Predicting U.S. Recessions in Real Time in a Big-Data Setting*

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February 2026

Abstract

We propose a novel approach for predicting recessions in real time in a *big data* environment. The context is one where we have a large set of variables known to be coincident with the business cycle, another large set known to lead the business cycle, and the dating of previous recessions. We employ principal component analysis to reduce the dimensionality of the coincident and leading sets of variables, and use canonical correlation analysis to establish the links between these two sets of variables, focusing on their cyclical features rather than noise. These cyclical features are then linked to the recession indicator via a structural probit model. In addition, we employ the expectation-maximization (EM) algorithm to solve the problem of publication lags in some coincident and leading series (the so-called "jagged-edge" problem), which enables us to use our model in real time.

In the empirical implementation of this framework, we are careful not to use future information to forecast the future. This requires devising an updating rule for the

*The authors gratefully acknowledge the support given by CNPq, FAPERJ, and CAPES-PrInt on different grants. This study was also financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001. The views expressed in the paper are those of the authors and do not necessarily reflect those of the Banco Central do Brasil and of Getulio Vargas Foundation. This paper supersedes Costa et al. (2023), cited below.

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vintages of data used in forecasting, an updating rule for the estimates of the structural probit model, and a real-time recursive technique for choosing the best model for forecasting based on past performance.

Using the receiver operating characteristic (ROC) curve, we observe that our forecasting strategy has a true positive rate (TPR) of around 94% coupled with a false positive rate (FPR) of around 8% in real time for reasonable choices of the cut-off point. Moreover, we find little difference between forecasting using available information in real time and forecasting using information available slightly *a posteriori*, indicating that the EM algorithm successfully solves the jagged-edge problem.

Keywords: Forecasting Recessions; Common Cycles; Canonical Correlation Analysis; Principal Component Analysis; Structural Probit Model.

JEL Classification: C14; C15; C22; C53; C55; E17; E31.

1 Introduction

In this paper, we propose a novel framework to predict U.S. recessions using information available in real time. It is a *big-data* approach, with the following ingredients: the use of the expectation-maximization (EM) algorithm to create balanced forecast vintages; the use of principal-component analysis (PCA) as a dimension-reduction device; the use of canonical-correlation analysis (CCA) to connect coincident and leading series *vis-a-vis* the U.S. business cycles; the use of a structural *probit* regression to forecast the probability of occurrence of a recession in real time (month t) using coincident and leading series; the use of the receiver operating characteristic (ROC) curve to measure forecast accuracy and to determine the state of the U.S. economy, i.e., whether or not it is a recession in real time.

When we applied our forecasting strategy to a large U.S. data set, we find that it can track well the state of the U.S. economy, producing accurate forecasts of probabilities of a recession in real time: the model fits well in-sample, and its out-of-sample recession predictions are surprisingly precise in real time. Using ROC-curve analysis, depending on the cutoff chosen, we achieve a true-positive rate (TPR) of 94% coupled with a false-positive rate (FPR) of 5% for predictions one-month *a posteriori*. In real time, we achieve a TPR of 94% with an FPR of 8%.

We now describe in some detail the main techniques underlying our results. To address the jagged-edge (or ragged-edge) problem (see, e.g., Giannone et al., 2008), we use the expectation–maximization (EM) algorithm to generate balanced real-time panels.[1] From these

[1]Since future information cannot be used, the EM algorithm is applied recursively: for each period t, a

panels, we extract common components via principal-component analysis (PCA), following Stock and Watson (2002). This *dense* method captures shared variation in large datasets (see Giannone et al., 2021). We apply PCA separately to two large sets: one containing series that are *coincident* with the U.S. business cycle (Stock and Watson, 2014), and another containing *leading* indicators of the U.S. business cycle (Costa et al., 2021).

Our modeling strategy builds on Issler and Vahid (2006), who use canonical-correlation analysis (CCA) to link coincident and leading series through a *structural* probit model based on the NBER recession indicator. The probability of a recession is a probit transformation of a linear combination of coincident series (bases cycles), while instruments are linear combinations of leading series. Their key identifying assumption is the existence of a common cycle between the unobserved state of the economy underlying the probit model and the bases cycles predictable by leading indicators – a dimension reduction feature that separates the cyclical signal from noise.[2]

To determine the best forecasting specification, we implement a dynamic selection algorithm that evaluates multiple probit models based on their past performance. We vary the explained variance of PCA (30–80%), estimate 36 different probit models, and use receiver operating characteristic (ROC) curve analysis to select the model with the highest cumulative area under the curve (AUC). This ensures real-time forecasts rely on the most accurate model given past data.[3]

There is a vast literature on predicting U.S. recessions. Stock and Watson (1989, 1991, 1993) were pioneers in this literature, asking whether it would be possible "to develop a formal probability model that gives rise to the indexes of leading and coincident variables." Their motivation was to use modern econometric tools to formalize the ideas behind the broad research agenda of Burns and Mitchell (1946), something Issler and Vahid (2006) have in common with their approach. Estrella and Mishkin (1998) evaluated the performance of financial variables (interest rates, spreads, stock prices, and monetary aggregates) in predicting the probability of recessions. They found that stock prices predicted recessions well at one- to three-quarter horizons, while the slope of the yield curve was more powerful beyond one quarter. The predictive power of the term structure is also documented in Rudebusch

new vintage is created using only information available up to t to predict missing data.

[2]Canonical-correlation analysis estimates the linear combination of coincident series that are most predictable from the coincident series (i.e., are most cyclical), and the optimal linear combinations of leading variables that predict them. It also provides a test that enables us to distinguish the cyclical components from noise.

[3]Because NBER recession dates are released with delay, the dependent variable is available only up to $t-h$. We assume a 24-month delay, given that the maximum observed in our sample is 24 months. Parameters are estimated using information up to $t-24$, while basis cycles use data up to t, enabling feasible real-time forecasts.

and Williams (2009), who argue that professional analysts do not adequately incorporate the information contained in the yield spread.

A dynamic probit model was used by Nyberg (2009), who found that in addition to the term spread, lagged stock return values and external spreads were important predictors of a recession. Nonlinear models and stochastic simulations were used by Anderson and Vahid (2001) to predict the probability of recession in the U.S. using the interest rate spread and the growth of the money stock (M2). Wright (2006) estimated several probit models and showed that adding the Fed Funds rate to the term spread outperformed the Estrella and Mishkin (1998)'s model. Christiansen et al. (2014) demonstrated that sentiment variables had superior predictive power compared to financial variables. Kotchoni and Stevanovic (2018) proposed an ARX model for forecasting GDP growth, where the X part stands for recession-probability, which indirectly involves its real-time forecasts.

There is also extensive research on dating recessions. Of course, this is related to the literature on forecasting recessions, but the final focus of interest is different. The dating-recessions literature follows the seminal work of Burns and Mitchell (1946), including, among others, Bry and Boschan (1971), Harding and Pagan (2002), Stock and Watson (2010, 2014) and Camacho et al. (2020). Since our aim is to develop a predictive model for the binary indicator generated by the NBER dating mechanism, but not to inspect the dating mechanism itself, we only review this literature when it intersects with the literature on forecasting recessions. Important papers on that list are related to the Markov-switching model of Hamilton (1989), whose complete dynamic statistical model can be used to predict recessions and, with the passage of time, determine historical turning points with increasing precision; see Chauvet (1998), whose work is similar to that of Stock and Watson (1989, 1991, 1993), and Chauvet and Hamilton (2006), who incorporate information on GDP growth to date recessions and Hamilton (2011), who highlights the difficulties of dating recessions in real time.

Finally, there is an emerging literature that applies machine learning (ML) methods to forecast economic variables. In general, these methods perform poorly when predictors are highly correlated, the dependent variable is highly persistent, and sample sizes are small – as is the case for forecasting recessions. Nevertheless, Vrontos et al. (2021) apply these methods to predict U.S. recessions and conclude that, while some ML methods outperform simple models that use only the yield-curve to predict recessions, their performance is not consistently better across different horizons. Their best results arise when they use the nine predictors selected more than 90% of the time by all ML methods using a simple logit or

probit link. On that basis, they recommend ML methods mainly as tools for eliminating irrelevant predictors.

Empirically, we employ a large set of variables believed, *a priori*, to be coincident with the U.S. business cycle (Stock and Watson, 2014) and another larger data set believed to be leading the U.S. business cycle (Costa et al., 2021). Our use of principal component analysis (PCA), canonical correlation analysis (CCA), and a generalized linear model (GLM) with a probit link function to connect a small number of basis cycles to recessions can be interpreted as bespoke dimension-reduction and regularization techniques designed to avoid overfitting and to produce robust forecasts. In this sense, we differ from most ML methods by employing *dense* rather than *sparse* techniques (see Giannone et al., 2021, for a comparison of dense and sparse techniques in forecasting).

The paper is organized as follows. Section 2 presents our methodology for predicting recessions in real time using big data. Section 3 provides a critical discussion of our methodology in relation to the existing literature, complemented by a partial review of the literature in the online appendix. Section 4 reports the empirical results of our recession/expansion forecasts for the U.S. economy. Section 5 concludes.

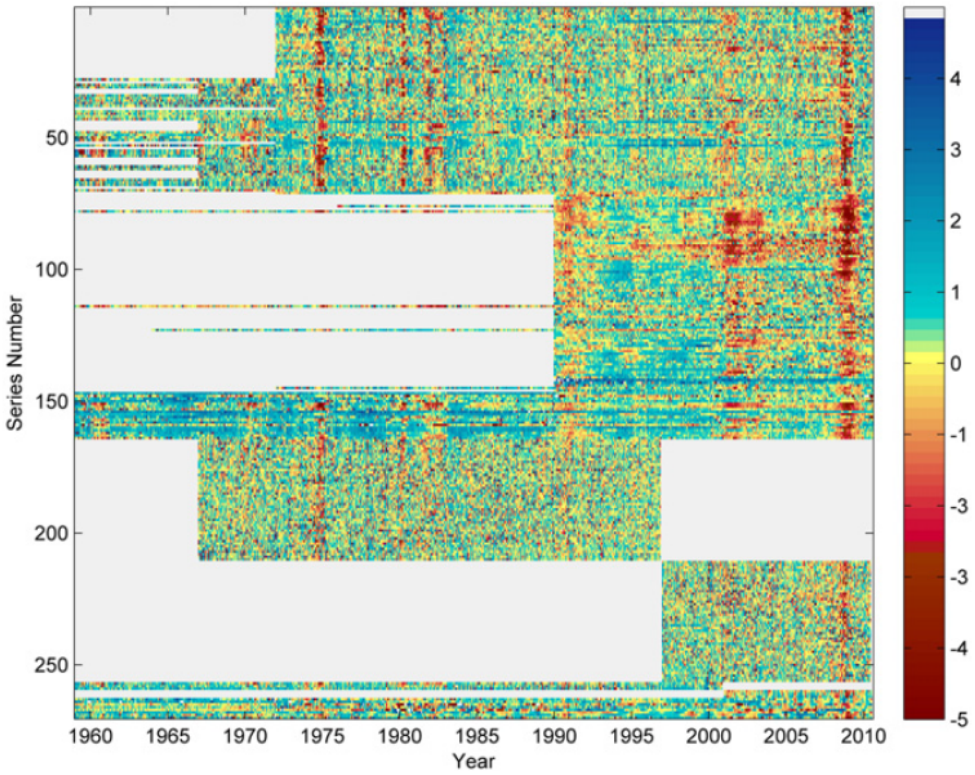
2 Real-Time Methodology

This section presents a self-contained summary of the methodology employed in this paper to predict U.S. recessions in real time in a big-data setting. Technical details are provided in the online appendix.

There are two critical problems to be solved in order to implement the *structural* probit model proposed by Issler and Vahid (2006) in a big-data setting: (i) how to solve the jagged-edge problem under these conditions and; (ii) how to generate feasible bases cycles and optimal instruments based on CCA in a big-data setting.

We solve the jagged-edge problem by implementing the EM algorithm in the form proposed by Schneider (2001). He extended it to incomplete, high-dimensional datasets. His regularized EM algorithm iteratively estimates optimally means and covariances while imputing missing data through Ridge Regressions. Unlike the standard EM algorithm, this method remains stable when variables exceed observations, effectively filtering noise and multicollinearity. It is thus well-suited for big-data panels with asynchronous releases, enabling consistent real-time imputation and forecasting. With it, we balance the panels of coincident (x_t) and leading (z_t) series, implementing different monthly vintages, which is a critical step for their use in real-time forecasting.

Figure 1 – Coincident Data Base (Stock and Watson, 2014)



Source: Stock and Watson (2014)

Figure 1 illustrates the challenges of working in a big-data environment. Overall, Stock and Watson (2014) employ a total of 270 coincident data series. Each of them falls into one of the four classes that have been traditionally used in business-cycle analysis: Employment, Income, Industrial Production and Sales. The heatmap allows us to spot U.S. recessions, which are shown in red, while white spaces indicate missing data. Indeed, missing data is a major problem. Less so for the past, but for the future, since one wants to implement real-time forecasting and cannot rely on discontinued data. We must stress that Figure 1 does not illustrate the jagged-edge problem, typical of the end of databases, where there is no alignment of the release of different series.

Consider now the data of the coincident series stacked in vector x_t, where n is the number of rows in x_t, and the leading series stacked in vector z_t, where $m \geq n$ is the number of rows in z_t. To implement standard CCA, the variance–covariance matrix of $(x_t', z_t')'$ must be full rank. However, in a big-data setting, the dimension of the column vector $(x_t', z_t')'$ usually exceeds the number of observations through time, making the variance–covariance matrix of $(x_t', z_t')'$ rank deficient; i.e., it is infeasible to implement standard CCA in this context.

To fix the infeasibility problem, we propose a traditional solution – the implementation of PCA separately on x_t and z_t, extracting respectively their reduced number of common components (factors), making it feasible to implement CCA using the extracted factors of x_t and

z_t as *coincident* and *leading* series, respectively. Of course, this type of data transformation will not change the coincident and leading characteristics of the of the x_t and z_t data sets, respectively.[4]

We now turn to the *structural* probit model proposed by Issler and Vahid (2006), adapted to real-time use. The decisions of the NBER Business Cycle Dating Committee are characterized as follows:

$$\text{NBER}_t = \begin{cases} 1 & \text{if } \mathbb{E}(y_t^* \mid I_{t+h}) < 0, \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where y_t^* is a variable representing the unobserved state of the U.S. economy, i.e., the latent U.S. business cycle, I_{t+h} is the information set used in computing expectations of y_t^*, using information up to $t+h$, and NBER_t is a dummy variable signaling U.S. recessions by the committee in period t. Equation (1) makes it clear that future information is used by the NBER-committee in determining the state of the economy in period t – ($\mathbb{E}(y_t^* \mid I_{t+h})$). Of course, this key feature must be taken into account in building the *structural* Probit model.

The key identifying assumption in Issler and Vahid (2006) is the following:

$$\mathbb{E}(y_t^* - \beta_0 - \beta_1 c_{1t} - \beta_2 c_{2t} \cdots - \beta_k c_{kt} \mid I_{t-1}) = 0, \tag{2}$$

where $c_{it} = \alpha_i' x_t$, $i = 1, 2, \ldots, k$ are bases cycles computed by CCA, predictable from I_{t-1}. In a nutshell, they assume that there is a common cycle between the latent U.S. business cycle and the k bases cycles of the U.S. economy; see Vahid and Engle (1993) for a formal definition. This essentially means that the dynamics of the U.S. business cycle can be fully captured by these k bases cycles.

It is straightforward to verify that, by construction, this identifying assumption renders correlation between basis cycles and the error term in the probit model, requiring instruments to be used.[5] Moreover, the identifying assumption in combination with delayed decisions by the NBER committee yields a serially-correlated error as well (interested readers can refer to the online appendix for a technical discussion).

The next step of empirical analysis is to estimate the probit model proposed in Issler and Vahid (2006). The k bases cycles $\{c_{1t}, c_{2t}, \cdots, c_{kt}\}$ are those that can be statistically predicted by the leading series in CCA. In this context, we estimate a *structural* probit model, using the two stage conditional maximum likelihood (2SCML) method of Rivers and Vuong

[4]In this context, we can choose the number of factors to be used in real time, which is identical to choosing the proportion of the variance of these data sets that is explained by this chosen factors.

[5]There is an additional reason to use instruments – the basis cycles have to be estimated using data, so, they suffer from measurement error. From CCA, the optimal instruments are linear combinations of the leading series explaining those basis cycles.

Table 1 – NBER Peaks and Troughs Dating Delays

Turning point	Dated	Announcement	NBER Comm. Delay
peak	jul/1990	apr/1991	9
trough	mar/1991	dec/1992	21
peak	mar/2001	nov/2001	8
trough	nov/2001	jul/2003	20
peak	dec/2007	dec/2008	12
trough	jun/2009	sep/2010	15
peak	feb/2020	jun/2020	4
trough	apr/2020	jul/2021	15

Source: NBER Homepage
Note: Delay measured in months.

(1988). The first stage involves regressing the basis cycles $\{c_{1t}, c_{2t}, \cdots, c_{kt}\}$ on k optimal instruments (linear combinations of the leading series), saving the residuals, which we denote by $\{\hat{v}_{1t}, \hat{v}_{2t}, \cdots, \hat{v}_{kt}\}$. In the second stage, both the basis cycles $\{c_{1t}, c_{2t}, \cdots, c_{kt}\}$ and the first-stage residuals $\{\hat{v}_{1t}, \hat{v}_{2t}, \cdots, \hat{v}_{kt}\}$ are included as regressors in the probit model:

$$\Pr\left(\text{NBER}_t = 1\right) = \Phi\left(-\left(\beta_0 + \beta_1 c_{1t} + \cdots + \beta_k c_{kt} + \beta_{k+1}\hat{v}_{1t} + \beta_{k+2}\hat{v}_{2t} + \cdots + \beta_{2k}\hat{v}_{kt}\right)\right), \quad (3)$$

where $\Phi(\cdot)$ is the standard Gaussian cumulative distribution function (CDF). The second-stage estimates of $\beta_0, \beta_1, \beta_2, \cdots, \beta_k$ in the probit model are the 2SCML estimates – denoted by $\widehat{\beta}_0, \widehat{\beta}_1, \widehat{\beta}_2, \cdots, \widehat{\beta}_k$.[6] Based on these estimates, we can predict in *real time* the probability of a recessions in period t using:

$$\Pr\left(\widehat{\text{NBER}_t} = 1\right) = \Phi\left(-\left(\widehat{\beta}_0 + \widehat{\beta}_1 c_{1t} + \widehat{\beta}_2 c_{2t} + \cdots + \widehat{\beta}_k c_{kt}\right)\right). \quad (4)$$

There is an important issue regarding the use of this model in real time. As noted above, the NBER Committee declares a recession in period t with a delay – say, in period $t + h$. Thus, if we are in period t, we would only have available the dependent variable of the probit model (3) up to $t - h$. Our practical solution in this case is to estimate the parameters of the structural probit model using only the dependent variable and combinations of coincident and leading variables up to $t - h$. Table 1 presents NBER dated peaks and troughs and their respective delays in the forecasting sample we use in this paper. It reaches a maximum delay of 21 months. Thus, in our out-of-sample forecasting exercise, we employ $h = 24$ to ensure that in the forecasting sample we can always run equation (4) pseudo-out-of-sample.

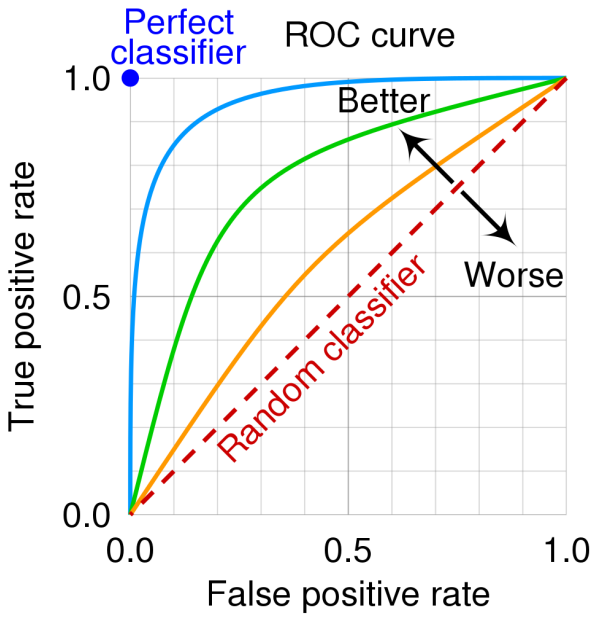
At time t, although the dependent variable is not available, the coincident and leading series are. Hence, the EM algorithm, PCA and CCA can be used in sequence to create bases

[6]The estimation of the variance-covariance matrix of the βs requires the use of robust methods.

cycles and optimal instruments that employ only information up to period t. Using $\widehat{\beta}_0, \widehat{\beta}_1, \widehat{\beta}_2, \cdots, \widehat{\beta}_k$, which are estimated based on information up to period $t-h$, and $\{c_{1t}, c_{2t}, \cdots, c_{kt}\}$ which employ information up to period t, we ensure that the final forecast from equation (4) contains no information beyond what is available at time t to compute $\Pr(\widehat{\text{NBER}_t} = 1)$.[7]

The final step of the methodology provides a decision-making tool to make a call of whether the U.S. economy is in recession or not. We propose to make this call using receiver operating characteristic (ROC) curves.

Figure 2 – Receiver Operating Characteristic (ROC) Curves



Source: Wikipedia

A ROC Curve plots the true positive rate (TPR) against the false positive rate (FPR) as the classification threshold varies; see Fawcett (2006). Thresholds in $[0, 1]$ serve as decision rules to classify states – *recession* versus *no-recession*. When the predicted recession probability exceeds the threshold, a recession state is chosen; otherwise, a no-recession state is chosen. In a *pseudo*-out-of-sample exercise, these classifications are compared to NBER-dated recessions. In machine-learning terms, the TPR corresponds to *recall* or detection probability, and the FPR to the *false alarm rate*. Ideally, we aim to maximize the former and minimize the latter.

The ROC curve can also be interpreted as a plot of test power versus Type I error, summarizing all relevant performance measures in a single graph (see Figure 2). Preferred points lie in the Northwest region, with TPR close to one and FPR near zero. In our real-

[7]Some future information may creep into our pseudo-out-of-sample forecasts due to seasonal adjustment and data revisions. We do not deal with those issues here. However, this limitation also applies to the rest of the literature.

time forecasting setup, we compute ROC curves to evaluate models that explain different proportions of the variance in the coincident or leading datasets obtained from principal-component analysis. This evaluation is recursive, allowing model selection to change in real-time each month. We consider three criteria: (i) the *area under the curve* (AUC), averaged across forecasts; (ii) a restricted AUC over $[0, 0.2]\times[0.8, 1]$ ($AUC20$); and (iii) a finer subset $[0, 0.1]\times[0.9, 1]$ ($AUC10$), emphasizing regions with low false-positive rates and high detection accuracy.

3 Comparisons with the Literature

This section presents a critical discussion of the techniques proposed here in light of the existing literature. For the sake of completeness, the online appendix presents the most relevant portion of this literature.

The U.S. experience in forecasting rare and extreme events, such as recessions, shows us that we should not be too optimistic when using them in real time. As noted by Hamilton (2011), it is often observed that the fit of different models is very good in sample, but they often fail in their behavior out of sample. Indeed, Hamilton (2011) warns us of the difficulties related to predicting recessions in real-time:

> *"If people could predict recessions, they probably would not happen. Firms would not be stuck with inventories, labor, and capital they turn out not to need, and the Federal Reserve would probably ease its policy stance earlier. Economists are used to viewing magnitudes such as stock prices as difficult or impossible to predict if the market is functioning properly, and it may be that economic recessions, by their very nature, imply similar fundamental limitations for forecasting."*

We believe economists understand the difficulty of predicting recessions in real time. So, why do they try to do it? Well, the rewards that a good prediction model would have is very high as well – which has certainly motivated this literature. Moreover, we live more and more in a world where big-data, machine learning and artificial intelligence are commonplace, which challenges their use in solving the relevant problems of the day.

A problem for real-time models that employ the decisions of the NBER-Committee relates to the fact that it usually dates recessions with a delay ranging from 6 months to a year (sometimes even closer to two years). This issue is basically ignored throughout the literature. However, it implies that NBER-Committee decisions cannot be used *directly* as a real-time

device for forecasting recessions. Issler and Vahid (2006) recognize this, but, they do not discard their *indirect* use, something we employ here:

> *"Suppose that we are asked to construct an index of the health status of a patient. Also, suppose that we know that the best indicator of the health of the patient is the results of a blood test. However, blood samples cannot be taken too frequently, and test results are only available with a lag, sometimes too long to be useful. Our index therefore must be a function of variables such as blood pressure, pulse rate and body temperature that are readily available at regular frequencies. In order to estimate the best way to combine these variables into an index, would we (i) use the historical data on these variables only, or (ii) use the historical blood test results as well? The answer is, obviously, the latter."*

Indeed, these releases delays do not imply that we cannot use NBER-Committee decisions in a forecasting model *ex-post*, since the literature recognizes that these decisions are an accurate description of the state of the U.S. economy. Here, not only we fit the probit model using the NBER-decisions, but we also employ estimated parameters with a sufficient lag for them to be useful in real time.

A related issue to the use of NBER-committee decisions is that it employs future information regarding the state of the U.S. business cycle (y_t^*). Issler and Vahid (2006) assume that the committee declares a recession if $\mathbb{E}(y_t^* \mid I_{t+h}) < 0$, which implies that regressors and the error term of the probit model will be correlated by construction given their identifying assumption, i.e., given equation (2). This entails a *structural* probit model and the use of instruments, which of course differs from most of the literature, see, e.g., Stock and Watson (1989, 1991, 1993), Estrella and Mishkin (1998), Chauvet (1998), Nyberg (2009), and Kotchoni and Stevanovic (2018), *inter alia*, where strict-exogeneity of regressors is assumed. The key role for the instruments used in their model is to filter noise in the regressors of the probit model, something embedded in CCA.

Although Stock and Watson (2014) do not explicitly propose a model to predict recessions, they compare two business-cycle modeling techniques for dating them: *date then average* and *average then date*. The former is their preferred approach and the latter is the preferred technique of Chauvet and Hamilton (2006) and Hamilton (2011), who focus on aggregate series such as GDP. The key message in Stock and Watson (2014) is about the usefulness of employing large databases for dating business cycles. It can be seen as a form of portfolio diversification for data use – since a *dense* technique avoids having a handful of variables

guiding the dating of recessions.[8]

In business-cycle research, there are two classic ways of implementing *dense* techniques in the context of forecasting recessions: (i) principal component analysis, proposed by Stock and Watson in several articles, and (ii) canonical correlation analysis, proposed in the common-feature literature (Engle and Kozicki, 1993; Vahid and Engle, 1993; Engle and Issler, 1995), which Issler and Vahid (2006) follow. The first extracts a reduced number of factors from the database of potential predictors and then uses a bridge regression to forecast the variable(s) of interest. The second generalizes the idea behind a least squares regression. From two sets of data – coincident series and leading series – it recursively selects the linear combinations of the first set that have maximum correlation with linear combinations of the second, and a test of predictability implemented to exclude noise.

In this paper, we employ both, but with different roles. PCA is employed as a dimension-reduction device, allowing CCA to be feasible, whereas CCA is a key built-in technique of the *structural* probit model. We see an advantage for this specific role of CCA. In addition to separating *noise* and *signal* from the coincident and leading series, it still makes a forecasting bridge between them, all in a single optimization pass.

4 Empirical experiment

4.1 Data and empirical strategy

To ensure a sufficient number of recession episodes within the U.S. sample, we start the sample period in 1970:M1 and end it in 2023:M1 (637 monthly observations), yielding a total of 8 recessions over 53 years, approximately one every six and a half years.

The *coincident* series are drawn from the large database compiled by Stock and Watson (2010, 2014), discussed above. Their database was updated here through 2023:M1. Of the orginal 270 series, we excluded the *sales* series from the analysis, as they contain many missing values, both forward and backward. Furthermore, the weight attributed to sales in the coincident index of Issler and Vahid (2006) was only 6%, suggesting that their exclusion would have a minor effect on final results. This procedure resulted in 177 coincident series.

[8] Hamilton (2011) stresses why diversification could be decisive to improve forecasting recessions:

> *"What went wrong [in the 1990-91 recession]? One of the intriguing new leading indicators that Stock and Watson discovered was the spread between the yield on commercial paper and Treasury bills ... this spread had a dramatic spike prior to each of the recessions in their original sample, but did very little out of the ordinary in the 1990-91 recession, for which their model was on real-time display."*

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The complete list of these variables is provided in Appendix A.

Regarding the *leading* series, we relied primarily on the database compiled by (Costa et al., 2021), which was developed to forecast *Brent* oil prices. This database contains a total of 294 variables, mostly U.S. data; see Appendix A for the complete list of leading variables. In addition to the lagged leading series, we also include their higher-order lags as well as the lags of the coincident series, which are strong predictors of the coincident series themselves. With two lags of both sets, we end up with 942 series overall. Given that the total number of time-series observations is 617, we are indeed in a *big-data* setting where dimension-reduction techniques are required.

We could use the full sample from 1970:M1 to 2023:M1 to obtain the basis cycles and estimate $\beta_0, \beta_1, \beta_2, \cdots, \beta_N$ in equation (4), and then examine the quality of the model's predictions throughout the estimation sample. However, that exercise would not give us a feasible strategy for predicting recessions in real time. At time t, we only know the values of the leading variables and most of the coincident variables up to time t. Some of the coincident variables may be delayed by a few days or weeks, but we can delay our prediction slightly until all time-t values of the coincident series become available, or impute them using the EM algorithm. More importantly, the value of the dependent variable, the NBER recession indicator, will be "not available" (NA) at time t and will remain NA for many months thereafter. In particular, around turning points we may not know whether the value of the dependent variable equals zero or one for nearly two years, as shown in Table 1. As a result, at time t, our dynamic real-time procedure uses parameters estimated from the $t-24$ vintage of the data, as elaborated below.

The pseudo-real-time out-of-sample evaluation of our procedure starts in 1990:M1 and continues, one month at a time, until 2023:M1. The argument of the probit link function in equation (4) is ultimately a linear combination of the values of the coincident variables at time t because the basis cycles are linear combinations of the PCs of coincident series, and the PCs themselves are linear combinations of the coincident series. The coefficients used to compute this linear combination at time t are estimated based on the sample starting from 1970:M1 and ending at $t-24$. For example, to predict the recession probability at 1990:M1, we use the parameters estimated based on the 1970:M1 to 1988:M1 sample. This ensures that the procedure is applicable in real time because the 24-month lag is greater than the maximum delay in the Business Cycle Dating Committee's determination of business cycle peaks and troughs. Using these estimated coefficients and the values of coincident variables at time t, we calculate the argument of the probit link function.

To estimate the parameters of the structural probit model using the 1970:M1 to $t-24$ sample for each t, one needs to decide how many principal components (PCs) of the coincident variables and how many PCs of the leading variables to include in the analysis, and then determine the number of non-zero canonical correlations (CCs) between these two sets of PCs to specify the number of basis cycles in the model. Given the number of coincident and leading PCs, the number of non-zero CCs is determined by the test-based procedure described in Issler and Vahid (2006). The dynamic algorithm for choosing the number of coincident and leading PCs is as follows.

For each estimation sample, we select the best among several candidates, each characterized by a different number of PCs. We consider models whose PCs explain between 30% and 80% of the variance of their respective databases (coincident or leading), in increments of 10%. We let these models compete in real time, choosing the one with the best performance up to time t. We use the AUC (area under the ROC curve, explained in the previous section) to measure the performance of each model. This dynamic procedure allows the number of coincident and leading PCs to change as t evolves, depending on the accuracy of the competing models. To assess the sensitivity of the results to the use of AUC for choosing the number of PCs, we repeat the exercise using AUC10 and AUC20, which, as explained in the previous section, measure the area under different slices of the ROC curve.

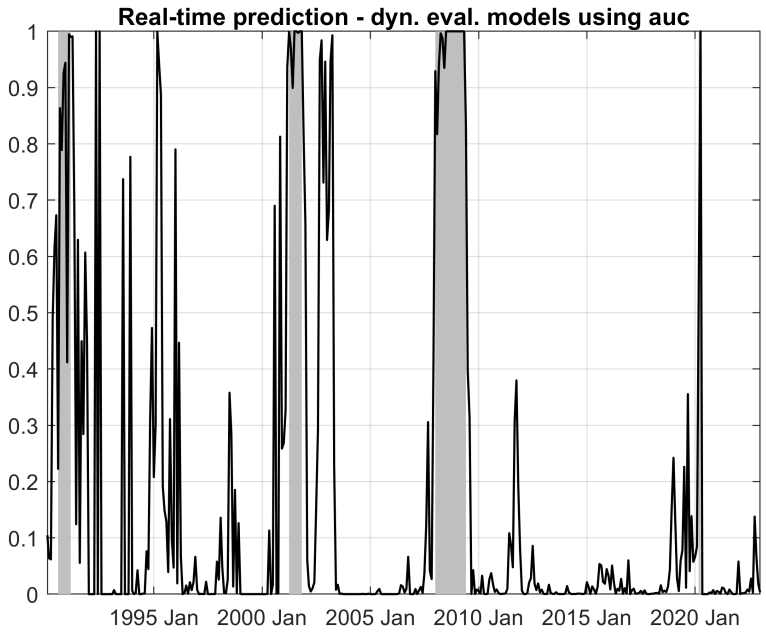
However, in real time, the time-t values of some coincident variables are not available at time t and become available only after one or two months (Appendix 5 provides a list of all variables and their publication lags). We use the EM algorithm proposed by Schneider (2001) to impute the values of these variables before calculating the argument of the link function at time t. To evaluate the effectiveness of this imputation method, we repeat the analysis using the values of the coincident variables available one month and two months after time t and compare the accuracy of the one-month and two-month *a posteriori* predictions with our real-time predictions.

4.2 Empirical results

The outcome of the *pseudo*-out-of-sample forecasting experiment is summarized in Figure 3. The black line connects the forecast of the probability of recession in each month from 1990:M1 to 2023:M1, as provided by the dynamically selected model based only on the information available up to that month. Gray areas represent the four recessions dated by the NBER during this period.

As can be seen in Figure 3, the predicted probabilities during the gray periods are almost

Figure 3 – Predictions of the dynamic evaluation exercise:
Real-time prediction using the AUC criterion



always greater than the usual threshold (0.5) used to translate probabilities into binary outcomes. However, there are also instances outside the gray areas where the predicted probabilities are high, i.e., considerably larger than 0.5. Of course, if false positives are costlier than missing true positives, the user would choose a threshold higher than 0.5 to translate these probabilities into binary outcomes. The first two columns of the top panel in Table 2 show the tradeoff between the true positive rate (TPR) and the false positive rate (FPR) for different thresholds. If the threshold is set at 0.5, the FPR is 7.5% and the TPR is 94.4%. If the threshold is set at 0.7, then, the FPR is reduced to 5%, but the TPR declines to 91.7%, illustrating the natural trade-off related to the choice of threshold.

Before discussing the sensitivity of our results to changes in different components of our modelling strategy, we present the choices made by our dynamic strategy during this forecasting experiment. Recall that, in each period, 36 different models were estimated using combinations of PCs that explained 30 to 80% of the variance of the coincident and leading databases, in 10% increments. Of these 36 models, the best was chosen based on the AUC score for forecasting in period t.

Figure 4 presents the area under the curve (AUC) for the best 9 models, out of 36, that is, the top *quartile* of the distribution. The model that employs principal components explaining 40% of the leading database and 30% of the coincident database is the best most of the time. On the other hand, models that explain a high proportion of the variance (either of the leading or the coincident database) tend to perform worse. This suggests that selecting models based on AUC effectively safeguards against overfitting.

Table 2 – Accuracy of predictions for different horizons and thresholds

	Real-time prediction accuracy (%)					
	AUC		AUC10		AUC20	
Threshold (%)	TPR	FPR	TPR	FPR	TPR	FPR
30	97.2	12.2	97.2	11.7	97.2	11.4
40	97.2	9.2	97.2	9.7	97.2	9.2
50	94.4	7.5	94.4	8.3	94.4	8.1
60	91.7	7.5	91.7	7.8	91.7	7.8
70	91.7	5	91.7	5.3	91.7	5.3
	1 month lag prediction accuracy (%)					
	AUC		AUC10		AUC20	
Threshold (%)	TPR	FPR	TPR	FPR	TPR	FPR
30	97.2	13.4	97.2	13.1	97.2	12.5
40	97.2	10.6	97.2	10.9	97.2	10.3
50	97.2	8.6	97.2	8.4	97.2	7.8
60	94.4	6.4	94.4	5.8	94.4	5.8
70	94.4	5	94.4	4.7	94.4	4.7
	2 month lag prediction accuracy (%)					
	AUC		AUC10		AUC20	
Threshold (%)	TPR	FPR	TPR	FPR	TPR	FPR
30	97.2	13.1	97.2	12.3	97.2	12.3
40	97.2	10.9	97.2	9.8	97.2	9.8
50	94.4	8.9	94.4	8.1	94.4	8.1
60	94.4	6.7	94.4	6.4	94.4	6.1
70	94.4	5.6	94.4	5.6	94.4	5.3

Figure 4 – Scores for each principal-component specification: AUC criterion

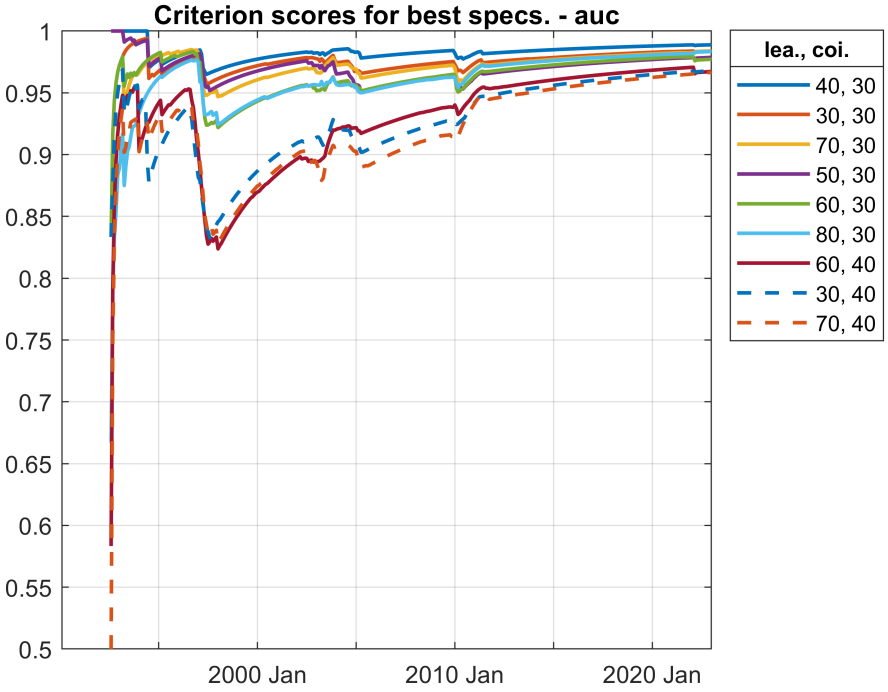


Figure 5 – Number of principal components and statistically significant canonical correlations: AUC criterion

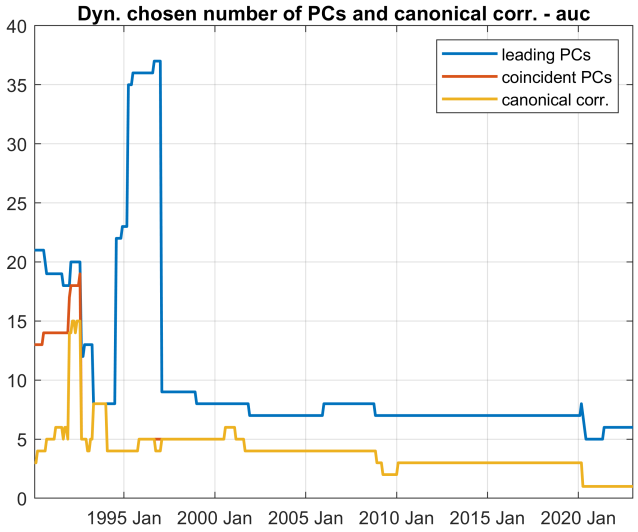
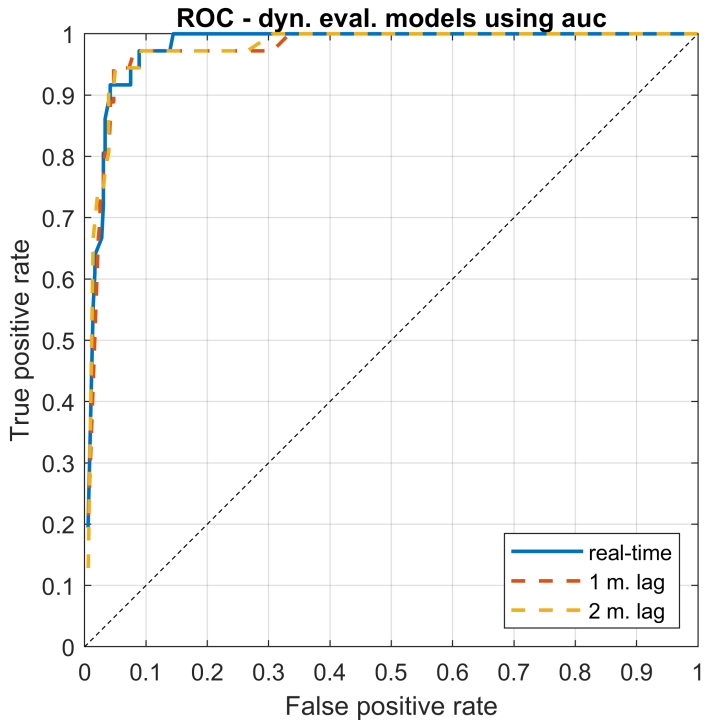


Figure 5 shows another view of this information. It presents the number of principal components and canonical correlations chosen dynamically by the program described above. The first thing to note is that, after the first few periods, the number of coincident PCs (orange line) and the number of significant canonical correlations between the coincident and leading PCs (yellow line) coincide. When these two coincide, it means that none of the coincident PCs can be considered to be a noise factor, that is, all of them are suitable for inclusion in a basis for the business cycle. In the first few periods, when a relatively large number of coincident PCs are chosen, the canonical correlation test effectively dismisses some of them as noise factors and safeguards against overfitting. After the year 2000, the

forecasting models involve fewer than five coincident PCs and fewer than ten leading PCs. We conclude that our procedure successfully avoids overfitting.

Figure 6 – ROC Curve of the dynamic evaluation exercise: AUC criterion



Finally, ROC-Curve analysis using the AUC criterion is presented in Figure 6. It displays TPRs and FPRs for different thresholds. Note that real time and *a posteriori* overall results with one- and two-month lags are very similar. Some of these ROC-Curve results are very close to the perfect classifier (0,1). So, our modeling strategy seems to produce sensible pseudo out-of-sample outcomes.

4.3 Sensitivity analysis

The analysis of the forecasting model shows that a small number of either principal components or canonical correlations capture the *commonality* of the coincident and leading databases and of the *cyclical* behavior of the U.S. economy. At each time t, the numbers of leading and coincident PCs were chosen by the grid search described above, with the AUC as the objective function. Measures of goodness of fit used as objective functions would select a larger number of principal components and lead to poor out-of-sample performance.

As discussed above, AUC proved to be a successful selection criterion. However, we explore the sensitivity of the previous results to some variants of AUC, namely AUC10 and AUC20, defined in Section 2. This exercise is interesting because AUC10 and AUC20 use as criterion for model selection the area under the curve for parts of the domain of the ROC

Curve that we the care the most, i.e., closer to the perfect classifier (0,1).

Next, we present pseudo-out-of-sample forecasting results, using the dynamic algorithm described above, when the criterion for choosing models use the area under the curve considering, respectively, only the $[0, 0.1] \times [0.9, 1]$ interval (AUC10) and the $[0, 0.2] \times [0.8, 1]$ interval (AUC20).

Figure 7 – Predictions of the dynamic evaluation exercise:
Real-time prediction using the *AUC10* criterion

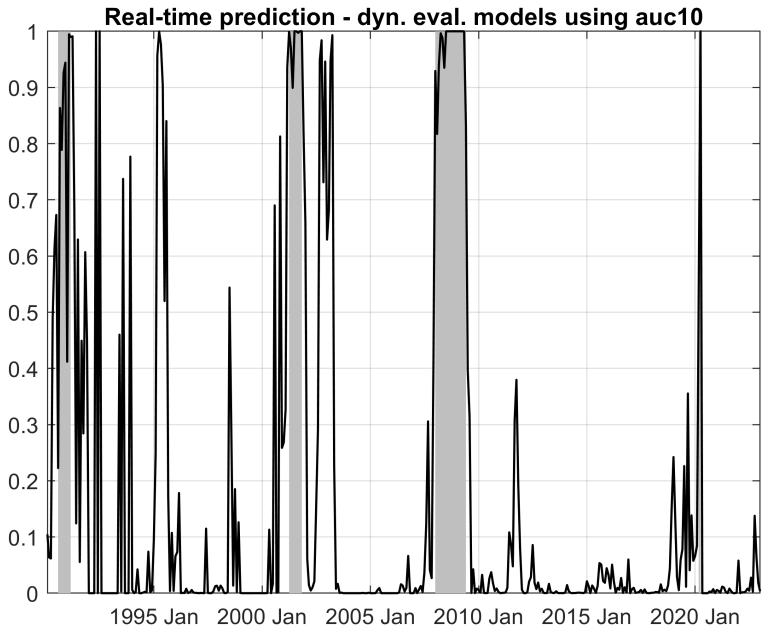
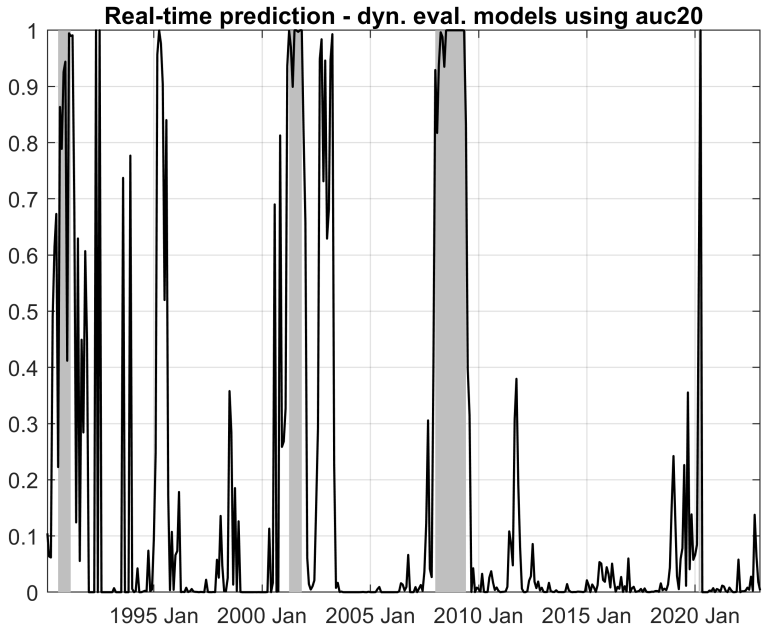


Figure 8 – Predictions of the dynamic evaluation exercise:
Real-time prediction using the *AUC20* criterion

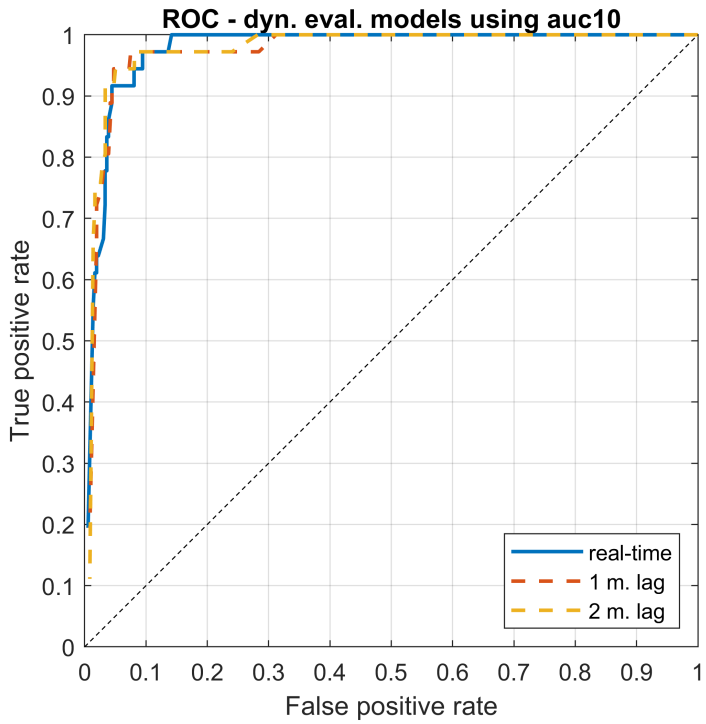


As can be seen in Figures 7 and 8, the predicted probabilities are very similar to those using the AUC criterion itself, presented in Figure 3 above. The main issue for all three criteria are a few false positive results previously discussed.

Looking back at Table 2 reinforces that the TPR and FPR based on various thresholds for models chosen using AUC, AUC10 and AUC20 are very similar. Indeed, there are no improvements when specific areas of the ROC curve are targeted rather than the entire curve itself.

Another important ingredient of our methodology is the use of the EM algorithm to impute the values of the few coincident variables that are not available at time t and become available only with one- or two-month lag. To assess the sensitivity of our results to this feature, we repeat our analysis once using data available after one month and again using data available after two months. The latter does not involve the use of the EM algorithm at all.

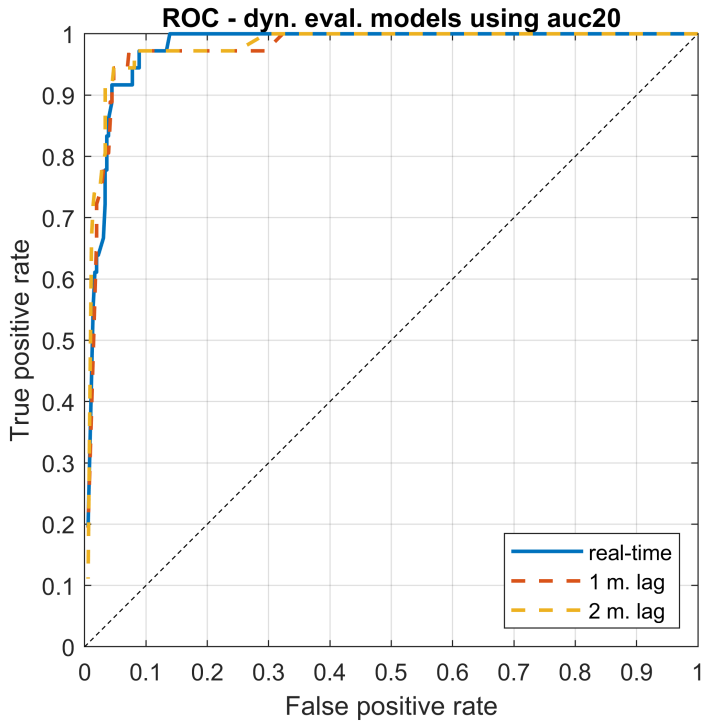
Figure 9 – ROC Curve of the dynamic evaluation exercise:
AUC10 criterion



The bottom two panels of Table 2 report the accuracy measures, as in the top panel, corresponding to these two *a posteriori* experiments. It can be seen that the accuracy measures do not improve uniformly when real data are used rather than the EM-imputed data. This can also be verified by comparing the ROC curves of the real-time forecasts with those of the *a posteriori* forecasts for the out-of-sample period plotted in Figure 6.

For the sake of completeness, we also present ROC-Curves when the AUC10 and AUC20 criteria are used instead of AUC; see Figures 9 and 10. As can be expected, given our evidence so far, results are very similar.

Figure 10 – ROC Curve of the dynamic evaluation exercise: *AUC20* criterion



5 Conclusion

In this paper, we propose a dynamic procedure for forecasting recessions in real time using all available variables known to be coincident with, or leading, the business cycle. This procedure employs several econometric techniques: it uses the EM algorithm to impute the values of the subset of coincident variables that are available only with a one- or two-month lag; it uses principal component analysis to estimate the common factors of the coincident variables as well as those of the leading variables; it uses canonical correlation analysis to eliminate noise factors and ensure that the coincident factors used for forecasting recessions are in fact cyclical factors; and it uses an instrumental variable probit model, with leading factors as instruments, to link the recession indicator to coincident factors to take into account the fact that the estimated coincident factors contain measurement error. The number of coincident and leading factors used at each point in time is determined by maximizing the AUC over a grid. The procedure also takes into account that the recession indicator is available only with a lag that can be as long as 24 months.

We evaluate this methodology with a pseudo-out-of-sample forecasting exercise for the period 1990:M1 to 2023:M1 based on U.S. data. Although we acknowledge the difficulty of evaluating a recession-forecasting algorithm based on any particular period, we assess the results reported in Table 2 and illustrated in Figures 3 and 10 to be promising. Moreover, we note that, except for a period in 2002-2003, all other false predictions in this exercise are

isolated single points. These could be avoided if a two-month persistence requirement was added to the rule for determining turning points. Such a modification would require one month of patience before translating the predicted probabilities into binary outcomes at the turning points. This delay is much shorter than the requirement imposed by other algorithms for determining turning points.

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Appendix A. Database

Coincident Series – Stock and Watson (2014)

Table 3 – Coincident series of economic activity

	Description	Name	tcode	rlags
	Industrial production			
1	Manufacturing: Durable Goods: Wood Product (NAICS = 321)	IPG321S	5	1
2	Manufacturing: Durable Goods: Nonmetallic Mineral Product (NAICS = 327)	IPG327S	5	1
3	Manufacturing: Durable Goods: Primary Metal (NAICS = 331)	IPG331S	5	1
4	Manufacturing: Durable Goods: Fabricated Metal Product (NAICS = 332)	IPG332S	5	1
5	Manufacturing: Durable Goods: Machinery (NAICS = 333)	IPG333S	5	1
6	Manufacturing: Durable Goods: Computer and Electronic Product (NAICS = 334)	IPG334S	5	1
7	Manufacturing: Durable Goods: Electrical Equipment, Appliance, and Component (NAICS = 335)	IPG335S	5	1
8	Manufacturing: Durable Goods: Transportation Equipment (NAICS = 336)	IPG336S	5	1
9	Manufacturing: Durable Goods: Furniture and Related Product (NAICS = 337)	IPG337S	5	1
10	Manufacturing: Durable Goods: Miscellaneous (NAICS = 339)	IPG339S	5	1
11	Manufacturing: Non-Durable Goods: Food (NAICS = 311)	IPG311S	5	1
12	Manufacturing: Non-Durable Goods: Beverage (NAICS = 3121)	IPG3121S	5	1
13	Manufacturing: Non-Durable Goods: Tobacco (NAICS = 3122)	IPG3122S	5	1
14	Manufacturing: Non-Durable Goods: Textile Mills (NAICS = 313)	IPG313S	5	1
15	Manufacturing: Non-Durable Goods: Textile Product Mills (NAICS = 314)	IPG314S	5	1
16	Manufacturing: Non-Durable Goods: Apparel (NAICS = 315)	IPG315S	5	1
17	Manufacturing: Non-Durable Goods: Leather and Allied Product (NAICS = 316)	IPG316S	5	1
18	Manufacturing: Non-Durable Goods: Paper (NAICS = 322)	IPG322S	5	1
19	Manufacturing: Non-Durable Goods: Printing and Related Support Activities (NAICS = 323)	IPG323S	5	1
20	Manufacturing: Non-Durable Goods: Petroleum and Coal Products (NAICS = 324)	IPG324S	5	1
21	Manufacturing: Non-Durable Goods: Chemical (NAICS = 325)	IPG325S	5	1
22	Manufacturing: Non-Durable Goods: Plastics and Rubber Products (NAICS = 326)	IPG326S	5	1
23	Mining, Quarrying, and Oil and Gas Extraction: Oil and Gas Extraction (NAICS = 211)	IPG211S	5	1
24	Mining, Quarrying, and Oil and Gas Extraction: Mining (Except Oil and Gas) (NAICS = 212)	IPG212S	5	1
25	Mining, Quarrying, and Oil and Gas Extraction: Support Activities for Mining (NAICS = 213)	IPG213S	5	1
26	Utilities: Electric Power Generation, Transmission, and Distribution (NAICS = 2211)	IPG2211S	5	1
27	Utilities: Natural Gas Distribution (NAICS = 2212)	IPG2212S	5	1
28	Durable Consumer Goods: Automotive Products	IPB51110S	5	1
29	Durable Consumer Goods: Autos and Trucks, Consumer	IPB51111S	5	1
30	Durable Consumer Goods: Auto Parts and Allied Goods	IPB51112S	5	1
31	Durable Consumer Goods: Other Durable Goods	IPB51120S	5	1
32	Durable Consumer Goods: Computers, Video and Audio Equipment	IPB51121S	5	1
33	Durable Consumer Goods: Appliances, Furniture, and Carpeting	IPB51122S	5	1
34	Durable Consumer Goods: Miscellaneous Durable Goods	IPB51123S	5	1
35	Non-Durable Nonenergy Consumer Goods: Foods and Tobacco	IPB51211S	5	1
36	Non-Durable Nonenergy Consumer Goods: Clothing	IPB51212S	5	1
37	Non-Durable Nonenergy Consumer Goods: Chemical Products	IPB51213S	5	1
38	Non-Durable Nonenergy Consumer Goods: Paper Products	IPB51214S	5	1
39	Non-Durable Nonenergy Consumer Goods: Miscellaneous Non-Durable Goods	IPB51215S	5	1
40	Non-Durable Consumer Energy Products: Consumer Energy Products	IPB51220S	5	1
41	Non-Durable Consumer Energy Products: Fuels	IPFUELS	5	1
42	Non-Durable Consumer Energy Products: Residential Utilities	IPB51222S	5	1
43	Equipment: Transit Equipment	IPB52110S	5	1

Table 3 – Coincident series of economic activity (continued)

	Description	Name	tcode	rlags
44	Equipment: Information Processing and Related Equipment	IPB52120S	5	1
45	Equipment: Industrial and Other Equipment	IPB52130S	5	1
46	Equipment: Industrial Equipment	IPB52131S	5	1
47	Equipment: Other Equipment	IPB52132S	5	1
48	Equipment: Oil and Gas Well Drilling and Manufactured Homes	IPB52200S	5	1
49	Equipment: Defense and Space Equipment	IPB52300S	5	1
50	Durable Goods Materials: Consumer Parts	IPB53110S	5	1
51	Durable Goods Materials: Equipment Parts	IPB53120S	5	1
52	Durable Goods Materials: Computer and Other Board Assemblies and Parts	IPB53121S	5	1
53	Durable Goods Materials: Semiconductors, Printed Circuit Boards, and Other	IPB53122S	5	1
54	Durable Goods Materials: Other Equipment Parts	IPB53123S	5	1
55	Durable Goods Materials: Other Durable Materials	IPB53130S	5	1
56	Durable Goods Materials: Basic Metals	IPB53131S	5	1
57	Durable Goods Materials: Miscellaneous Durable Materials	IPB53132S	5	1
58	Non-Durable Goods Materials: Textile Materials	IPB53210S	5	1
59	Non-Durable Goods Materials: Paper Materials	IPB53220S	5	1
60	Non-Durable Goods Materials: Chemical Materials	IPB53230S	5	1
61	Non-Durable Goods Materials: Other Non-Durable Materials	IPB53240S	5	1
62	Non-Durable Goods Materials: Containers	IPB53241S	5	1
63	Non-Durable Goods Materials: Miscellaneous Non-Durable Materials	IPB53242S	5	1
64	Energy Materials: Primary Energy	IPB53310S	5	1
65	Energy Materials: Converted Fuel	IPB53320S	5	1
66	Construction Supplies	IPB54100S	5	1
67	Business Supplies	IPB54200S	5	1
68	Non-Energy Business Supplies	IPB54210S	5	1
69	Commercial Energy Products	IPB54220S	5	1
	Employment			
70	Logging	CES1011330001	5	0
71	Oil and Gas Extraction	CES1021100001	5	0
72	Mining (Except Oil And Gas)	CES1021200001	5	0
73	Support Activities for Mining	CES1021300001	5	0
74	Construction of Buildings	CES2023600001	5	0
75	Heavy and Civil Engineering Construction	CES2023700001	5	0
76	Specialty Trade Contractors	CES2023800001	5	0
77	Wood Product Manufacturing	CES3132100001	5	0
78	Nonmetallic Mineral Product Manufacturing	CES3132700001	5	0
79	Primary Metal Manufacturing	CES3133100001	5	0
80	Fabricated Metal Product Manufacturing	CES3133200001	5	0
81	Machinery Manufacturing	CES3133300001	5	0
82	Computer And Electronic Product Manufacturing	CES3133400001	5	0
83	Electrical Equipment, Appliance, And Component Manufacturing	CES3133500001	5	0
84	Transportation Equipment Manufacturing	CES3133600001	5	0
85	Furniture And Related Product Manufacturing	CES3133700001	5	0
86	Miscellaneous Manufacturing	CES3133900001	5	0
87	Food Manufacturing	CES3231100001	5	0
88	Nondurable Goods: Beverages and Tobacco Products	CES3231200001	5	0
89	Textile Mills	CES3231300001	5	0
90	Textile Product Mills	CES3231400001	5	0
91	Apparel Manufacturing	CES3231500001	5	0
92	Nondurable Goods: Leather and Allied Products	CES3231600001	5	0

Table 3 – Coincident series of economic activity (continued)

	Description	Name	tcode	rlags
93	Paper Manufacturing	CES3232200001	5	0
94	Printing and Related Support Activities	CES3232300001	5	0
95	Petroleum And Coal Products Manufacturing	CES3232400001	5	0
96	Chemical Manufacturing	CES3232500001	5	0
97	Plastics And Rubber Products Manufacturing	CES3232600001	5	0
98	Merchant Wholesalers, Durable Goods	CES4142300001	5	0
99	Merchant Wholesalers, Nondurable Goods	CES4142400001	5	0
100	Wholesale Trade Agents And Brokers	CES4142500001	5	0
101	Motor Vehicle and Parts Dealers	CES4244100001	5	0
102	Furniture And Home Furnishings Retailers	CES4244200001	5	0
103	Electronics And Appliance Retailers	CES4244300001	5	0
104	Building Material And Garden Equipment And Supplies Dealers	CES4244400001	5	0
105	Food And Beverage Retailers	CES4244500001	5	0
106	Health And Personal Care Retailers	CES4244600001	5	0
107	Gasoline Stations And Fuel Dealers	CES4244700001	5	0
108	Clothing, Clothing Accessories, Shoe, And Jewelry Retailers	CES4244800001	5	0
109	Sporting Goods, Hobby, Musical Instrument, Book, And Miscellaneous Retailers	CES4245100001	5	0
110	General Merchandise Retailers	CES4245200001	5	0
111	Other Miscellaneous Retailers	CES4245300001	5	0
112	Nonstore Retailers	CES4245400001	5	0
113	Air Transportation	CES4348100001	5	0
114	Rail Transportation	CES4348200001	5	0
115	Water Transportation	CES4348300001	5	0
116	Truck Transportation	CES4348400001	5	0
117	Transit and Ground Passenger Transportation	CES4348500001	5	0
118	Pipeline Transportation	CES4348600001	5	0
119	Scenic and Sightseeing Transportation	CES4348700001	5	0
120	Support Activities for Transportation	CES4348800001	5	0
121	Couriers and Messengers	CES4349200001	5	0
122	Warehousing and Storage	CES4349300001	5	0
123	Utilities	CES4422000001	5	0
124	Publishing Industries	CES5051100001	5	0
125	Motion Picture and Sound Recording Industries	CES5051200001	5	0
126	Broadcasting And Content Providers	CES5051500001	5	0
127	Telecommunications	CES5051700001	5	0
128	Computing Infrastructure Providers, Data Processing, Web Hosting, And Related Services	CES5051800001	5	0
129	Web Search Portals, Libraries, Archives, And Other Information Services	CES5051900001	5	0
130	Monetary Authorities-Central Bank	CES5552100001	5	0
131	Credit Intermediation and Related Activities	CES5552200001	5	0
132	Securities, Commodity Contracts, Funds, Trusts, And Other Financial Vehicles, Investments, And Related Activities	CES5552300001	5	0
133	Insurance Carriers and Related Activities	CES5552400001	5	0
134	Financial Activities: Funds, Trusts, and Other Financial Vehicles	CES5552500001	5	0
135	Real Estate	CES5553100001	5	0
136	Rental and Leasing Services	CES5553200001	5	0
137	Lessors Of Nonfinancial Intangible Assets (Except Copyrighted Works)	CES5553300001	5	0
138	Professional, Scientific, And Technical Services	CES6054000001	5	0
139	Management of Companies and Enterprises	CES6055000001	5	0
140	Administrative And Support And Waste Management And Remediation Services	CES6056000001	5	0
141	Private Educational Services	CES6561000001	5	0
142	Health Care	CES6562000101	5	0
143	Social Assistance	CES6562400001	5	0

Table 3 – Coincident series of economic activity (continued)

	Description	Name	tcode	rlags
144	Arts, Entertainment, and Recreation	CES7071000001	5	0
145	Accommodation	CES7072100001	5	0
146	Food Services and Drinking Places	CES7072200001	5	0
147	Federal	CES9091000001	5	0
148	State Government	CES9092000001	5	0
149	Local Government	CES9093000001	5	0
150	Durable Goods	DMANEMP	5	0
151	Nondurable Goods	NDMANEMP	5	0
152	Construction	USCONS	5	0
153	Private Education And Health Services	USEHS	5	0
154	Financial Activities	USFIRE	5	0
155	Government	USGOVT	5	0
156	Information	USINFO	5	0
157	Leisure and Hospitality	USLAH	5	0
158	Mining and Logging	USMINE	5	0
159	Professional and Business Services	USPBS	5	0
160	Other Services	USSERV	5	0
161	Retail Trade	USTRADE	5	0
162	Wholesale Trade	USWTRADE	5	0
163	Trans/Utilities (USTPU−USTRADE−USWTRADE)	USPU	5	0
	Personal Income			
164	Wages and salaries: Private industries: Goods-producing industries: Manufacturing	A552RC1M027SBEA	5	1
165	Wages and salaries: Private industries: Distributive industries	A212RC1M027SBEA	5	1
166	Wages and salaries: Private industries: Service industries	A218RC1M027SBEA	5	1
167	Wages and salaries: Private industries: Goods-producing industries: Manufacturing	N552RC1M027SBEA	5	1
168	Wages and salaries: Private industries: Services-producing industries: Trade, transportation, and utilities	N234RC1M027SBEA	5	1
169	Wages and salaries: Private industries: Services-producing industries: Other services-producing industries	N235RC1M027SBEA	5	1
170	Compensation of employees, received: Wage and salary disbursements: Government	B202RC1	5	1
171	Compensation of Employees, Received: Supplements to Wages and Salaries	A038RC1	5	1
172	Proprietors' income with inventory valuation and capital consumption adjustments: Farm	B042RC1	5	1
173	Proprietors' income with inventory valuation and capital consumption adjustments: Nonfarm	A045RC1	5	1
174	Rental income of persons with capital consumption adjustment	A048RC1	5	1
175	Personal Income Receipts on Assets: Personal Interest Income	PII	5	1
176	Personal Income Receipts on Assets: Personal Dividend Income	PDI	5	1
177	Personal current taxes	W055RC1	5	1

Source: All series were obtained from the FRED database. Industrial production series are provided by the Board of Governors of the Federal Reserve System; employment series by the U.S. Bureau of Labor Statistics; and personal income series by the U.S. Bureau of Economic Analysis.

Note: "Name" means the series' internal name usually provided in the release data files. "tcode" means the code of the transformation applied to the series. "rlags" means the approximated lag of the last observation available in relation to t. We consider the lag to be zero if the observation of $t-1$ is normally available by the 15th of month t. Transformation codes: (1) no transformation, (2) Δx_t, (3) $\Delta^2 x_t$, (4) $\log(x_t)$, (5) $\Delta \log(x_t)$, (6) $\Delta^2 \log(x_t)$, (7) $\Delta\left(x_t/x_{t-1}-1\right)$.

Leading Series – Costa et al. (2021)

Table 4 – Leading series of economic activity

	Description	Name	Source	tcode	rlags
	Outcome and income				
1	Real Personal Income	RPI	FRED-MD	5	1
2	Real personal income ex transfer receipts	W875RX1	FRED-MD	5	1
3	IP Index	INDPRO	FRED-MD	5	1
4	IP: Final Products and Nonindustrial Supplies	IPFPNSS	FRED-MD	5	1
5	IP: Final Products (Market Group)	IPFINAL	FRED-MD	5	1
6	IP: Consumer Goods	IPCONGD	FRED-MD	5	1
7	IP: Durable Consumer Goods	IPDCONGD	FRED-MD	5	1
8	IP: Nondurable Consumer Goods	IPNCONGD	FRED-MD	5	1
9	IP: Business Equipment	IPBUSEQ	FRED-MD	5	1
10	IP: Materials	IPMAT	FRED-MD	5	1
11	IP: Durable Materials	IPDMAT	FRED-MD	5	1
12	IP: Nondurable Materials	IPNMAT	FRED-MD	5	1
13	IP: Manufacturing (SIC)	IPMANSICS	FRED-MD	5	1
14	IP: Residential Utilities	IPB51222S	FRED-MD	5	1
15	IP: Fuels	IPFUELS	FRED-MD	5	1
16	Capacity Utilization: Manufacturing	CUMFNS	FRED-MD	2	1
	Labor market				
17	Help-Wanted Index for United States	HWI	FRED-MD	5	2
18	Ratio of Help Wanted/No. Unemployed	HWIURATIO	FRED-MD	2	2
19	Civilian Labor Force	CLF16OV	FRED-MD	5	1
20	Civilian Employment	CE16OV	FRED-MD	5	1
21	Civilian Unemployment Rate	UNRATE	FRED-MD	2	1
22	Average Duration of Unemployment (Weeks)	UEMPMEAN	FRED-MD	2	1
23	Civilians Unemployed - Less Than 5 Weeks	UEMPLT5	FRED-MD	5	1
24	Civilians Unemployed for 5-14 Weeks	UEMP5TO14	FRED-MD	5	1
25	Civilians Unemployed - 15 Weeks& Over	UEMP15OV	FRED-MD	5	1
26	Civilians Unemployed for 15-26 Weeks	UEMP15T26	FRED-MD	5	1
27	Civilians Unemployed for 27 Weeks and Over	UEMP27OV	FRED-MD	5	1
28	Initial Claims	CLAIMSx	FRED-MD	5	1
29	All Employees: Total nonfarm	PAYEMS	FRED-MD	5	1
30	All Employees: Goods-Producing Industries	USGOOD	FRED-MD	5	1
31	All Employees: Mining and Logging: Mining	CES1021000001	FRED-MD	5	1
32	All Employees: Construction	USCONS	FRED-MD	5	1
33	All Employees: Manufacturing	MANEMP	FRED-MD	5	1
34	All Employees: Durable goods	DMANEMP	FRED-MD	5	1
35	All Employees: Nondurable goods	NDMANEMP	FRED-MD	5	1
36	All Employees: Service-Providing Industries	SRVPRD	FRED-MD	5	1
37	All Employees: Trade, Transportation& Utilities	USTPU	FRED-MD	5	1
38	All Employees: Wholesale Trade	USWTRADE	FRED-MD	5	1
39	All Employees: Retail Trade	USTRADE	FRED-MD	5	1
40	All Employees: Financial Activities	USFIRE	FRED-MD	5	1
41	All Employees: Government	USGOVT	FRED-MD	5	1
42	Avg Weekly Hours : Goods-Producing	CES0600000007	FRED-MD	1	1
43	Avg Weekly Overtime Hours : Manufacturing	AWOTMAN	FRED-MD	2	1
44	Avg Weekly Hours : Manufacturing	AWHMAN	FRED-MD	1	1

Table 4 – Leading series of economic activity (continued)

	Description	Name	Source	tcode	rlags
45	Avg Hourly Earnings : Goods-Producing	CES0600000008	FRED-MD	5	1
46	Avg Hourly Earnings : Construction	CES2000000008	FRED-MD	5	1
47	Avg Hourly Earnings : Manufacturing	CES3000000008	FRED-MD	5	1
	Housing				
48	Housing Starts: Total New Privately Owned	HOUST	FRED-MD	4	1
49	Housing Starts, Northeast	HOUSTNE	FRED-MD	4	1
50	Housing Starts, Midwest	HOUSTMW	FRED-MD	4	1
51	Housing Starts, South	HOUSTS	FRED-MD	4	1
52	Housing Starts, West	HOUSTW	FRED-MD	4	1
53	New Private Housing Permits (SAAR)	PERMIT	FRED-MD	4	1
54	New Private Housing Permits, Northeast (SAAR)	PERMITNE	FRED-MD	4	1
55	New Private Housing Permits, Midwest (SAAR)	PERMITMW	FRED-MD	4	1
56	New Private Housing Permits, South (SAAR)	PERMITS	FRED-MD	4	1
57	New Private Housing Permits, West (SAAR)	PERMITW	FRED-MD	4	1
	Consumption, orders, and inventories				
58	Real personal consumption expenditures	DPCERA3M086SBEA	FRED-MD	5	1
59	Real Manu. and Trade Industries Sales	CMRMTSPLx	FRED-MD	5	2
60	Retail and Food Services Sales	RETAILx	FRED-MD	5	1
61	New Orders for Consumer Goods	ACOGNO	FRED-MD	5	2
62	New Orders for Durable Goods	AMDMNOx	FRED-MD	5	1
63	New Orders for Nondefense Capital Goods	ANDENOx	FRED-MD	5	1
64	Unfilled Orders for Durable Goods	AMDMUOx	FRED-MD	5	1
65	Total Business Inventories	BUSINVx	FRED-MD	5	2
66	Total Business: Inventories to Sales Ratio	ISRATIOx	FRED-MD	2	2
67	Consumer Sentiment Index	UMCSENTx	FRED-MD	2	1
	Money and credit				
68	M1 Money Stock	M1SL	FRED-MD	5	1
69	M2 Money Stock	M2SL	FRED-MD	5	1
70	Real M2 Money Stock	M2REAL	FRED-MD	5	1
71	Monetary Base	BOGMBASE	FRED-MD	5	1
72	Total Reserves of Depository Institutions	TOTRESNS	FRED-MD	5	1
73	Reserves Of Depository Institutions	NONBORRES	FRED-MD	7	1
74	Commercial and Industrial Loans	BUSLOANS	FRED-MD	5	1
75	Real Estate Loans at All Commercial Banks	REALLN	FRED-MD	5	1
76	Total Nonrevolving Credit	NONREVSL	FRED-MD	5	2
77	Nonrevolving consumer credit to Personal Income	CONSPI	FRED-MD	2	2
78	Consumer Motor Vehicle Loans Outstanding	DTCOLNVHFNM	FRED-MD	5	2
79	Total Consumer Loans and Leases Outstanding	DTCTHFNM	FRED-MD	5	2
80	Securities in Bank Credit at All Commercial Banks	INVEST	FRED-MD	5	1
	Interest and exchange rates				
81	Effective Federal Funds Rate	FEDFUNDS	FRED-MD	2	1
82	3-Month AA Financial Commercial Paper Rate	CP3Mx	FRED-MD	2	1
83	3-Month Treasury Bill	TB3MS	FRED-MD	2	1
84	6-Month Treasury Bill	TB6MS	FRED-MD	2	1
85	1-Year Treasury Rate	GS1	FRED-MD	2	1
86	5-Year Treasury Rate	GS5	FRED-MD	2	1

Table 4 – Leading series of economic activity (continued)

	Description	Name	Source	tcode	rlags
87	10-Year Treasury Rate	GS10	FRED-MD	2	1
88	Moody's Seasoned Aaa Corporate Bond Yield	AAA	FRED-MD	2	1
89	Moody's Seasoned Baa Corporate Bond Yield	BAA	FRED-MD	2	1
90	3-Month Commercial Paper Minus FEDFUNDS	COMPAPFFx	FRED-MD	1	1
91	3-Month Treasury C Minus FEDFUNDS	TB3SMFFM	FRED-MD	1	1
92	6-Month Treasury C Minus FEDFUNDS	TB6SMFFM	FRED-MD	1	1
93	1-Year Treasury C Minus FEDFUNDS	T1YFFM	FRED-MD	1	1
94	5-Year Treasury C Minus FEDFUNDS	T5YFFM	FRED-MD	1	1
95	10-Year Treasury C Minus FEDFUNDS	T10YFFM	FRED-MD	1	1
96	Moody's Aaa Corporate Bond Minus FEDFUNDS	AAAFFM	FRED-MD	1	1
97	Moody's Baa Corporate Bond Minus FEDFUNDS	BAAFFM	FRED-MD	1	1
98	Trade Weighted U.S. Dollar Index	TWEXAFEGSMTHx	FRED-MD	5	1
99	Switzerland / U.S. Foreign Exchange Rate	EXSZUSx	FRED-MD	5	1
100	Japan / U.S. Foreign Exchange Rate	EXJPUSx	FRED-MD	5	1
101	U.S. / U.K. Foreign Exchange Rate	EXUSUKx	FRED-MD	5	1
102	Canada / U.S. Foreign Exchange Rate	EXCAUSx	FRED-MD	5	1
	Prices				
103	PPI: Finished Goods	WPSFD49207	FRED-MD	5	1
104	PPI: Finished Consumer Goods	WPSFD49502	FRED-MD	5	1
105	PPI: Intermediate Materials	WPSID61	FRED-MD	5	1
106	PPI: Crude Materials	WPSID62	FRED-MD	5	1
107	Crude Oil, spliced WTI and Cushing	OILPRICEx	FRED-MD	5	1
108	PPI: Metals and metal products	PPICMM	FRED-MD	5	1
109	CPI : All Items	CPIAUCSL	FRED-MD	5	1
110	CPI : Apparel	CPIAPPSL	FRED-MD	5	1
111	CPI : Transportation	CPITRNSL	FRED-MD	5	1
112	CPI : Medical Care	CPIMEDSL	FRED-MD	5	1
113	CPI : Commodities	CUSR0000SAC	FRED-MD	5	1
114	CPI : Durables	CUSR0000SAD	FRED-MD	5	1
115	CPI : Services	CUSR0000SAS	FRED-MD	5	1
116	CPI : All Items Less Food	CPIULFSL	FRED-MD	5	1
117	CPI : All items less shelter	CUSR0000SA0L2	FRED-MD	5	1
118	CPI : All items less medical care	CUSR0000SA0L5	FRED-MD	5	1
119	Personal Cons. Expend.: Chain Index	PCEPI	FRED-MD	5	1
120	Personal Cons. Exp: Durable goods	DDURRG3M086SBEA	FRED-MD	5	1
121	Personal Cons. Exp: Nondurable goods	DNDGRG3M086SBEA	FRED-MD	5	1
122	Personal Cons. Exp: Services	DSERRG3M086SBEA	FRED-MD	5	1
	Stock market				
123	S& P's Common Stock Price Index: Composite	S& P 500	FRED-MD	5	1
124	S& P's Common Stock Price Index: Industrials	S& P: indust	FRED-MD	5	1
125	S& P's Composite Common Stock: Dividend Yield	S& P div yield	FRED-MD	2	1
126	S& P's Composite Common Stock: Price-Earnings Ratio	S& P PE ratio	FRED-MD	5	3
127	VIX	VIXCLSx	FRED-MD	1	1
	Industrial production				
128	Production of Total Industry in Austria	AUTPROINDMISMEI	FRED	5	3
129	Production of Total Industry in Belgium	BELPROINDMISMEI	FRED	5	2
130	Production of Total Industry in Brazil	BRAPROINDMISMEI	FRED	5	2

Table 4 – Leading series of economic activity (continued)

	Description	Name	Source	tcode	rlags
131	Production of Total Industry in Canada	CANPROINDMISMEI	FRED	5	3
132	Production of Total Industry in Chile	CHLPROINDMISMEI	FRED	5	1
133	Production of Total Industry in Czech Republic	CZEPROINDMISMEI	FRED	5	2
134	Production of Total Industry in Denmark	DNKPROINDMISMEI	FRED	5	2
135	Production of Total Industry in Finland	FINPROINDMISMEI	FRED	5	3
136	Production of Total Industry in France	FRAPROINDMISMEI	FRED	5	2
137	Production of Total Industry in Germany	DEUPROINDMISMEI	FRED	5	2
138	Production of Total Industry in Greece	GRCPROINDMISMEI	FRED	5	2
139	Production of Total Industry in Hungary	HUNPROINDMISMEI	FRED	5	2
140	Production of Total Industry in Ireland	IRLPROINDMISMEI	FRED	5	2
141	Production of Total Industry in Israel	ISRPROINDMISMEI	FRED	5	3
142	Production of Total Industry in Italy	ITAPROINDMISMEI	FRED	5	2
143	Production of Total Industry in Japan	JPNPROINDMISMEI	FRED	5	1
144	Production of Total Industry in Korea	KORPROINDMISMEI	FRED	5	1
145	Production of Total Industry in Netherlands	NLDPROINDMISMEI	FRED	5	2
146	Production of Total Industry in Norway	NORPROINDMISMEI	FRED	5	2
147	Production of Total Industry in Poland	POLPROINDMISMEI	FRED	5	1
148	Production of Total Industry in Portugal	PRTPROINDMISMEI	FRED	5	1
149	Production of Total Industry in Russian Federation	RUSPROINDMISMEI	FRED	5	3
150	Production of Total Industry in Spain	ESPPROINDMISMEI	FRED	5	2
151	Production of Total Industry in Sweden	SWEPROINDMISMEI	FRED	5	2
152	Production of Total Industry in Turkey	TURPROINDMISMEI	FRED	5	2
153	Production of Total Industry in United Kingdom	GBRPROINDMISMEI	FRED	5	2
154	Industrial Production: Durable Manufacturing	IPDMAN	FRED	5	0
155	Industrial Production: Durable Goods: Iron and Steel Products	IPG3311A2S	FRED	5	0
156	Industrial Production: Durable Goods: Alumina and Aluminum Production and Processing	IPG3313S	FRED	5	0
157	Industrial Production: Durable Goods: Raw Steel	IPN3311A2RS	FRED	5	1
158	Industrial Production: Durable Goods: Automotive Products	IPB51110S	FRED	5	0
159	Industrial Production: Durable Goods: Cement and Concrete Product	IPG3273S	FRED	5	0
160	Industrial Production: Durable Goods: Primary Metal	IPG331S	FRED	5	0
161	Industrial Production: Durable Goods: Machinery	IPG333S	FRED	5	0
162	Industrial Production: Durable Goods: Aerospace and Misc. Transportation Equipment	IPG3364T9S	FRED	5	0
163	Industrial Production: Non-Durable Goods: Food	IPG311S	FRED	5	0
164	Industrial Production: Non-Durable Goods: Petroleum and Coal Products	IPG324S	FRED	5	0
165	Industrial Production: Non-Durable Goods: Chemical	IPG325S	FRED	5	0
166	Industrial Production: Non-Durable Goods: Plastics and Rubber Products	IPG326S	FRED	5	0
167	Industrial Production: Non-Durable Goods: Petroleum Refineries	IPG32411S	FRED	5	0
168	Industrial Production: Non-Durable Goods: Pharmaceutical and Medicine	IPG3254S	FRED	5	0
169	Industrial Production: Non-Durable Goods: Plastics Material and Resin	IPN325211S	FRED	5	2
170	Industrial Production: Construction Supplies	IPB54100S	FRED	5	0
171	Industrial Production: Non-Energy, Total	IPX5001ES	FRED	5	0
172	Industrial Production: Energy, Total	IPB50089S	FRED	5	0

Table 4 – Leading series of economic activity (continued)

	Description	Name	Source	tcode	rlags
173	Industrial Production: Electric and Gas Utilities	IPUTIL	FRED	5	0
174	Industrial Production: Electric Power Generation, Transmission, and Distribution	IPG2211S	FRED	5	0
175	Industrial Production: Mining: Oil and Gas Extraction	IPG211S	FRED	5	0
176	Industrial Production: Mining: Copper, Nickel, Lead, and Zinc Mining	IPG21223S	FRED	5	0
177	Industrial Production: Mining: Coal Mining	IPN2121S	FRED	5	0
178	Industrial Production: Mining: Iron Ore Mining	IPN21221S	FRED	5	3
179	Industrial Production: Mining: Drilling Oil and Gas Wells	IPN213111S	FRED	5	0
	Economic uncertainty				
180	Policy-related economic uncertainty index for Australia	EPU_Australia	Economic Policy Uncertainty	1	1
181	Policy-related economic uncertainty index for Brazil	EPU_Brazil	Economic Policy Uncertainty	1	1
182	Policy-related economic uncertainty index for Canada	EPU_Canada	Economic Policy Uncertainty	1	1
183	Policy-related economic uncertainty index for Chile	EPU_Chile	Economic Policy Uncertainty	1	1
184	Policy-related economic uncertainty index for China	EPU_China	Economic Policy Uncertainty	1	1
185	Policy-related economic uncertainty index for Colombia	EPU_Colombia	Economic Policy Uncertainty	1	1
186	Policy-related economic uncertainty index for France	EPU_France	Economic Policy Uncertainty	1	1
187	Policy-related economic uncertainty index for Germany	EPU_Germany	Economic Policy Uncertainty	1	1
188	Policy-related economic uncertainty index for Greece	EPU_Greece	Economic Policy Uncertainty	1	1
189	Policy-related economic uncertainty index for India	EPU_India	Economic Policy Uncertainty	1	1
190	Policy-related economic uncertainty index for Ireland	EPU_Ireland	Economic Policy Uncertainty	1	1
191	Policy-related economic uncertainty index for Italy	EPU_Italy	Economic Policy Uncertainty	1	1
192	Policy-related economic uncertainty index for Japan	EPU_Japan	Economic Policy Uncertainty	1	1
193	Policy-related economic uncertainty index for Korea	EPU_Korea	Economic Policy Uncertainty	1	1
194	Policy-related economic uncertainty index for Netherlands	EPU_Netherlands	Economic Policy Uncertainty	1	1
195	Policy-related economic uncertainty index for Russia	EPU_Russia	Economic Policy Uncertainty	1	1
196	Policy-related economic uncertainty index for Spain	EPU_Spain	Economic Policy Uncertainty	1	1
197	Policy-related economic uncertainty index for Singapore	EPU_Singapore	Economic Policy Uncertainty	1	1
198	Policy-related economic uncertainty index for UK	EPU_UK	Economic Policy Uncertainty	1	1
199	Policy-related economic uncertainty index for US	EPU_US	Economic Policy Uncertainty	1	1
200	Geopolitical Risk Index of Caldara and Iacoviello: Argentina	GPRC_ARG	Geopolitical Risk	1	0
201	Geopolitical Risk Index of Caldara and Iacoviello: Brazil	GPRC_BRA	Geopolitical Risk	1	0
202	Geopolitical Risk Index of Caldara and Iacoviello: China	GPRC_CHN	Geopolitical Risk	1	0
203	Geopolitical Risk Index of Caldara and Iacoviello: Colombia	GPRC_COL	Geopolitical Risk	1	0
204	Geopolitical Risk Index of Caldara and Iacoviello: Hong Kong	GPRC_HKG	Geopolitical Risk	1	0

Table 4 – Leading series of economic activity (continued)

	Description	Name	Source	tcode	rlags
205	Geopolitical Risk Index of Caldara and Iacoviello: India	GPRC_IND	Geopolitical Risk	1	0
206	Geopolitical Risk Index of Caldara and Iacoviello: Indonesia	GPRC_IDN	Geopolitical Risk	1	0
207	Geopolitical Risk Index of Caldara and Iacoviello: Israel	GPRC_ISR	Geopolitical Risk	1	0
208	Geopolitical Risk Index of Caldara and Iacoviello: Korea	GPRC_KOR	Geopolitical Risk	1	0
209	Geopolitical Risk Index of Caldara and Iacoviello: Malaysia	GPRC_MYS	Geopolitical Risk	1	0
210	Geopolitical Risk Index of Caldara and Iacoviello: Mexico	GPRC_MEX	Geopolitical Risk	1	0
211	Geopolitical Risk Index of Caldara and Iacoviello: Philippines	GPRC_PHL	Geopolitical Risk	1	0
212	Geopolitical Risk Index of Caldara and Iacoviello: Russia	GPRC_RUS	Geopolitical Risk	1	0
213	Geopolitical Risk Index of Caldara and Iacoviello: Saudi Arabia	GPRC_SAU	Geopolitical Risk	1	0
214	Geopolitical Risk Index of Caldara and Iacoviello: South Africa	GPRC_ZAF	Geopolitical Risk	1	0
215	Geopolitical Risk Index of Caldara and Iacoviello: Thailand	GPRC_THA	Geopolitical Risk	1	0
216	Geopolitical Risk Index of Caldara and Iacoviello: Turkey	GPRC_TUR	Geopolitical Risk	1	0
217	Geopolitical Risk Index of Caldara and Iacoviello: Ukraine	GPRC_UKR	Geopolitical Risk	1	0
218	Geopolitical Risk Index of Caldara and Iacoviello: Venezuela	GPRC_VEN	Geopolitical Risk	1	0
219	Geopolitical Risk Index of Caldara and Iacoviello: Recent GPR	GPR	Geopolitical Risk	1	0
220	Geopolitical Risk Index of Caldara and Iacoviello: Recent GPR Threats	GPRT	Geopolitical Risk	1	0
221	Geopolitical Risk Index of Caldara and Iacoviello: Recent GPR Acts	GPRA	Geopolitical Risk	1	0
222	Geopolitical Risk Index of Caldara and Iacoviello: Historical GPR	GPRH	Geopolitical Risk	1	0
223	Geopolitical Risk Index of Caldara and Iacoviello: Historical GPR Threats	GPRHT	Geopolitical Risk	1	0
224	Geopolitical Risk Index of Caldara and Iacoviello: Historical GPR Acts	GPRHA	Geopolitical Risk	1	0
	Leading indicator				
225	OECD Composite Leading Indicator (CLI) for Australia	CLI_Australia	OECD	2	0
226	OECD Composite Leading Indicator (CLI) for Brazil	CLI_Brazil	OECD	2	0
227	OECD Composite Leading Indicator (CLI) for Canada	CLI_Canada	OECD	2	0
228	OECD Composite Leading Indicator (CLI) for China	CLI_China	OECD	2	0
229	OECD Composite Leading Indicator (CLI) for France	CLI_France	OECD	2	0
230	OECD Composite Leading Indicator (CLI) for Germany	CLI_Germany	OECD	2	0
231	OECD Composite Leading Indicator (CLI) for India	CLI_India	OECD	2	0
232	OECD Composite Leading Indicator (CLI) for Indonesia	CLI_Indonesia	OECD	2	0
233	OECD Composite Leading Indicator (CLI) for Italy	CLI_Italy	OECD	2	0
234	OECD Composite Leading Indicator (CLI) for Japan	CLI_Japan	OECD	2	0

Table 4 – Leading series of economic activity (continued)

	Description	Name	Source	tcode	rlags
235	OECD Composite Leading Indicator (CLI) for Korea	CLI_Korea	OECD	2	0
236	OECD Composite Leading Indicator (CLI) for Mexico	CLI_Mexico	OECD	2	0
237	OECD Composite Leading Indicator (CLI) for South Africa	CLI_South_Africa	OECD	2	0
238	OECD Composite Leading Indicator (CLI) for Spain	CLI_Spain	OECD	2	0
239	OECD Composite Leading Indicator (CLI) for Turkey	CLI_Turkey	OECD	2	0
240	OECD Composite Leading Indicator (CLI) for United Kingdom	CLI_UK	OECD	2	0
241	OECD Composite Leading Indicator (CLI) for United States of America	CLI_USA	OECD	2	0
242	OECD Composite Leading Indicator (CLI) for Big four European	CLI_Big4_European	OECD	2	0
243	OECD Composite Leading Indicator (CLI) for G7	CLI_G7	OECD	2	0
244	OECD Composite Leading Indicator (CLI) for NAFTA	CLI_NAFTA	OECD	2	0
245	OECD Composite Leading Indicator (CLI) for Major five Asia	CLI_Major5_Asia	OECD	2	0
	Real business conditions in the U.S.				
246	Aruoba-Diebold-Scotti Business Conditions Index	ADS_INDEX	Federal Reserve Bank of Philadelphia	1	0
	Quantitative Easing				
247	Total Assets (US$ trillions), Federal Reserve	QE_FED	Federal Reserve Bank of St. Louis	5	0
248	Total Assets (US$ trillions), Federal Reserve + European Central Bank + Bank of Japan	QE_FED_ECB_BOJ	Federal Reserve Bank of St. Louis	5	0
	Energy Outlook				
249	Liquid Fuels Consumption, World (million barrels per day)	STEO.PATC_WORLD.M	Short-Term Energy Outlook, U.S. EIA	5	0
250	Liquid Fuels Consumption, OECD (million barrels per day)	STEO.PATC_OECD.M	Short-Term Energy Outlook, U.S. EIA	5	0
251	Liquid Fuels Consumption, non-OECD (million barrels per day)	STEO.PATC_NON_OECD.M	Short-Term Energy Outlook, U.S. EIA	5	0
252	Crude Oil Production Capacity, OPEC (million barrels per day)	STEO.COPC_OPEC.M	Short-Term Energy Outlook, U.S. EIA	5	0
253	Petroleum Product Supply, Total (million barrels per day)	STEO.PASUPPLY.M	Short-Term Energy Outlook, U.S. EIA	5	0
254	Crude Oil Production, U.S. (million barrels per day)	STEO.COPRPUS.M	Short-Term Energy Outlook, U.S. EIA	5	0
255	Crude Oil and Other Liquids Inventory, U.S. (million barrels)	STEO.PASC_US.M	Short-Term Energy Outlook, U.S. EIA	5	0
256	Petroleum Net Imports, U.S. (million barrels per day)	STEO.PAIMPORT.M	Short-Term Energy Outlook, U.S. EIA	5	0
257	Net Inventory Withdrawals, Crude Oil and Other Liquids, U.S. (million barrels per day)	STEO.T3_STCHANGE_US.M	Short-Term Energy Outlook, U.S. EIA	5	0
258	Natural Gas Henry Hub Spot Price, U.S. (dollars per thousand cubic feet)	STEO.NGHHMCF.M	Short-Term Energy Outlook, U.S. EIA	5	0
259	Cost of Coal Delivered to Electric Generating Plants, U.S. (dollars per million Btu)	STEO.CLEUDUS.M	Short-Term Energy Outlook, U.S. EIA	5	0
260	Coal Production, U.S. (million short tons)	STEO.CLPRPUS_TON.M	Short-Term Energy Outlook, U.S. EIA	5	0
261	Coal Consumption, U.S. (million short tons)	STEO.CLTCPUS_TON.M	Short-Term Energy Outlook, U.S. EIA	5	0
262	Consumption of Electricity, U.S. (billion kilowatthours)	STEO.ELCOTWH.M	Short-Term Energy Outlook, U.S. EIA	5	0
263	Raw Steel Production, U.S. (million short tons per day)	STEO.RSPRPUS.M	Short-Term Energy Outlook, U.S. EIA	5	0

Table 4 – Leading series of economic activity (continued)

	Description	Name	Source	tcode	rlags
264	Aircraft Utilization, U.S. (revenue ton-miles/day thousands)	STEO.RMZZPUS.M	Short-Term Energy Outlook, U.S. EIA	5	0
265	Vehicle Miles Traveled, U.S. (million miles/day)	STEO.MVVMPUS.M	Short-Term Energy Outlook, U.S. EIA	5	0
	Financial markets				
266	Europe Brent Spot FOB U$/BBL Daily	EUROPE_BRENT_SPOT_FOB_U$	Thomson Reuters	5	0
267	Baltic Exchange Dry Index (BDI)	BALTIC_DRY	Thomson Reuters	5	0
268	CBOE SPX VOLATILITY VIX	VIX	Thomson Reuters	1	0
269	US Dollar index DXY	US_DOLLAR_INDEX	Thomson Reuters	5	0
270	MSCI Emerging Markets U$	MSCI_EM	Thomson Reuters	5	0
271	MSCI World U$	MSCI_WORLD	Thomson Reuters	5	0
272	EURO STOXX 50	EURO_STOXX50	Thomson Reuters	5	0
273	S& P500 ES ENERGY	SP500_ENERGY	Thomson Reuters	5	0
274	S& P GSCI Energy Total Return - RETURN IND. (OFCL)	SP_GSCI_ENERGY	Thomson Reuters	5	0
275	CRB BLS Spot Index (1967=100)	CRB	Thomson Reuters	5	0
276	CRB BLS Spot Index Metals	CRB_METALS	Thomson Reuters	5	0
277	CRB BLS Spot Index Foodstuffs	CRB_FOOD	Thomson Reuters	5	0
278	Futures Brent crude oil, Intercontinental Exchange (ICE), 1 month	FUTURE_BRENT_M1	Thomson Reuters	5	0
279	Futures Brent crude oil, Intercontinental Exchange (ICE), 2 months	FUTURE_BRENT_M2	Thomson Reuters	5	0
280	Futures Brent crude oil, Intercontinental Exchange (ICE), 3 months	FUTURE_BRENT_M3	Thomson Reuters	5	0
281	Futures Brent crude oil, Intercontinental Exchange (ICE), 4 months	FUTURE_BRENT_M4	Thomson Reuters	5	0
282	Futures Brent crude oil, Intercontinental Exchange (ICE), 5 months	FUTURE_BRENT_M5	Thomson Reuters	5	0
283	Futures Brent crude oil, Intercontinental Exchange (ICE), 6 months	FUTURE_BRENT_M6	Thomson Reuters	5	0
284	Futures Brent crude oil, Intercontinental Exchange (ICE), 7 months	FUTURE_BRENT_M7	Thomson Reuters	5	0
285	Futures Brent crude oil, Intercontinental Exchange (ICE), 8 months	FUTURE_BRENT_M8	Thomson Reuters	5	0
286	Futures Brent crude oil, Intercontinental Exchange (ICE), 9 months	FUTURE_BRENT_M9	Thomson Reuters	5	0
287	Futures Brent crude oil, Intercontinental Exchange (ICE), 10 months	FUTURE_BRENT_M10	Thomson Reuters	5	0
288	Futures Brent crude oil, Intercontinental Exchange (ICE), 11 months	FUTURE_BRENT_M11	Thomson Reuters	5	0
289	Futures Brent crude oil, Intercontinental Exchange (ICE), 12 months	FUTURE_BRENT_M12	Thomson Reuters	5	0
290	Futures Brent crude oil, Intercontinental Exchange (ICE), 24 months	FUTURE_BRENT_M24	Thomson Reuters	5	0
291	Futures Brent crude oil, Intercontinental Exchange (ICE), 36 months	FUTURE_BRENT_M36	Thomson Reuters	5	0
292	Futures Brent crude oil, Intercontinental Exchange (ICE), 48 months	FUTURE_BRENT_M48	Thomson Reuters	5	0
293	Futures Brent crude oil, Intercontinental Exchange (ICE), 60 months	FUTURE_BRENT_M60	Thomson Reuters	5	0
294	Futures Brent crude oil, Intercontinental Exchange (ICE), 72 months	FUTURE_BRENT_M72	Thomson Reuters	5	0

Note: "Name" means the series' internal name usually provided in the release data files. "tcode" means the code of the transformation applied to the series. "rlags" means the approximated lag of the last observation available in relation to t. We consider the lag to be zero if the observation of $t-1$ is normally available by the 15th of month t. Transformation codes: (1) no transformation, (2) Δx_t, (3) $\Delta^2 x_t$, (4) $\log(x_t)$, (5) $\Delta \log(x_t)$, (6) $\Delta^2 \log(x_t)$, (7) $\Delta \left(x_t/x_{t-1} - 1\right)$.

Online Appendix to *Predicting U.S. Recessions in Real Time in a Big-Data Setting*

Main techniques for dating recessions and computing their probability of occurrence

This online appendix is not intended to be a literature review on forecasting recessions. Rather, its focus is on papers closely related to our approach to the subject. Some of the broader literature is already reviewed on the main paper itself.

Stock and Watson (1989, 2002, 2014)

In different papers, Stock and Watson have had a large contribution to (and influence on) the literature of dating recessions and computing their probability of occurrence. In this section, we will focus mainly on three of their papers for the sake of space.

Stock and Watson (1989) laid the foundations for what most of this literature would become in the future. They ask: (i) "is it possible to develop a formal probability model that gives rise to the indexes of leading and coincident variables?"; (ii) "what are the best variables to use as components of the leading index?"; (iii) "given these variables, what is the best way to combine them to produce useful and reliable indexes?"

Instead of focusing on an aggregate measure of economic activity, they follow Burns and Mitchell (1946, p.3) definition that a business cycle "consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals..." So, Stock and Watson (1989) proposed the statistical foundations for implementing the main ideas proposed by Burns and Mitchell. By looking at a large number of economic-activity series at the same time, they opted not to follow a single aggregate series as GDP, which led further down the road to the use of techniques that could

deal with big data.

To model coincident and leading indices of economic activity, they constructed a state-space model where X_t denotes an $n \times 1$ vector of the logarithms of macroeconomic variables that are hypothesized to move contemporaneously with overall economic conditions. X_t consists of two components: the common unobserved scalar variable, or "index," C_t, and an n-dimensional component, u_t, which stands for the idiosyncratic component. The state-space model reads:

$$\begin{array}{rcl} \underset{n\times 1}{\Delta X_t} & = & \underset{n\times 1}{\beta} + \underset{n\times 1}{\gamma\left(L\right)}\underset{1\times 1}{\Delta C_t} + \underset{n\times 1}{u_t}\,, \\ \underset{n\times n}{D\left(L\right)u_t} & = & \underset{n\times 1}{\varepsilon_t}\,, \\ \underset{1\times 1}{\phi\left(L\right)}\Delta C_t & = & \delta + \eta_t, \end{array}$$

where L denotes the lag operator, and $\phi\left(L\right)$, $\gamma\left(L\right)$ and $D\left(L\right)$ are, respectively, scalar, vector, and matrix lag polynomials.

They describe their model as follows: "The main identifying assumption expresses the core notion of the dynamic factor model that the co-movements of the multiple time series arise from the single source ΔC_t." So, based on the estimates of the state-space model above, their coincident index is $C_{t|t}$ – the minimum mean square error linear estimate of this single common factor, produced by applying the Kalman filter to the estimated system. The leading index, on the other hand, is the estimate of the growth of this unobserved factor over the next six months, computed using a set of leading variables, i.e., $C_{t+6|t} - C_{t|t}$.

Regarding the issue of prediction of recessions and expansions, they link the leading index of economic activity with a recession index – an estimate of the probability that the economy will be in a recession six months hence.

Stock and Watson (2002) delves into forecasting using principal components when employing a multitude of predictors. So, their approach can be viewed as a big-data approach, where one employs a dimension-reduction mechanism for estimating common dynamic factors across a large set of variables. It addresses the challenge of making accurate predictions in high-dimensional datasets, typical in economic analyses. The authors distill essential information from a vast array of economic variables using principal component analysis (PCA), which reduces the dimensionality of the data and helps to identify key patterns and statistical relationships in the database.

To fix ideas, consider the joint model for $(X_t', y_t)'$, where the objective is to predict y_{t+h}

employing the large dataset of predictors X_t, i.e., N is large:

$$\begin{aligned} \underset{N\times 1}{X_t} &= \underset{N\times r}{\Lambda}\ \underset{r\times 1}{F_t} + \underset{N\times 1}{e_t}\,, \\ \underset{1\times 1}{y_{t+h}} &= \underset{1\times r}{\beta_F'}\ \underset{r\times 1}{F_t} + \underset{1\times m}{\beta_w'}\ \underset{m\times 1}{w_t} + \underset{1\times 1}{\varepsilon_{t+h}}, \end{aligned}$$

where the vector F_t embeds r latent factors, w_t includes m additional predictors for y_{t+h}, e.g., its own lags, Λ, β_F', and β_w' are appropriate loadings, and errors e_t are cross-sectional diversifiable.

The classical way of estimating factors F_t is by using PCA, with the loadings later estimated by least squares. One of the key points discussed is PCA's role in mitigating multicollinearity, a common issue in regression analysis with numerous predictors. By transforming the original predictors into a smaller set of orthogonal components, PCA alleviates multicollinearity, thus enhancing the stability and interpretability of the regression model.

The article also explores the practical implementation of PCA-based forecasting methods, offering insights into model selection, estimation techniques, and evaluation metrics. Empirical results underscore the effectiveness of the approach in generating accurate forecasts for various economic indicators. Notably, in some cases, a small number of factors can capture close to or more than 50% of the variation in a large dataset.

According to Stock and Watson (2014), there are two main approaches in the business cycle dating literature. The first approach, initiated by Burns and Mitchell (1946), involves identifying turning points individually in a large number of time series, and then searching for a common date called an aggregate turning point. Stock and Watson refer to this approach as *"date-then-average"*. By incorporating information from various economic indicators, this approach provides a robust and comprehensive assessment of turning point probabilities, thereby enhancing the accuracy and reliability of turning point forecasts. This approach leverages the collective wisdom embedded within multiple economic indicators to capture the nuanced dynamics of the business cycle.

The second, more recent approach, seeks turning points in only a few, or just one, aggregate time series (e.g., GDP). Stock and Watson call this approach *"average-then-date"*. This method begins by aggregating information from various economic indicators, typically computing the average value of each predictor over a specified period, such as a quarter. Subsequently, specific dates are assigned to each observation based on its corresponding quarter, thus aligning the aggregated data with a time series framework. The idea is to improve the

accuracy and reliability of turning point estimates by synthesizing information from multiple sources into a unified and interpretable format.

The authors examine both approaches and propose a non-parametric definition of turning points, allowing the construction of estimators, sampling distributions, and standard errors of turning points using a sample of a set of 270 time series. In addition, Stock and Watson highlight the importance of real-time data in turning point estimation, enabling policymakers and analysts to react promptly to changes in economic conditions.

This last point raises some controversy, since their approach has generalized the single-variable "dating" approach of Harding and Pagan (2006). As is well-known, real-time use of these techniques is not straightforward, because it requires dealing with endpoints in the "dating" process. For dating protocols that require a minimum 6-month period to date a recession, one has to predict the series being dated 6-months ahead, which brings forecast-uncertainty into "dating," once interest lies with "date-than-average." However, the forecast uncertainty six months later can be substantial, which may be a problem for the final "average" estimated in real time.

Despite this potential shortcoming, historical results for dating recessions are impressive and come very close to those obtained by the NBER committee.

Chauvet and Hamilton (2006) and Hamilton (2011)

Hamilton's (2011) article aims to answer whether there is any effective technique for dating recessions in real time. Part of the literature uses the techniques proposed in Hamilton's seminal article (Hamilton, 1989) on models of two (or more) regimes, with a latent state variable representing the regimes of the economy, driven by a Markov Chain.

Hamilton (2011) asks the following question: given that we have NBER dates for the U.S., what is the advantage of trying to implement an automatic mechanism (algorithm) for forecasting U.S. recessions? The author answers this question as follows:

1. *Timeliness.* The Business Cycle Dating Committee has issued its announcements of the beginning and end of recessions usually much after these events. For example, the NBER dated the recession of 1990-91, which started in August 1990 and ended in March 1991, much later than it has started – on April 1991. Regarding the end of the 2001 recession, it was announced in July 2003 – 28 months after the recession was considered over.

2. *Apolitical Mechanism.* A purely objective algorithm for determining recession dates in real time ensures that the process is completely apolitical. Although no one has accused the NBER of altering its announcements based on political considerations, there is undeniably pressure to delay the announcement that a recession has begun or speed up the announcement that a recovery has begun if the goal is to help the incumbent.

3. *Structural Mechanism.* Creating a mechanical way of recognizing the inflection points of business cycles allows us to elucidate what we really mean when we say "the economy is in recession". If the dates assigned by the NBER represent the answer, what is the question? The whole process seems to assume that there are some very different factors operating in the economy at different times, and that these changes have observable implications. Mechanization of the dating procedure can help clarify exactly how and why we assign the dates we do.

The next question asked by Hamilton is *why is it so difficult to implement a recession-prediction algorithm for the U.S.*? Again, the answer is given in three different ways:

1. *Predictability.* If people could predict recessions, they probably wouldn't happen. Firms would not be stuck with inventories, labor and capital they would not need, and the Fed would likely ease its monetary policy stance sooner. Economists know that stock prices are difficult (or impossible) to predict if the market is working properly. It may be that economic recessions, by their very nature, imply similar limitations to their forecasting.

2. *Data revision.* The data available in real time may send different signals than the same data later reviewed. For example, the real GDP growth rates for each quarter of 2001, as reported in the late 2002 *vintage*, show 3 successive quarters of declining real GDP, which sounds unmistakably like a recession. However, data from the same quarters by the January 30, 2002 *vintage* show that the recession was already over. This shows the difficulty of using GDP data to date recessions, as these are subject to many revisions that, in some cases, may change the perception of the state of the economy depending on the *vintage*.

3. *Changes over time.* One factor that makes it difficult to recognize real-time business cycle turning points is the fact that key economic relationships continually change over time and with available information.

In a slightly less optimistic tone, Hamilton then proposes to aim for something more modest, trying to recognize a turning point soon after it has occurred using robust algorithms against the revised data and structural changes out-of-sample, which seems to have a reasonable track record (at least until now). The algorithm that Hamilton (2011) proposes is based on the approach in Chauvet and Hamilton (2006).

Chauvet and Hamilton consider the following question: what is different about the behavior of GDP during the quarters that the NBER classifies as recessions compared to those characterized as expansions? They answered this question by collecting the growth rate of U.S. GDP between 1947Q2 and 2004Q2, in which the NBER ended up describing 45 of these quarters as part of an economic recession. This subsample of 45 observations has an average growth rate of -1.2% (expressed as annual growth) and a standard deviation of 3.5. The remaining 180 expansion quarters had a mean of 4.5 and a standard deviation of 3.2. The observed sample of 225 observations can be seen as a mixture of these two distributions, with 20% coming from the distribution of recession periods and the remaining 80% from the distribution of booming periods.

Let $S_t = 1$ if the quarter t is eventually declared by the NBER as part of a recession, and $S_t = 2$ if quarter t is eventually declared part of an expansion. Denote the GDP growth rate by y_t. We can define the joint probability that the quarter t is declared a recession and has a GDP growth rate of y_t as follows:

$$P\left(S_t = 1, y_t\right) = f\left(y_t \left| S_t = 1\right.\right) P\left(S_t = 1\right),$$

where $f\left(y_t \left| S_t = 1\right.\right)$ is the conditional density of y_t given $S_t = 1$, in which $P\left(S_t = 1\right)$ is the probability of occurrence of a recession, previously calculated as 0.2. Analogously:

$$P\left(S_t = 2, y_t\right) = f\left(y_t \left| S_t = 2\right.\right) P\left(S_t = 2\right),$$

where $P\left(S_t = 2\right) = 0.8$. The optimal inference that interests us is to know what is the probability of a recession being dated by the NBER when we have a certain value of GDP growth as a condition:

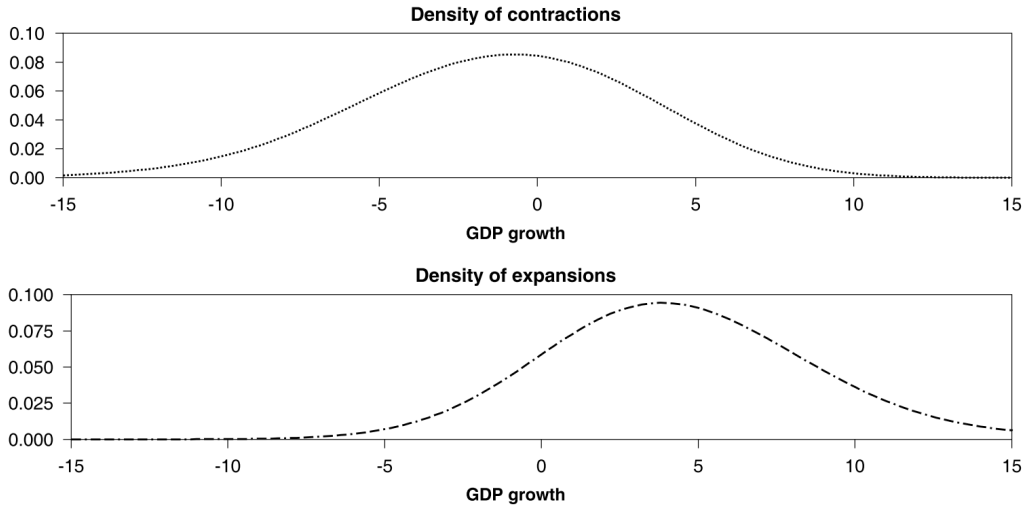
$$P\left(S_t = 1 \left| y_t\right.\right) = \frac{P\left(S_t = 1, y_t\right)}{f\left(y_t\right)} = \frac{P\left(S_t = 1, y_t\right)}{P\left(S_t = 1, y_t\right) + P\left(S_t = 2, y_t\right)},$$

so we can simplify:

$$P\left(S_t = 1, y_t\right) = f\left(y_t \left| S_t = 1\right.\right) \times 0.2,$$
$$P\left(S_t = 2, y_t\right) = f\left(y_t \left| S_t = 2\right.\right) \times 0.8.$$

When we separate the observations into contractions and expansion periods, we obtain the following densities in figure 1.

Figure 1 – Conditional probability density function (pdf)



Source: Hamilton (2011)

This shows that these densities have very different means, although their respective variances are not very different. The average of recessive periods is a GDP growth (annualized) of -1.2%, whereas the average of expansion periods is of 4.5%. Therefore, if we observe a GDP growth of 6%, for example, the probability of a recession being dated is quite low. On the other hand, if we observe a GDP growth of -6%, this probability will be quite high.

This rule (or algorithm) seems to satisfy the requirements of being simple and robust. Unfortunately, this is not very useful, since the vast majority of observations will fall into a range where they will not provide clear signals. However, there is a second feature of NBER dates that can be quite useful - the value of S_t it is quite likely to be the same as S_{t-1}. For 95% of the observations for which $S_{t-1} = 2$, S_t was also equal to 2, whereas 78% of the observations for which $S_{t-1} = 1$ were also followed by $S_t = 1$. So, even if y_t alone does not give us a very useful idea of the signal, the value of y_{t-1} can help us refine it. Obviously, there is no reason to stop conditioning in the period $t - 1$, when we can condition the model using information

up to the beginning of the sample, i.e., calculating:

$$P\left(S_t = 1 \left| y_t, y_{t-1}, \cdots, y_1 \right.\right),$$

which is a filtered version of the probability of occurrence of a recession dated by the NBER.

Chauvet and Hamilton (2006) also considered a smoothed version of it, which uses the entire sample, $y_1, y_2, \cdots, y_T$, as follows:

$$P\left(S_t = 1 \left| y_T, y_{T-1}, \cdots, y_1 \right.\right).$$

The estimation of the model involves the following steps. It is assumed that:

$$\begin{aligned} y_t \left| S_t = 1 \right. &\sim \mathcal{N}\left(\mu_1, \sigma^2\right), \\ y_t \left| S_t = 2 \right. &\sim \mathcal{N}\left(\mu_2, \sigma^2\right). \end{aligned}$$

The density of the first observation is given by:

$$f\left(y_1; \mu_1, \mu_2, \sigma^2, \pi\right) = \pi\phi\left(y_1; \mu_1, \sigma^2\right) + (1-\pi)\,\phi\left(y_1; \mu_2, \sigma^2\right),$$

where π is the unconditional probability of the occurrence of a recession dated by the NBER and $\phi(\cdot)$ is the probability density function (pdf) of a Normal random variable. Next, Chauvet and Hamilton compute recursively the conditional densities $P\left(S_t = 1 \left| y_t, y_{t-1}, \cdots, y_1 \right.\right)$ and then characterize the *conditional* log-likelihood function as follows – where the θ vector includes the parameters of interest:

$$\mathcal{L}\left(\theta; y_T, y_{T-1}, \cdots, y_1\right) = \sum_{t=1}^{T} \log\left[f\left(y_t \left| y_{t-1}, y_{t-2}, \cdots, y_1 \right.; \theta\right)\right].$$

The results of the estimation of the model of Chauvet and Hamilton (2006), were compared with those from Hamilton for the GDP data, classified according to the NBER:

Table 1 – Parameter estimates

Table 1
Parameter estimates based on (1) the characteristics of expansions and recessions as classified by the NBER, and (2) the values that maximize the observed sample log likelihood of postwar GDP growth rates over the period 1947:Q2–2004:Q2.

Parameter	Interpretation	Value from NBER classifications	Value from GDP alone
μ_1	Average growth in expansion	4.5	4.62
μ_2	Average growth in recession	−1.2	−0.48
σ	Standard deviation of growth	3.4	3.34
p_{11}	Prob. expansion continues	0.95	0.92
p_{22}	Prob. recession continues	0.78	0.74

Note: Reproduced from Chauvet and Hamilton (2006).

Source: Hamilton (2011)

The results are apparently excellent, with the exception of average GDP growth in NBER recessions. However, we must keep in mind that they were obtained in an *in-sample* analysis. As Hamilton citing Niels Bohr reminded us, predictions are very difficult, especially about the future, i.e., *out-of-sample*.

Hamilton (2011) also discusses the results of two experiments. In the first, the filtered probability is calculated as $P\left(S_t = 1 \,|y_t, y_{t-1}, \cdots, y_1\right)$ using the latest GDP vintage (available in 2004). In the second experiment, to evaluate the usefulness of this algorithm in real time (on date t), he discusses the use of GDP data that would be available in t according to its vintage; see the database maintained by the Federal Reserve Bank of Philadelphia - Croushore and Stark (2003). These data are used both to estimate the parameter vector θ and to make inferences about $P\left(S_t = 1 \,|\cdot\right)$. However, the use of such data resulted in a considerable deterioration of the results. Therefore, Hamilton recommends waiting an extra quarter to use the revised data, which allows for additional precision, before dating recession in t.

Thus, the proposed mechanism is to make inferences about S_t only after the next quarter's GDP growth rate, y_{t+1}, is available, calculating $P\left(S_t = 1 \,|y_{t+1}, y_t, \cdots, y_1 \,; \widehat{\theta}_{t+1}\right)$, where $\widehat{\theta}_{t+1}$ represents the parameters estimated by maximum likelihood using as data $y_1, y_2, \cdots, y_t, y_{t+1}$.

In order to implement the real-time algorithm, based on $P\left(S_t = 1 \,|y_{t+1}, y_t, \cdots, y_1 \,; \widehat{\theta}_{t+1}\right)$, Chauvet and Hamilton (2006) recommended the following decision rule. When $P\left(S_t = 1 \,|y_{t+1}, y_t, \cdots, y_1 \,; \widehat{\theta}_{t+1}\right)$ first exceeds 0.65, a recession is declared. At this point, the probable start of the recession is attributed to the beginning of the most recent set of observations for which $P\left(S_{t-j} = 1 \,|y_{t+1}, y_t, \cdots, y_1 \,; \widehat{\theta}_{t+1}\right)$ exceeds 0.5. The recession call remains in effect until $P\left(S_t = 1 \,|y_{t+1}, y_t, \cdots, y_1 \,; \widehat{\theta}_{t+1}\right)$ falls below 0.35, time at which the

probable end point for the recession is assigned as the beginning of the most recent set of observations for which $P\left(S_{t-j}=1\,|y_{t+1},y_t,\cdots,y_1\,;\widehat{\theta}_{t+1}\right)$ is smaller than 0.5. The results of this implementation of the real-time algorithm are shown below:

Table 2 – Turning points of business cycle in the U.S.

Table 2
Business cycle turning points and dates on which announcements were issued by NBER and the GDP-based algorithm.

Start of recessions				
Peak as determined by NBER	Date NBER made declaration	Recession start as determined by algorithm	Date algorithm made declaration	Algorithm announcement lead (−) or lag (+) in months
1969:Q4	N.A.	1969:Q2	May 1970*	N.A.
1973:Q4	N.A.	1973:Q4	May 1974*	N.A.
1980:Q1	Jun 1980	1979:Q2	Nov 1979*	−7
1981:Q3	Jan 1982	1981:Q2	Feb 1982*	+1
1990:Q3	Apr 1991	1989:Q4	Feb 1991*	−2
2001:Q1	Nov 2001	2001:Q1	Feb 2002*	+3
2007:Q4	Dec 2008	2007:Q4	Jan 2009	+1
Start of expansions				
Trough as determined by NBER	Date NBER made declaration	Recession end as determined by algorithm	Date algorithm made declaration	Algorithm announcement lead (−) or lag (+) in months
1970:Q4	N.A.	1970:Q4	Aug 1971*	N.A.
1975:Q1	N.A.	1975:Q1	Feb 1976*	N.A.
1980:Q3	Jul 1981	1980:Q2	May 1981*	−2
1982:Q4	Jul 1983	1982:Q4	Aug 1983*	+1
1991:Q1	Dec 1992	1991:Q4	Feb 1993*	+2
2001:Q4	Jul 2003	2001:Q3	Aug 2002*	−12
2009:Q2	Sep 2010	2009:Q2	Apr 2010	−5

Notes: Starred entries denote simulated real-time declarations, unstarred are actual real-time declarations. N.A. indicates that the information is not available.

Source: Hamilton (2011)

The results in the table above show that the peak and valley dates of the algorithm and the NBER are identical or very close. As for the timeliness of the algorithm's dates versus the NBER, there is no clear advantage. In fact, half the time NBER dates peaks and valleys before the algorithm, and half the time NBER dates peaks and valleys after the algorithm.

Issler and Vahid (2006)

Here we present a summary of the techniques proposed in Issler and Vahid (2006) to model the U.S. business cycles and to predict recessions, relying heavily on their own text. For a complete account, readers are referred to their paper.

The canonical-correlation approach of Issler and Vahid follows the common features literature, initiated by Engle and Kozicki (1993), Vahid and Engle (1993) and Engle and Issler (1995). There, economic series share common components that can be removed by linear combination. Examples are trends, cycles, seasonality, volatility, etc. The best known exam-

ples are common trends (cointegration, after Engle and Granger, 1987), and common cycles (common serial correlation, after Engle and Kozicki, 1993).

Issler and Vahid (2006) employ canonical-correlation analysis to model U.S. business cycles and to predict U.S. recessions relying on the NBER-committee dating of those episodes. Hotelling (1935, 1936) introduced canonical-correlation analysis as a multivariate-statistic tool. Akaike (1976) properly referred to canonical variables as "the information interface channels between past and present" and referred to canonical correlations as the "strength" of these channels.

In the context of Issler and Vahid, consider a set of traditional *coincident* series regarding the U.S. business cycles (income, output, employment and sales), denoted by $x_t = (x_{1t}, x_{2t}, x_{3t}, x_{4t})'$, and the set of m ($m \geq 4$) of their predictors collected in a vector z_t (this includes lags of x_t and the lags of the *leading* series). Canonical-correlation analysis transforms x_t into four independent linear combinations $A(x_t) = (\alpha_1' x_t, \alpha_2' x_t, \alpha_3' x_t, \alpha_4' x_t)$, with the property that $\alpha_1' x_t$ is the linear combination of x_t that is more (linearly) predictable using z_t, i.e., using $\gamma_1' z_t$; $\alpha_2' x_t$ is the second most linearly predictable using z_t, i.e., using $\gamma_2' z_t$, after controlling for $\alpha_1' x_t$; and so on.

As a result, the linear combinations $\alpha_i' x_t$ are not correlated with each other, and the four linear combinations of z_t, $\Gamma(z_t) = (\gamma_1' z_t, \gamma_2' z_t, \gamma_3' z_t, \gamma_4' z_t)$ have the property that $\gamma_i' z_t$ is the linear combination of z_t which has the highest quadratic correlation with $\alpha_i' x_t$, for $i = 1, 2, 3, 4$, and are not correlated with each other as well. The R^2s between $\alpha_i' x_t$ and $\gamma_i' z_t$ for $i = 1, 2, 3, 4$, denoted by $(\lambda_1^2, \lambda_2^2, \lambda_3^2, \lambda_4^2)$, are the squares of the canonical correlations between x_t and z_t. Finally, we can test recursively whether or not these canonical correlations are statistically zero – a null hypothesis that implies no prediction from the z_ts to the x_ts. This allows for separating *cycles* from *noise*.

Next, they characterize the Probit model using the NBER-committee dating of recessions:

$$\text{NBER}_t = \begin{cases} 1 & \text{if } \mathbb{E}(y_t^* \mid I_{t+h}) < 0, \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where y_t^* is a variable representing the unobserved state of the U.S. economy, i.e., the latent U.S. business cycle, NBER_t is a dummy signaling U.S. recessions as declared by the NBER committee.

We must stress that future information is used by the NBER-committee in determining the

state of the economy in period t – $(\mathbb{E}(y_t^* \mid I_{t+h}))$. The key identifying assumption in Issler and Vahid is the following:

Hypothesis 1 (Issler and Vahid, 2006): *There is a linear index (of the cyclical parts) of the coincident series that has exactly the same pattern of correlation with previous information as the unobserved state of the economy.*

Advancing to their empirical results, they only found three significant cycles, $c_{it} = \alpha_i' x_t$, $i = 1, 2, 3$, that are predictable from the past, so *Hypothesis 1* boils down to:

$$\mathbb{E}(y_t^* - \beta_0 - \beta_1 c_{1t} - \beta_2 c_{2t} - \beta_3 c_{3t} \mid I_{t-1}) = 0. \tag{2}$$

Using equation (2), it follows that:

$$\begin{aligned} \mathbb{E}\left(y_t^* \mid I_{t-1}\right) &= \beta_0 + \beta_1 \mathbb{E}\left(c_{1t} \mid I_{t-1}\right) + \beta_2 \mathbb{E}\left(c_{2t} \mid I_{t-1}\right) + \beta_3 \mathbb{E}\left(c_{3t} \mid I_{t-1}\right) \\ &= \beta_0 + \beta_1 c_{1t} + \beta_2 c_{2t} + \beta_3 c_{3t} + \omega_t, \end{aligned} \tag{3}$$

where c_{it} is decomposed as $c_{it} = \mathbb{E}\left(c_{it} \mid I_{t-1}\right) - \omega_{it}$, $i = 1, 2, 3$, $\omega_t = \beta_1 \omega_{1t} + \beta_2 \omega_{2t} + \beta_3 \omega_{3t}$, and $\mathbb{E}\left(\omega_t \mid I_{t-1}\right) = 0$. It becomes clear that ω_t is correlated with c_{it}, $i = 1, 2, 3$. Moreover, since we can always write:

$$\mathbb{E}\left(y_t^* \mid I_{t+h}\right) = \mathbb{E}\left(y_t^* \mid I_{t-1}\right) + \xi_t + \xi_{t+1} \cdots + \xi_{t+h}, \tag{4}$$

where ξ_{t+j} is the "surprise" associated with the new information arriving in period $t + j$, $j = 0, 1, 2, ..., h$, we arrive at:

$$\begin{aligned} \mathbb{E}\left(y_t^* \mid I_{t+h}\right) &= \beta_0 + \beta_1 c_{1t} + \beta_2 c_{2t} + \beta_3 c_{3t} + u_t, \\ u_t &= \omega_t + \xi_t + \xi_{t+1} \cdots + \xi_{t+h}, \end{aligned} \tag{5}$$

where u_t is unpredictable given information in period $t - 1$, that is, $\mathbb{E}\left(u_t \mid I_{t-1}\right) = 0$, but it has an $MA(h)$ structure, being correlated with c_{it}, $i = 1, 2, 3$, mainly due to the term ω_t.

To consistently estimate $\beta_0, \beta_1, \beta_2$ and β_3, Issler and Vahid employ the two-stage conditional maximum likelihood estimator (2SCML) proposed by Rivers and Vuong (1988) due to its relative simplicity. This method uses instrumental variables. The natural instruments are the variables z_t, since the canonical-correlation analysis yields estimates of $\gamma_1' z_t$, $\gamma_2' z_t$, $\gamma_3' z_t$,

which are the best linear predictors c_{1t}, c_{2t}, c_{3t}, respectively. In this context, these are "strong" instruments.

Issler and Vahid also propose a coincident index – "instrumental variable coincident index" (IVCI) – relying on estimates of betas and cycles:

$$\begin{aligned} \Delta IVCI_t &= \widehat{\beta}_1\widehat{c_{1t}} + \widehat{\beta}_2\widehat{c_{2t}} + \widehat{\beta}_3\widehat{c_{3t}} \\ &= \widehat{\beta}_1\widehat{\alpha}_1'x_t + \widehat{\beta}_2\widehat{\alpha}_2'x_t + \widehat{\beta}_3\widehat{\alpha}_3'x_t \\ &= \left(\widehat{\beta}_1\widehat{\alpha}_1' + \widehat{\beta}_2\widehat{\alpha}_2' + \widehat{\beta}_3\widehat{\alpha}_3'\right)x_t, \end{aligned} \tag{6}$$

which are a simple linear combination of the coincident series x_t. A leading index can also be obtained using (6) by replacing c_{1t}, c_{2t}, c_{3t} with their linear optimal predictors $\lambda_1\gamma_1'z_t$, $\lambda_2\gamma_2'z_t$, $\lambda_3\gamma_3'z_t$, respectively. The "instrumental variable leading index" (IVLI) is a linear combination of z_t:

$$\Delta IVLI_t = \mathbb{E}_{t-1}\left(\widehat{\beta}_1\widehat{c_{1t}} + \widehat{\beta}_2\widehat{c_{2t}} + \widehat{\beta}_3\widehat{c_{3t}}\right) = \left(\widehat{\beta}_1\widehat{\lambda}_1\widehat{\gamma}_1' + \widehat{\beta}_2\widehat{\lambda}_2\widehat{\gamma}_2' + \widehat{\beta}_3\widehat{\lambda}_3\widehat{\gamma}_3'\right)z_t, \tag{7}$$

where the operator $\mathbb{E}_{t-1}(\cdot) = \mathbb{E}(\cdot \mid I_{t-1})$ represents the conditional expectation using information up to $t-1$.

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