_{1t} w_{2t}] = \gamma^2 \sigma^2_{\tilde{z}}$$

and

16) $$E[w_{1t} w_{2t-1}] = \gamma^2 \varphi \sigma^2_{\tilde{z}} .$$

From equations 15 and 16, we see that:

17) $$\varphi = \frac{E[w_{1t} w_{2t-1}]}{E[w_{1t} w_{2t}]} .$$

To obtain an estimate of σ^2_v, we note that equation 2 implies:

18) $$\sigma^2_v = (1 - \varphi^2)\sigma^2_{\tilde{z}} \text{, where } \sigma^2_{\tilde{z}} = \frac{1}{\gamma^2} E[w_{1t} w_{2t}] .$$

Finally, in estimating parameters for a particular x_{it}, the choice of instrument indicator (x_{2t}) will depend on whether x_{it} is from the ISM data release or not. For example, if x_{it} corresponds to a component of the Purchasing Managers Index, then x_{2t} will be payroll employment; otherwise, it will be the PMI New Orders Index. Table A2 presents a partial listing of the indicator parameter estimates. Table A3 lists all of the component data series in the CFNAI.

[1]NBER recessions are designated from peak to trough. For these exercises, we consider the peak and trough months as part of the recession period.

TABLE A3

CFNAI component data series

Production and income (21 series)		
CUMFG	DLV	Capacity utilization: Manufacturing SA, percent of capacity
IP	DLN	Industrial Production Index SA, 1992=100
IP51	DLN	Industrial Production: Consumer goods SA, 1992=100
IP5102	DLN	Industrial Production: Durable consumer goods SA, 1992=100
IP51021	DLN	Industrial Production: Nondurable consumer goods SA, 1992=100
IP52001	DLN	Industrial Production: Business equipment SA, 1992=100
IP53	DLN	Industrial Production: Materials SA, 1992=100
IP53011	DLN	Industrial Production: Materials: Durable SA, 1992=100
IP53017	DLN	Industrial Production: Materials: Nondurable SA, 1992=100
IP54	DLN	Industrial Production: Intermediate products SA, 1992=100
IPDG	DLN	Industrial Production: Durable manufacturing SA, 1992=100
IPFP	DLN	Industrial Production: Final products SA, 1992=100
IPMFG	DLN	Industrial Production: Manufacturing SA, 1992=100
IPMIN	DLN	Industrial Production: Mining SA, 1992=100
IPND	DLN	Industrial Production: Nondurable manufacturing SA, 1992=100
IPTP	DLN	Industrial Production: Products SA, 1992=100
IPUTI	DLN	Industrial Production: Utilities SA, 1992=100
NAPMC	LV	Institute for Supply Management: Manufacturing: Composite Index SA, percent
NAPMOI	LV	Institute for Supply Management: Manufacturing: Diffusion Index, Production SA, percent
YPDHM	DLN	Disposable personal income SAAR, billions of chained 1996$
YPLTPMH	DLN	Real personal income less transfer payments SAAR, billions of chained 1996$
Employment, unemployment and labor hours (24 series)		
A0M005	DLV	Weekly initial claims for unemployment insurance SA, thousands
LACONSA	DLN	All employees: Construction SA, thousands
LADURGA	DLN	All employees: Durable goods manufacturing SA, thousands
LAFIREA	DLN	All employees: Finance, insurance, and real estate SA, thousands
LAGOODA	DLN	All employees: Goods-producing industries SA, thousands
LAGOVTA	DLN	All employees: Government SA, thousands
LAMANUA	DLN	All employees: Manufacturing SA, thousands
LAMINGA	DLN	All employees: Mining SA, thousands
LANAGRA	DLN	Employees on nonfarm payrolls SA, thousands
LANDURA	DLN	All employees: Nondurable goods manufacturing SA, thousands
LAPRIVA	DLN	All employees: Private nonfarm payrolls SA, thousands
LARTRDA+LAWTRDA	DLN	All employees: Retail and wholesale trade SA, thousands
LASERPA	DLN	All employees: Service-producing industries SA, thousands
LASRVSA	DLN	All employees: Services SA, thousands
LATPUTA	DLN	All employees: Transportation and public utilities SA, thousands
LE	DLN	Civilian employment: Sixteen years & over SA, thousands
LENA	DLN	Civilian employment: Nonagricultural industries SA, thousands
LHELP	DLN	Index of help-wanted advertising in newspapers SA, 1987=100
LHELPR	DLN	Ratio: Help-wanted advertising in newspapers/number unemployed SA
LOMANUA	DLV	Average weekly overtime hours: Manufacturing SA, hours
LR	DLV	Civilian unemployment rate SA, percent
LRM25	DLV	Civilian unemployment rate: Men, 25–54 years SA, percent
LRMANUA	DLV	Average weekly hours: Manufacturing SA, hours
NAPMEI	LV	Institute for Supply Management: Manufacturing: Diffusion Index, Employment SA, percent
Personal consumption and housing (13 series)		
CBHM	DLN	Personal consumption expenditures SAAR, billions of chained 1996$
CDBHM	DLN	Personal consumption expenditures: Durable goods SAAR, billions of chained 1996$
CDMNHM	DLN	Personal consumption expenditures: New autos SAAR, millions of chained 1996$
CNBHM	DLN	Personal consumption expenditures: Nondurable goods SAAR, billions of chained 1996$
CONDO9	LN	Construction contracts, millions of square feet
CSBHM	DLN	Personal consumption expenditures: Services SAAR, billions of chained 1996$
HPT	LN	Housing units authorized by building permit SAAR, thousands of units
HSM	LN	Manufacturers' shipment of mobile homes SAAR, thousands of units
HST	LN	Housing starts SAAR, thousands of units
HSTMW	LN	Housing starts: Midwest SAAR, thousands of units
HSTNE	LN	Housing starts: Northeast SAAR, thousands of units
HSTS	LN	Housing starts: South SAAR, thousands of units
HSTW	LN	Housing starts: West SAAR, thousands of units

TABLE A3 (CONTINUED)

CFNAI component data series

Manufacturing and trade sales (11 series)		
NAPMVDI	LV	Institute for Supply Management: Manufacturing: Diffusion Index, Vendor Deliveries SA, percent
RSDH	DLN	Real retail sales: Durable goods SA, millions of chained 1996$
RSH	DLN	Real retail sales SA, millions of chained 1996$
RSNH	DLN	Real retail sales: Nondurable goods SA, millions of chained 1996$
TSMDH	DLN	Sales: Manufacturing: Durable Goods SA, millions of chained 1996$
TSMH	DLN	Sales: Manufacturing SA, millions of chained 1996$
TSMNH	DLN	Sales: Manufacturing: Nondurable goods SA, millions of chained 1996$
TSTH	DLN	Real manufacturing and trade: Sales SA, millions of chained 1996$
TSWDH	DLN	Sales: Wholesale: Durable goods SA, millions of chained 1996$
TSWH	DLN	Sales: Merchant wholesalers SA, millions of chained 1996$
TSWNH	DLN	Sales: Wholesale: Nondurable goods SA, millions of chained 1996$
Inventories and orders (16 series)		
A0M007	DLN	Real manufacturers' new orders: Durable goods industries, billions of chained 1996$
A0M008	DLN	Real manufacturers' new orders: Consumer goods & materials SA, millions of 1996$
A0M020	DLN	Contracts and orders for plant and equipment, billions of chained 1996$
A0M027	DLN	Real manufacturers' new orders: Nondefense capital goods industries SA, millions of 1996$
NAPMII	LV	Institute for Supply Management: Manufacturing: Diffusion Index, Inventory SA, percent
NAPMNI	LV	Institute for Supply Management: Manufacturing: Diffusion Index, New orders SA, percent
TIMDH	DLN	Inventories: Manufacturing: Durable goods EOP, SA, millions of chained 1996$
TIMH	DLN	Inventories: Manufacturing EOP, SA, millions of chained 1996$
TIMNH	DLN	Inventories: Manufacturing: Nondurable goods EOP, SA, millions of chained 1996$
TIRH	DLN	Inventories: Retail trade EOP, SA, millions of chained 1996$
TITH	DLN	Real manufacturing & trade inventories EOP, SA, millions of chained 1996$
TIWH	DLN	Inventories: Merchant wholesalers EOP, SA, millions of chained 1996$
TRMH	DLV	Inventory/sales ratio: Manufacturing SA, chained 1996$
TRRH	DLV	Inventory/sales ratio: Retail trade SA, chained 1996$
TRTH	DLV	Real manufacturing and trade: Inventory/sales ratio SA, chained 1996$
TRWH	DLV	Inventory/sales ratio: Merchant wholesalers SA, chained 1996$

Notes: The variable mnemonics are those from HaverAnalytics. For a series y_t, the stationary transformations are as follows: LV: $x_t = y_t$; DLV: $x_t = y_t - y_{t-1}$; LN: $x_t = \ln(y_t)$; and DLN: $x_t = \ln(y_t) - \ln(y_{t-1})$. SA is seasonally adjusted. SAAR is seasonally adjusted annual rate. EOP is end of period.

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