Improved Forecasting with Leading Indicators: The Principal Covariate Index

Christiaan Heij[*], Dick van Dijk, Patrick J.F. Groenen

Econometric Institute
Erasmus University Rotterdam

Econometric Institute Report EI2007-23

Abstract

We propose a new method of leading index construction that combines the need for data compression with the objective of forecasting. This so-called principal covariate index is constructed to forecast growth rates of the Composite Coincident Index. The forecast performance is compared with an alternative index based on principal components and with the Composite Leading Index of the Conference Board. The results show that the new index, which takes the forecast objective explicitly into account, provides significant gains over other single-index methods, both in terms of forecast accuracy and in terms of predicting recession probabilities.

Keywords: index construction, business cycles, turning points, principal component, principal covariate, time series forecasting

JEL Classification: C32, C53, E17

[*]Corresponding author. Address: Econometric Institute, Erasmus University Rotterdam, P.O. Box 1738, 3000 DR Rotterdam, The Netherlands. E-mail: heij@few.eur.nl, Fax: +31-10-4089162, Tel: +31-10-4081269.

1 INTRODUCTION

The construction and use of composite coincident and leading indexes to measure and forecast the state of the economy has a long tradition, starting with the work of Mitchell and Burns (1938) on business cycles. Index methods have received renewed interest over the last decade of the previous century, with important contributions by, among others, Diebold and Rudebusch (1991), Hamilton and Perez-Quintos (1996) and Stock and Watson (2002a), and the interest remains strong, see Marcellino (2006) for a recent overview. One of the developments that has led to this 'revival' of index methods is the increasing availability of large data sets, consisting of up to several hundreds of economic variables. Such large data sets make the need to summarize the information by means of an index more pressing.

The construction of an index in a data-rich environment requires some kind of data compression. The so-called diffusion index method of Stock and Watson (2002a) is of special interest in this respect, as it performs relatively well in many cases. The idea of a diffusion index is to summarize the information in a set of relevant economic variables by taking a weighted average of these variables. The weights are determined in such a way that the amount of variation in the variables that is captured by the index is as large as possible. In statistical terms, the index consists of the (first) principal component of the set of economic variables, after appropriate scaling so that all variables have zero mean and unit variance. The Principal Component Regression (PCR) method has been used for macroeconomic forecasting in Stock and Watson (1999, 2002a, 2006), while its use within the area of monetary policy is investigated by Bernanke and Boivin (2003) and Bernanke, Boivin and Eliasz (2005), among others. Several extensions of the diffusion index method have been proposed, see Boivin and Ng (2005) for a forecast comparison and Shintani (2005) for nonlinear diffusion index models.

In the PCR method, the index is constructed from the underlying economic variables without explicit reference to the variable that is to be predicted. That is, the index is constructed in a way that does not depend on the forecast objective. In this paper we propose a new index, the 'Principal Covariate Index', which is based on a forecast oriented method of data compression. This principal covariate regression (PCOVR) method was introduced by De Jong and Kiers (1992) in the context of static regression models and extended to a time series forecasting setting in Heij, Groenen, and Van Dijk (2006). The idea is that more accurate forecasts may be obtained by taking the specific forecasting purpose into account when constructing the index.

We assess the benefits of combining the need for data compression with the objective of forecasting in an empirical application to forecast the Composite Coincident Index (CCI) of the Conference Board. We forecast CCI growth rates over horizons ranging between one quarter and two years, based on diffusion index models where the index is constructed from the ten leading indicator variables that together make up the Composite Leading Index (CLI) of the Conference Board. We consider three index methods: PCR, PCOVR, and the CLI itself. The outcomes show that considerable forecast gains can be obtained by using PCOVR, that is, by tuning the index to the specific forecast task at hand.

The paper is structured as follows. We outline the PCR and PCOVR methodology in Section 2, and we describe the data and forecast evaluation methods in Section 3. The in-sample fit and the out-of-sample forecast quality of the three index methods is compared in Sections 4 and 5, while Section 6 considers forecasting recession probabilities. In Section 7, we compare the forecast accuracy if the three methods are employed within a richer class of forecast models and if a larger set of 128 economic variables is used in the construction of the indexes. Section 8 concludes, and the Appendix contains a summary of the data.

2 INDEX CONSTRUCTION AND FORECASTING

In this section, we provide a brief description of the PCR and PCOVR methods for constructing composite leading indexes and their use in forecasting a target variable. For further details of the PCR method we refer to Stock and Watson (2002a, 2006), for the PCOVR method to Heij, Groenen and Van Dijk (2006).

We use the following notation. Let y_t denote the economic variable that we wish to forecast, and let h be the forecast horizon of interest. We denote the h-step ahead forecast of y_{t+h} based on information available at the end of period t by $\hat{y}_{t+h,t}$. In the empirical application that we consider here, y_t is taken to be the growth rate over the previous h months of the Conference Board's Composite Coincident Index (CCI) or one of its components, so that $\hat{y}_{t+h,t}$ is the predicted h-month growth rate in months $t+1$ through $t+h$. Let the number of leading indicator variables or predictor variables be N, and let x_{it} denote the value of the i-th predictor at time t. Two questions should be answered in order to produce a forecast of y_{t+h} by means of a composite index. The first question is how the composite index should be constructed from the individual leading indicator variables x_{it}. The second question is how the index should be related to the target variable. Marcellino (2006) provides a comprehensive overview of approaches that have been considered to resolve these issues. Many popular methods construct the composite index, denoted f_t, by taking a linear combination of the leading indicators, that is,

$$f_t = \gamma_1 x_{1t} + \gamma_2 x_{2t} + \cdots + \gamma_N x_{Nt}. \tag{1}$$

Following Stock and Watson (2002a), we refer to f_t as a diffusion index (DI), or simply as an index. The relationship between the composite index and the target variable is usually assumed to be linear, so that the forecast $\hat{y}_{t+h,t}$ is given by

$$\hat{y}_{t+h,t} = \alpha + \beta f_t. \tag{2}$$

Sometimes, $\hat{y}_{t+h,t}$ is called a composite leading index, see Marcellino (2006), but we will reserve this name for the index f_t. Both the PCR and PCOVR methods make use of a DI of the form (1) and a linear forecasting rule as in (2), but they differ crucially in the way the coefficients α, β, and γ_i, $i = 1, \ldots, N$, are obtained from the data.

The PCR approach consists of two sequential steps. First, the coefficients γ_i are chosen by maximizing the variance of the index values $\{f_t\}_{t=1}^{T-h}$, under the normalization constraint that $\sum_{i=1}^{N} \gamma_i^2 = 1$, where T denotes the current forecast origin. This is motivated by the fact that in this way the maximal amount of variation present in the set of predictors x_{it}, $i = 1, \ldots, N$, is retained. The solution is given by the first principal component of the N (normalized) predictor variables. Another interpretation is that the first principal component provides the best possible approximation of the set of (normalized) predictors by means of a single index, that is, it minimizes the sum of squared errors

$$\sum_{i=1}^{N} \sum_{t=1}^{T-h} (x_{it} - \delta_i f_t)^2, \tag{3}$$

where the coefficient δ_i is chosen in an optimal way by regressing the i-th predictor x_{it} on the index f_t. In the second step of PCR, the coefficients α and β are obtained by regressing y_{t+h} on the PCR index f_t, that is, by minimizing

$$\sum_{t=1}^{T-h}(y_{t+h} - \alpha - \beta f_t)^2. \tag{4}$$

Finally, the forecast $\hat{y}_{T+h,T}$ is obtained from (2), using the estimates of α and β and f_T, the index value at time T, which is constructed by means of (1) using the estimates of γ_i and the observed values of the predictors x_{iT}.

Although the purpose of the PCR index is to provide forecasts of y_{t+h}, the construction of the index f_t in the first step does not depend on this target variable. Marcellino (2006) mentions this as the main drawback of non-model based composite indexes such as the PCR index. The forecast accuracy can possibly be improved by incorporating the forecasting aim in the construction of the index. Several model-based approaches are available for this purpose, see Marcellino (2006) for discussion and Carriero and Marcellino (2007) for an empirical comparison. Here we consider an alternative approach, which retains the simplicity of non-model based composite indexes but which takes the forecasting aim explicitly into account. This Principal Covariate Regression (PCOVR) method corresponds to minimizing a single objective function, which is defined as a weighted average of the data compression objective (3) and the forecasting objective (4). That is, the coefficients α, β, γ_i, and δ_i are determined jointly by minimizing

$$w_1 \sum_{t=1}^{T-h}(y_{t+h} - \alpha - \beta f_t)^2 + w_2 \sum_{i=1}^{N}\sum_{t=1}^{T-h}(x_{it} - \delta_i f_t)^2, \tag{5}$$

with $f_t = \sum_{i=1}^{N} \gamma_i x_{it}$, and where $w_1 > 0$ and $w_2 > 0$ are weights that express the relative importance of the two objectives. In our applications, the predictors are normalized so that $\sum_{t=1}^{T-h} x_{it}^2 = 1$, and we define $w_1 = w/\sum_{t=1}^{T-h} y_{t+h}^2$ and $w_2 = (1-w)/\sum_{i=1}^{N}\sum_{t=1}^{T-h} x_{it}^2 = (1-w)/N$, where $0 < w < 1$. With this scaling, $w = 0.5$ corresponds to equal weights for the two objectives in terms of normalized variables y_t and x_{it}. If $w \to 0$ then $w_1 \to 0$, so that the PCOVR criterion (5) becomes equivalent to (3) and the PCOVR index becomes equivalent to PCR, whereas for $w \to 1$ the index will focus almost exclusively on approximating the target variable y_{t+h}. In our applications, we choose the weight w by means of cross validation, using a small grid of weights to choose from. The grid values considered for w are 0.01, 0.1, 0.3, 0.5, 0.7, and 0.9. Once the coefficients are estimated by minimizing (5), the forecast $\hat{y}_{T+h,T}$ is constructed in the same way as in the PCR method described before.

The Conference Board's CLI can be used in a similar way for forecasting y_{T+h}. If f_T denotes the value of the CLI at time t, then we may construct the forecast $\hat{y}_{T+h,T} = \alpha + \beta f_T$ using estimates of α and β that are obtained by means of a regression as in (4).

3 DATA, FORECASTING, AND EVALUATION

3.1 Data

In the main part of our empirical analysis, the target variable that we aim to predict is the annualized h-month growth rate of the Conference Board's CCI, defined by $y_t = (1200/h) \times \log(z_t/z_{t-h})$, where z_t is the original CCI series. In Section 7, we consider forecasting h-month growth rates of each of the four components of the CCI, that is, employees on nonagricultural payrolls, personal income less transfer payments, industrial production, and manufacturing and trade sales. The set of predictors x_{it} consists of the ten components of the Conference Board's CLI, that is, average weekly hours in manufacturing, average weekly initial claims for unemployment insurance, manufacturers' new orders for consumer goods and materials, manufacturers' new orders for nondefense capital goods, vendor performance slower deliveries diffusion index, building permits for new private housing units, the S&P 500 stock price index, M2 money supply, the spread between the 10-year Treasury bond rate and the Federal Funds rate, and the University of Michigan index of consumer expectations. We refer to the Business Cycle Indicators Handbook of the Conference Board (2001) for further background on these leading indicator variables.

Monthly data for the CCI and CLI are obtained from the Conference Board, and monthly data for the ten leading indicator variables are taken from Stock and Watson (2005). The common sample period runs from January 1959 to December 2003. We apply the same data transformations to the CLI components as in Stock and Watson (2002a, 2005) to obtain stationary variables. The CLI itself is transformed to stationarity by taking monthly growth rates. Appendix A provides further information on the data.

3.2 Recursive forecasting

The CLI, PCR, and PCOVR methods are compared in terms of their simulated out-of-sample forecast performance. This means that, for given forecast origin T and forecast horizon h, the CLI, PCR, and PCOVR indexes are constructed as described in Section 2, providing a forecast $\hat{y}_{T+h,T}$ of the CCI growth rate over the coming h months. Note that, in computing this forecast, the used information consists of the data on the predictor variables x_{it} and the target variable y_t up to and including time T, so that the forecast is indeed out-of-sample in this sense. We consider forecast horizons h equal to 3, 6, 12, and 24 months. As the sample period 1959-2003 may contain structural breaks, we use a moving window of ten years with 120 monthly observations to construct the index and to estimate the forecast equation. By moving the forecast origin T sequentially forward by one month at a time, we obtain a series of forecasts $\hat{y}_{T+h,T}$ and corresponding forecast errors $e_{T+h,T} = y_{T+h} - \hat{y}_{T+h,T}$. For each forecast horizon, the first forecast origin T_0 is the end of December 1969, while the final forecast is constructed for the growth rate during the h-month period ending in December 2003. Hence, the final forecast origin and the number of forecasts depend on the forecast horizon. More precisely, the last forecast origin lies h months before December 2003, as this is the last month for which the forecast can be compared with the actual h-month growth rate. The number of forecasts for horizon h is therefore equal to $n_h = 408 - h$.

3.3 Forecast evaluation

The out-of-sample forecast quality of the leading index methods is assessed in two ways. First, we examine the accuracy of the h-month growth rate forecasts by means of the mean squared forecast error (MSE), defined as $\frac{1}{n_h} \sum_{T=T_0}^{T_0+n_h-1} e^2_{T+h,T}$.

Second, we consider the ability of the diffusion indexes to signal turning points or oncoming recessions, which comes closer to the original objective of leading indicator variables as envisaged by Mitchell and Burns (1938). We use the common rule of thumb to define a recession as the occurrence of two subsequent quarters of negative growth in the CCI. For a given forecast origin T, the forecasts of the three and six month growth rates of the CCI, $\hat{y}_{T+3,T}$ and $\hat{y}_{T+6,T}$, are transformed into a probability forecast for the occurrence of a recession during the next six months, as follows. As the growth rate forecasts are annualized, the predicted (non-annualized) growth rates over the coming two quarters are given by $\hat{y}_{Q1,T} = \frac{1}{4}\hat{y}_{T+3,T}$ and $\hat{y}_{Q2,T} = \frac{1}{2}\hat{y}_{T+6,T} - \frac{1}{4}\hat{y}_{T+3,T}$. The recession probability forecast, $\hat{p}_T$, is obtained by estimating the probability that both these growth rates are negative. For this purpose we assume that the two growth rates are jointly normally distributed, with means $\hat{y}_{Q1,T}$ and $\hat{y}_{Q2,T}$ and with a covariance matrix estimated from the past ten years of observations on the actual quarterly growth rates. The recession probability forecasts can be transformed into recession signals by imposing a threshold value. In our application, a recession is signalled at time T if $\hat{p}_T$ exceeds the average recession probability over the preceding ten years.

4 COMPARISON OF IN-SAMPLE PROPERTIES

Before evaluating the out-of-sample predictive accuracy of the index-based forecast methods discussed in the two foregoing sections, we first provide some insight into their in-sample characteristics. Figure 1 shows the six-month growth rate of the CCI together with the CLI, PCR, and PCOVR index series over the period from July 1963 until June 2003, which is the final forecast origin considered for six-month growth rate forecasts. The CLI is constructed directly from the index data as reported by the Conference Board, see Appendix A for details. On the other hand, the plotted PCR and PCOVR index series consist of four parts, being the index series as constructed at the forecast origins June in the years 1973, 1983, 1993, and 2003, which are based on the in-sample period covering the preceding ten years. For ease of comparison, all three index series are scaled such that they have the same mean and variance as the CCI growth rate over each of the four subperiods. The visual evidence in Figure 1 clearly indicates that the PCOVR index follows the CCI series more closely than the other two indexes. This holds true also for the other forecast horizons of three, twelve, and twenty-four months. These results are not shown here to save space, but are available upon request.

- insert Figure 1 about here -

Further evidence supporting the relatively better approximation of the CCI growth rate by the PCOVR index is provided in Table 1, which shows the correlations between the CCI growth rate and the three index series. More precisely, at each forecast origin T, the index series are constructed over a time window of ten years, running from month $T-119$ till the current month T. The correlations of the PCR and PCOVR indexes with the h-month CCI growth rate in Table 1 consist of their correlation over this in-sample period of ten years, averaged over the set of all considered forecast origins. The PCOVR index has clearly the largest correlation with the CCI growth rate for all time periods and for all forecast horizons considered. This reflects the fact that the PCOVR index is tuned towards the variable to be predicted, whereas this does not hold true for the CLI and the PCR index.

- insert Table 1 about here -

The three indexes are constructed from the same underlying set of ten leading indicator variables. Table 2 shows the correlation of each index with the individual indicators, averaged across the considered forecast origins. The importance of the variables differs among the three indexes. For instance, manufacturing hours is strongly present in the PCR index, but much less so in the CLI. The correlations with the PCR index are often larger than those with the PCOVR index. This is not surprising, as the PCR index minimizes the residuals resulting from approximating the predictor variables by the index, see (3). On the other hand, the PCOVR index takes the correlation with the predicted variable into account as well, see (5). Further, the correlations with the PCOVR index depend on the forecast horizon. The largest correlation in the short run (for $h = 3$ and 6) is obtained for Building Permits, whereas in the long run (for $h = 12$ and 24) this is obtained for the Interest Rate Spread.

- insert Table 2 about here -

5 COMPARISON OF OUT-OF-SAMPLE FORECASTS

We now turn to the out-of-sample predictive accuracy achieved by the three index methods. Figure 2 shows the six-month CCI growth rate together with the corresponding forecasts obtained from the CLI, PCR, and PCOVR indexes for all forecast origins from December 1969 until June 2003. The CLI- and PCR-based forecasts seem to miss many of the up- and downward movements of the CCI, whereas PCOVR follows these cycles much more closely. Table 3 shows this in more detail by means of the correlations between the actual growth rates and the out-of-sample forecasts. For all forecast horizons and subperiods considered, PCOVR provides the highest correlation, often outperforming the CLI and PCR methods by a substantial margin. For example, for the complete out-of-sample period 1970-2003, the correlation between the six-month CCI growth rate and the PCOVR forecast is 0.66, as compared to 0.32 and 0.36 for the CLI and PCR forecasts, respectively. It also becomes clear from the table that the correlations tend to be the highest for all three index methods for the relatively volatile period 1970-1983. The correlations are smaller for the decade 1984-1993, while in the final subperiod 1994-2003 the CLI and PCR based forecasts often even have a negative correlation with the actual growth rate. PCOVR performs reasonably well in all periods, with the single exception of 24-month ahead forecasts from 1994 onwards. Still, PCOVR does substantially better than PCR and CLI also in this case.

- insert Figure 2 and Table 3 about here -

The mean squared forecast error (MSE) of the three indexes is reported in Table 4. The column 'var(y)' shows the variance of the actual h-month CCI growth rate, and the following four columns show the MSE relative to this variance. For comparison, the column 'Const' reports the MSE that is obtained without using an index by simply taking the average growth rate over the preceding ten years as the forecast. The fact that this naive model has a (relative) MSE that is smaller than 1 in most cases shows that the mean growth rate varies over time, at least for forecast horizons longer than three months. In the far majority of cases, PCOVR provides the most accurate forecasts and achieves the lowest (relative) MSE values. For example, for the complete out-of-sample period 1970-2003, the relative MSE for the PCOVR forecasts of the 6-month growth rate equals 0.50, as compared to 0.72 for both the CLI and PCR forecasts. The improvement achieved by PCOVR relative to CLI and PCR is of similar magnitude for horizons up to 12 months and is approximately equal to 30%. It becomes considerably smaller for the 24-month ahead forecasts, although the reduction in MSE at this horizon is still 13% relative to PCR. From the results for subperiods, we find that the gains of PCOVR are most spectacular for the relatively volatile period 1970-1983, where it performs up to twice as well as PCR for $h = 12$ months. The main exception to the superior performance of the PCOVR forecasts is the period 1984-1993, following the Great Moderation, that is, the dramatic reduction in the volatility of many US macroeconomic variables, see Stock and Watson (2002b) and Sensier and van Dijk (2004), among others. For example, for the 6-month CCI growth rate, the variance declined by almost 80% from 14.34 during the period 1970-1983 to only 3.03 during the post-moderation period 1984-1993. Note that, especially during the first years of the period 1984-1993, the index and the corresponding forecast are constructed using 10-year observation windows that for a large part consist of data from the pre-moderation period. These are no longer representative of the behavior of the CCI at the relevant forecast origin, which negatively affects the accuracy of the index forecasts. This explains why the simple 'Constant' model performs relatively well in this period. It seems that the PCOVR index is most sensitive to the structural break in variance, and PCR and CLI even perform somewhat better than PCOVR over this period. This is perhaps not unexpected, as the PCOVR index depends directly on the target variable. Reassuringly, PCOVR is again consistently the best method over the last decade 1994-2003. During this final subperiod, the CLI and PCR methods do not recover and still do not provide more accurate forecasts than the 'Constant' model.

- insert Table 4 about here -

6 RECESSION FORECASTS

In the foregoing section, we compared the quality of growth rate forecasts of the different leading index methods. Of particular interest are turning point forecasts, or forecasts of business cycle recessions and expansions. In fact, it is often claimed that leading indicators are mainly intended for that purpose. Specific models for turning point predictions using leading indicators have been developed, for instance, by Chauvet and Hamilton (2006) based on Markov-Switching models and by Birchenhall et al. (2002) based on probit models. The Chicago Fed National Activity Index, CFNAI (2000), which is obtained by applying PCR to a set of 85 monthly indicators of economic activity, is also used for turning point predictions, see Evans, Liu and Pham-Kanters (2002), even though this index is not explicitly constructed for this purpose. In this section, we evaluate the performance of the three index methods (CLI, PCR, and PCOVR) in predicting future recessions.

As described in Section 3.3, the three- and six-month ahead CCI growth rate forecasts are used to obtain an estimate of the probability of negative growth during the coming two quarters, which is the rule that we use to define a recession. More precisely, we distinguish three possible regimes for the coming two quarters: a recession if actual growth is negative in both quarters, an expansion if it is positive in both quarters, and a mixed regime if growth is positive in one of the quarters and negative in the other one. The corresponding future recession indicator R_t is defined by $R_t = 1$ for a recession, $R_t = 0$ for an expansion, and $R_t = 0.5$ for a mixed regime. This recession variable is shown in the top panel of Figure 3, together with the recession periods as defined by the NBER. The recession indicator R_t is based exclusively on future growth rates, whereas the NBER recession variable considers both future and past growth rates. This explains why the variable R_t tends to lead both the start and the end of NBER recession periods. In what follows, we will consider the empirical future recession indicator R_t. Use of the NBER index leads to similar results, which are not reported here but which are available upon request.

The series of recession probability forecasts for CLI, PCR, and PCOVR are shown in the lower three panels of Figure 3. The graphs clearly show that the PCOVR index is more successful in detecting recessions than CLI and PCR. This holds for all recessions that occurred during the sample period, but is most pronounced for the 1974 recession. The first of the so-called 'double-dip recessions' in 1980 is predicted relatively well by all three indexes, but the second in 1981-1982 comes out less clearly in the predictions. The same applies for the 1991 recession. None of the three indexes succeeds well in predicting the most recent recession in

2001, although the PCOVR index indicates increased recession risk from 2002 onwards. In general, recession probabilities are low in non-recession periods, except for some time after the 1991 recession and a short period around the start of 1996.

- insert Figure 3 about here -

The difference in quality of the turning point forecasts is also demonstrated by the average recession probability forecasts in the three regimes. In the 38 actual future recession periods, the average recession probability forecast is 0.12 for CLI and PCR, and 0.30 for PCOVR. In the 292 expansion periods and in the 72 actual periods with a mixed regime, the average recession probabilities are 0.29 and 0.23 for CLI, 0.26 and 0.23 for PCR, and 0.24 and 0.29 for PCOVR. Obviously, PCOVR is considerably better in signaling recessions, and it does not provide more false signals than the other two index methods. This is further clarified in Table 5, where we consider only the recession and expansion periods. The recession probability forecasts are translated into a recession signal if the current recession probability exceeds the average probability over the preceding ten years. The advantage of using this time-dependent and index-based threshold is that it provides an automatic compensation for consistent over- or underestimation of the actual recession risk. The upper panel in Table 5 shows a classification table for each of the three index methods. The actual number of recession months is 38, and all three methods signal a larger number of recession months: 97 for CLI, 121 for PCR, and 70 for PCOVR. Of the 38 recession months, 19 are predicted correctly by CLI, 25 by PCR, and 24 by PCOVR, and of the 292 expansion months 214 are predicted well by CLI, 196 by PCR, and 246 by PCOVR. Again, PCOVR outperforms the other two index methods. The lower panel in Table 5 shows the corresponding quadratic probability scores (QPS). Let $\hat{p}_T$ be the recession probability forecast computed at the end of month T, then the QPS is defined as

$$\text{QPS} \;=\; \frac{2}{330}\sum(R_T - \hat{p}_T)^2.$$

Here the average is taken over the 330 months corresponding to future recessions and expansions in the period from January 1970 till June 2003. We also compute QPS values for recession and expansion periods separately. PCOVR has the smallest QPS over the full forecast period, and especially so for the recession periods, whereas its QPS is only slightly larger than that of CLI and PCR in expansion periods.

- insert Table 5 about here -

Next, we perform an encompassing-type of test by considering the additional predictive power of one of the three index-based forecasts in the presence of another one. For this purpose, we use a probit model to fit the binary future recession indicator R_T for future recessions and expansions, omitting the months with a mixed future regime. The recession indicator R_T is predicted from the index-based forecasts $\hat{y}_T^{Q1}$ and $\hat{y}_T^{Q2}$ of the CCI growth rate during the next two quarters. This provides an evaluation of the quality of ex ante recession forecasts, as the actual value of R_T is known only after a delay of six months, whereas the forecasts $\hat{y}_T^{Q1}$ and $\hat{y}_T^{Q2}$ are computed at the end of the current month T. The fitted probit models are defined by

$$\text{Prob}(R_T = 1) \;=\; \Phi\Big(a + b_1\widehat{y}_{1T}^{Q1} + b_2\widehat{y}_{1T}^{Q2} + c_1\widehat{y}_{2T}^{Q1} + c_2\widehat{y}_{2T}^{Q2}\Big),$$

where Φ denotes the cumulative distribution function of the standard normal distribution, and where $\widehat{y}_{iT}^{Q1}$ and $\widehat{y}_{iT}^{Q2}$ denote the growth rate forecasts of index method $i = 1, 2$ made at the end of month T. The predictive power of index method 2 in addition to that of index method 1 can be evaluated by testing for the joint significance of the coefficients c_1 and c_2. We test this restriction by means of a Likelihood Ratio (LR) test. As the growth rate forecasts over the next two quarters are updated every month, the monthly forecasts will contain considerable serial correlation, and the same holds true for the recession indicator. To mitigate the effects of this correlation, we perform the test also on a quarterly basis by using only one third of the observations, that is, only the ones corresponding to forecast origins in the months March, June, September, and December of each year.

- insert Table 6 about here -

Table 6 shows the results for the PCR and PCOVR indexes. Focusing on the results for monthly data, the upper part of the table shows the coefficients b_i and c_i in the probit model, where an asterisk indicates significance at the 5% level. The future recession index depends most strongly on the growth forecast for the coming quarter and less on that for the second quarter from now. The lower part of the table shows the number of observations and the number of recessions, as well as some model statistics. Comparing the values of the log-likelihood, the Akaike criterion, and the McFadden R^2, the model with only the PCOVR index performs approximately equally well as the model that contains both indexes, whereas the model with only the PCR index performs far worse. The results of the LR test imply that PCR does not add predictive power to PCOVR in forecasting recessions (with p-value equal to 0.41), whereas PCOVR does significantly add to PCR (p-value 0.00). This means that the PCOVR index provides significant predictive information for recessions that is not captured in the PCR index, whereas PCR does not contain any useful information that is not already present in PCOVR. The results for the quarterly data, shown in the right part of Table 6, are the same.

Similar tests can be performed to compare PCOVR with CLI and PCR with CLI, with the following results. The PCOVR index provides additional forecast power over CLI (p-value 0.00), but CLI has no additional information as compared to PCOVR (with an LR test p-value of 0.09 for monthly data and of 0.15 for quarterly data). The results of comparing PCR with CLI are somewhat mixed. For monthly data, the information in PCR is more relevant, as the p-value for omitting PCR is equal to 0.00 as compared to 0.19 for omitting CLI. On the other hand, for quarterly data, the information in both indexes is relevant, with p-value equal to 0.02 for omitting CLI and 0.04 for omitting PCR. Summarizing the above, as compared to the indexes PCR and CLI, the PCOVR index contains all information that is relevant for forecasting future recessions and expansions.

7 RESULTS FOR RICHER MODELS AND DATA

Until now, we considered a relatively small set of ten leading indicator variables that is compressed in an index f_t that is used in a simple, static model $\hat{y}_{t+h,t} = \alpha + \beta f_t$ to forecast the CCI growth rate. An advantage of this approach is that it focuses on leading indicators of prime interest as we use the variables considered by the Conference Board in constructing their CLI, and that it is relatively straightforward to compute and interpret the constructed PCR and PCOVR indexes and their forecasts. In this section, we investigate the relative performance of the index methods in settings that are more complex. Specifically, we consider the use of forecast models with lagged effects and the use of more predictor variables in constructing the indexes. In addition, we consider forecasting the four CCI component series.

7.1 Forecasting with dynamic models

Future growth perspectives may depend not only on the current values of leading indicator variables, but also on their values in the near past. This motivates the use of lagged index values in the forecast model. Further, current and past CCI growth rates may also be of importance in predicting future movements, so that it may help to include lagged values of CCI in the model. Using the notation of Section 3.1, let z_t denote the CCI series in levels, with corresponding monthly growth rate $v_t = \Delta \log(z_t)$. This is related to the predicted annualized h-month CCI growth rate y_t by means of $y_t = (1200/h) \times \sum_{j=0}^{h-1} v_{t-j}$. If we add q lagged index values and r lagged terms of v_t in the forecast equation, this gives

$$\hat{y}_{t+h,t} = \alpha + \sum_{j=0}^{q} \beta_{1j} f_{t-j} + \sum_{j=0}^{r} \beta_{2j} v_{t-j}.$$

Stock and Watson (1999, 2002a) call this the DI-AR-Lag model, as the forecasts are based on the diffusion index f_t and its lags and on autoregressive terms corresponding to current and lagged values of the one-month growth rate. To apply this model, specific values for the lag orders q and r should be chosen. The results in Stock and Watson (2002a, 2006) show that the Bayes Information Criterion (BIC) works rather well in this respect, so we will follow their procedure of model selection and forecasting. We consider the set of forecast models with index lag $q \leq 2$ and with autoregressive lag $r \leq 5$. We also incorporate models without autoregressive terms, and we indicate this by writing $r = -1$. This gives a set of $3 \times 7 = 21$ candidate models, with $0 \leq q \leq 2$ and $-1 \leq r \leq 5$.

For all three index methods, BIC is used to determine the lag orders q and r at each forecast origin T, based on a moving estimation window consisting of the past ten years of observations. For PCOVR, in addition the weights $w_1 = w / \sum_{t=1}^{T-h} y_{t+h}^2$ and $w_2 = (1-w)/N$ in the criterion function (5) should be selected, that is, we should choose the weight $0 < w < 1$. We consider the same grid of values for w as before, that is, 0.01, 0.1, 0.3, 0.5, 0.7, and 0.9. For each fixed weight, the optimal lag orders are selected from the 21 candidate models by means of BIC. Finally, among the six resulting models, the optimal weight w is selected by cross validation.

Table 7 reports the mean squared error of the h-month growth rate forecasts with DI-AR-Lag models using either the CLI, PCR, or PCOVR index method. This table has the same structure as Table 4. The column 'var(y)' shows the variance of the actual CCI growth rate, and the following four columns show the MSE relative to this variance. The column 'AR' reports the MSE that is obtained without using an index, that is, by using only autoregressive terms in the forecast equation, which forms the natural benchmark for the DI-AR-lag models. If the MSE values of the AR model are compared with those of the 'Constant' model in Table 4, it turns out that the AR model has a consistently smaller MSE, so that apparently it helps to include lagged growth rates in forecasting. Still, it is beneficial to include indexes in the forecast equation, as in the majority of cases the index-based forecasts are considerably more accurate than the AR forecasts. For the full forecast period from 1970 till 2003, the PCOVR forecasts are most accurate on average, with the exception of a forecast horizon of six months for which CLI performs somewhat better. The results for the three subperiods show again that PCOVR gains in particular in the volatile period until 1983. After the reduction in macroeconomic volatility during the first half of the 1980s, the best results are obtained by CLI, with the AR model as a close second best. This indicates that index-based forecasts may be somewhat less useful in periods with moderate variations in growth rates, as it seems to pay to keep models as simple as possible in such periods.

It is also of interest to compare the results for the more complex, dynamic models in Table 7 with those for the simple, static model in Table 4. It turns out that the CLI and PCR method benefit from allowing lagged index values and lagged growth rates to enter the forecast equation, as in almost all cases the relative MSE values in Table 7 are lower than those in Table 4. By contrast, the relative MSE values for the PCOVR forecasts from the static and dynamic models are rather similar, suggesting that the current value of the PCOVR index is a sufficient measure to capture the predictive information in the leading indicator variables for future CCI growth. An exception is the final sub-period 1994-2003, where the MSE of PCOVR for DI-AR-lag models in Table 7 is more than 10% lower than that of the DI models in Table 4 for horizons of six, twelve, and twenty-four months.

- insert Tables 7 and 8 about here -

Table 8 provides information on the structure of the dynamic forecast equations. The table reports the average of the index lag q and of the autoregressive lag r selected by BIC for the three index methods, and also the average of the selected weight w for PCOVR. The PCR model tends to use fewer index lags than CLI and PCOVR, and the number of lags varies considerably over the three subperiods. Further, the PCOVR model has on average much fewer AR lags than PCR and CLI, and these two index methods in turn often use more lags than the pure AR model. The number of AR lags varies substantially over the three subperiods. As concerns the weight w used in the PCOVR index method, the average weight is larger in volatile periods and for longer forecast horizons. This is in line with the intuition that it helps more to tune the index towards the predicted variable when this variable is subject to severe fluctuations, so that a larger weight should be used in such periods. Similarly, the longer the forecast horizon h is, the more it will exhibit long-term up- and downswings, and the more it pays to stay closer to the past values of the predicted variable.

7.2 Forecasting the four coincident indicator variables

The composite coincident index is based on four indicators, that is, production, employment, income, and sales. As these four variables are of interest themselves, we investigate whether the leading index methods are useful for forecasting the growth rates of these component series. We confine ourselves to the DI-AR-Lag models discussed above and consider the AR model again as a benchmark. The resulting mean squared forecast errors, expressed relative to the variance of the forecast target variable, are reported in Table 9. The 'Gain' columns express the percentage gain in MSE of the PCOVR index as compared to the PCR index, and the 'Ave' rows contain the relative MSE averaged over the four considered forecast horizons h. When evaluated over the complete forecast period 1970-2003, PCOVR renders the most accurate forecasts, except for short-term ($h = 3$) forecasting of employment and income, and long-term ($h = 24$) forecasting of income and sales. If the MSE's are averaged over the four considered forecast horizons, PCOVR provides the best forecasts of production, income and sales, with gains of around 7% as compared to PCR. For employment, PCR and PCOVR perform equally well on average, although

PCR is better in short-term forecasting while PCOVR outperforms in long-term forecasting. For each of the four variables, the volatility is by far highest in the period 1970-1983, and in many cases PCOVR performs best during this period. On the other hand, PCR and PCOVR experience problems in forecasting during the period 1984-1993, where the forecast models are estimated for a large part with data before the volatility reduction. The simpler CLI performs better in this period. Over the last decade of the sample period, PCOVR seems to pick up some of its good forecast properties, again with the exception of employment.

- insert Table 9 about here -

7.3 Forecasting with more leading indicator variables

As a final extension, we consider the effect of incorporating a larger set of economic variables in constructing the PCR and PCOVR indexes. As noted in the introduction, one of the main reasons for the renewed interest in index methods is the increasing availability of large data sets. The CFNAI of the Chicago Fed, for example, is based on the PCR index method applied to a set of 85 economic variables, while the macroeconomic forecasts in Stock and Watson (1999, 2002a, 2005) are based on even larger data sets of between 130 and 170 variables. Although a larger data set suggests the availability of more information, it is an open question whether this additional information can be exploited in constructing the index and, in particular, whether it leads to improved forecasting performance. The issue of data selection in index construction and business cycle modelling is discussed, among others, by Banerjee and Marcellino (2006), Boivin and Ng (2006), Forni, Hallin, Lippi and Reichlin (2003), Issler and Vahid (2006), and Lown and Morgan (2006).

Here we employ a data set of 128 variables, taken from Stock and Watson (2005). These 128 variables include the previously considered set of ten leading indicators. The PCOVR index is constructed in two steps, where first the set of 128 predictors is summarized by means of ten principal components, and then the PCOVR model (5) is estimated using these ten components for x_{it} to obtain the PCOVR index f_t. This is done in order to prevent overfitting by reducing the number of coefficients γ_i in (5) from 128 to 10. The same procedure could be followed for the PCR index, but as the leading principal component among the set of ten principal components is the same as that of the original 128 variables, we can equally well apply principal components directly on the original data set. We also performed the forecast analysis by selecting a subset of the 128 variables, corresponding to the set used by the CFNAI. As the results are similar to those obtained for the full data set, we do not report them separately.

Table 10 presents the mean squared errors for the CCI growth rate forecasts as obtained from indexes based on the set of 128 predictor variables. For ease of comparison, the three rightmost columns in the table repeat the results for PCR and PCOVR based on the ten CLI component series that were reported before in Table 7. The table shows that, over the full forecast period 1970-2003, PCOVR outperforms the two alternative leading index methods. The gains are substantial and increase with the forecast horizon, from 9% for $h = 3$ to slightly less than 30% for $h = 12$ and 24. As before, the gains of PCOVR relative to CLI and PCR are mainly due to considerably better performance in the period 1970-1983. On average, PCR performs best in the period 1984-1993, and AR and CLI do relatively well from 1994 till 2003.

If we compare the results with those based on the original ten CLI components, it follows that extending the set of predictor variables enhances the performance of PCOVR for short forecast horizons of three and six months. No improvement is found for two-year ahead forecasts ($h = 24$), while the one-year ahead forecasts of PCOVR based on ten variables are even more accurate than those based on 128 variables. The subperiod results confirm that the PCOVR index benefits from the additional information that is present in the larger data set in the majority of cases, but not always. The same applies for the PCR index. For instance, for the one-year horizon, the MSE over the period 1970-1983 rises from 0.18 for ten predictors to 0.28 for 128 predictors for PCOVR, while for PCR we find an even larger increase from 0.28 to 0.52. This means that incorporating additional variables in constructing the indexes does not automatically lead to more accurate forecasts and that it may be worthwhile to select the variables carefully, see also Boivin and Ng (2006) and Bai and Ng (2007).

- insert Table 10 about here -

8 CONCLUSION

We compared three methods for constructing a composite index of leading indicators to summarize the information that is present in a large set of variables. Two of these methods, the Composite Leading Index of the Conference Board and the Principal Component Regression Index that is used by the Chicago Fed as its National Activity Index, select the index weights independent from the variable that is to be predicted and independent from the forecast horizon. As an alternative, we proposed the Principal Covariate Index that combines the objectives of index construction and forecasting. This index provides considerably more accurate forecasts of the growth rates of the Composite Coincident Index of the Conference Board and it also performs best in predicting recessions. This enhanced insight in future perspectives may be of help for many decision makers, including bankers, investors, governments, producers, and consumers.

We mention three issues that are of interest for future research. One is the use of real-time data, as opposed to revised data that are available only after a time delay. This issue has recently received much interest, see, for instance, Chauvet and Piger (2007) and McGuckin, Ozyildirim and Zarnowitz (2007). Other studies indicate that the forecast results obtained for real-time data do not seem to differ much from those for revised data, see Bernanke and Boivin (2003). A second issue is that of structural breaks and the choice of the data period used to estimate the forecast model, see Banerjee, Marcellino and Masten (2006) and Pesaran and Timmermann (2007). Finally, it is of interest to apply variable selection techniques before constructing the index, see Bair, Hastie, Paul, and Tibshirani (2006) and Bai and Ng (2007).

References

Bai, Jushan, and Serena Ng. (2007). "Forecasting Economic Time Series Using Targeted Predictors." Working Paper.

Bair, Eric, Trevor Hastie, Debashis Paul and Robert Tibshirani. (2006). "Prediction by supervised principal components." *Journal of the American Statistical Association*, 101, 119-137.

Banerjee, Anindya, and Massimiliano G. Marcellino. (2006). "Are there any Reliable Leading Indicators for US Inflation and GDP Growth?" *International Journal of Forecasting*, 22, 137-151.

Banerjee, Anindya, Massimiliano G. Marcellino, and Igor Masten. (2006). "Forecasting Macroeconomic Variables Using Diffusion Indexes in Short Samples with Structural Change." Working Paper.

Bernanke, Ben S., and Jean Boivin. (2003). "Monetary Policy in a Data-rich Environment." *Journal of Monetary Economics*, 50, 525-546.

Bernanke, Ben S., Jean Boivin, and Piotr Eliasz. (2005). "Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach." *Quarterly Journal of Economics*, 120, 387-422.

Birchenhall, Chris R., Hans Jessen, Denise R. Osborn, and Paul Simpson. (1999). "Predicting U.S. Business-Cycle Regimes." *Journal of Business and Economic Statistics*, 17, 313-323.

Boivin, Jean, and Serena Ng. (2005). "Understanding and Comparing Factor-Based Forecasts." *International Journal of Central Banking*, 1, 117-151.

Boivin, Jean, and Serena Ng. (2006). "Are More Data Always Better for Factor Analysis?." *Journal of Econometrics*, 132, 169-194.

Carriero, Andrea, and Massimiliano G. Marcellino. (2007). "A Comparison of Methods for the Construction of Composite Coincident and Leading Indexes for the UK." *International Journal of Forecasting*, 23, 219-236.

Chicago Fed. (2000). CFNAI Background Release. Website:
`http://www.chicagofed.org/economic_research_and_data/files/cfnai_background.pdf`

Chauvet, Marcelle, and James D. Hamilton. (2006) "Dating Business Cycle Turning Points." In *Nonlinear Time Series Analysis of Business Cycles*, edited by Milas, Costas, Philip Rothman and Dick Van Dijk. pp. 1-54. Amsterdam: North-Holland.

Chauvet, Marcelle, and Jeremy Piger. (2007). "A Comparison of the Real-Time Performance of Business Cycle Dating Methods." Federal Reserve Bank of St Louis Working Paper 2005-021A, to appear in *Journal of Business and Economic Statistics*.

Conference Board, The. (2001). Business Cycle Indicators Handbook. Website:
`http://www.conference-board.org/publications/describebook.cfm?id=852`

De Jong, Sijmen, and Henk A.L. Kiers. (1992). "Principal Covariate Regression." *Chemometrics and Intelligent Laboratory Systems*, 14, 155-164.

Diebold, Francis X., and Glenn D. Rudebusch. (1991). "Forecasting Output with the Composite Leading Index: An Ex Ante Analysis." *Journal of the American Statistical Association*, 86, 603-610.

Evans, Charles L., Chin Te Liu, and Genevieve Pham-Kanters. (2002). "The 2001 Recession and the Chicago Fed National Activity Index: Identifying Business Cycle Turning Points." *Economic Perspectives*, Federal Reserve Bank of Chicago 3Q/2002, 26-43.

Forni, Mario, Marc Hallin, Marco Lippi, and Lucrezia Reichlin. (2003). "Do Financial Variables Help Forecasting Inflation and Real Activity in the Euro Area?" *Journal of Monetary Economics*, 50, 1243-1255.

Hamilton, James D., and Gabriel Perez-Quiros. (1996). "What Do the Leading Indicators Lead?" *Journal of Business*, 69, 27-49.

Heij, Christiaan, Patrick J.F. Groenen, and Dick van Dijk. (2006). "Time Series Forecasting by Principal Covariate Regression." *Econometric Institute Report* EI2006-37, Econometric Institute, Rotterdam.

Issler, Joao V., and Farshid Vahid. (2006). "The Missing Link: Using the NBER Recession Indicator to Construct Coincident and Leading Indices of Economic Activity." *Journal of Econometrics*, 132, 281-303.

Lown, Cara, and Donald P. Morgan. (2006). "The Credit Cycle and the Business Cycle: new Findings Using the Loan Officer Opinion Survey." *Journal of Money, Credit, and Banking*, 38, 1575-1597.

Marcellino, Massimiliano G. (2006). "Leading Indicators." In *Handbook of Economic Forecasting, Volume 1*, edited by Graham Elliott, Clive W.J. Granger and Allan Timmermann. pp. 879-960. Amsterdam: North-Holland.

McGuckin, Robert H., Ataman Ozyildirim, and Victor Zarnowitz. (2007). "A More Timely and Useful Index of Leading Indicators." *Journal of Business and Economc Statistics*, 25, 110-120.

Mitchell, Wesley C., and Arthur F. Burns. (1938). "Statistical Indicators of Cyclical Revivals." *NBER Bulletin* 69, New York.

Pesaran, M. Hashem, and Allan Timmermann. (2007). "Selection of Estimation Window in the Presence of Breaks." *Journal of Econometrics*, 137, 134-161.

Sensier, Marianne, and Dick van Dijk. (2004). "Testing for Volatility Changes in U.S. Macroeconomic Time Series." *Review of Economics and Statistics*, 86, 833-839.

Shintani, Mototsugu. (2005). "Nonlinear Forecasting Analysis Using Diffusion Indexes: An Application to Japan." *Journal of Money, Credit, and Banking*, 37, 517-538.

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

Stock, James H., and Mark W. Watson. (2002a). "Macroeconomic Forecasting Using Diffusion Indexes." *Journal of Business and Economic Statistics*, 20, 147-162.

Stock, James H., and Mark W. Watson. (2002b). "Has the Business Cycle Changed and Why?" In *NBER Macroeconomics Annual*, edited by Mark Gertler and Kenneth S. Rogoff. pp. 159-218. Cambridge: MIT Press.

Stock, James H., and Mark W. Watson. (2005). "Implications of Dynamic Factor Models for VAR Analysis." *Working Paper.*

Stock, James H., and Mark W. Watson. (2006). "Forecasting with Many Predictors." In *Handbook of Economic Forecasting, Volume 1*, edited by Graham Elliott, Clive W.J. Granger and Allan Timmermann. pp. 515-554. Amsterdam: North-Holland.

A APPENDIX: DATA

Most of the data are taken from Stock and Watson (2005). This database contains monthly observations on a set of 132 economic variables from January 1959 to December 2003, giving 540 observations on each variable. We exclude four of these variables, corresponding to regional housing starts that have missing observations. The remaining 128 variables are used as predictors in Section 7, and we refer to Stock and Watson (2005) for details on these variables. In the rest of the paper, we focus on a set of ten leading indicator predictor variables that we describe in some more detail. Further, we use the Conference Board's Composite Coincident Indicator (CCI), transformed in a way that is compatible with that of the other variables. This indicator is based on a set of four coincident indicators, each of which is also predicted in Section 7.

The table provides the names and codes of the variables in Stock and Watson (2005) and in the Business Cycle Indicators Handbook of the Conference Board (2001). The ten leading and four coincident indicators are all taken directly from Stock and Watson (2005), and the CCI and CLI are taken from the Conference Board. The table shows also the applied data transformation (column 'TRF'), with the following acronyms: 'lv' for 'leave as is' (take the variable in levels and apply no data transformation), 'Δlv' for 'take first difference', 'ln' for 'take natural logarithm', and 'Δln' for 'take first difference of natural logarithm' (corresponding to the monthly growth rate).

Table A: Coincident and Leading Indicators

Name	SW Code	CB Code	TRF
Coincident Indicators			
Employees on nonagricultural payrolls	ces002	BCI-41	Δln
Personal income less transfer payments	a0m051	BCI-51	Δln
Industrial production index	ips10	BCI-47	Δln
Manufacturing and trade sales	a0m057	BCI-57	Δln
Leading Indicators			
Average weekly hours (manufacturing)	a0m001	BCI-01	lv
Average weekly initial claims for unemployment insurance	a0m005	BCI-05	Δln
Manufacturers' new orders (consumer goods and materials)	a0m008	BCI-08	Δln
Manufacturers' new orders (nondefense capital goods)	a0m027	BCI-27	Δln
Vendor performance (slower deliveries diffusion index)	pmdel	BCI-32	lv
Building permits (new private housing units)	hsbr	BCI-29	ln
Stock prices (500 common stocks)	fspcom	BCI-19	Δln
Money Supply (M2)	fm2dq	BCI-106	Δln
Interest rate spread (10Y T-Bonds less Federal Funds)	sfygt10	BCI-129	lv
Index of consumer expectations (University of Michigan)	hhsntn	BCI-83	Δlv

Notes: The table shows the name and codes of four coincident indicators and ten leading indicators as used by the Conference Board and in the paper of Stock and Watson (2005). The column 'TRF' indicates the transformation that is applied to obtain stationary variables.

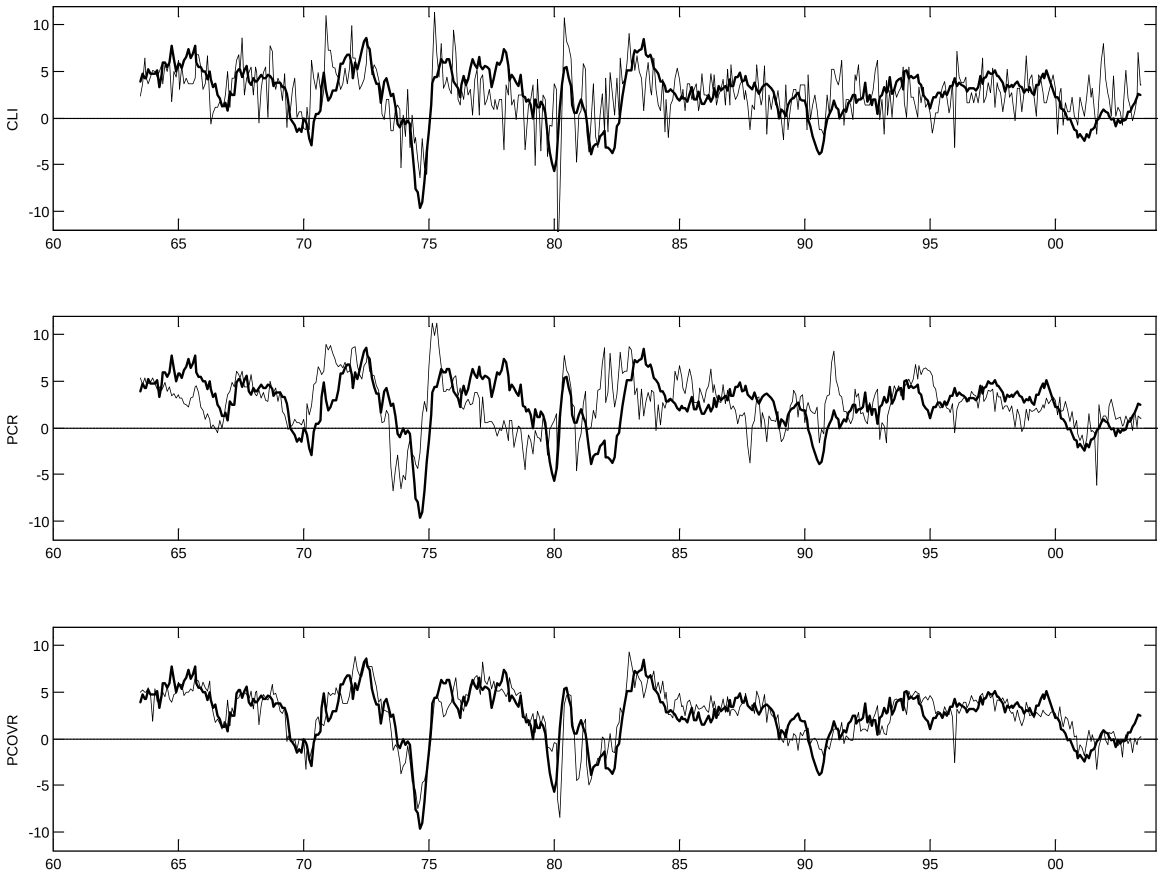

Figure 1: CCI six-month growth rate (bold line) and three index series (CLI, PCR, and PCOVR, thin lines).

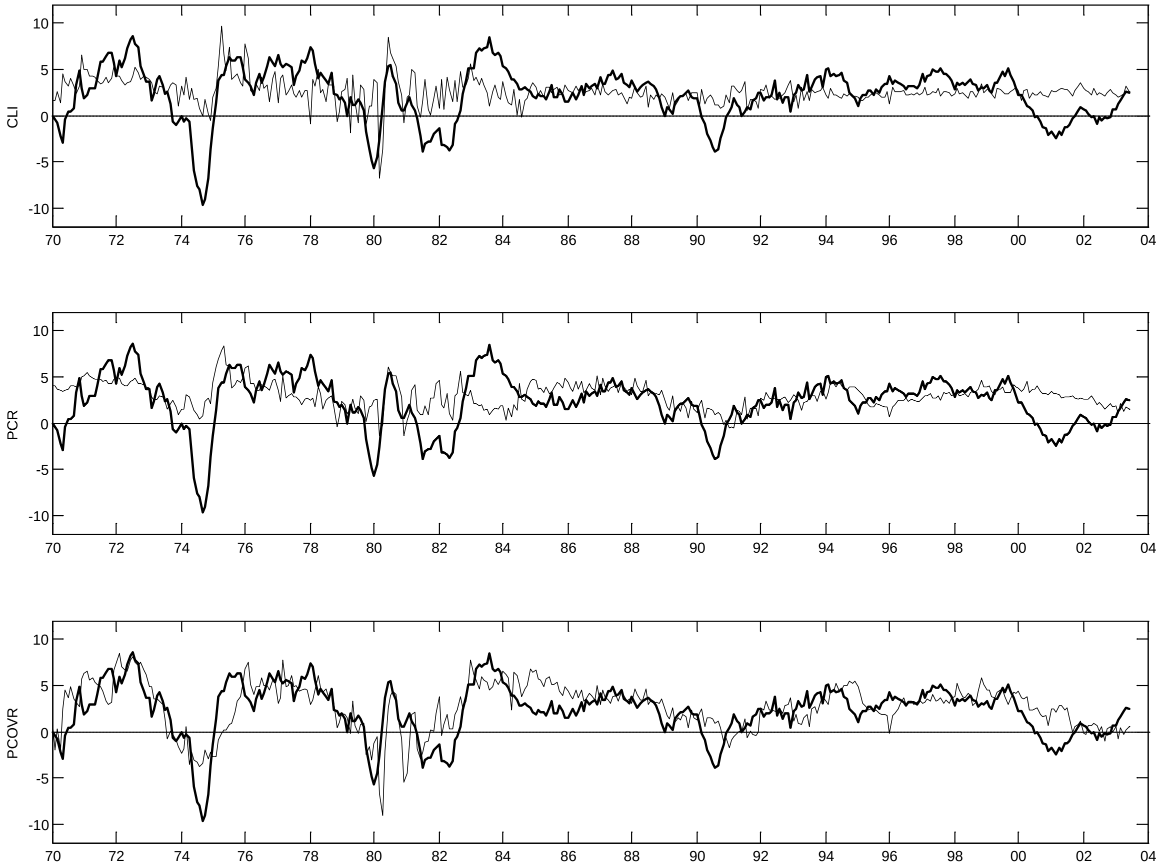

Figure 2: CCI six-month growth rate (bold line) and three index-based forecasts (CLI, PCR, and PCOVR, thin lines).

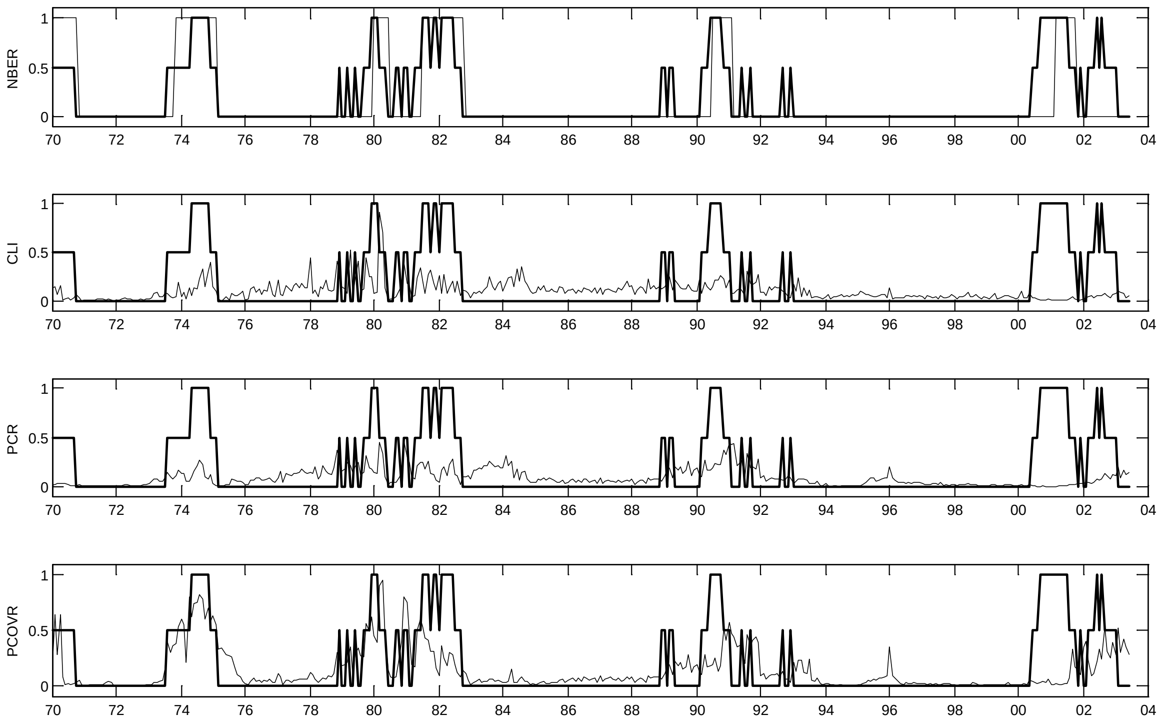

Figure 3: Future recessions (bold line) and NBER recession indicator (top panel, thin line), and three index-based recession probability forecasts (lower three panels, CLI, PCR, and PCOVR, thin lines).

Table 1: Within-sample correlations between indexes and CCI

Forecast Period (Sample Size)	Index	h = 3	6	12	24
1970-2003	CLI	0.41	0.41	0.41	0.41
(408-h)	PCR	0.45	0.52	0.56	0.52
	PCOVR	0.71	0.76	0.78	0.72
1970-1983	CLI	0.49	0.49	0.49	0.49
(168)	PCR	0.33	0.48	0.65	0.67
	PCOVR	0.73	0.81	0.88	0.75
1984-1993	CLI	0.16	0.16	0.16	0.16
(120)	PCR	0.65	0.62	0.57	0.42
	PCOVR	0.74	0.73	0.72	0.74
1994-2003	CLI	0.17	0.17	0.16	0.15
(120-h)	PCR	0.44	0.47	0.44	0.39
	PCOVR	0.65	0.72	0.71	0.63

Notes: For CLI, the table shows the (absolute) correlation of CLI with the CCI growth rate over the indicated forecast periods. For PCR and PCOVR, the table shows average correlations, as the index series is re-estimated every month. At forecast origin T, the PCR and PCOVR indexes are estimated over a window of 120 months, corresponding to the months $T-119 \leq t \leq T$, and the absolute value of the correlation between this series and the predicted variable over the same estimation window is computed. This correlation is averaged over all forecast origins in the considered forecast period. For instance, for 1970-2003 and forecast horizon $h = 12$, the correlations are averaged over the 396 forecast origins from 1970.01 till 2002.12.

Table 2: Correlations between three indexes and ten leading indicators

		Leading Indicator									
		Hours	Unemp.	Orders	Orders	Vendor	Build.	SP500	Money	Int.	Cons.
Index	h	Manuf.	Claims	Cons.	Cap.	Perf.	Permits	Index	M2	Spread	Expect.
CLI		0.06	0.57	0.54	0.25	0.17	0.21	0.44	0.46	0.45	0.43
PCR		0.62	0.34	0.34	0.14	0.67	0.51	0.35	0.55	0.64	0.30
PCOVR	3	0.51	0.41	0.37	0.17	0.44	0.67	0.20	0.44	0.52	0.17
	6	0.44	0.38	0.34	0.15	0.41	0.63	0.24	0.48	0.59	0.21
	12	0.37	0.33	0.30	0.12	0.47	0.52	0.26	0.53	0.67	0.23
	24	0.42	0.27	0.22	0.06	0.52	0.30	0.25	0.57	0.78	0.27

Notes: For CLI, the table shows the (absolute) correlation of CLI with the ten leading indicators over the 405 months from 1970.01 till 2003.09. For PCR and PCOVR, the table shows average (absolute) correlations, as the index series is re-estimated every month, see Table 1. For PCR, the average is taken over the 405 months from 1970.01 till 2003.09. For PCOVR, the index depends on the forecast horizon, and the average is taken over the 408-h months from 1970.01 till 2003.(12-h).

Table 3: Out-of-sample correlations between index-based forecasts and CCI

Forecast Period (Sample Size)	Index	h			
		3	6	12	24
1970-2003	CLI	0.32	0.32	0.33	0.27
(408-h)	PCR	0.31	0.36	0.44	0.43
	PCOVR	0.62	0.66	0.68	0.54
1970-1983	CLI	0.40	0.42	0.42	0.37
(168)	PCR	0.34	0.45	0.60	0.61
	PCOVR	0.65	0.71	0.80	0.70
1984-1993	CLI	0.14	0.18	0.26	0.40
(120)	PCR	0.45	0.43	0.51	0.44
	PCOVR	0.52	0.51	0.51	0.64
1994-2003	CLI	−0.21	−0.11	−0.17	−0.22
(120-h)	PCR	0.22	0.14	−0.13	−0.64
	PCOVR	0.53	0.54	0.41	−0.06

Notes: The table shows the correlation of the CCI growth rate with each index-based forecast of this growth rate over the indicated forecast periods. The forecast periods and forecast horizons h are the same as in Table 1.

Table 4: Mean squared prediction errors of CCI

Forecast Period (Sample Size)	h	var(y)	Const	CLI	PCR	PCOVR
1970-2003	3	10.66	1.08	0.93	0.95	0.68
(408-h)	6	8.17	0.86	0.72	0.72	0.50
	12	5.93	0.65	0.53	0.50	0.34
	24	3.67	0.39	0.34	0.31	0.27
1970-1983	3	19.32	1.08	0.88	0.92	0.60
(168)	6	14.34	0.83	0.66	0.64	0.40
	12	9.79	0.60	0.47	0.39	0.19
	24	5.81	0.36	0.31	0.24	0.21
1984-1993	3	4.36	1.03	1.04	0.98	0.98
(120)	6	3.03	0.72	0.73	0.72	0.88
	12	2.10	0.48	0.49	0.46	0.88
	24	1.56	0.36	0.32	0.33	0.35
1994-2003	3	4.62	1.15	1.20	1.09	0.93
(120-h)	6	4.00	1.03	1.03	1.03	0.89
	12	3.48	0.91	0.92	1.02	0.80
	24	2.85	0.74	0.74	0.89	0.69

Notes: The column 'var(y)' shows the variance of the predicted variable, the annualized h-month growth rate of the CCI, and the other columns show the MSE of each method relative to this variance. The column 'Const' shows the MSE obtained by forecasting the growth rate at each forecast origin by the average over the last 10 years. The forecast periods and the forecast horizons h are the same as in Table 1.

Table 5: Recession classifications and QPS

Classifications	CLI			PCR			PCOVR		
	Actual		Forec.	Actual		Forec.	Actual		Forec.
	Yes	No	Total	Yes	No	Total	Yes	No	Total
Forecast Yes	19	78	97	25	96	121	24	46	70
Forecast No	19	214	233	13	196	209	14	246	260
Actual Total	38	292	330	38	292	330	38	292	330

QPS	CLI	PCR	PCOVR
All Observations(330)	0.206	0.200	0.160
Expansions (292)	0.028	0.023	0.035
Recessions (38)	1.575	1.556	1.119

Notes: The top panel shows the number of correct and incorrect classifications of recession and expansion periods, with forecasts (Yes for a recession, No for no recession) in rows and with the actual regime in columns. For each index method, a recession is signaled if and only if the currently predicted recession probability exceeds the historical average predicted probability (by the same method) over the preceding 10 years, or over a shorter period at initial times when less previous forecasts are available. The bottom panel shows the quadratic probability scores of each index method over the recession and expansion periods from 1970.01 to 2003.06.

Table 6: Probit models for recessions and expansions

Frequency	Monthly			Quarterly		
Index	Both	PCR	PCOVR	Both	PCR	PCOVR
Coefficients						
Constant	-0.33	-0.08	-0.32	0.34	0.28	0.11
$\widehat{y}^{Q1}$ (PCR)	0.64	-1.14*		-0.09	-1.98*	
$\widehat{y}^{Q2}$ (PCR)	-0.64	-0.52		-0.38	-0.07	
$\widehat{y}^{Q1}$ (PCOVR)	-1.48*		-1.32*	-1.30*		-1.21*
$\widehat{y}^{Q2}$ (PCOVR)	-0.33		-0.48	-0.74		-0.97
Model Statistics						
# Observations	330	330	330	104	104	104
# Recessions	38	38	38	14	14	14
Log-Likelihood	-73.8	-104.8	-74.7	-22.8	-34.2	-23.2
Akaike Criterion	0.48	0.65	0.47	0.54	0.71	0.50
McFadden R^2	0.37	0.11	0.37	0.44	0.17	0.43
Likelihood Ratio		62.0	1.8		22.7	0.8
p-value		0.00	0.41		0.00	0.68

Notes: The upper half of the table shows the coefficients of probit models explaining the recession indicator in terms of the one-to-three and four-to-six months ahead growth forecasts of the PCR or PCOVR index models (a * denotes significance at the 5% level). The data period consists of future recession and expansion months, excluding months with a mixed future regime. The lower half of the table shows various model statistics. The p-value is for the Likelihood Ratio test that one of the indexes can be omitted, using the $\chi^2(2)$ distribution. The results are shown for two cases, one based on monthly updates of the forecasts and the other where the forecasts are used only quarterly.

Table 7: Mean squared prediction errors of DI-AR-Lag forecasts of CCI

Forecast Period (Sample Size)	h	var(y)	AR	CLI	PCR	PCOVR
1970-2003	3	10.66	0.80	0.71	0.75	0.69
(408-h)	6	8.17	0.70	0.50	0.55	0.55
	12	5.93	0.54	0.42	0.39	0.32
	24	3.67	0.38	0.32	0.30	0.28
1970-1983	3	19.32	0.82	0.70	0.70	0.62
(168-h)	6	14.34	0.72	0.48	0.49	0.48
	12	9.79	0.53	0.39	0.28	0.18
	24	5.81	0.36	0.31	0.22	0.22
1984-1993	3	4.36	0.91	0.84	1.02	0.99
(120-h)	6	3.03	0.65	0.65	0.71	0.92
	12	2.10	0.43	0.43	0.45	0.87
	24	1.56	0.36	0.29	0.37	0.39
1994-2003	3	4.62	0.66	0.68	0.85	0.91
(120-h)	6	4.00	0.54	0.53	0.77	0.79
	12	3.48	0.61	0.62	0.93	0.68
	24	2.85	0.61	0.61	0.88	0.59

Notes: The table shows the mean squared prediction errors of DI-AR-Lag forecasts of the CCI growth rate. The table has the same structure as Table 4, where no lagged indexes and no AR terms are used in the forecast model.

Table 8: Characteristics of DI-AR-Lag forecast models for CCI

		Index Lag (q)			AR Lag (r)				w
Forecast Period	h	CLI	PCR	PCOVR	AR	CLI	PCR	PCOVR	PCOVR
1970-2003	3	0.93	0.27	0.69	1.69	2.71	0.82	0.16	0.34
	6	1.31	0.49	1.15	1.17	3.66	1.74	-0.16	0.48
	12	1.44	0.59	1.32	0.66	0.35	1.46	-0.44	0.56
	24	1.32	0.51	1.18	-0.67	-0.43	-0.34	-0.51	0.59
1970-1983	3	0.96	0.25	1.17	1.33	1.79	2.15	0.16	0.41
	6	1.99	0.81	1.62	0.86	4.12	4.40	0.33	0.58
	12	1.99	0.96	1.68	0.49	-1.00	3.85	-0.38	0.75
	24	1.22	0.60	0.46	-1.00	-0.12	-0.63	-0.81	0.43
1984-1993	3	1.32	0.44	0.50	1.23	2.62	-0.50	-0.79	0.06
	6	1.65	0.35	0.51	0.50	4.26	-0.27	-0.81	0.12
	12	1.94	0.41	0.82	0.14	0.50	0.00	-0.42	0.22
	24	1.79	0.44	1.52	-0.99	-0.90	0.38	-0.27	0.49
1994-2003	3	0.02	0.00	0.04	2.69	2.69	0.30	0.80	0.19
	6	0.01	0.00	0.81	2.30	2.25	-0.13	0.24	0.43
	12	0.00	0.00	1.08	1.37	1.26	-0.57	0.25	0.59
	24	0.00	0.00	1.15	0.10	0.17	-1.00	0.20	0.59

Notes: The table shows the average over different forecast intervals of the index lag q and of the AR lag r, selected by BIC, and also of the average PCOVR weight w, selected by cross validation. Absence of current and lagged AR terms is expressed by $r = -1$, so that a negative average for r means that these AR terms are missing in many of the forecast models.

Table 9: Mean squared prediction errors of four coincident indicators

Period	h	var(y)	AR	CLI	PCR	PCOVR	Gain	var(y)	AR	CLI	PCR	PCOVR	Gain
				Production						Employment			
1970-	3	43.45	0.90	0.72	0.84	0.77	8.84	7.03	0.55	0.40	0.49	0.54	−10.96
2003	6	31.11	0.74	0.56	0.60	0.57	4.34	6.08	0.57	0.44	0.51	0.51	1.28
	12	20.41	0.51	0.36	0.32	0.29	11.49	4.77	0.55	0.47	0.44	0.44	0.63
	24	11.25	0.29	0.26	0.22	0.22	0.61	3.06	0.43	0.35	0.35	0.31	10.82
	Ave	26.56	0.61	0.48	0.50	0.46	7.00	5.24	0.52	0.41	0.45	0.45	−0.38
1970-	3	80.87	0.87	0.67	0.77	0.69	10.60	12.19	0.66	0.46	0.54	0.62	−14.43
1983	6	57.22	0.72	0.50	0.51	0.49	3.48	10.04	0.63	0.49	0.53	0.54	−2.02
	12	35.25	0.48	0.31	0.22	0.15	29.98	7.20	0.58	0.49	0.38	0.28	26.22
	24	18.98	0.27	0.24	0.15	0.15	1.41	4.23	0.41	0.31	0.26	0.19	26.11
1984-	3	14.69	1.11	0.86	1.18	1.22	−3.61	3.05	0.30	0.28	0.55	0.58	−4.71
1993	6	9.38	0.74	0.72	0.79	0.99	−25.50	2.74	0.34	0.31	0.59	0.82	−39.16
	12	5.37	0.36	0.34	0.42	0.82	−98.03	2.37	0.44	0.43	0.73	1.14	−55.75
	24	3.16	0.17	0.15	0.22	0.33	−50.94	1.86	0.62	0.53	0.72	0.93	−28.92
1994-	3	18.65	1.00	1.01	1.05	0.99	5.70	3.43	0.26	0.27	0.25	0.29	−14.08
2003	6	14.68	0.94	0.92	1.00	0.84	15.88	3.22	0.30	0.29	0.29	0.36	−24.94
	12	12.06	0.76	0.76	0.89	0.74	16.73	2.91	0.36	0.37	0.41	0.64	−54.46
	24	9.11	0.61	0.62	0.75	0.59	21.24	2.44	0.53	0.53	0.68	0.65	3.34
				Income						Sales			
1970-	3	13.43	1.01	0.94	0.95	0.98	−2.33	46.70	1.04	0.91	0.93	0.87	6.24
2003	6	9.04	0.79	0.67	0.72	0.60	15.68	27.98	0.66	0.57	0.53	0.49	7.59
	12	6.23	0.55	0.45	0.45	0.37	18.98	16.71	0.40	0.31	0.25	0.22	10.88
	24	3.70	0.34	0.29	0.29	0.30	−2.06	9.48	0.23	0.21	0.17	0.17	−3.44
	Ave	8.10	0.67	0.59	0.60	0.56	7.03	25.22	0.58	0.50	0.47	0.44	6.38
1970-	3	19.26	1.01	0.89	0.92	0.92	−0.40	82.95	1.04	0.87	0.87	0.75	13.17
1983	6	11.73	0.74	0.55	0.59	0.48	17.88	52.58	0.71	0.56	0.50	0.42	15.78
	12	7.50	0.45	0.33	0.29	0.21	27.36	31.98	0.43	0.32	0.23	0.19	18.72
	24	4.29	0.30	0.26	0.21	0.24	−17.11	18.28	0.25	0.24	0.18	0.18	−1.39
1984-	3	7.89	1.10	1.09	1.00	0.94	5.50	21.99	1.04	0.98	1.11	1.23	−11.00
1993	6	4.98	0.73	0.73	0.73	0.62	14.51	10.50	0.48	0.59	0.54	0.69	−27.32
	12	2.82	0.44	0.41	0.41	0.59	−44.94	4.95	0.21	0.26	0.24	0.34	−40.35
	24	1.81	0.32	0.28	0.33	0.35	−5.83	3.00	0.14	0.15	0.16	0.11	29.59
1994-	3	9.91	1.06	1.12	1.10	1.21	−10.57	20.48	1.06	1.05	1.11	1.14	−2.67
2003	6	7.29	0.79	0.80	0.92	0.97	−5.68	10.30	0.56	0.50	0.57	0.59	−2.77
	12	5.73	0.75	0.76	0.81	0.65	19.76	5.11	0.30	0.27	0.33	0.28	15.71
	24	3.99	0.53	0.55	0.63	0.49	22.68	3.07	0.17	0.16	0.20	0.15	25.75

Notes: The columns 'var(y)' show the variance of the predicted variable, the growth rate of each of four coincident indicators, and the next four columns show the relative MSE, as compared to this variance, of the AR forecasts and of the index-based DI-AR-Lag forecasts, generated by CLI, PCR, and PCOVR. The columns 'Gain' show the percentage MSE gain of PCOVR as compared to PCR, and the rows 'Ave' show the average MSE over the four considered forecast horizons.

Table 10: MSE for CCI of index-based forecasts using 128 variables

# Variables			128					10		
Forecast Period	h	var(y)	AR	CLI	PCR	PCOVR	Gain	PCR	PCOVR	Gain
1970-2003	3	10.66	0.80	0.71	0.67	0.60	9.18	0.75	0.69	8.18
	6	8.17	0.70	0.50	0.60	0.47	21.74	0.55	0.55	0.69
	12	5.93	0.54	0.42	0.54	0.38	29.78	0.39	0.32	16.68
	24	3.67	0.38	0.32	0.39	0.28	28.98	0.30	0.28	7.42
1970-1983	3	19.32	0.82	0.70	0.67	0.58	12.58	0.70	0.62	11.22
	6	14.34	0.72	0.48	0.60	0.43	28.95	0.49	0.48	2.91
	12	9.79	0.53	0.39	0.52	0.28	45.41	0.28	0.18	34.18
	24	5.81	0.36	0.31	0.38	0.21	46.03	0.22	0.22	1.25
1984-1993	3	4.36	0.91	0.84	0.71	0.77	−8.75	1.02	0.99	3.57
	6	3.03	0.65	0.65	0.54	0.68	−25.67	0.71	0.92	−29.88
	12	2.10	0.43	0.43	0.37	0.63	−70.28	0.45	0.87	−92.49
	24	1.56	0.36	0.29	0.32	0.45	−40.78	0.37	0.39	−5.17
1994-2003	3	4.62	0.66	0.68	0.66	0.57	13.87	0.85	0.91	−6.67
	6	4.00	0.54	0.53	0.62	0.56	8.84	0.77	0.79	−2.61
	12	3.48	0.61	0.62	0.65	0.67	−2.69	0.93	0.68	27.35
	24	2.85	0.61	0.61	0.60	0.67	−12.37	0.88	0.59	32.85

Notes: The table shows the variance of the predicted variable, the CCI growth rate, and the relative MSE of AR forecasts and of the DI-AR-Lag forecasts generated by CLI, PCR, and PCOVR, based on a set of 128 predictor variables. The table has the same structure as Table 9. The column 'Gain' shows the percentage MSE gain of PCOVR compared to PCR. The last three columns show the results of PCR and PCOVR obtained by using 10 instead of 128 predictor variables, and the MSE's for PCR and PCOVR in these columns are copied from Table 7.