A More Timely and Useful Index of Leading Indicators

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1. Introduction[†]

Most of the macroeconomic data for the United States require considerable time to collect, process, and release, so that they only are available with lags to the public as well as the government that is their main source. Lags of one to two months are common for principal economic indicators. In most foreign countries, there are fewer weekly and monthly and more quarterly and annual series; the lags tend to be longer, sometimes as long as 3-5 months. At the same time, some indicators are everywhere available promptly; in particular, financial market price and yield data are available electronically in real time during each trading day.

The publication lags and revision schedules vary greatly across the time series used to create the composite indexes of leading (and coincident and lagging) indicators. For the United States, most indicators have lags of about one month or slightly longer, but the real manufacturing and trade sales (a component of the coincident index) lag by two months. However, the U.S. leading index, as well as the leading indexes for other countries, also includes stock prices and interest rate spreads that have no significant data lags. These financial market indicators convey a great deal of information with predictive value. Yet until recently, these indicators were represented in the leading index, not by their most recent monthly values, but by their values in the preceding month for which data for other indicators were also available. This practice originated in the perceived need to match all components of the index strictly in calendar time and the reluctance to impute (forecast) values to the missing series.[1]

The failure to use the most recent available data in the leading index introduces errors and is a major shortcoming. Moreover, tests of the efficacy of the leading indicators often rely on historical data series that reflect revisions of the indicator data, not information available at the time of publication. So there are great disparities in the degree of uncertainty surrounding the true values of the published data. Some, like the national income and product (NIPA) series, are quarterly and subject to a long string of revisions that are frequently sizable. Others, like the high-frequency stock and bond price data, are not subject to revision. The data revisions are presumably reducing measurement errors, but they add to uncertainty and forecasting errors, as do the data lags.

This paper describes how The Conference Board solved the timeliness problem and assesses the efficacy of the new composite leading index using out-of-sample tests with both historical and real-time. We find that the new procedure has significant gains and that the resulting leading index is more timely and useful.

The paper begins (section 2) with a description of the traditional method used to construct the composite leading index and contrasts it with the new, timelier method. Section 3 presents our model and testing methodology, including the forecasting equations we use. It also discusses the coincident (CI) or current conditions index (CCI) that the leading index is designed to predict and includes consideration of other measures of the economy such as GDP and industrial production (IP). Empirical results are provided in Section 4. We end with brief concluding comments.

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1 Some producers of leading indexes still use the practice or a variant of it that leaves late arriving indicators out of composite indicator measures.

2. Construction of the Composite Leading Index

2.1 The Logic and Consequences of the Traditional Method

There is much variation among business cycles in duration and magnitude, causes and consequences. The contributions of different factors differ over time. This helps to explain why composite indexes that combine different indicators generally work better over time than do their individual components (selected for the best past performance). The leading index, for example, represents better the multicausal, multifactor nature of the economic movements than does each of its following components: the average workweek, unemployment insurance claims, new investment commitments (orders, contracts, housing permits), real money supply, yield spread, stock prices, and consumer expectations. The contributions of these components vary over time, depending on the differential characteristics of each cycle. The leading series themselves vary in timing, smoothness, currency, etc. The index gains from this diversification. [2]

However, many technical problems arise from this diversity, perhaps none more vexing than those stemming from the fact that some indicators are available promptly, others with substantial lags. The traditional method employed since the early post-World War II years successively by the National Bureau of Economic Research (NBER), the Bureau of Economic Analysis (BEA) in the U.S. Department of Commerce, and lately The Conference Board (TCB) incorporated two rules. First, all components of the index refer to the same month. Second, only actual data – no forecasts – are used. Thus, the index published in March used information for January because these were the latest data on real indicators, e.g., new orders for nondefense capital goods and new orders for consumer goods and materials. The financial indicators for January were also included, even though February readings were available at least for two of them, namely the stock market price index and the long minus short interest rate spread. Also available, but not used, was the February value of nominal money supply, M2, since the consumer price deflator used to produce the real money supply indicator lags by one month.

The adapted procedure had its logic. The set of the data used was time-consistent, since it covered the same period, as usual in index construction. In addition, by consisting of actual data, the index avoided errors inevitably associated with forecasting.

Nevertheless, the methodology ignored currently available financial data in favor of one-month old data on the same variables with presumably less relevance and less predictive value. This is a major shortcoming. Furthermore, the procedure had no good way of coping with the serious problem of missing data. The practice followed occasionally in the U.S. and routinely in most foreign countries has been to calculate the indexes with a partial set of components – e.g., a minimum of 40 to 60 percent depending on the country according to the OECD.[3] An equally arbitrary rule of at least 50 percent of components was adopted in the United States.

While any rule based on less than the full complement of the data allows the indexes to be more up-to-date, all such rules raise serious problems. First, there is the very undesirable trade-off between the coverage and the timing of the index: the more complete its coverage, the less timely is the index. Moreover, without a full set of components, the effective weights used to calculate the contributions of the components often change dramatically depending on which series, and how many of them, are missing.

A simple formalization of the traditional method of cyclical index construction can complete this assessment and facilitate the comparisons with alternative methods provided later in the paper. Table 1 sets out an example of the availability of the components of the U.S. Leading Index for a publication date in the third week in March. Let X_t be the vector of the indicator series that are available in "real time," i.e., in the current publication period, t. These are generally financial indicators such as stock prices, bond prices, interest rates, and yield spreads. They are available through the end of the previous

[2] The indicator approach is just one of many approaches to business cycle analysis. Developed by Burns and Mitchell (1946), it has been a major component of the NBER business cycle program and has proved useful over the years. The Conference Board assumed responsibility for the production of the Leading Index in 1995 from the Commerce Department.

[3] See web page http:// www.oecd.org/std/li1.htm

Table 1 Data Availability of the Components of the U.S. Leading Index

	Data Availability for March Release (Release 3rd week of March)		
	Dec.	**Jan.**	**Feb.**
Manufacturers' new orders, consumer goods and materials	x	x	
Manufacturers' new orders, nondefense capital goods	x	x	
Money supply, M2	x	x	
Average weekly hours, manufacturing	x	x	x
Average weekly initial claims for unemployment insurance	x	x	x
Vendor performance, slower deliveries diffusion index	x	x	x
Building permits, new private housing units	x	x	x
Stock prices, 500 common stocks	x	x	x
Interest rate spread, 10-year Treasury bonds less federal funds	x	x	x
Index of consumer expectations	x	x	x
Old Index	x	x	
New Index	x	x	x

month, February. Thus, in this case, t is the month of February.

Let Y_t be the vector of the indicator series that have data lags such that these series are not available in the current publication period. Variables in Y_t are generally data on various aspects of real macroeconomic activity and price indexes. Specifically, here, they include new orders for consumer goods and materials, new orders for nondefense capital goods, and money supply. (In fact, nominal money supply is available but the personal consumption expenditure deflator used to deflate it is not.) In the U.S., these variables as a rule lag behind X_t by one month (i.e., the reported data refer to Y_{t-1}). In this case, the old index methodology would calculate the reading for January (the month with a complete set of components) instead of for February (where only 70 percent of the components are available).

Let $I(\cdot)$ denote the indexing procedure used to transform the data into the index number for each month.[4] Then, $I_t = I(\cdot)$ denotes the value of the index in the publication month, t. Hence, under the traditional procedure the most recent value of the index for month t is $I_t^{Old} = I(X_{t-1}, Y_{t-1})$; its previous value is $I_{t-1}^{Old}(X_{t-2}, Y_{t-2})$, and so on. Although available in the publication month, X_t values are not used, which amounts to throwing away the most up-to-date information.

2.2 The New Leading Index

The observation that 70 percent of the components of the leading index are available by the third week in March motivates the new procedure to make the index more timely. The new Leading Index incorporates the most recent monthly values for the X_t variables and short-term forecasts of the Y_t variables for the matching period. Thus, instead of the old index, which in the best (U.S.) case is written as $I_t^{Old} = I(X_{t-1}, Y_{t-1})$, we have an alternative index $\hat{I}_t^{New} = I(X_t, \hat{Y}_t)$, for all t = 1... T. Here the symbol ^ refers to a magnitude based at least in part on some kind of forecasting and t refers to the latest complete

[4] On details of indexing, see The Conference Board, Business Cycle Indicators Handbook, 2001.

month at the time the value of the index is released (e.g., February for the index published in the beginning of March).[5]

The time series indicators used to construct the index tend to move ahead of the business cycle. For example, businesses adjust hours before changing employment by hiring or firing, or they place new orders for machinery and equipment before completing investment plans, etc. Thus, the composite index of leading indicators is designed to help predict changes in the economy when they are represented by the coincident index. The old leading index performed this function with errors, partly, perhaps largely, due to missing data and other measurement problems. In the new index, a large source of errors lies presumably in the deficient forecasts of $\hat{Y}_t$.

For the new procedure to be preferred, it is necessary that the errors of $\hat{I}_t^{New}$ are on balance over time smaller than those of I_t^{Old} and that it does a better job of forecasting the economy. Conceivably, $\hat{I}_t^{New}$ could be inferior to I_t^{Old}. However, using X_t instead of X_{t-i} gives $\hat{I}_t^{New}$ considerable advantage because the indicator is timelier (more than half a month for the U.S.). Other reasons for expecting the procedure to be an improvement are: (1) the errors of the $\hat{Y}_t$ forecast should be limited, since they typically will be for short intervals (one or a few months), (2) the individual errors of the components of the vector $\hat{Y}_t$ may offset each other when combined to form the composite index.

There are various ways to forecast Y_t. Here, we follow the current procedures of The Conference Board and use a simple autoregressive model of order two. While one might argue for an alternative, after much experimentation, and due consideration of the practical needs of monthly production schedules, the simple twice lagged autoregressive hot box imputation method was adopted.[6]

3. Forecasting with the Leading Index

3.1 The Coincident Index as a Measure of Current Economic Conditions

The Leading Index is widely regarded as a tool to forecast changes in the direction of aggregate economic activity and in particular the business cycle turning points. The latter have been historically determined by the reference chronologies of the National Bureau of Economic Research (NBER), but they are well approximated by the dates of peaks and troughs in the Coincident Index. In fact the coincident index provides a broad monthly measure of the current condition of the economy.

This current conditions index is highly correlated with real GDP, but it has several advantages as a target measure for testing the new composite leading economic index. Unlike GDP, which is only available quarterly, the CCI is available monthly. The CCI is also made-up of more variables than output,

[5] The $\hat{Y}_t$ forecasts for the U.S. are restricted to one month ahead, but for other countries multi-step forecasts of $\hat{Y}_t$ are necessary.

[6] For practical reasons associated with production of the indexes on a monthly basis, it is advisable to use the same forecast model for fixed periods of a year or two. Therefore, we focus on relatively simple lag structures that can be easily implemented and these are fixed for the entire sample period. Ideally, the number of lags, i, should be chosen optimally on a case-by-case basis.

The simplest procedure would be to forecast the missing data using an autoregressive process of order one where the constant is constrained to be zero and the coefficient is constrained to be one (i.e. $\hat{Y}_t = Y_{t-1}$). While this model improves on the old index, the results of the unconstrained autoregressive processes are better, hence preferred.

In our tests, AR(i) models with lag lengths, i, varying from one to four were examined. We found that the results that improve strongly for $i = 1,2$ and only mildly for $i = 3, 4,$ and are generally acceptable for all models.

We rejected adding the available data in X_t to help forecast Y_t (that is, using lagged values of X_t as well as lagged Y_t to forecast Y_t). This procedure, even though it could provide somewhat better forecasts, raises important complications because the series in X_t are components of the composite index, and using the values of X_t in both the index and the forecast could distort the weighting scheme in favor of the financial variables.

including employment, personal income, manufacturing and trade sales, and industrial production. These four components cover all areas of the economy. In fact, these indicator series are the key ones used by the NBER business cycles dating committee. Moreover, the CCI is more closely linked to cyclical turning points than GDP. (See Zarnowitz, 2001).

Some argue GDP is correct measure, but GDP is only available quarterly. This means that forecast tests depend heavily on the interpolation procedures used to transform CI and GDP to common frequencies. This is one reason many studies use IP as the targeted variable. We report, in addition to results for the CI, tests based on one of its components alone, the industrial production index (IP). IP provides a monthly index and thus eliminates the interpolation issues with GDP. More importantly, it also allows us to benchmark our results to those of critics of the leading index who have argued that it does not do well when confronted with real-time data.[7]

3.2 Forecast Models

In order to evaluate the contribution of the composite leading index we use it to forecast the change in the natural logarithm (ln) of the coincident index ($\Delta_j CI_t$), where the notation Δ_j denotes the growth rate in the variables over the past j months. Using this measure of movements in the overall performance of the economy we ask whether the change in the natural logarithm of the leading index ($\Delta_j LI_t$) helps improve those predictions. Our goal is two-fold: 1) to assess the predictive ability of the old and new leading indexes and 2) to evaluate the gains from making the leading index more timely by using the procedure described above.

We test whether adding lags of the leading index to an autoregression for $\Delta_j CI_t$ reduces out-of-sample forecast errors. That is, we regress $\Delta_j CI_t$ on its own lags, $\Delta_j CI_{t-1}$ to $\Delta_j CI_{t-k}$ (where the number of lags, k, varies), and construct a series of forecast errors to create a benchmark against which to evaluate the forecast errors of equations that use lags of the leading index. Our benchmark equation is

[7] Nonetheless, tests with GDP were supportive of the new procedure.

$$\Delta_j CI_t = \beta_0 + \sum_{i=1}^{k} \beta_i \Delta_j CI_{t-i} + \varepsilon_{1,t} \quad \text{Eq. (1)}$$

where $\Delta_j CI_t$ is set equal to the "true" index calculated after all revisions to the data are made. So, this forecast variable remains the same over all vintages and forecast models. Then we add lags of the leading index, $\Delta_j LI_{t-1}$ to $\Delta_j LI_{t-k}$, for the old and the new leading indexes and compare the quality of the resulting predictions. Equation (2) adds lags of the old index:

$$\Delta_j CI_t = \beta_0 + \sum_{i=1}^{k} \beta_i \Delta_j CI_{t-i} + \sum_{i=1}^{k} \delta_i \Delta_j LI^{old}_{t-i} + \varepsilon_{2,t}$$

Eq. (2)

and Equation (3) adds lags of the new leading index:

$$\Delta_j CI_t = \beta_0 + \sum_{i=1}^{k} \beta_i \Delta_j CI_{t-i} + \sum_{i=1}^{k} \delta_i \Delta_j LI^{new}_{t-i} + \varepsilon_{3,t}$$

Eq. (3)

For each equation, we allow the number of lags on the right hand side to vary (i.e., k = 1,3,6,9). We also allow the span, j, over which the change in the natural logarithm of the variables is calculated to vary (i.e., j = 1,2,3,6,9). This gives 20 different combinations of spans and lags for which a forecast model is estimated. This variety of models accommodates the many different ways the leading index is used to make forecasts of the state of the economy and to mimic several different rules of thumb.[8] In each case, sequences of forecast errors are constructed for forecasts of 1,3 and 6 months ahead. For brevity, in this paper we report the 9 combinations of spans and lags where j = 3 and k = 3,6,9, but our findings are consistent with the larger set of results not reported here.[9]

[8] While a thorough analysis of the predictive ability of the leading index would account for trending properties of the data and would allow for varying and optimally selected lag lengths of the data, that is not our objective here and is left for future research. In these different versions we always use the same number of lags for both the coincident index and the leading index on the right hand side and we use the same span of changes on both sides of the equation.

[9] An appendix with complete listings for all forecasts are available from the authors.

3.3 Data Structure and Out-of-Sample Forecasts

In order to compare the new and the old index on a consistent basis, we calculated the indexes using real-time data on each of its ten components. This puts the old and the new indexes on equal footing by abstracting from changes in definitions, changes in base years, changes in standardization factors and other methodological changes in the index. It also allows us to assess recent criticisms of the LEI: Diebold and Rudebusch (1991) find that the leading index doesn't add much forecasting power in a real-time setting. In order to facilitate our discussion of the timeliness issues we follow Diebold and Rudebusch (1991) in setting up database matrices. The data matrix for the leading index is given in Table 2. The data in the Table only starts in 1989 since the vintages of real time data on the components of the leading index are available only since then.[10]

In Table 2, each column of the data matrix refers to a different vintage of the leading index while the rows show the history of the index available within each vintage. For example, in the first column of the data matrix we have the January 1989 vintage of the leading index which has observations beginning in January 1959 for both the old and the new indexes. The history of the index in this vintage runs through November 1988 for the old index but through December 1988 for the new index because of the new procedure that makes the leading index more timely. There are 144 such vintages (columns) in our data matrix and in the forecast exercises described below each vintage is used to generate a separate forecast for the coincident index.

The coincident index, which is the basis for the real time regressions we report, has a similar data matrix, but instead of real time data in each column we use the January 2001 vintage of the coincident

Table 2 Data Structure of New Leading Index

	Month Leading Index Released (Month of Press Release)						
Data for this month	**j = 1989:01**	**j = 1989:02**	**.**	**j = t**	**.**	**j = 2000:11**	**j = 2000:12**
i = 1959:01	LI $(i)_j$	LI $(i)_j$	.	LI $(i)_j$	.	LI $(i)_j$	LI $(i)_j$
i = 1959:02	LI $(i)_j$	LI $(i)_j$	.	LI $(i)_j$	.	LI $(i)_j$	LI $(i)_j$
i = 1959:03	LI $(i)_j$	LI $(i)_j$	.	LI $(i)_j$	.	LI $(i)_j$	LI $(i)_j$
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
i = 1988:11	LI $(i)_j$	LI $(i)_j$	.	LI $(i)_j$	.	LI $(i)_j$	LI $(i)_j$
i = 1988:12	$LI^{old}(i)_j = 0$, $LI^{new}(i)_j$	LI $(i)_j$	.	LI $(i)_j$	.	LI $(i)_j$	LI $(i)_j$
i = 1989:01	0	$LI^{old}(i)_j = 0$, $LI^{new}(i)_j$	.	LI $(i)_j$	.	LI $(i)_j$	LI $(i)_j$
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
i = t-1	0	0	.	$LI^{old}(i)_j = 0$, $LI^{new}(i)_j$	.	LI $(i)_j$	LI $(i)_j$
i = t	0	0	.	0	.	LI $(i)_j$	LI $(i)_j$
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
i = 2000:10	0	0	.	0	.	$LI^{old}(i)_j = 0$, $LI^{new}(i)_j$	LI $(i)_j$
i = 2000:11	0	0	.	0	.	0	$LI^{old}(i)_j = 0$, $LI^{new}(i)_j$

index as "truth". Thus the leading index is asked to predict the "true" coincident index, that is, the one that is observed after all revisions of the individual indicators have been made. This ensures that all models are forecasting the same series of changes in the CCI and that the series are consistent across benchmark years.

With this description of the data structure we can now more clearly outline our testing procedure. We use the one-month-ahead forecast to be concrete. Analogous procedures were used for the 3 and 6-month ahead tests. For each equation we start by estimating a regression for the sample of data from January 1959 to December 1988 (R = 360), using the first column of the data matrix, we produce a forecast of $\Delta_j CI_t$ for January 1989 (R+1).

Next, we use the data from January 1959 to January 1989 (in the second column of the data matrix), re-estimate all coefficients, and form a second one-step-ahead forecast of $\Delta_j CI_t$ for February 1989 (R+2). This process continues until the entire sample of

[10] Since the new index is timelier it has an extra observation in each column. Also note that when the log changes are calculated the starting month of the samples are adjusted accordingly.

T = 504 observations (January 1959 to December 2000) is exhausted, and we are left with P = T – R = 144 regression forecasts (January 1989 to December 2000) for each of the three equations. For each equation, a sequence of forecast errors, $\hat{e}_t$, for t = 1,...,P, is then constructed by subtracting the forecasts from the actual realizations of $\Delta_j CI_t$ (the next observation in the next column of the data matrix). Mean square errors, $MSE = \frac{\sum_{t=1}^{P} e_t^2}{P}$, serve to summarize these numbers.

We repeated the same exercise for 3-month ahead and 6-month ahead forecasts using the same models. In these cases, the three equations can be written as

$$\Delta_j CI_t = \beta_0 + \sum_{i=1}^{k} \beta_i \Delta_j CI_{t-p-i} + \varepsilon_{1,t} \quad \text{Eq. (1)'}$$

$$\Delta_j CI_t = \beta_0 + \sum_{i=1}^{k} \beta_i \Delta_j CI_{t-p-i} + \sum_{i=1}^{k} \delta_i \Delta_j LI_{t-p-i}^{old} + \varepsilon_{2,t}$$

Eq. (2)'

$$\Delta_j CI_t = \beta_0 + \sum_{i=1}^{k} \beta_i \Delta_j CI_{t-p-i} + \sum_{i=1}^{k} \delta_i \Delta_j LI_{t-p-i}^{new} + \varepsilon_{3,t}$$

Eq. (3)'

where p = 3, 6 refers to the p-month ahead forecast.

3.4 Measuring the Gain from Making the Leading Index More Timely

The structure of the tests does not account for the difference in timeliness of the new and old index. Since the old index is one month behind the new index, a one-month-ahead forecast of $\Delta_j CI_t$ using the old index is not directly comparable with a one-month-ahead forecast using the new index. For example, in the first vintage a one-month ahead forecast is a forecast of $\Delta_j CI_{1988:12}$ using the old index but using new index gives a forecast for $\Delta_j CI_{1989:01}$.

Put another way, in order to measure the gain from the new procedure it is necessary to ensure that the mean squared error comparisons of the old and new indexes take account of the more timely new index. That is, we need to fix the forecast period so that both indexes are used to forecast the same period which implies two different ways to make the same forecast. The new index with its more timely procedure offers one way. Another way is to bring the old index up to date by one month using a separate autoregressive model of order 2 and then forecasting the growth rate of the coincident index in the forecast period comparable to the one allowed by the new index.[11]

To illustrate the procedures consider the above example where the number of lags, k, on the right hand side is 1 and growth rates are calculated as three month changes in the natural logarithms of the variables. First, we need to update the old index for which we use the following autoregressive model

$$\hat{LI}_{1989:01-1}^{old} = \hat{\alpha}_1 + \hat{\alpha}_2 \hat{LI}_{1989:01-1-1}^{old} + \hat{\alpha}_3 \hat{LI}_{1989:01-1-2}^{old}$$

Then, we use this forecast as the December 1988 observation of the old index (after calculating the appropriate growth rate) to forecast the growth in the coincident index for January 1989. That is,

$$\Delta_3 \hat{CI}_{1989:01} = \hat{\beta}_0 + \hat{\beta}_1 \Delta_3 \hat{CI}_{1989:01-1} + \hat{\delta}_1 \Delta_3 \hat{LI}_{1989:01-1}^{old}$$

Thus, we make the forecast in two steps[12] to provide the basis for a direct measure of the gains in predictive ability from making the leading index more timely. We also apply this two step procedure when constructing 3-month ahead and 6-month-ahead forecasts in order to make the forecasts comparable with the forecasts from the equation using the new leading index.

4. Empirical Results

The results of our analyses are summarized in four basic tables. Table 3 shows the mean squared errors (MSEs) of forecasts from the benchmark autoregressive model using only lagged values of the changes in the coincident index to forecast the coincident indicator. The table compares the MSEs for the benchmark forecast using historic, fully revised values of the leading index and using real time values of the leading index. Thus, columns (4) and (5) show out-of-sample forecast MSEs for historical and real-time data respectively. Table 4 is identical to Table 3,

[11] This is the simplest way to forecast the old index and is also consistent with the other forecasts we use.

[12] Note that this forecast model also requires that we know the growth rate of the coincident index from December 1988 on the right hand side. We can easily generate a forecast for this from the same model using the observations for November 1988.

except it reports results from forecasts of industrial production.

Each Table (as do Tables 5 and 6) report the results from 9 representative forecast models. The first 3 rows are all models with 3 lags of the right-hand side variables. Forecasts in rows 4-6 use 6 lags and rows 7-9 are based on models with 9 lags. For each lag structure we report 1,3, and 6 month-ahead forecasts.

Examination of Table 3 reveals two basic conclusions. First, the leading index improves the forecast over and above that contained in the autoregressive benchmark forecast. In only one forecast is the MSE higher with the addition of the leading index terms (6 month ahead with 3 lags). Although there is an additional instance where the indicators fail to improve the forecast. Table 4 also supports the proposition that the leading indicators are useful forecasting instruments. Importantly, the test we use here is severe, since we are predicting ln changes, not levels, in the measures of economic activity.

The second pattern in the Table is that the real-time forecasts are generally worse than the historical in-sample forecasts. This is to be expected, but the size of the differences offers no evidence that the historical leading index is based on an empirically based fitting exercise with series added and subtracted to gain high historical correlations. Rather, the results are more consistent with the findings of Klein (1999a,b) who looked at the historical record of changes in the components of the LEI and concluded that the overwhelming majority of changes came from discontinued or changes in particular indicators. (See also Zarnowitz (1992), Chapter, 11, esp. Table 11.3 and surrounding text.) A notable exception is the addition of money supply in the late 1970s that reflected real shifts in structure; changes in the banking industry and the changing nature of Federal reserve policy and operations.

Tables 5 and 6 report the results for the same set of 9 forecast models as those shown in Tables 3 and 4. While the results in Tables 3 and 4 provide strong support for the usefulness of the leading index as a forecast tool, Tables 5 and 6 directly compare the performance of the old leading index with the new one.

A glance at Table 5 shows dramatic gains from the new procedure. In every model but one the more timely information in the new index reduces the MSE of the forecast. The one exception, a 6-month ahead forecast using 3 lags, the MSEs are virtually the same, 2.567 for the old index and 2.571 for the new index. Table 6 shows no exceptions; the forecasts of IP are always better with the new procedure.

Aside from the basic findings, the results in both Tables are sensible: the longer the forecast, the higher the error. For example, as the length of the forecast goes from 1 month-ahead to 6 months- ahead for forecasts of CI using 6 lags, the MSE rises from .694 to 2.390. Similar magnitudes show up for other lag structures.

Adding more lags of the leading index generally lowers the MSE, but the effects are relatively small. Comparing the values of column 4 for rows 1, 4, and 7; 2,5 and 8; or 3, 6, and 9 show steady declines in MSEs as the number of lags increases.

5. Concluding Thoughts

In this paper we examined a new composite index procedure that makes the leading index much more timely. The procedure combines current financial information with forecasts or estimates of real variables that are only available with a lag. It is a superior alternative to using the 50 percent or similar rules described in the introduction. The new index is constructed with a complete set of components using actual and forecasted data. This approach to constructing the leading index uses available information more efficiently than the old method and appears to have significant advantages over it.

Empirical evidence points to stock prices and/or interest rate spreads as good leading indicators and predictors of business cycle turning points (see, for example Stock and Watson (1989, 1999), Estrella and Mishkin (1998) and Chauvet (1998-99)). Although the selected financial series are useful as leading indicators, the composite leading index should be better because it includes, in addition to these series, measures of real economic activity, and hence is more comprehensive. The quality as leading indicators of the selected real activity series is, according to many tests, not worse than that of the selected financial indicators. [13]

If so, why is there evidence to the contrary in ex-ante analyses? Part of the reason could be that the leading index was not as up-to-date as the financial indicators. The old procedure for calculating the

[13] Comparison of the performance of real versus financial indicators indicates that the quality of their performance in anticipating recessions varies across business cycles.

leading index left out the most recent data for financial indicators. This may be responsible for the poor performance of the leading index found in several recent studies. Our real-time out-of-sample tests conducted here suggest the composite leading index provides useful information for business cycle forecasts.

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Table (3)
U.S. Leading Index (LI) Helps to Forecast Growth in the U.S. Coincident Index

	Length of forecast in CI in months	Lags included	Mean Squared Errors of Forecast Models (MSEx10^5)		
			Lags of CI Only	Lags Historical LI	Lags of Real Time LI
	(1)	(2)	(3)	(4)	(5)
1	1	3	0.539	0.513*	0.531*
2	3	3	1.739	1.583*	1.687*
3	6	3	2.287	2.468	2.517
4	1	6	0.515	0.477*	0.478*
5	3	6	1.671	1.442*	1.509*
6	6	6	2.237	2.210*	2.187*
7	1	9	0.510	0.462*	0.465*
8	3	9	1.622	1.378*	1.436*
9	6	9	2.449	2.135*	2.108*

* Denotes significance relative to the model in column 3 at the 5 % level using the encompassing t-statistic described in Clark and McCracken (2001).

Table (4)
U.S. Leading Index (LI) Helps to Forecast Growth in U.S. Industrial Production

	Length of forecast in IP in months	Lags included	Mean Squared Errors of Forecast Models (MSEx10^5)		
			Lags of IP Only	Lags Historical LI	Lags of Real Time LI
	(1)	(2)	(3)	(4)	(5)
1	1	3	3.592	3.129*	3.168*
2	3	3	9.001	6.922*	7.099*
3	6	3	9.510	10.368*	10.763*
4	1	6	3.392	2.932*	2.905*
5	3	6	8.762	6.545*	6.604*
6	6	6	9.560	9.990*	9.874*
7	1	9	2.904	2.456*	2.422*
8	3	9	8.590	6.291*	6.235*
9	6	9	9.821	9.919*	9.768*

* See note to Table 3

Table (5)
The More Timely Procedure Dramatically Improves the Ability of the U.S. Leading Index (LI) to Forecast the U.S. Coincident Index

	Length of forecast in CI in months	Lags included	Mean Squared Errors of Forecast Models (MSEx10^5)	
			Lags of Old Real Time LI**	Lags of New Real Time LI
	(1)	(2)	(3)	(4)
1	1	3	0.779*	0.521*
2	3	3	2.072*	1.681*
3	6	3	2.567*	2.571
4	1	6	0.694*	0.469*
5	3	6	1.870*	1.503*
6	6	6	2.390*	2.253*
7	1	9	0.750*	0.448*
8	3	9	1.719*	1.439*
9	6	9	2.403*	2.174*

* See note to Table 3
** Uses the two-step procedure described in section 3.4 to put the old and new indexes on consistent basis for forecasting.

Table (6)
The More Timely Procedure Dramatically Improves the Ability of the U.S. Leading Index (LI) to Forecast U.S. Industrial Production

	Length of forecast in IP in months	Lags included	Mean Squared Errors of Forecast Models (MSEx10^5)	
			Lags of Old Real Time LI**	Lags of New Real Time LI
	(1)	(2)	(3)	(4)
1	1	3	4.399*	3.179*
2	3	3	7.260*	7.193*
3	6	3	11.741*	11.008*
4	1	6	4.042*	2.921*
5	3	6	7.535*	6.713*
6	6	6	11.138*	10.196*
7	1	9	4.258*	2.424*
8	3	9	7.511*	6.410*
9	6	9	11.528*	10.081*

* See Note to Table 3
** See Note to Table 5