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A Comparison of Methods for the Construction of Composite Coincident and Leading Indexes for the UK*

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Abstract

In this paper we provide an overview of recent developments in the methodology for the construction of composite coincident and leading indexes, and apply them to the UK. In particular, we evaluate the relative merits of factor based models and Markov switching specifications for the construction of coincident and leading indexes. For the leading indexes we also evaluate the performance of probit models and pooling. The results indicate that alternative methods produce similar coincident indexes, while there are more marked differences in the leading indexes.

Keywords: Forecasting, Business Cycles, Leading Indicators, Coincident Indicators, Turning Points

J.E.L. Classification: E32, E37, C53

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1 Introduction

In the recent past there has been a renewed interest in coincident and leading indicators as a tool for monitoring the economy and predicting its future behaviour. Such an interest was also in part stimulated by a set of theoretical developments, which have presumably eliminated or at least reduced the drawbacks of traditional composite coincident and leading indexes (CCI and CLI, respectively).

Stock and Watson (1989, SW) improved in five main respects the by then current practice in indicator analysis. First, they formalized Burns and Mitchell's (1946) notion that business cycles represent co-movements in a set of series by estimating a coincident index of economic activity as the unobservable factor in a dynamic factor model. Second, they stressed the importance of the choice of candidate leading indicators and introduced a systematic regression based selection. Third, they jointly modelled the coincident and the leading indicators. Fourth, they introduced a state space framework that allows the joint resolution of a set of data problems such the identification and removal of outliers, the treatment of data revisions, and the use of indicators whose most recent unavailable data can be substituted with forecasts. Finally, they developed an index of leading indicators that produces early warnings of recession, in the form of a probability that a recession will take place in the next six months. The topics were further developed in Stock and Watson (1991, 1992).

Another very important article in this context is Hamilton (1989), whose main contribution to the business cycle literature is threefold. First, he showed that, using the available data on one or more coincident series, it is possible to infer the probability of being in an expansion or in a recession. Second, it is possible to jointly model coincident and leading indicators, since the latter should be driven by the same Markov process but with a lead (Hamilton and Perez-Quiros (1996)). Third, and related to the previous point, the method can be easily used to produce point or probability forecasts of the coincident variable, but also analytical forecasts of the probability of being in recession in or within a certain future date.

Stock and Watson (1989) and Hamilton (1989) have generated an impressive amount of subsequent research, and in this paper we wish to provide an overview of those contributions more closely related to the construction of CCIs and CLIs, additional theoretical details can be found in Marcellino (2005). As an illustration of the implementation of the newer techniques, we will construct and compare a variety of CCIs and CLIs for the UK.

The paper is organized as follows. In Section 2 we describe and implement alternative techniques for the construction of composite coincident indexes. In Section 3 we present

and apply a variety of methods for building composite leading indexes, and for using them as forecasting devices. In Section 4 we summarize the main findings and conclude.

2 Alternative methods for the construction of CCIs

The variables we combine into a composite coincident index (CCI) for the UK are very similar to those traditionally considered for the US, see e.g. Marcellino (2005), and coincide with those selected by the Conference Board (CB) for their CCI, which represents our benchmark due to its long established tradition. Specifically, we consider Industrial Production, Retail Sales, Employment, and Real Household Disposable Income, over the sample 1978-2004, at the monthly frequency.

There exist different methods to summarize the information in the four series into a single CCI, see e.g. Marcellino (2005) for details. The simplest procedure requires to transform the single components of the CCI so that they have similar ranges, and then aggregate them using a set of weights. We will refer to the resulting index as non-model based (NMB) CCI. The NMB CCI is very similar to the one produced by the Conference Board, and we will use it as a benchmark for the more sophisticated CCIs in the ensuing analysis.

A second procedure for the construction of a CCI was introduced by Stock and Watson (1989, SW) for the US, and it is based on a parametric factor model for the components of the composite index. Following Stock and Watson, we have considered the following specification:

$$\begin{cases} y_{it} = \gamma_i \Delta C_t + u_{it}, & i = 1, \dots, 4 \\ u_{it} = \psi_{1i} u_{it-1} + \psi_{2i} u_{it-2} + \varepsilon_{it}; \\ \varepsilon_{it} \sim iidN(0, \sigma_i^2); & i = 1, 2, 3, 4; \end{cases} \quad (1)$$

$$\begin{aligned} \Delta C_t &= \varphi_1 \Delta C_{t-1} + \varphi_2 \Delta C_{t-2} + v_t; & v_t &\sim iidN(0, 1) \\ cov(\varepsilon_{it}, v_s) &= 0 \quad \forall i, \forall s, \forall t, \end{aligned} \quad (2)$$

where y_{it} indicates the demeaned log difference of each indicator, ΔC_t the common factor driving all the indicators (the log difference of the CCI), and u_{it} the idiosyncratic component of each indicator.¹ The cumulated values of the estimated common factor will be

¹The single coincident indicators present either a trending behaviour or at least persistent deviations from the mean. These features are confirmed by ADF unit root tests, which do not reject the null hypothesis of a unit root for any of the indicators. Instead, the results of cointegration tests conducted in a VAR framework are not conclusive, they substantially depend on the lag length, the deterministic

referred to as the parametric factor based (SW) CCI.

One problem with the SW CCI is that standard diagnostic tests on the residuals $\widehat{\varepsilon}_{it}$ of the model in (1) in the UK indicate lack of normality and serial correlation. The former seems due to a few outlying observations but can be hardly eliminated by inserting dummy variables into the model. Increasing the number of lags is also not effective for eliminating the detected serial correlation of the residuals. However, these changes in model specification do not alter substantially the estimated factor, which provides evidence in favour of the robustness of the computed SW CCI.

An alternative solution to address the misspecifications of the parametric factor model in (1) is to resort to nonparametric techniques to estimate the common factor and obtain alternative factor-based CCIs. The two most common techniques were suggested by Stock and Watson (2002a, 2002b, SW2) in the time domain, and by Forni, Hallin, Lippi and Reichlin (2000, FHLR) in the frequency domain. Basically, SW2 suggested to estimate the common factors as the static principal components of the variables, namely, of the single coincident indexes in our case. FHLR proposed to use the dynamic principal components to better capture the dynamics of the model. The latter approach has the disadvantage that the estimated factors are combinations of lags, contemporaneous values and leads of the single series, and the use of leads prevents a real time implementation. A modified procedure which admits a real time implementation was suggested by Forni, Hallin, Lippi and Reichlin (2005, FHLR2). Details on these methods can be found in the original papers, and in Altissimo et al. (2001) and Marcellino (2005) in a CCI context. Both methods are particularly suited when the number of variables under analysis is large, but the evidence in Marcellino (2005a) for the US and Carriero, Favero and Marcellino (2006) for euro area countries suggests that they can produce reliable CCIs also when applied to a limited number of coincident indicators. We will refer to the non-parametric factor based indicators as SW2 and FHLR2 CCIs.²

In the three panels of Figure 1 we graph the levels, six month percentage changes and filtered versions of the (standardized) NMB CCI and of the three versions of the factor based CCIs, namely, SW, SW2 and FHLR2.³ The different CCIs seem to move

component included into the VAR, and the type of cointegration test applied (Johansen's (1988) trace or eigenvalue statistic). When BIC is used to select the lag length of the VAR and the deterministic component, it then also selects models without cointegration. Since all the factor based methods require the input variables to be weakly stationary, we model the log differences of the single coincident indicators.

²More specifically, the SW2 CCI is the first static principal component of the four coincident series, while to construct the FHLR2 CCI we apply their two-step procedure, set the bandwidth parameter at $M=12$, and use one factor both in the first step (i.e. to compute the variance covariance matrix of the common components obtained using FHLR) and in the second step.

³The filtered CCIs are obtained by applying the bandpass HP filter proposed in Artis, Marcellino and

closely together, for any transformation. The use of growth rates or filtered data also emphasizes the close similarity of the indexes at turning points. The visual impression is confirmed by their correlations, which are often higher than 0.80. The smallest similarity is between the SW and SW2 CCIs, and the latter seems more reliable due to the mentioned problems of the estimated parametric factor model. We then aggregate the monthly values to quarterly, and compare the indexes across themselves and with real GDP growth. The similarity across the indexes is confirmed at the quarterly frequency. In terms of correlation with GDP growth, the lowest value is 0.62 for the SW CCI.⁴ However, the comparison with GDP growth should be interpreted with care. Even though such a comparison is standard in the literature, it is not clear that GDP is a good overall measure of the status of the economy, since its growth can be uncorrelated with higher employment or disposable income, as the prolonged jobless recovery in the US at the beginning of the new millennium or the persistently high unemployment rates in Europe testify.⁵

Both the NMB CCI and the factor-based CCIs assume that the economic conditions can be summarized by a continuous variable. An alternative approach treats the single unobservable force underlying the evolution of the coincident indicators as discrete rather than continuous. Basically, the CCI in this context represents the status of the business cycle (expansion/recession mapped into a 0/1 variable), which determines the behaviour of all the coincident indicators that can change substantially over different phases of the cycle. Hamilton's (1989) Markov switching model provides a convenient statistical framework to estimate such a discrete CCI. More specifically, the Markov switching (MS) CCI coincides with an estimate of the unobservable current status of the economy, $\hat{s}_{t|t}$. Hamilton (1994) or Krolzig (1997) provide details on the computation of $\hat{s}_{t|t}$, and also formulae to calculate $\hat{s}_{t|T}$, i.e., the smoothed estimator of the probability of being in a given status in period t .⁶

In the upper and middle panels of Figure 2 we compare the 6 month growth rate in the NMB CCI with the smoothed and filtered probability of recession ($\hat{s}_{t|T}$ and $\hat{s}_{t|t}$) resulting from a MS-VAR(1) for the four components of the NMB CCI. We would expect higher

Proietti (2004) to emphasize the business cycle frequencies between 1.5 and 8 years.

⁴Detailed results are available upon request.

⁵If GDP is accepted as an overall measure of the status of the economy, a monthly estimate of GDP evolution would represent a natural alternative CCI. For the UK, Mitchell et al. (2005) suggest a formal procedure to combine information about a range of monthly series into indications of short-term movements in output. Their assessment of the efficacy of the approach to evaluate the state of economic activity is rather satisfactory.

⁶The basic Markov switching model can be extended in several dimensions, for example to allow for more states and cointegration among the variables, see e.g. Krolzig, Marcellino and Mizon (2002), or time-varying probabilities, as e.g. in Diebold, Lee and Weinbach (1994) or Filardo (1994).

probability of recessions associated with marked slowdowns in the growth of the NMB CCI, which indeed appears to be the case. The recessions at the end of the '70s and in the early '90s are correctly picked up, and minor episodes of declining growth in the NMB CCI are also in generally associated with an increase in the estimated probability of recession.

Factor-based and Markov switching models are suited to capture two complementary characteristics of business cycles, namely, the diffusion of cyclical fluctuations across many series and the different behaviour of the variables during expansions and recessions. Diebold and Rudebusch (1996) suggested to combine the two approaches, by allowing the factor underlying SW's model to evolve according to a Markov switching model. Estimation of the factor-based MS model using Gibbs sampler techniques was proposed by Kim and Nelson (1998) and Filardo and Gordon (1999). Following Kim and Nelson (1998), it is therefore possible to obtain both a continuous and a discrete CCI, labeled KN1 and KN2, respectively. The former is the cumulated value of the estimated common factor, as for the SW CCI, while the latter is the estimated probability of recession, $\hat{s}_{t|t}$, as in the MS CCI, but estimated from the MS factor model.

In the third panel of Figure 2 we plot the six-month percentage change in the KN1 CCI, and the discrete KN2 CCI. The former is similar to the SW2 and FHLR2 factor-based indexes (also in terms of correlations), and the latter tends to increase during recessions. However, KN2 misses the recession in the early '90s, and provides weaker signals in the late '70s. This is clear from Figure 3, where we report the dating of the UK recessions (based on the Bry-Boschan algorithm applied to the SW CCI), and the probability of recessions from the Markov switching VAR and factor models.

A final interesting comparison regards the dating of the UK business cycle. For example, a comparison of the Economic Cycle Research Institute (ECRI) peak and trough dates with those in Artis (2002) reveals that the UK recessions lasted longer according to the former. Similarly, the recession of the early '90s lasted longer according to Birchenhall et al. (2001) than to Artis, Marcellino and Proietti (2004). Moreover, Artis et al. (2004) also indicate a high probability of recession in 2001. These differences can be due to the use either of alternative dating techniques or of a different CCI.

To understand whether the construction method of the CCI matters, we have applied the Bry-Boschan dating algorithm to the IP series, to the NMB CCI and to the SW CCI. The results indicate that the choice of the CCI can indeed play a role even when the same dating technique is used. In particular, the recessions of the late '70s and early '90s seem longer when measured on the NMB or SW CCI than with IP. Moreover, IP suggests the

presence of a recession at the beginning of the new millennium, which is absent according to the SW CCI and very short with the NMB CCI.⁷

In summary, all the methods for the construction of continuous composite coincident indexes yield similar results when measured in terms of correlation. However, there are some differences in the exact dating of recessions, in particular when IP is used as a single coincident indicator, and the discrete indexes appear to provide imprecise indications about the arrival of a recessionary period.

3 Alternative methods for the construction of CLIs

As in the case of the CCIs, the selection of the indicators to be included into a Composite Leading Index (CLI) is a fundamental first step. Following Moore and Shiskin (1967), a leading indicator should possess the following properties: (i) consistent timing (i.e., to systematically anticipate peaks and troughs in the target variable, possibly with a rather constant lead time); (ii) conformity to the general business cycle (i.e., have good forecasting properties not only at peaks and troughs); (iii) economic significance (i.e., being supported by economic theory either as possible causes of business cycles or, perhaps more importantly, as quickly reacting to negative or positive shocks); (iv) statistical reliability of data collection (i.e., provide an accurate measure of the quantity of interest); (v) prompt availability without major later revisions (i.e., being timely and regularly available for an early evaluation of the expected economic conditions, without requiring subsequent modifications of the initial statements); (vi) smooth month to month changes (i.e., being free of major high frequency movements).

Most of these properties can be formally evaluated, but selecting the indicators and testing their properties can be a very time-demanding task. Therefore, we rely on the selection of the leading indicators made by the Conference Board.⁸

The use of a single leading indicator is dangerous because economic theory and experience teach that recessions can have different sources and characteristics. A combination of leading indicators into composite indexes can therefore be more useful in capturing the signals coming from different sectors of the economy. The construction of a composite index can be undertaken either in a non-model-based framework or with reference to a specific econometric model of the evolution of the leading indicators, possibly jointly with

⁷Detailed results are available upon request.

⁸Specifically, the single leading indicators we consider are Order Book Volume, Volume of Expected Output, House Building Starts, Fixed Interest Price Index, All Share Price Index, New Orders of Engineering Industries, Productivity, and Operating Surplus of Corporations.

the target variable.

A non-model-based (NMB) CLI is constructed following the procedure outlined in the previous Section for the NMB-CCI, namely, the single leading indicators are averaged, possibly after a set of suitable transformations such as seasonal adjustment, differencing and standardization. Our NMB CLI for the UK is very similar to the one constructed by the Conference Board, and it will be our benchmark for the comparison of the more sophisticated CLIs.

The main advantage of NMB CLIs is simplicity. Non-model-based indexes are easy to build, easy to explain, and easy to interpret, which are very valuable assets, in particular for the general public and for policy makers. Moreover, simplicity is often a plus also for forecasting. With an NMB CLI there is no estimation uncertainty, no major problems of overfitting, and the literature on forecast pooling suggests that equal weights work pretty well in practice, see e.g. Stock and Watson (2003), even though here variables rather than forecasts are pooled. However, from an econometric point of view, NMB CLIs are also subject to several criticisms, see e.g. Emerson and Hendry (1996) and Marcellino (2005). First, there is no explicit reference to the target variable in the construction of the composite index, e.g. in the choice of the weighting scheme. Second, the weighting scheme is fixed over time, with periodic revisions mostly due either to data issues, such as changes in the production process of an indicator, or to the past unsatisfactory performance of the index. Third, lagged values of the target variable are typically not included in the leading index, while there can be economic and statistical reasons underlying the persistence of the target variable that would favor such an inclusion. Fourth, lagged values of the single indicators are typically not used in the index, while they could provide relevant information, e.g. because not only the point value of an indicator but also its evolution over a period of time matter for anticipating the future behavior of the target variable. Finally, if some indicators and the target variable are cointegrated, the presence of short run deviations from the long run equilibrium could provide useful information on future movements of the target variable.

Most of the issues raised for the NMB CCIs are addressed by the model based procedures, where the single leading indicators are combined into a CLI in a formal econometric context. This topic is analyzed in details in Marcellino (2005), here we summarize the main results, focusing on those which are useful to interpret the empirical findings for the UK.

3.1 Linear methods

A linear VAR provides the simplest model based framework to understand the relationship between coincident and leading indicators, the construction of regression based composite indexes, the role of the latter in forecasting, and the consequences of invalid restrictions or unaccounted cointegration. Following Marcellino (2005), we group the m coincident indicators in the vector y_t , and the n leading indicators in x_t . For the moment, (y_t, x_t) is assumed to be weakly stationary and its evolution is described by the VAR(1):

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} c_y \\ c_x \end{pmatrix} + \begin{pmatrix} A & B \\ C & D \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} e_{yt} \\ e_{xt} \end{pmatrix}, \quad (3)$$

$$\begin{pmatrix} e_{yt} \\ e_{xt} \end{pmatrix} \sim i.i.d. \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \Sigma_{yy} & \Sigma_{yx} \\ \Sigma_{xy} & \Sigma_{xx} \end{pmatrix} \right).$$

It immediately follows that the expected value of y_{t+1} conditional on the past is $c_y + Ay_t + Bx_t$, so that for x to be a useful set of leading indicators it must be $B \neq 0$. When $A \neq 0$, lagged values of the coincident variables also contain useful information for forecasting. Both hypotheses are easily testable and, in case both $A = 0$ and $B = 0$ are rejected, a composite regression based leading indicator for y_{t+1} (considered as a vector) can be constructed as

$$CLI1_t = \hat{c}_y + \hat{A}y_t + \hat{B}x_t, \quad (4)$$

where the $\hat{\cdot}$ indicates the OLS estimator. Standard errors around this CLI can be constructed using standard methods for VAR forecasts, see e.g. Lütkepohl (2004). Moreover, recursive estimation of the model provides a convenient tool for continuous updating of the weights.

A similar procedure can be followed when the target variable is dated $t + h$ rather than $t + 1$. For example, when $h = 2$,

$$\begin{aligned} CLI1_t^{h=2} &= \hat{c}_y + \hat{A}\hat{y}_{t+1|t} + \hat{B}\hat{x}_{t+1|t} \\ &= \hat{c}_y + \hat{A}(\hat{c}_y + \hat{A}y_t + \hat{B}x_t) + \hat{B}(\hat{c}_x + \hat{C}y_t + \hat{D}x_t). \end{aligned} \quad (5)$$

As an alternative, the model in (3) can be re-written as

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \tilde{c}_y \\ \tilde{c}_x \end{pmatrix} + \begin{pmatrix} \tilde{A} & \tilde{B} \\ \tilde{C} & \tilde{D} \end{pmatrix} \begin{pmatrix} y_{t-h} \\ x_{t-h} \end{pmatrix} + \begin{pmatrix} \tilde{e}_{yt} \\ \tilde{e}_{xt} \end{pmatrix} \quad (6)$$

where a $\tilde{\cdot}$ indicates that the new parameters are a combination of those in (3), and \tilde{e}_{xt} and

\tilde{e}_{yt} are correlated of order $h - 1$. The specification in (6) can be estimated by OLS, and the resulting *CLI* written as

$$\widetilde{CLI1}_t^h = \widehat{c}_y + \widehat{A}y_t + \widehat{B}x_t. \quad (7)$$

The main disadvantage of this latter method, often called dynamic estimation, is that a different model has to be specified for each forecast horizon h . On the other hand, no model is required for the leading indicators, and the estimators of the parameters in (6) can be more robust than those in (3) in the presence of mis-specification, see e.g. Clements and Hendry (1996) for a theoretical discussion and Marcellino, Stock and Watson (2005) for an extensive empirical analysis of the two competing methods (showing that dynamic estimation is on average slightly worse than the iterated method for forecasting US macroeconomic time series). For the sake of simplicity, in the rest of the paper we will focus on $h = 1$ whenever possible.

Consider now the case where the target variable is a composite coincident indicator,

$$CCI_t = wy_t, \quad (8)$$

where w is a $1 \times m$ vector of weights. To construct a model based *CLI* for the *CCI* in (8) two routes are available. First, and more common, we could model CCI_t and x_t with a finite order VAR, say

$$\begin{pmatrix} CCI_t \\ x_t \end{pmatrix} = \begin{pmatrix} d_{CCI} \\ d_x \end{pmatrix} + \begin{pmatrix} e(L) & F(L) \\ g(L) & H(L) \end{pmatrix} \begin{pmatrix} CCI_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} u_{CCI_t} \\ u_{x_t} \end{pmatrix}, \quad (9)$$

where L is the lag operator and the error process is white noise. Repeating the previous procedure, the composite leading index for $h = 1$ is

$$CLI2_t = \widehat{d}_{CCI} + \widehat{e}(L)CCI_t + \widehat{F}(L)x_t. \quad (10)$$

Yet, in this case the VAR is only an approximation for the generating mechanism of (wy_t, x_t) , since in general the latter should have an infinite number of lags or an MA component.

The alternative route is to stick to the model in (3), and construct the *CLI* as

$$CLI3_t = wCLI1_t, \quad (11)$$

namely, aggregate the composite leading indicators for each of the components of the *CCI*, using the same weights as in the *CCI*. Lütkepohl (1987) showed in a related context that in general aggregating the forecasts (*CLI3*) is preferable than forecasting the aggregate (*CLI2*) when the variables are generated by the model in (3), while this is not necessarily the case if the model in (3) is also an approximation and/or the y variables are subject to measurement error. Stock and Watson (1992) overall found little difference in the performance of *CLI2* and *CLI3* for the US.

Both *CLI2* and *CLI3* are directly linked to the target variable, incorporate distributed lags of both the coincident and the leading variables (depending on the lag length of the VAR), the weights can be easily periodically updated using recursive estimation of the model, and standard errors around the point forecasts (or the whole distribution under a distributional assumption for the error process in the VAR) are readily available. Therefore, this simple linear model based procedure already addresses several of the main criticisms to the non-model-based composite index construction.

An assumption we have maintained so far is that both the coincident and the leading variables are weakly stationary, while in practice it is likely that the behaviour of most of these variables is closer to that of integrated process. Following Sims, Stock and Watson (1990), this is not problematic for consistent estimation of the parameters of VARs in levels such as (3), and therefore for the construction of the related *CLIs*, even though inference is complicated and, for example, hypotheses on the parameters could not be tested using standard asymptotic distributions. An additional complication is that in this literature, when the indicators are $I(1)$, the VAR models are typically specified in first differences rather than in levels, without prior testing for cointegration. Continuing the VAR(1) example, the adopted model would be

$$\begin{pmatrix} \Delta y_t \\ \Delta x_t \end{pmatrix} = \begin{pmatrix} c_y \\ c_x \end{pmatrix} + \begin{pmatrix} e_{yt} \\ e_{xt} \end{pmatrix}, \quad (12)$$

rather than possibly

$$\begin{aligned} \begin{pmatrix} \Delta y_t \\ \Delta x_t \end{pmatrix} &= \begin{pmatrix} c_y \\ c_x \end{pmatrix} - \left(\begin{pmatrix} I_m & 0 \\ 0 & I_n \end{pmatrix} - \begin{pmatrix} A & B \\ C & D \end{pmatrix} \right) \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} e_{yt} \\ e_{xt} \end{pmatrix} \\ &= \begin{pmatrix} c_y \\ c_x \end{pmatrix} - \alpha \beta' \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} e_{yt} \\ e_{xt} \end{pmatrix}, \end{aligned} \quad (13)$$

where β is the matrix of cointegrating coefficients and α contains the loadings of the

error correction terms. As usual, omission of relevant variables yields biased estimators of the parameters of the included regressors, which can translate into biased and inefficient composite leading indicators. See Emerson and Hendry (1996) for additional details and generalizations and, e.g., Clements and Hendry (1999) for the consequences of omitting cointegrating relations when forecasting. As long as $m+n$ is small enough with respect to the sample size, the number and composition of the cointegrating vectors can be readily tested, see e.g. Johansen (1988) for tests within the VAR framework, and the specification in (13) used as a basis to construct model based *CLIs* that take also cointegration into proper account.⁹

To illustrate the empirical implementation of the techniques described so far, we now consider forecasting the (one month symmetric percentage change in the) NMB CCI, using six alternative linear specifications. A bivariate VAR for the NMB CCI and the NMB CLI. A univariate AR for the NMB CCI. A bivariate ECM for the NMB CCI and CLI, as in equation (13), where one cointegrating vector is imposed and its coefficient recursively estimated. A VAR for the four components of the NMB CCI and the NMB CLI, as in equation (9). A VAR for the NMB CCI and the eight components of the NMB CLI. Finally, a VAR for the four components of the NMB CCI and the eight components of the NMB CLI, as in equation (3). Notice that most of these models are non-nested, except for the AR which is nested in some of the VARs, and for the bivariate VAR which is nested in the ECM.

The models are compared on the basis of their forecasting performance one and six-month-ahead over the period 1985:1-2004:12. The forecasts are computed recursively with the first estimation sample being 1977:4-1984:12 for one step ahead forecasts and 1977:4-1984:6 for six step ahead forecasts. The lag length of the models is chosen by BIC over the full sample. Recursive BIC selects smaller models for the initial samples, but their forecasting performance is slightly worse. The forecasts are computed using both the standard iterated method, and dynamic estimation (as described in equation (6)). We use final vintage data, since real time vintages were not available to us. This can bias the evaluation towards the usefulness of a CLI when the composition of the latter is modified during the evaluation period. However, we use fixed weights and components over the

⁹A linear VAR model also underlies the construction of the well known Stock and Watson's (1989, SW) CLI for the US. The intuition is that if the single leading indicators are also driven by the (leads of the) common cyclical force, then a linear combination of their present and past values can contain useful information for predicting the *CCI*, see Marcellino (2005) for details. A comparison of the NMB and SW CLIs for the UK indicates that the former provides earlier and more reliable signals of recessions, details are available upon request. Therefore, in the following empirical analysis we will focus on the NMB CLI and evaluate whether it is possible to improve upon it.

whole period under analysis. Moreover, we focus on the comparison of alternative models for the same vintage of data, rather than on showing that a specific method performs well.

The comparison is based on the MSE and MAE relative to the bivariate VAR for the NMB CCI and CLI. The Diebold and Mariano (1995) test for the statistical significance of the loss differentials is also computed. The results are reported in Table 1 and a few comments can be made. First, as for the US, the simple AR model performs very well, it generates the lowest MSE and MAE at both forecast horizons, with statistically significant gains of about 20% in terms of MSE six-step ahead. This finding indicates that the lagged behaviour of the CCI contains useful information that should be included into a leading index. Second, taking cointegration into account does not improve the forecasting performance with respect to a VAR in differences. Third, forecasting the four components of the CCI_{CB} and then aggregating the forecasts decreases the MSE at the longer horizon. Finally, the ranking of iterated forecasts and dynamic estimation is quite clear cut, the former is systematically better than the latter in our application.

3.2 Markov switching models

Up to now we have implicitly assumed that the goal of the CLI is forecasting a continuous variable, the CCI. Yet, leading indicators were originally developed for forecasting business cycle turning points. Simulation based methods can be used to derive forecasts of a binary recession/expansion indicator within a linear framework, and these in turn can be exploited to forecast the probability that a recession will take place within, or at, a certain horizon.

For example, let us consider the model in (9) and assume that the parameters are known and the errors are normally distributed. Then, drawing random numbers from the joint distribution of the errors for period $t + 1, \dots, t + n$ and solving the model forward, it is possible to get a set of simulated values for $(CCI_{t+1}, \Delta x_{t+1}), \dots, (CCI_{t+n}, \Delta x_{t+n})$. Repeating the exercise many times, a histogram of the realizations provides an approximation for the conditional distribution of $(CCI_{t+1}, \Delta x_{t+1}), \dots, (CCI_{t+n}, \Delta x_{t+n})$ given the past. Given this distribution and a rule to transform the continuous variable CCI into a binary recession indicator, e.g. the three months negative growth rule, the probability that a given future observation can be classified as a recession is computed as the fraction of the relevant simulated future values of the CCI that satisfy the rule. The procedure can be easily extended to allow for parameter uncertainty by drawing parameter values from the distribution of the estimators rather than treating them as fixed. Normality

of the errors is also not strictly required since re-sampling can be used, see e.g. Wecker (1979), Kling (1987) and Fair (1993) for additional details and examples.

As an alternative procedure, the MS model introduced in Section 2 to define the MS CCI can be also exploited to evaluate the forecasting properties of a single or composite leading indicator. In particular, a simplified version of the model proposed by Hamilton and Perez-Quiros (1996) can be written as

$$\begin{aligned}\Delta y_t - c_{s_t} &= a(\Delta y_{t-1} - c_{s_{t-1}}) + b(\Delta x_{t-1} - d_{s_{t+r-1}}) + u_{yt}, \\ \Delta x_t - d_{s_{t+r}} &= c(\Delta y_{t-1} - c_{s_{t-1}}) + d(\Delta x_{t-1} - d_{s_{t+r-1}}) + u_{xt}, \\ u_t &= (u_{yt}, u_{xt})' \sim i.i.d.N(0, \Sigma),\end{aligned}\tag{14}$$

where y and x are univariate, s_t evolves according to a Markov chain, and the leading characteristics of x are represented not only by its influence on future values of y but also by its being driven by future values of the state variable, s_{t+r} .

Hamilton and Perez-Quiros (1996) found that their model provides only a weak signal in the case of the US recessions of 1960, 1970 and 1990. Moreover, the evidence in favor of the nonlinear cyclical factor is weak and the forecasting gains for predicting GNP growth or its turning point are minor with respect to a linear VAR specification. Even weaker evidence in favor of the MS specification was found when a cointegrating relationship between GNP and lagged *CLI* is included in the model¹⁰.

To evaluate the usefulness of the MS feature for forecasting UK recessions, we compare univariate and bivariate models, with and without Markov switching, for predicting one step ahead the turning points of the IP index, using the NMB CLI as the leading indicator (jointly with the NMB CCI in the VAR), and the same estimation and forecast sample as in the linear VAR example. The turning point probabilities for the linear models are computed by simulations, as described at the beginning of this Section, using a two consecutive negative growth rule to identify recessions. For the MS we use the filtered recession probabilities, see Marcellino (2005) for details on their computation. We also add to the comparison a probit model where the expansion/recession indicator (Bry-Boschan based on IP) is regressed on six lags of the NMB CLI. This model will be analyzed in detail in the next subsection.

The results of the turning point forecast comparison are summarized in Table 2, where we report the MSE and MAE for each model relative to the probit, and the Diebold and

¹⁰K. Lahiri and J. Wang (1994) for the first time successfully utilized the Hamilton model to generate recession probabilities from the index of leading indicators.

Mariano (1995) test for the statistical significance of the loss differentials. Notice that the MSE is just a linear transformation of the Quadratic Probability Score (QPS) criterion of Diebold and Rudebusch (1989). The figures indicate that the probit model produces the lowest MSE, while the univariate MS model is best based on the MAE criterion. The turning point probabilities for the five models are graphed in Figure 4, together with the Bry-Boschan dated recessions (shaded areas). The figure highlights that the MS models correctly assign a high probability of recession in the early 90s, but for too long a period of time. Instead, they only give a light signal of recession at the beginning of the new millennium. The performance of the probit model is also not impressive, with an estimated probability of recession not higher than .80 even during recessions, and a few false alarms in the first part of the forecast sample and in the late '90s. Finally, there are no major changes in the results when the target variable becomes the turning points in the NMB CCI.¹¹

3.3 Binary models

In the models we have analyzed so far to relate coincident and leading indicators, the dependent variable is continuous, even though forecasts of business cycle turning points are feasible either directly (MS models) or by means of simulation methods (linear models). A simpler and more direct approach treats the business cycle phases as a binary variable, and models it using a logit or probit specification.

In particular, let us assume that the economy is in recession in period t , $R_t = 1$, if the unobservable variable s_t is larger than zero, where the evolution of s_t is governed by

$$s_t = \beta' y_{t-1} + e_t. \quad (15)$$

Therefore,

$$\Pr(R_t = 1) = \Pr(s_t > 0) = F(\beta' y_{t-1}), \quad (16)$$

where $F(\cdot)$ is either the cumulative normal distribution function (probit model), or the logistic function (logit model). The model can be estimated by maximum likelihood, and the estimated parameters combined with current values of the leading indicators to

¹¹Artis et al. (1995) consider the possible contribution of the 'longer' and 'shorter' leading indicators published by the Central Statistical Office (CSO) to predict the turning-points in the economic cycle. They find that the longer index leads the coincident series by about ten months at the peak and thirteen at the trough on average, and the shorter index by five months at the peak and nine at the trough; but there is substantial variation.

provide an estimate of the recession probability in period $t + 1$, i.e.,

$$\widehat{R}_{t+1} = \Pr(R_{t+1} = 1) = F(\widehat{\beta}'y_t). \quad (17)$$

The logit model was adopted for the US, e.g., by Stock and Watson (1991) and the probit model by Estrella and Mishkin (1998), while Birchenhall et al. (1999) provided a statistical justification for the former in a Bayesian context. Binary models for European countries were investigated by Estrella and Mishkin (1997), Bernard and Gerlach (1998), Birchenhall, Osborn and Sensier (2001), Osborn, Sensier and Simpson (2001). Marcellino (2005) summarizes pros and cons of this class of models.

Notice that, as in the case of MS or linear models, the estimated probability of recession, \widehat{R}_{t+1} , should be transformed into a 0/1 variable using a proper rule. The common choices are of the type $\widehat{R}_t \geq c$ where c is typically 0.5.

We now consider in more details the turning point forecasting performance of the probit model for the UK, which from the previous subsection was good in comparison to MS and linear models, but not so good in absolute terms.

In particular, we consider whether the CLI_{SW} , or CLI_{SW} and CLI_{NMB} jointly, or the three-month ten-year interest rate spread, or the latter and the two CLIs jointly, have a better predictive performance than the CLI_{NMB} only. The estimation and forecasting sample is as in the first empirical example, and the specification of the probit models is as in the second example, namely, six lags of each CLI are used as regressors (more specifically, the symmetric one month percentage changes for CLI_{NMB} and the one month growth rates for the other $CLIs$).

From Table 3, the model with the two CLIs is favoured for one-step ahead turning point forecasts. Repeating the analysis for six-month-ahead forecasts, the gap across models shrinks, except for the term spread only that remains worse, and the model with the CLI_{NMB} only yields the lowest MSE and MAE. However, the recession probabilities derived from these models, graphed in Figure 5, never reach one and are sometimes rather high even in the lack of a subsequent recession.

3.4 Pooling

Since the pioneering work of Bates and Granger (1969), it is well known that pooling several forecasts can yield a mean square forecast error (msfe) lower than that of each of the individual forecasts, see Timmermann (2005) for a comprehensive overview and Clements and Hendry (2004) for possible explanations. Hence, rather than selecting a

preferred forecasting model, it can be convenient to combine all the available forecasts, or at least some subsets.

Several pooling procedures are available. The three most common methods in practice are linear combination, with weights related to the msfe of each forecast (see e.g. Granger and Ramanathan (1984)), median forecast selection, and predictive least squares, where a single model is chosen, but the selection is recursively updated at each forecasting round on the basis of the past forecasting performance. Stock and Watson (1999) and Marcellino (2004) presented a detailed study of the relative performance of these pooling methods, using a large dataset of, respectively, US and Euro area macroeconomic variables, and taking as basic forecasts those produced by a range of linear and non-linear models. In general simple averaging with equal weights produces good results, more so for the US than for the euro area.

Camacho and Perez-Quiros (2002) focused on pooling leading indicator models using regression based weights as suggested by Granger and Ramanathan (1984). Hence, the pooled forecast is obtained as

$$\widehat{y}_{t+1|t} = w_1\widehat{y}_{t+1|t,1} + w_2\widehat{y}_{t+1|t,2} + \dots + w_p\widehat{y}_{t+1|t,p}, \quad (18)$$

and the weights, w_i , are obtained as the estimated coefficients from the linear regression

$$y_t = \omega_1\widehat{y}_{t|t-1,1} + \omega_2\widehat{y}_{t|t-1,2} + \dots + \omega_p\widehat{y}_{t|t-1,p} + u_t \quad (19)$$

which is estimated over a training sample using the forecasts from the single models to be pooled, $\widehat{y}_{t|t-1,i}$, and the actual values of the target variable.

Camacho and Perez-Quiros (2002) evaluated the role of pooling not only for GDP growth forecasts but also for turning point prediction. The pooled recession probability is obtained as

$$\widehat{r}_{t+1|t} = F(a_1\widehat{r}_{t+1|t,1} + a_2\widehat{r}_{t+1|t,2} + \dots + a_p\widehat{r}_{t+1|t,p}), \quad (20)$$

where $F(\cdot)$ is the cumulative distribution function of a normal variable, and the weights, a_i , are obtained as the estimated parameters in the probit regression

$$r_t = F(\alpha_1\widehat{r}_{t|t-1,1} + \alpha_2\widehat{r}_{t|t-1,2} + \dots + \alpha_p\widehat{r}_{t|t-1,p}) + e_t, \quad (21)$$

which is again estimated over a training sample using the recession probabilities from the single models to be pooled, $\widehat{r}_{t|t-1,i}$, and the actual values of the recession indicator, r_t .¹²

¹²The pooling method described above was studied from a theoretical point of view by Li and Dorfman

To assess the role of pooling for forecasting the growth rate of the UK NMB CCI, we combine together the forecasts from the six linear models in Section 3.1 (i.e., AR, VAR, ECM and the three VARs with disaggregated components of the CCI or of the CLI or of both), using either equal weights or the inverse of the MSEs obtained over the training sample 1985:1-1988:12. The results are reported in the upper panel of Table 4. They indicate very clearly that pooling works, the gains are large, over 30%, and statistically significant. Moreover, the simple average works at least as well as the more sophisticated weighting scheme.

For IP turning point prediction, middle panel of Table 4, pooling linear and MS models cannot beat the benchmark probit model, even when using the better performing equal weights for pooling or adding the probit model with the CLI_{NMB} index as regressor into the forecast combination.

Finally, also in the case of probit forecasts for the UK IP turning points, lower panel of Table 4, a single model performs better than the pooled forecast for both one and six month horizons, and equal weights slightly outperforms MSE based weights for pooling. Marcellino (2005) reached similar conclusions for the US.

4 Conclusions

In this paper we have provided an overview of recent developments in the methodology for the construction of composite coincident and leading indicators. We have then applied several methods for the construction and evaluation of CCIs and CLIs for the UK.

About coincident indexes, factor based techniques are promising for building continuous CCIs. They can handle very large information sets and, in the more sophisticated versions, automatically lead/lag the component series. Moreover, they can take cointegration into account, and provide a unified framework for handling data problems such as missing observations or data revision (see e.g. Angelini et al. (2005)). However, in practice the results are not very different from those obtained from a simple average of the standardized index components.

Discrete CCIs, in the form of probabilities of recessions, can be obtained within the framework of Markov switching models. While the results for the UK are interesting, an accurate fine tuning of the models is important to obtain reliable results.

About leading indexes, the target can be a continuous variable, such as a CCI, or a discrete variable, such as the turning points of a CCI. Different models can be adopted to

(1996) in a Bayesian context.

relate a set of leading variables to the target, e.g. linear or Markov switching specifications, and the leading variables could be summarized in a first step by means of a factor model. The results for the UK suggest that lagged values of the CCI contain useful information in addition to that provided by standard leading variables, and that probit models are better than linear or Markov switching specifications for predicting turning points, using an MSE criterion.

Another interesting empirical result is that forecast pooling seems to be quite useful to predict future values of a UK CCI, much less so for its turning points, in line with previous results for the US.

The main implication of the findings in this paper for the future of economic forecasting is that the attention should focus more on the construction of composite leading indexes than of coincident indexes. Moreover, the selection of the components of the index is very important, since the best leading indicators change over time. Finally, the procedures for turning point forecasts should be refined, since most of the existing methods do not produce yet systematically satisfying results. The many important improvements in the recent past for the construction and evaluation of composite leading indexes documented and applied in this paper suggest that these additional issues can be also successfully addressed.

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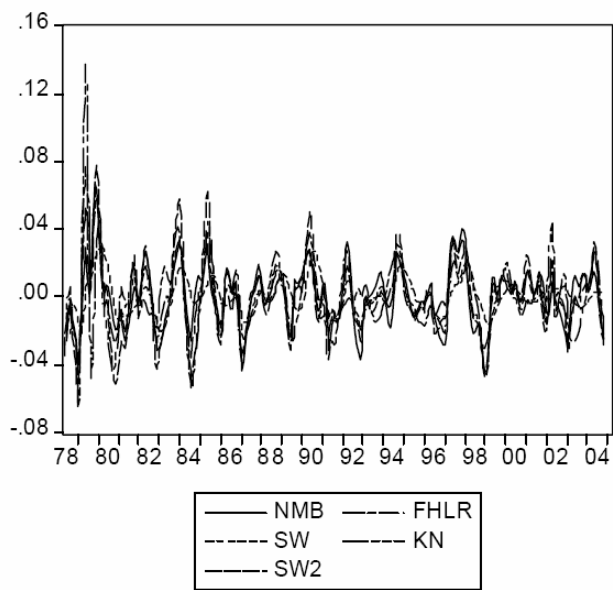
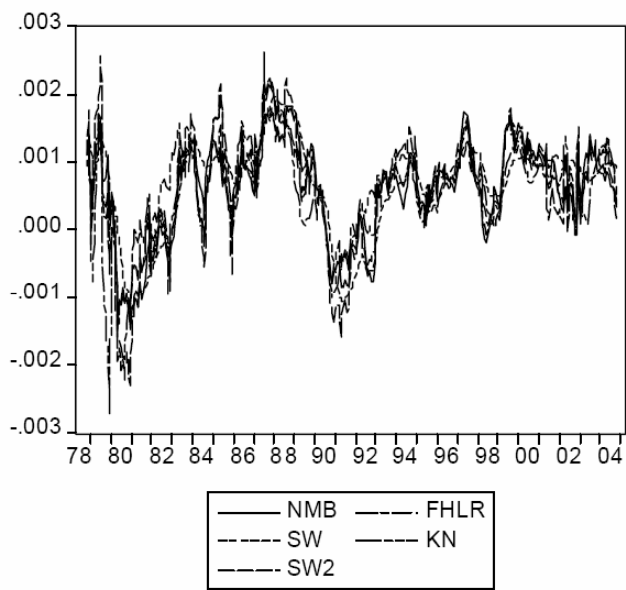
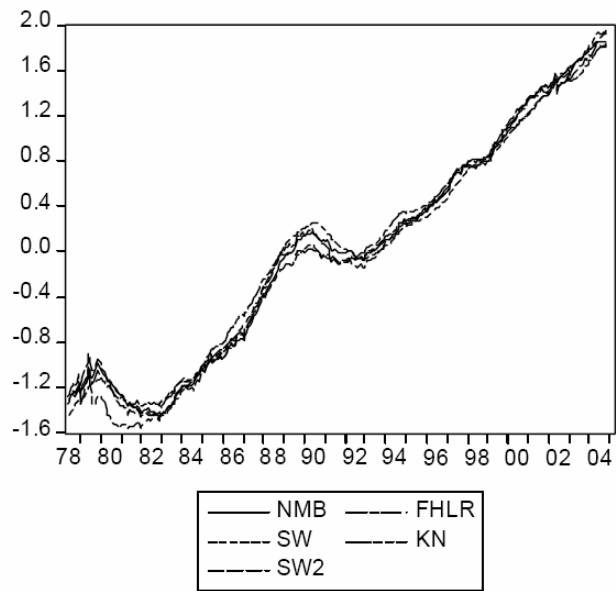


Figure 1: Coincident Indexes

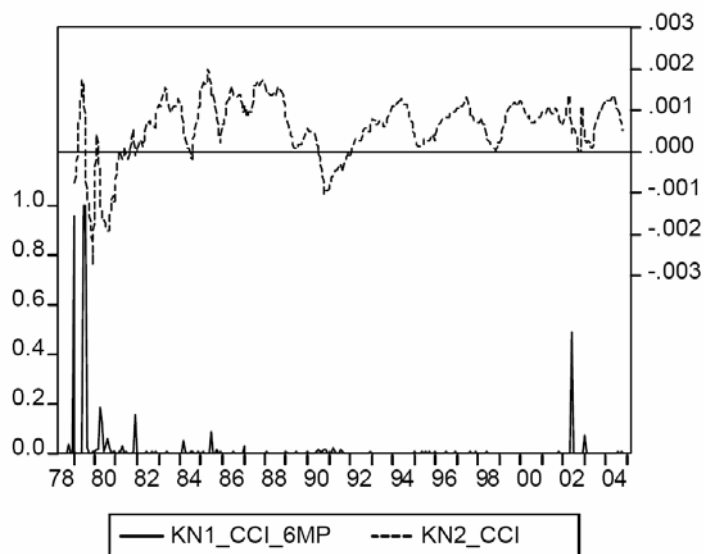
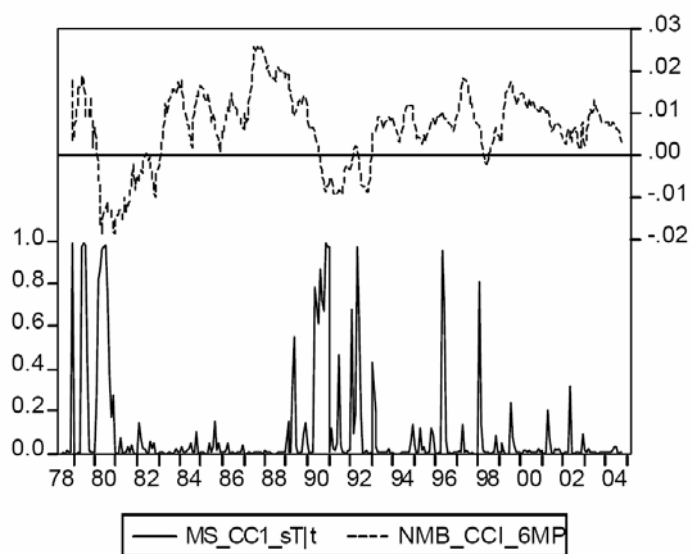
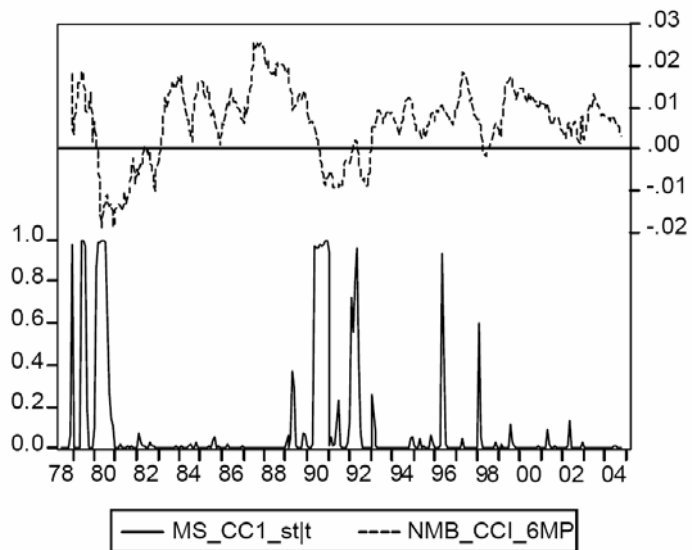


Figure 2: Probabilities. Upper and medium panel: smoothed and filtered, Markov Switching based probabilities of recession, and 6-month percentage change in the NMB CCI. Lower panel: discrete and continuous CCI (KN1 and KN2) from Markov Switching factor model.

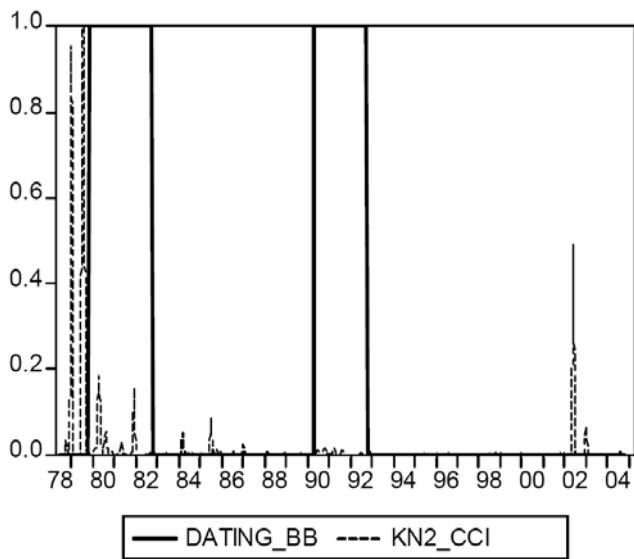
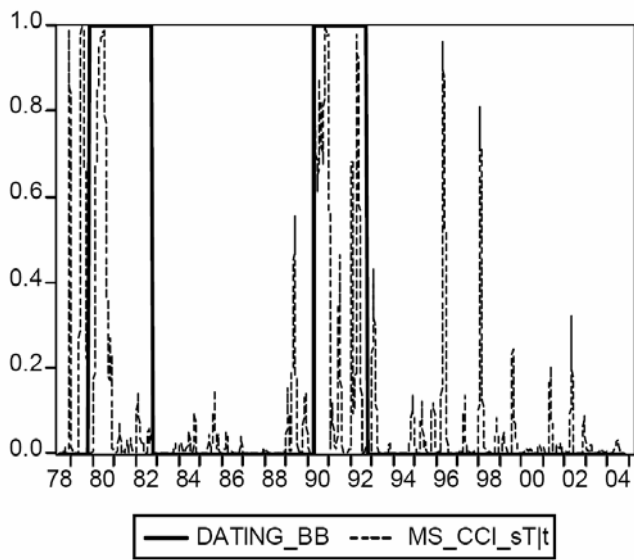
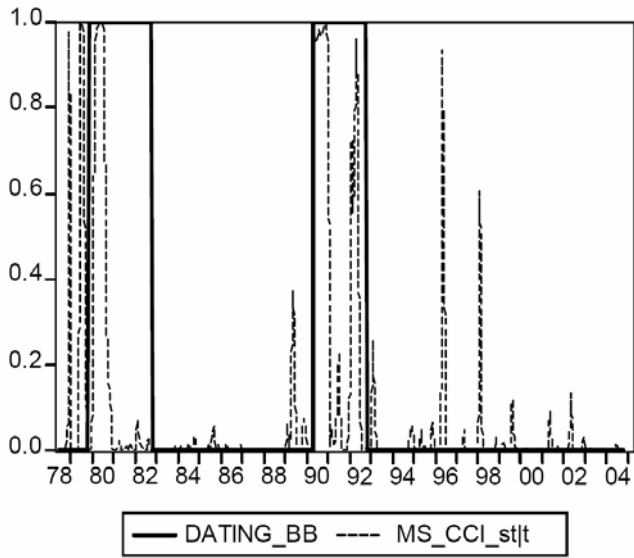


Figure 3: Bry-Boschan dating of UK recessions and probability of recession from Markow Switching VAR and factor model.

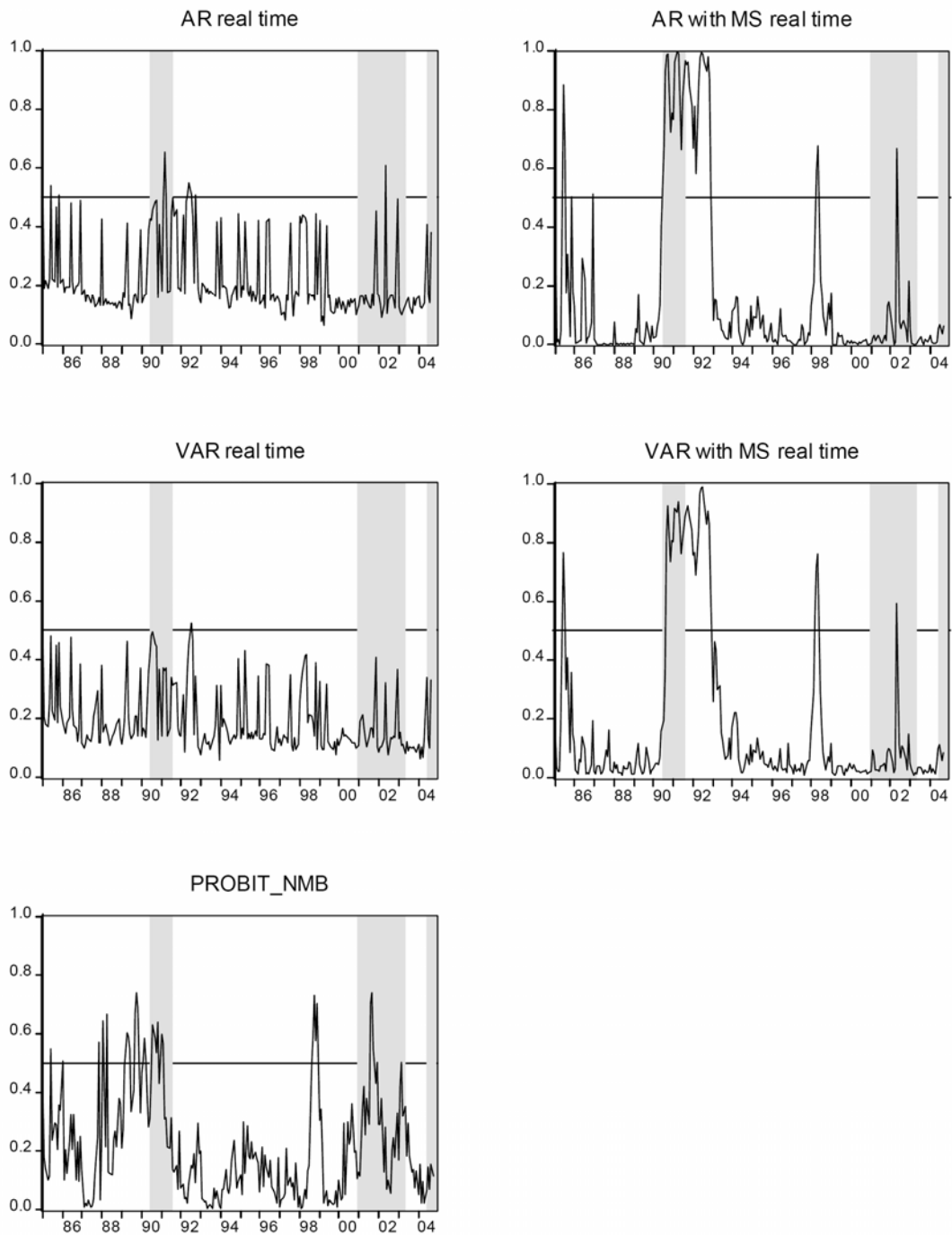


Figure 4: Turning point probabilities from alternative models. Shaded areas are recessionary periods, according to the Bry-Boschan algorithm applied to the IP index.

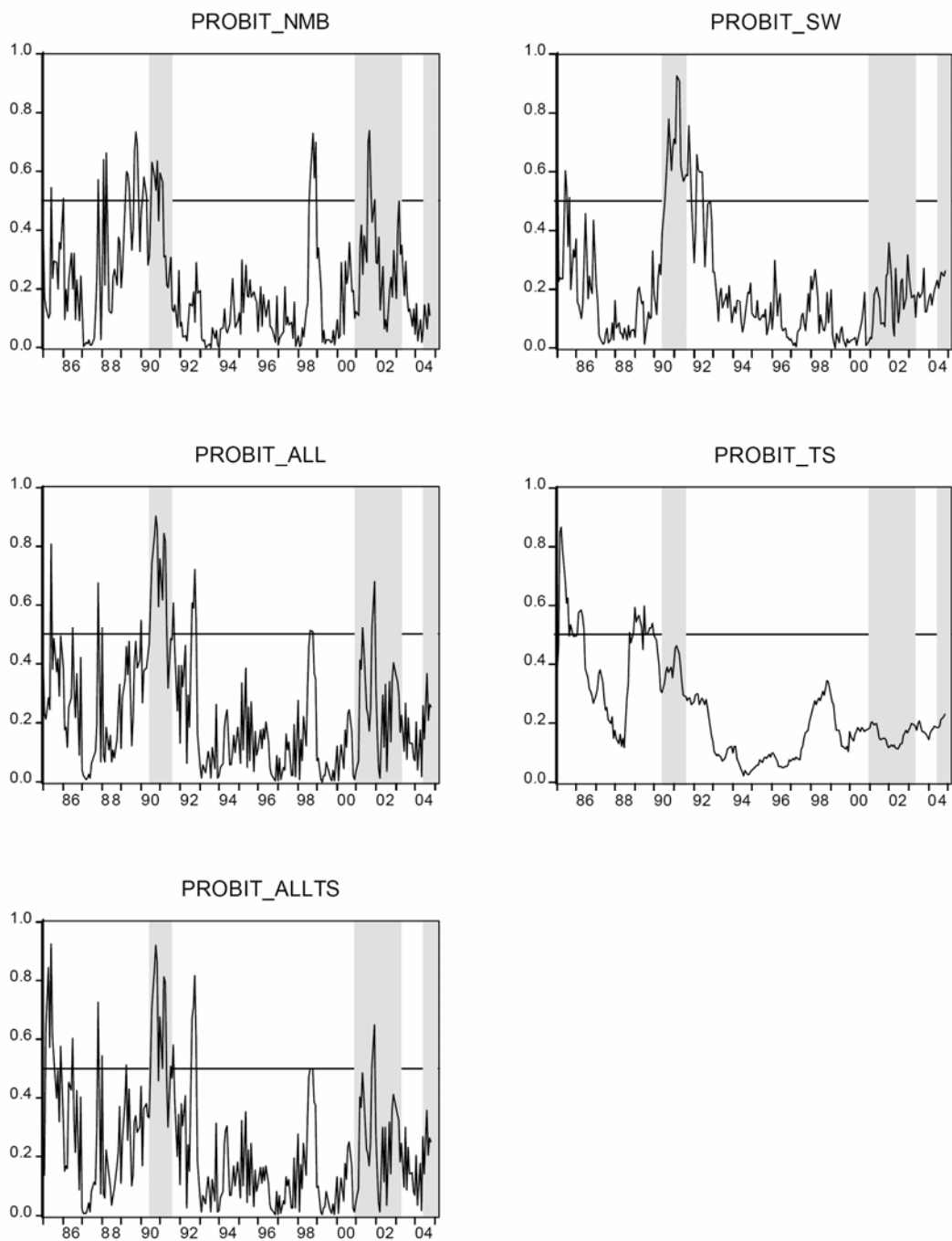


Figure 5: Turning point probabilities from alternative probit models. Shaded areas are recessionary periods, according to the Bry-Boschan algorithm applied to the IP index.

Table 1: Forecast comparison of alternative VAR models for CCINMB and CLINMB

		1 step-ahead		6 step-ahead DYNAMIC		6 step-ahead ITERATED	
		Relative MSE	Relative MAE	Relative MSE	Relative MAE	Relative MSE	Relative MAE
CCI + CLI	VAR(2)	1	1	1	1	1	1
CCI	AR(2)	0.980	0.985	0.959	0.987	0.797 ***	0.901 ***
CCI + CLI coint	VECM(2)	1.185 *	1.079	1.067	1.013	1.041	1.018
4 comp. of CCI + CLI	VAR(2)	1.082	1.053	1.270 **	1.145 **	0.956	1.014
CCI + 8 comp. of CLI	VAR(1)	1.249 **	1.113 **	1.279 **	1.064 *	1.093	1.027
4 comp. CCI + 8 comp. CLI	VAR(1)	1.022	1.010	1.249 **	1.134 **	0.950	0.994
		MSE	MAE	MSE	MAE	MSE	MAE
	VAR(2)	0.000	0.001	0.000	0.001	0.000	0.002

Note: Forecast sample is: 1985:1 – 2004:12. First estimation sample is 1977:4 – 1984:12 (for 1 step-ahead) or 1977:4 – 1984:6 (for 6 step-ahead), recursively updated. Lag length selection by BIC. MSE and MAE are mean square and absolute forecast error. VAR for CCICB and CLICB is benchmark. *, **, *** indicate significance at 10%, 5%, 1% of the Diebold-Mariano test for the null hypothesis of no significant difference in MSE or MAE with respect to the benchmark.

Table 2: Turning point predictions

Target	Model	Relative MSE	Relative MAE
NBER (1 step-ahead)	univariate	1.097	1.123
	univariate MS	1.269	0.874
	bivariate	1.092	1.077
	bivariate MS	1.291	0.939
	probit CLI_CB	1	1
	probit	MSE 0.1547	MAE 0.2882

Note: One-step ahead turning point forecasts for the BB expansion/recession indicator. Linear and MS models (as in Hamilton and Perez-Quiros (1996)) for CCICB and CLICB. Six lags of CLICB are used in the probit model. *, **, *** indicate significance at 10%, 5%, 1% of the Diebold-Mariano test for the null hypothesis of no significant difference in MSE or MAE with respect to the benchmark.

Table 3: Forecasting performance of alternative CLIs using probit models for BB recession/expansion classification

Target	Model	Relative MSE		Relative MAE	
BB on IP (1 step-ahead)	CLI_CB	1		1	
	CLI_SW	0.978		0.961	
	4 CLI	0.935		0.979	
	termspread	1.284	**	1.228	***
	4 CLI+spread	1.007		1.009	
BB on IP (6 step-ahead)	CLI_CB	1		1	
	CLI_SW	1.044		1.068	
	4 CLI	1.058		1.061	*
	termspread	1.315	**	1.205	***
	4 CLI+spread	1.194	**	1.114	**
CLI_CB	1 step-ahead	0.1547		0.2882	
	6 step-ahead	0.1527		0.2932	

Note: Forecast sample is: 1985:1 – 2004:12. First estimation sample is 1977:4 – 1984:12 (for 1 step-ahead) or 1977:4 – 1984:6 (for 6 step-ahead), recursively updated. Lag length selection by BIC. MSE and MAE are mean square and absolute forecast error. VAR for CCICB and CLICB is benchmark. *, **, *** indicate significance at 10%, 5%, 1% of the Diebold-Mariano test for the null hypothesis of no significant difference in MSE or MAE with respect to the benchmark.

Table 4: Evaluation of forecast pooling

Combine	Relative MSE		Relative MAE		Relative MSE		Relative MAE	
Predicting CCI_CB growth								
	MSE-weighted				simple average			
6 linear models (1month)	0.7437	***	0.8326	***	0.7415	***	0.8313	***
6 linear models (6month dynamic)	0.8244		0.8981		0.8184		0.8965	
6 linear models (6month iterated)	0.6457	***	0.783	***	0.6436	***	0.7827	***
Predicting NBER turning points								
	MSE-weighted				simple average			
4 linear and MS models (1m)	1.2486		1.1236		1.2826		1.1088	
4 linear and MS models + probit (1m)	1.0994		1.0907		1.1761		1.0951	
Predicting NBER turning points								
	MSE-weighted				simple average			
3 single index PROBIT (1m)	1.1506		1.1065		1.1404		1.1006	
3 single index PROBIT + all (1m)	1.1189		1.0909		1.1087		1.0846	
3 single index PROBIT (6m)	1.2880		1.1694	**	1.2803		1.1671	**
3 single index PROBIT + all (6m)	1.2711		1.162	**	1.2657		1.1599	**

Note: Forecast sample is: 1985:1 – 2004:12. First estimation sample is 1977:4 – 1984:12 (for 1 step-ahead) or 1977:4 – 1984:6 (for 6 step-ahead), recursively updated. Lag length selection by BIC. MSE and MAE are mean square and absolute forecast error. VAR for CCICB and CLICB is benchmark. *, **, *** indicate significance at 10%, 5%, 1% of the Diebold-Mariano test for the null hypothesis of no significant difference in MSE or MAE with respect to the benchmark.

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