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Abstract

Using OECD composite leading indicators (CLI), we assess empirically whether the ability of the country-specific CLIs to predict economic activity has diminished in recent years, e.g. due to rapid advances in globalisation. Overall, we find evidence that the CLI encompasses useful information for forecasting industrial production, particularly over horizons of four to eight months ahead. The evidence is particularly strong when taking cointegration relationships into account. At the same time, we find indications that the forecast accuracy has declined over time for several countries. Augmenting the country-specific CLI with a leading indicator of the external environment and employing forecast combination techniques improves the forecast performance for several economies. Over time, the increasing importance of international dependencies is documented by relative performance gains of the extended model for selected countries.

Keywords: Leading Indicator, Business Cycle, Forecast Comparison, Globalisation, Structural Change

JEL Classification: C53, E32, E37, F47

Non-technical summary

As monetary policy decisions affect the economy with long and varying lags, it is crucial to have an educated judgement about the economic conditions and outlook prevailing at the time. Leading indicators constitute an important tool in applied business cycle analysis to form such a judgement.

A potential shortcoming of country-specific leading indicators is that their components are commonly *domestic* variables. Accordingly, their ability to predict economic activity might have diminished due to the rapid advances in globalisation, as reflected in the deepening of international financial and trade linkages.

Against this background, this paper analyses (1) whether the empirical relationships established in the past are still appropriate today, and (2) whether augmenting the available leading indicators with information on the outlook for important trading partners can improve the forecasting performance.

It looks into this issue based on the OECD composite leading indicators (CLI) across 11 countries and uses industrial production as the reference series over the period from January 1975 to April 2008. The first fifteen years of data is used for the initial estimation and the period from January 1991 is used for conducting recursive rolling-window estimation and pseudo out-of-sample forecasting over horizons of up to twelve months.

Assessing the properties of the OECD CLI, we find clear evidence that the forecast properties of a model making use of composite leading indicators are significantly better than naïve autoregressive forecast benchmarks. We document evidence that taking cointegration relationships between the CLI and industrial production into account is useful as it improves the accuracy of the forecasts of economic activity for several economies in our sample. Regarding the evolution of the forecast accuracy over time we find, for most countries, indications that it indeed declined over time, while for others it is more difficult to discern a clear pattern.

For analysing of whether adding information on the international business cycle improves the forecast accuracy of the OECD indicator, we augment the basic forecast equation, which includes the country-specific leading indicators with a leading indicator for the external environment, constructed from the CLI of the other OECD countries. This further tends to improve the forecast performance for several economies. Performance increases are particularly pronounced when forecast combination techniques are employed. Over time, we find forecast performance of the "open economy" specification to improve relative to the "closed economy" specification for some countries, indicating that the ongoing process of globalisation might increase the relevance of international dependencies for the projection of economic developments of selected countries in our sample.

1 Introduction

Monetary policy decisions affect the economy with long and varying lags. It is therefore crucial to have an educated judgement about the economic conditions and outlook prevailing at the time. Leading indicators constitute an important tool in applied business cycle analysis to form such a judgement.[2] A main potential shortcoming of country-specific leading indicators is, however, that their components are commonly *domestic* variables. The ability of such leading indicators to predict economic activity might have diminished due to the rapid advances in globalisation, as reflected in the deepening of international financial and trade linkages. Notwithstanding the significant structural changes that have taken place at the global level over recent years, to our knowledge the possible implications for the leading indicator properties have not been addressed in a systematic fashion as yet.

This paper aims at filling this gap. It looks into this issue based on the OECD composite leading indicators (CLI) across 11 countries and uses, in line with common practice, industrial production as the reference series. The OECD CLI has the advantage (1) to be widely monitored by practitioners and (2) to be available for a wide variety of countries, on a monthly basis and over a long time span (see also Camba-Mendez et al., 1999).

The objective of the paper is two-fold. Firstly, we assess the properties of the OECD CLI and check whether its accuracy has declined over time as the process of globalisation has evolved. In line with standard practice, the assessment is made on the basis of root mean squared forecast errors calculated – as suggested in Marcellino, Stock and Watson (2005) – based on iterated multi-step forecasts up to one year ahead. The analysis is based on a data sample between January 1975 and April 2008, using the first fifteen years for estimation purposes and the remainder of the sample for the recursive estimation and pseudo out-of-sample forecasting, based on information available at the time the forecast is carried out. We find clear evidence that the forecast properties of a model making use of the domestic CLI are significantly better than naïve autoregressive benchmark forecast. We also document evidence that taking cointegration relationships between the CLI and industrial production into account is useful as it further improves the accuracy of the forecasts of industrial production. However, regarding the evolution of the forecast accuracy over time we find indications that it indeed declined over time for most of the countries.

Secondly, we analyse whether adding information on the international business cycle improves the forecast accuracy of the OECD indicator. To this end, we augment the basic forecast equation, which includes the country-specific leading indicators (and lagged values of domestic industrial production) with a leading indicator for the external environment, constructed from the CLI of the other OECD countries. The results appear quite promising. In spite of differences in the results across models and countries, we find that the inclusion of external leading indicators can improve the forecast performance quite substantially. This is particularly the case if forecast combination techniques are employed. For some countries, we also find evidence that the projections stemming from models augmented with international information are improving over time relative to the model focusing purely on domestic infor-

[2] The academic interest in empirical analysis of leading indicators has been revived about two decades ago when Stock and Watson (1989) discussed improvements in leading-indicator theory. This stimulated a vivid debate on the different aspects of leading indicators, ranging from the choice of the leading indicators and various prediction frameworks to the presentation of different evaluation benchmarks, and strengthened the capacity to assess these indicators (see Marcellino, 2006, for a comprehensive review).

mation. However, these conclusions are subject to the caveat that the variation of relative forecast performance is substantial over time.

2 Data and stylised facts

The OECD CLI is published on a monthly basis with a lag of two months. This means that, for example, in December, the CLI for October is published. Accordingly, the CLI incorporates elements of both a coincident and a leading indicator of economic activity, but even its potential coincident indicator properties are useful because at the time of publication of the October CLI actual business cycle data is available only up to September for most OECD countries.

Compared to a single indicator variable, composite indicators have the advantage that they eliminate the noise of individual variables and reduce the risk of false signals. More specifically, the OECD CLI is constructed on the basis of criteria which are broadly consistent with those proposed by Marcellino (2006). It is based on (seasonally-adjusted) time series with potential leading indicator properties, which are aggregated into a composite indicator. The component series of CLI cover a wide range of short-term indicators, which are selected for each country according to a number of criteria: *Firstly*, there must be an economic reason for a leading relationship with the reference series. The components may include variables which can cause business cycle fluctuations (e.g. short-term interest rates), express market expectations, measure economic activity at an early stage (e.g. housing starts) or adjust quickly to changes in economic activity (e.g. overtime work). *Secondly*, the cycles of these series should lead those of the reference series. *Thirdly*, data quality needs to be ensured in terms of availability and timeliness and revisions should be small.

The composition and number of series (five to eleven) included in the country-specific CLI varies across countries. These series are aggregated in a detrended and scaled form into the composite indicator (following some transformations) using equal weights.[3] While Camba-Mendez et al. (1999) as well as Emerson and Hendry (1996) have criticised such a weighting scheme as suboptimal, Marcellino (2006) points out the analogy to the literature on forecast pooling which suggests that equal weights work pretty well in practice.[4] The final set of component series is selected in order to maximise the performance of the CLI in terms of detecting economic cycles. While the CLI was originally designed to detect early signals for turning points (Nilsson and Guidetti, 2008), these indicators are also used to evaluate the cycle as a whole.

[3] For details, see http://www.oecd.org/dataoecd/4/33/15994428.pdf.
[4] See e.g. Stock and Watson (2003).

Chart 1: Leading indicator and industrial production in OECD countries

(monthly data, annual rates of growth)

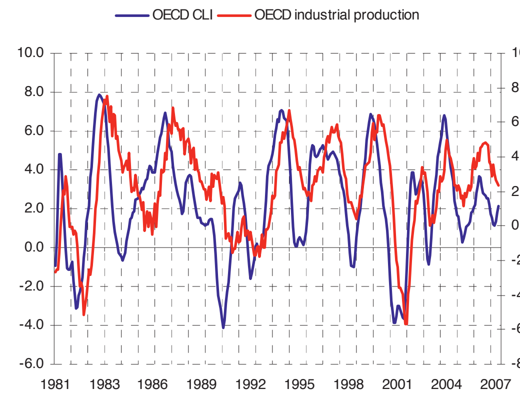
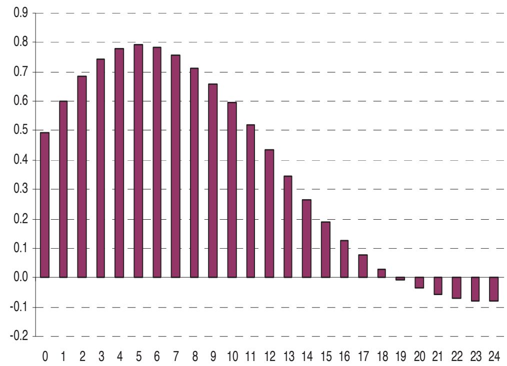


Chart 2: Cross-correlation between OECD CLI and industrial production annual growth



Source: OECD, MEI

We analyse the relationship between the CLI and economic activity for 11 industrialised countries (Canada, Denmark, the United Kingdom, Japan, Sweden, the United States, Germany, Spain, France, Greece and Italy), eight of which are members of the European Union. As the reference series for economic activity, we choose industrial production (covering all sectors excluding construction). We prefer industrial production over GDP as reference series for various reasons: Firstly, the OECD CLI has been deliberately constructed to anticipate cycles in industrial production. Nilsson and Guidetti (2008) motivate this choice by the fact that industrial production constitutes the most cyclical subset of the aggregate economy and that it is available promptly and on a monthly basis for most OECD economies. Secondly, while industrial production represents only a small and declining fraction of economic activity, many service activities, such as transport, are linked to industrial activity. Accordingly, the cyclical profiles of industrial production and GDP are closely related and the projected development of industrial production provides valuable information for assessing the outlook for GDP.[5] Owing to these merits, industrial production has become a common benchmark series in the academic literature.[6] Thirdly, the lower frequency of GDP data results in a sample too short for studying the intertemporal behaviour of leading indicators and structural changes on the basis of pseudo out-of-sample forecasting, which is a key objective in this paper.[7]

Visual inspection suggests that there is indeed a close correlation between the OECD aggregate CLI and, with some time shift, the annual rate of change in industrial production. The CLI anticipates movements in industrial production growth (see Chart 1). Cross correlations reveal that the leading indicator properties are most pronounced at a lead time of around half a year at the OECD aggregate and diminish quickly thereafter, which implies that the leading

[5] Giannone et al. (2008) and Rünstler and Sédillot (2003) underline the high predictive content of industrial production for GDP in the US and the euro area, respectively. A similar result for major OECD countries is presented by Sédillot and Pain (2003). See also Steindel (2004) for an assessment of the relationship between industrial production and GDP.

[6] See e.g. Diebold and Rudebusch (1991), Stock and Watson (2002, 2003), Zizza (2002), Bruno and Lupi (2003), Marcellino, Stock and Watson (2003), D'Agostino et al. (2006) or Rossi and Sekhposyan (2008).

[7] Similarly, Banerjee et al. (2005) stress that in their setup of quarterly GDP pseudo out-of-sample forecasts the calculation of reliable statistical tests for a significant performance difference of alternative models is precluded by the length of the series, forcing them to resort to a simple comparison of point RMSE estimates.

indicator is likely to become less precise as the lead periods exceed half a year (see Chart 2). A similar pattern over time is found for most OECD countries. Looking at these countries in more detail suggests that the correlation between the CLI and industrial production is strongest for the United States, Canada, Japan and Germany, while it appears to be weaker for smaller open economies such as Portugal, Greece and Ireland, which indeed might be more affected by the global environment.

3 Econometric analysis

A comprehensive empirical evaluation of the properties of the OECD CLI has many dimensions, which are addressed in turn.

Firstly, the question arises of whether the analysis should be carried out with respect to an in-sample or with respect to an out-of-sample forecast. In this context, Carriero and Marcellino (2007) stress that it is always possible to explain past economic growth reasonably well when a set of parameters is carefully chosen, but that there is no reason to expect that such equations will necessarily be good forecasting tools. Accordingly, the aim must be to describe and evaluate an out-of-sample forecasting strategy rather than simply to find an equation which happens to fit the data.

Secondly, within the wide range of methodologies that can be chosen to assess the link between the leading indicators and the business cycle, we focus on linear models, the most widely followed avenue in the literature.

Specifically, we use the unrestricted VAR model of the form

$$\Delta z_t = \sum_{j\in J} A_j \Delta z_{t-j} + \varepsilon_t \ , \tag{1}$$

where Δz_t is a vector of month-on-month log-differenced endogenous variables to be described in detail below, ε_t is a vector of white-noise innovations, and the A_j are matrices of coefficients (including the intercept) to be estimated. J denotes the set of lags included in the estimation. Lag selection is described in detail below.

Based on this model, the 1-step ahead forecast of Δz_t is the expectation

$$\mathrm{E}_t\left\{\Delta z_{t+1}\right\} = \sum_{j\in J} A_j \Delta z_{t+1-j} \tag{2}$$

conditional on past and present information available in period t. Simple forward-iteration of this equation then allows to derive arbitrary h-step ahead forecasts according to

$$\mathrm{E}_t\left\{\Delta z_{t+h}\right\} = \sum_{j\in J\cap\{1\ldots h-1\}} A_j\, \mathrm{E}_t\left\{\Delta z_{t+h-j}\right\} + \sum_{j=J\cap\{h\ldots p\}} A_j \Delta z_{t+h-j} \ . \tag{3}$$

Forecasting beyond the next period $(h>1)$ requires a choice between employing iterated multi-step forecasts or direct forecasts. In theory, iterated forecasts as discussed above are more efficient if correctly specified but direct forecasts are more robust to model misspecification (see Bhansali, 2002, for an overview). We therefore additionally employ direct forecasts of Δz_t. This obviously requires a specific model to be estimated for each forecast horizon. The h-step ahead forecast of Δz_t based on this model is then

$$\mathrm{E}_t\left\{\Delta z_{t+h}\right\} = \sum_{j\in J_h} A_{h,j}\Delta z_{t-j} \ , \tag{4}$$

where, notably, the matrices $A_{h,j}$ and the set of included lags J_h now vary with the forecast horizon h.

Given that the leading indicator variables and industrial production are integrated time series in levels (see the appendix for the relevant ADF tests), we focus on log-differenced representations of the respective series. To overcome the implied information loss for the estimation (see Clements and Hendry, 1999, chapter 1, and Emerson and Hendry, 1996), we also consider cointegration frameworks of the following form for our forecasting models:[8]

$$\Delta z_t = \Pi \cdot z_{t-1} + \sum_{j\in J} A_j \cdot \Delta z_{t-j} + \varepsilon_t \ , \tag{5}$$

where Π can be decomposed as $\Pi = \alpha\beta'$. α are the factor loadings and β the long-term cointegration coefficients. The forecast is carried out again iteratively based on the equation

$$\begin{aligned} \mathrm{E}_t\left\{z_{t+1}\right\} &= z_t + \mathrm{E}_t\left\{\Delta z_{t+1}\right\} \\ &= (I+\Pi)\cdot z_t + \sum_{j\in J} A_j \cdot \Delta z_{t+1-j} \end{aligned} \tag{6}$$

We statistically assess the difference in forecast accuracy between two models (F, B) by performing recursive rolling-window estimations, using a window of constant width R of the overall sample of size T.[9] Using the recursively estimated models we calculate the test statistic proposed by Diebold and Mariano (1995) for h-step ahead pseudo out-of-sample forecasts. We base the statistic on the loss function $L_{t,h}$ computed as the difference of the squared forecast errors associated with the two forecasts being compared,

$$L_{t,h} = \left(\mathrm{E}^F_{t-h}\left\{\Delta^{12} z_t\right\} - \Delta^{12} z_t\right)^2 - \left(\mathrm{E}^B_{t-h}\left\{\Delta^{12} z_t\right\} - \Delta^{12} z_t\right)^2 , \tag{7}$$

where $\mathrm{E}^F_{t\text{-}h}\left\{\Delta^{12} z_t\right\}$ is the h-step ahead forecast of the year-on-year change of the variable z derived at time t-h by means of one of the models outlined above and $\mathrm{E}^B_{t\text{-}h}\left\{\Delta^{12} z_t\right\}$ is the equivalent forecast of a benchmark model. Averaging over all available rolling forecasts over time and dividing by the estimated standard deviation $\hat{\sigma}_h$ of $L_{t,h}$ produces the well-known Diebold/Mariano statistic[10]

$$d_h = \frac{1}{\hat{\sigma}} \cdot \frac{1}{T-(R+h)} \cdot \sum_{j=R+h}^{T} L_{j,h} \tag{8}$$

with a limiting t distribution that can be tested against the null hypothesis of equality of the forecast performance of the respective models.

[8] The appendix presents Johansen cointegration tests for the different combinations of variables. Note that the CLI and industrial production are cointegrated by construction however, since the trend-restored CLI underlying the present analysis is calculated by applying the trend of the industrial production index to the amplitude-adjusted CLI. See http://www.oecd.org/dataoecd/4/33/15994428.pdf for details.

[9] We additionally calculated forecasts based on a recursively growing sample. This does not substantially alter our results.

[10] Autocorrelations arising through overlapping forecast windows are taken into account up to an order of $h-1$ in the estimation of $\hat{\sigma}$. Additionally, we use the small sample adjustment suggested by Harvey et al. (1997).

While this method delivers a conveniently interpretable measure of relative forecasting accuracy over the *sample as a whole*, we also employ the "Fluctuation" test recently developed by Giacomini and Rossi (2008) to assess changes in the relative forecast performance of two models *over time*. This allows inference with respect to changes in the relative forecasting performance, e.g. due to the presence of structural instability. Basically, Giacomini and Rossi (2008) suggest a measure of local relative forecasting performance of the models, defined as a centred moving average of out-of-sample loss differentials similar to the ones employed in the Diebold/Mariano framework. Normalising this moving average with the loss sequence's estimated standard deviation $\hat{\sigma}_h$ and multiplying with the square root of the width of the respective loss window m to obtain a proper limiting distribution yields the Fluctuation test statistic

$$F_{h,t} = \frac{\sqrt{m}}{\hat{\sigma}} \cdot \frac{1}{m} \cdot \sum_{j=t-m/2}^{j=t+m/2-1} L_{j,h}, \tag{9}$$

where $t = R + h + m/2 \ldots T + (h - H) - (m/2 - 1)$. H denotes the largest forecast horizon considered in the analysis.[11] Giacomini and Rossi (2008) provide critical values for testing the null hypothesis that the local loss difference equals zero at a specific point in time t.

4 Empirical strategy and results

4.1 Leading indicator properties of the domestic CLI

The analysis is based on monthly data ranging from January 1975 to April 2008. After differencing, the first fifteen years of data, from February 1975 to January 1990 are exclusively used for estimation purposes. The second part, from February 1990 to April 2008 is used for conducting recursive rolling-window estimation and pseudo out-of-sample forecasting over horizons of up to $H = 12$ months ahead. We exclude the period after April 2008 because the global financial crisis is likely to have affected the (by assumption linear) link between the leading indicator and economic activity. Accordingly, the complete sample after differencing includes T = 399 observations. The rolling estimation is based on R = 180 observations, leaving 219 data points for pseudo out-of-sample forecasts.[12]

Lag selection is done for each model and for each forecasting point in time. For simplicity and comparability with other studies in the literature (e.g. d'Agostino et al, 2006), we use the Bayesian information criterion (BIC) to determine the appropriate lag length for the respective models. We also experimented with other selection criteria and found our results to be robust to these modifications. However, AIC and HQ often find higher lag-orders to be significant, resulting in much less parsimonious specifications.

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[11] Note that, in principle, the forecast horizon determines the number of available pseudo out-of-sample data points usable for forecast comparisons. However, we fix the number of forecasts we use to calculate the Giacomini/Rossi statistics by dropping the respective last available data points. This ensures that the critical values for significance levels are independent of the forecast horizon and allows a joint presentation in one chart (see e.g. Chart 3). In contrast, for the calculation of the Diebold-Mariano statistics the whole sample is used.

[12] While the employed tests are out-of-sample, the latest data vintage instead of "real time" data was used throughout. As emphasised by Diebold und Rudebusch (1991), such a procedure could yield biased results. However, this issue should be less problematic in the comparative analysis since all methods can be expected to be equally advantaged. This means that we test how well our approach does in a world of random shocks and possible structural changes. We do not examine the separate issue of how well it deals with inaccuracies in earlier vintages of data. From a practical perspective, an assessment based on "real time" data would require extensive additional work (using the paper-published version of the main economic indicators), since the OECD provides electronic "real time" CLI data only back until February 1999, a sample far too short for the type of analysis presented in this paper.

	CAN	DNK	GBR	JPN	SWE	USA	DEU	ESP	FRA	GRC	ITA
a. Forecasting performance of the domestic CLI model: Relative RMSE of VAR and UAR specification											
1 step	0.96	1.05**	1.00	0.93*	0.99	0.94**	0.95*	0.97*	0.97**	0.98	0.94**
4 step	0.91	1.08	0.95	0.92*	0.96*	0.89	0.82**	0.94**	0.92***	0.97	0.90***
8 step	0.91	1.01	0.95	0.90**	0.95*	0.91	0.83**	0.92**	0.95***	0.95*	0.90***
12 step	0.91**	1.00	0.95	0.88***	0.96	0.91**	0.88**	0.93**	0.96***	0.95*	0.91***
b. Forecasting performance of an error correction specification: Relative RMSE of VEC and VAR specification											
1 step	0.99	0.99	0.96*	0.96*	1.02	0.98	0.97	0.97	0.95**	0.97	0.98
4 step	0.95	1.14	0.93	0.80***	1.00	0.91	0.92	0.90	0.86***	1.01	0.92*
8 step	1.01	1.42**	0.92	0.69***	0.96	0.90	0.87	0.81*	0.84**	0.99	0.88**
12 step	1.07	1.40*	0.90	0.69***	0.92	0.91	0.90	0.78*	0.88	0.93	0.90*
c. Forecasting performance of an error-correction specification: Relative RMSE of VEC and UAR specification											
1 step	0.95	1.03	0.96	0.89***	1.01	0.92**	0.92**	0.94*	0.92***	0.95	0.92**
4 step	0.86*	1.23*	0.88	0.74***	0.96	0.81*	0.75**	0.85**	0.80***	0.98	0.82***
8 step	0.92	1.43**	0.88	0.62***	0.92	0.82**	0.72*	0.75**	0.80***	0.95	0.79***
12 step	0.97	1.40*	0.86	0.61***	0.89	0.82**	0.79	0.73**	0.84**	0.88	0.82**
d. Forecasting performance of the direct forecast: Relative RMSE of dVAR and VAR specification											
1 step	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4 step	0.94	0.90	0.97	0.92	1.03	0.95	0.98	1.06*	1.04	1.06*	0.98
8 step	1.04	0.94	0.98	0.83**	0.94	1.01	0.98	1.02	0.98	1.05	0.96
12 step	1.11*	0.99	1.01	0.84*	0.82	1.05	1.04	1.00	1.01	0.91	0.99

Table 1: Relative RMSE of different model specifications and Diebold/Mariano significance levels.
(* = 90%,** = 95%,*** = 99%)

For the unrestricted VAR models described by (3) and the direct forecast (4), all series are month-on-month log-differenced to ensure stationarity prior to estimation. For the error correction approach (6), log-level data is used for estimation and forecasting.[13] All model comparisons are, however, based on year-on-year log-differences, i. e. forecasts derived from the VEC models are differenced and the month-on-month projections derived from the VAR and dVAR models are cumulated to obtain year-on-year growth rates.

In the first step, we follow the traditional approach to assess the information content of the domestic CLI for domestic industrial production. We compare a simple univariate autoregression (UAR) of industrial production with $z_t = \left[\mathrm{IP}_t^k \right]$ to the three specifications (3), (4) and (6) outlined above and include the national leading indicator in the analysis, i. e. $z_t = \left[\mathrm{IP}_t^k \ \mathrm{CLI}_t^k \right]'$. Note that $k \in \{$CAN,DNK,GBR,JPN,SWE,USA,DEU,ESP,FRA,GRC, ITA$\}$ refers to the respective country analysed in the specific exercise.

Table 1a compares the forecasting performance of the VAR model (3) with the univariate autoregressive model UAR. It shows the RMSE of the CLI-based VAR model relative to that of the benchmark UAR model over selected forecast horizons $h \in \{1,4,8,12\}$. As such, values below 1 signal a better forecast performance of the CLI-based model than the respective

[13] We fix the number of cointegrating restrictions to 1. See Table A2 in the appendix for Johansen test results for the full sample. Similar rolling window tests for the subsamples actually used for estimation also mostly indicate 1, infrequently 0, cointegrating relationship. In line with the suggestion of Clements and Hendry (1995) we allow for the inclusion of 'spurious' level terms by imposing 1 cointegration vector in our estimations.

benchmark model. Asterisks mark the significance of the Diebold-Mariano test for the null hypothesis of no difference of the RMSE compared to the benchmark forecast.

Overall, the results suggest that the domestic CLI encompasses useful information about the future evolution of industrial production compared with the naïve benchmark model. For most economies included in our sample and for various forecasting horizons we observe substantial and often significant improvements of the VAR model vis-à-vis the UAR model. Some interesting patterns emerge: First, the major gains from the inclusion of the CLI in the forecasting model can be expected in the medium forecast horizon, i.e. for h between 4 and 8 months. This is in line with our observation in section 2 that the closest cross-correlation between the CLI and the reference series is found at around these lag orders. Second, forecast improvements appear to be somewhat more pronounced for the larger economies in our sample.

Accounting for cointegration between the CLI and industrial production further improves the forecasting performance. Table 1b shows the gains in forecasting performance when comparing the VEC model as defined in equation (6), $z_t = \left[\mathrm{IP}_t^k \ \mathrm{CLI}_t^k\right]'$, with the VAR model discussed in the previous paragraph.[14] The forecasts of the cointegrated CLI-based model are better for almost all economies and effectively over all forecast horizons, even though the improvements are often insignificant. Given this result, it does not come as a surprise that a model using the cointegration information contained in the CLI data also beats the univariate autoregressive forecast across most countries and horizons (see Table 1c). In fact, the table indicates an almost perfect dominance of the CLI-based error correction approach over the naïve univariate autoregression. Except for Denmark, we find the relative point-RMSEs to be below 1 and the Diebold-Mariano statistics often reject the null hypothesis of no significant difference in the RMSE with respect to the benchmark at the 90% significance level, in many cases even at the 99% level.

To conclude the assessment of the different model specifications, consider Table 1d for a comparison of the direct forecast model dVAR as defined in equation (4), $z_t = \left[\mathrm{IP}_t^k \ \mathrm{CLI}_t^k\right]'$, with the standard iterative VAR model.[15] Our results indicate no clear dominance of one model specification over the other. Depending on the forecast horizon and the country under observation, the relative RMSE are arbitrarily above and below 1 and only in very few occasions significant according to the Diebold-Mariano test.

Summing up, the previous analysis suggests that the CLI encompasses useful information about the future evolution of industrial production, particularly over horizons of around half a year. Thereby, it does not systematically matter whether the forecast is calculated iteratively from a VAR representation or whether it is directly derived from a horizon-specific model. A clear improvement can be expected from taking cointegration in the vector autoregressive framework into account. Accordingly, the analysis below relies on cointegration models. Furthermore, given the mixed picture obtained with respect to direct forecasts, we focus on iterative VAR models in view of their wide acceptance in applied forecasting.

[14] Note, however, that Clements and Hendry (1993) stress the limitations of mean squared forecast errors, in particular when comparing forecasts of cointegrated systems. They point out that rankings across models are subject to invariance failure, i.e. comparisons yield different results when alternative but isomorphic representations (such as comparisons of levels, differences or with cointegrating combinations) are chosen to compare models.

[15] Forecast performance is, by definition, the same for the 1-step ahead exercises.

4.2 The temporal dimension: Forecasting performance of CLI models over time

If the process of globalisation had an adverse impact on the reliability of the domestic CLI for anticipating developments in economic activity, the forecasting properties of the VEC model should have deteriorated over time. To assess this, we compute the Giacomini/Rossi Fluctuation test statistic (as described in section 3) based on a 5-year centred moving average of the VEC model's RMSE relative to the univariate autoregression UAR. The results for the forecast horizons $h \in \{1,4,8,12\}$ along with critical values for the 95% significance level are presented in Chart 3. Negative values of the displayed test statistic indicate a higher RMSE of the benchmark model and, thus, a better performance of the CLI-enhanced VEC model in the specific period. Accordingly, a negative test statistic below the lower dashed line indicates a significantly better forecast performance of the CLI-based model in the respective period.

In line with the results presented in Table 1c (with respect to the entire sample), the mostly negative test statistics shown in the graphs confirm the superiority of the VEC model over the UAR model for most economies, over most horizons and over most of the sample period under consideration. For several economies in our sample, however, the test statistics has been trending upwards, i.e. the relative forecasting performance of the VEC model decreases over time. This is particularly visible for Italy, Spain, Sweden and the United States, while the results are overall more mixed for Canada, France, the United Kingdom and Greece. For many countries, the Fluctuation test statistics approaches non-significant levels in recent years; for several countries, it has even crossed the zero line, indicating that the CLI encompassed little information in forecasting economic activity.

This loss of forecasting performance of the CLI-based model could be related to the ongoing process of international integration and the associated loss of forecasting power of purely domestic leading indicators. An additional hint pointing in this direction is the observation that performance gains for larger economies (such as Japan, the US or France) from including the CLI in the analysis appear to be more pronounced and subject to deterioration later than observed in other economies. This possibly reflects a lower dependency of these economies on international business cycles and, hence, a smaller loss of information of the domestic CLI owing to globalisation. In contrast, smaller economies showed a stronger deterioration in the forecasting power of the domestic CLI.

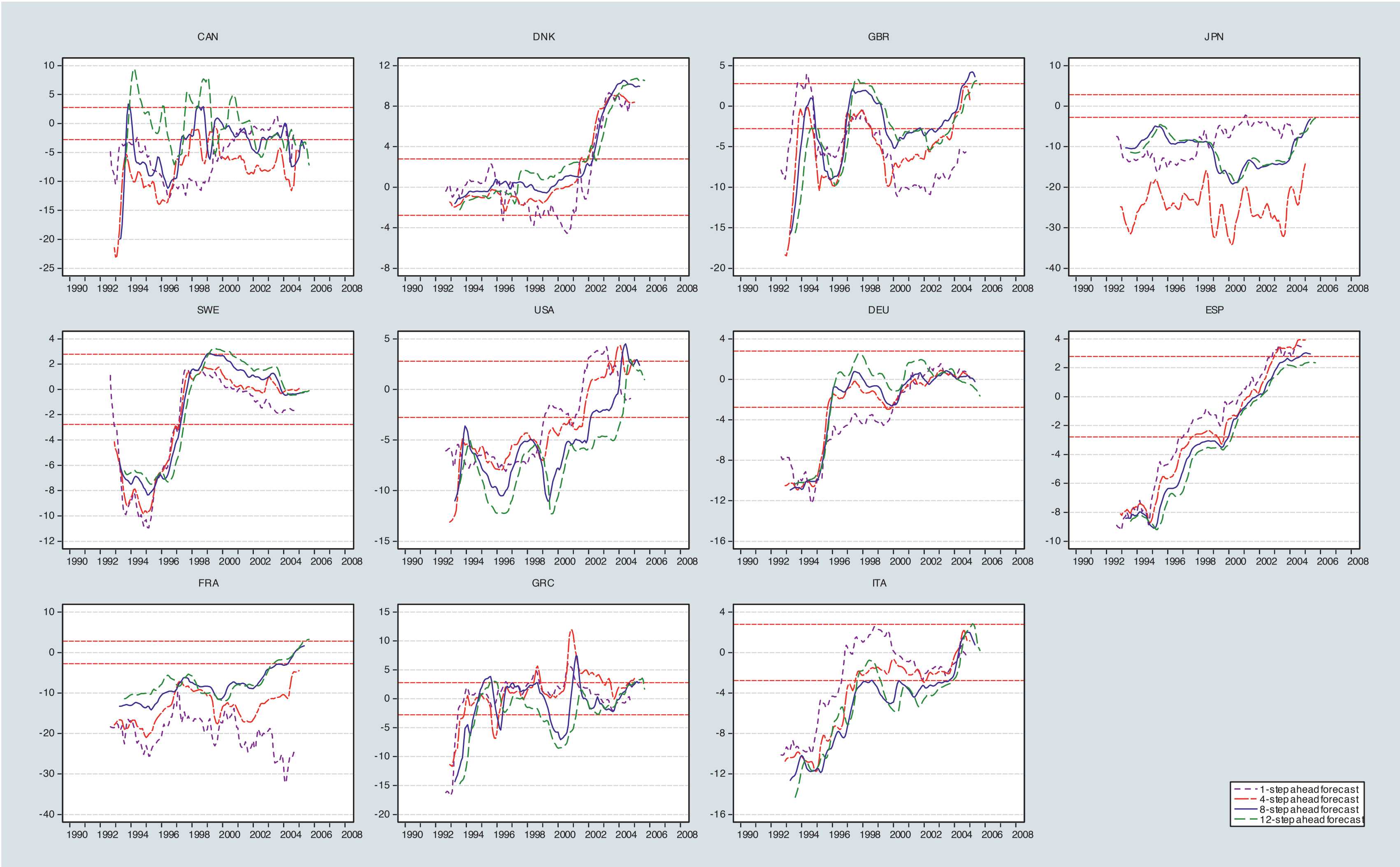

Chart 3: Forecasting performance of the VEC model relative to UAR over time.

Note: Giacomini/Rossi test statistics and critical values for the 95% significance levels (dashed lines). Negative values indicate a better performance of the VEC model compared to the univariate autoregression UAR.

5 The external dimension: Can international leading indicators improve domestic forecasts?

The prospect of a more pronounced global dimension in the forecasting of economic activity in individual countries raises the question whether augmenting the models with international indicators could again improve the forecast performance over time. To analyse this hypothesis in more detail, in a first step, we add the Total OECD composite leading indicator as provided by the OECD in the error correction model (6) by setting $z_t = \left[\mathrm{IP}_t^k \ \mathrm{CLI}_t^k \ \mathrm{CLI}_t^{\mathrm{OTO}} \right]'$. The model OTO is benchmarked against the exclusively domestic CLI-based VEC model presented before.

The relative RMSE and the associated Diebold/Mariano statistics for the countries in our sample are shown in Table 2a. There are indeed significant forecast performance gains for some smaller economies (Denmark, France and Greece).[16] For Canada and the UK, we still find some performance improvements as signalled by the point-RMSEs but these are not statistically significant. For other countries, by contrast, the inclusion of the OECD CLI effectively deteriorated the forecasts.

These mixed results could be due to the fact, that the OECD CLI does not properly reflect the global interdependencies of individual countries. For instance, Spain and Greece are rather dependent on the other European economies, while Canada is very dependent on the United States. To better account for such heterogeneity across countries, we include as an alternative to the total OECD CLI a (country-specific) external leading indicator $\mathrm{CLI}^{\mathrm{EXT},k}$. This $\mathrm{CLI}^{\mathrm{EXT},k}$ is calculated as a bilateral trade-weighted average[17] of the composite leading indicators of the trade partners included in the sample and analysed again in an error correction model with $z_t = \left[\mathrm{IP}_t^k \ \mathrm{CLI}_t^k \ \mathrm{CLI}_t^{\mathrm{EXT},k} \right]'$.[18] Results of a comparison of the EXT model with the VEC specification are quite similar to the comparison of OTO and VEC (see Table 2b). Some minor changes of forecast performance and significance levels do arise, however. For example, we find small improvements of the forecast for France, Greece, and, more pronounced, Spain when accounting for country heterogeneities. On the other hand, forecast performance for Denmark, the UK and Sweden is decreasing substantially.

As the forecasting literature regularly stresses the benefits of forecast combinations for the projection of macroeconomic developments,[19] we also combine the forecast of the "closed economy" VEC model with the respective better performing "open economy" model.[20] In-

[16] Forecast performance over short horizons appears to be negatively affected by the inclusion of external information.

[17] Trade weights are based on the import side of the trade matrix for the euro effective exchange rate, which is based on weights for the period 1999-2001.

[18] We also checked other methods to introduce international leading indicator data in our forecast. For instance, we employed other aggregation schemes and principal component techniques to derive external leading indicator indices and we assessed models including the US CLI next to the domestic CLI. The results are not systematically different from the results presented here.

[19] See e.g Elliot and Timmermann (2007) for a recent overview.

[20] Specifically, we choose the "open economy" model which performs better at the 8-step forecast horizon, judged by the point-RMSE of a direct comparison of OTO and EXT. If the point-RMSE at the 8-step horizon equals 1.00, we choose the model which performs better at the 4-step forecast horizon. Concretely, the EXT model is chosen for Japan, the US, Spain, France and Greece, while the OTO model is chosen for Canada, Denmark, the UK, Sweden, Germany and Italy.

	CAN	DNK	GBR	JPN	SWE	USA	DEU	ESP	FRA	GRC	ITA
a. Forecasting performance of the model with Total OECD CLI: Relative RMSE of OTO and VEC specification											
1 step	1.03*	0.96*	1.01	1.02	1.08**	1.01	1.04**	1.08**	1.00	1.00	0.99
4 step	0.98	0.79***	0.96	1.10***	1.09	1.06	1.09***	1.21	0.99	0.94**	1.03
8 step	0.95	0.70***	0.94	1.14***	1.04	1.04	1.12***	1.18	0.93*	0.92**	1.04
12 step	0.94*	0.66***	0.97	1.16**	1.04	1.01	1.08**	1.10	0.89**	0.90**	1.03
b. Forecasting performance of the model with trade weighted external CLI: Relative RMSE of EXT and VEC spec.											
1 step	1.02	0.94***	1.03	1.03*	1.13**	1.01	1.05***	0.99	1.00	0.98	1.00
4 step	0.97	0.79***	1.08	1.09***	1.39*	1.02	1.12***	0.95	0.97	0.93***	1.07
8 step	0.95	0.75***	1.07	1.13***	1.28	1.03	1.12**	0.95	0.87*	0.90**	1.08
12 step	0.95	0.74**	1.09	1.16***	1.25	1.03	1.09*	1.00	0.84*	0.91*	1.05
c. Forecasting performance of the combined forecast: Relative RMSE of COMB and VEC specification											
1 step	1.01	0.97***	0.99	1.01	1.01	1.00	1.01	0.97**	0.99	0.98**	0.99
4 step	0.98	0.87***	0.94***	1.03**	0.97	1.00	1.03**	0.90***	0.96**	0.95***	1.01
8 step	0.97	0.81***	0.93**	1.05***	0.93	1.01	1.05**	0.88**	0.90***	0.93***	1.01
12 step	0.96**	0.79***	0.95	1.06**	0.94	1.01	1.03	0.92	0.89**	0.93**	1.01

Table 2: Relative RMSE of different open economy model specifications and Diebold/Mariano significance levels. (* = 90%,** = 95%,*** = 99%)

deed, forecast combination leads to a notable improvement in the projections of industrial production (Table 2c).[21]

We find that using international information in the form of a combined forecast (COMB) yields performance gains in the projection of industrial production of most economies in our sample. Compared to the "closed economy" VEC model, significant improvements at least on the 95% level, often even on 99% level, are obtained for Canada, Denmark, the UK, Spain, France and Greece. The improvements appear to be particularly pronounced in the medium forecast horizon, while gains over the very short (1-step ahead) horizon are rather contained. In contrast, we find no significant impact of the use of international leading indicators in the case of Sweden, the US and Italy, while forecasts of the Japanese and German economy tend to worsen when international data is included in the model.

Finally, we employ again the Giacomini/Rossi Fluctuation test to analyse the relative performance of the "closed" and "open economy" models over time. Chart 4 displays the Giacomini/Rossi statistics of the combined forecast COMB benchmarked against the "closed economy" VEC model. We again display test statistics for the forecast horizons $h \in \{1,4,8,12\}$ along with critical values for the 95% significance level.

[21] For simplicity, we use an unweighted average of the two models' forecasts. Other weighting schemes (e.g. according to historical forecast performance) tend to improve the combined forecast not substantially. Newbold and Harvey (2002) extensively discuss different weighting schemes.

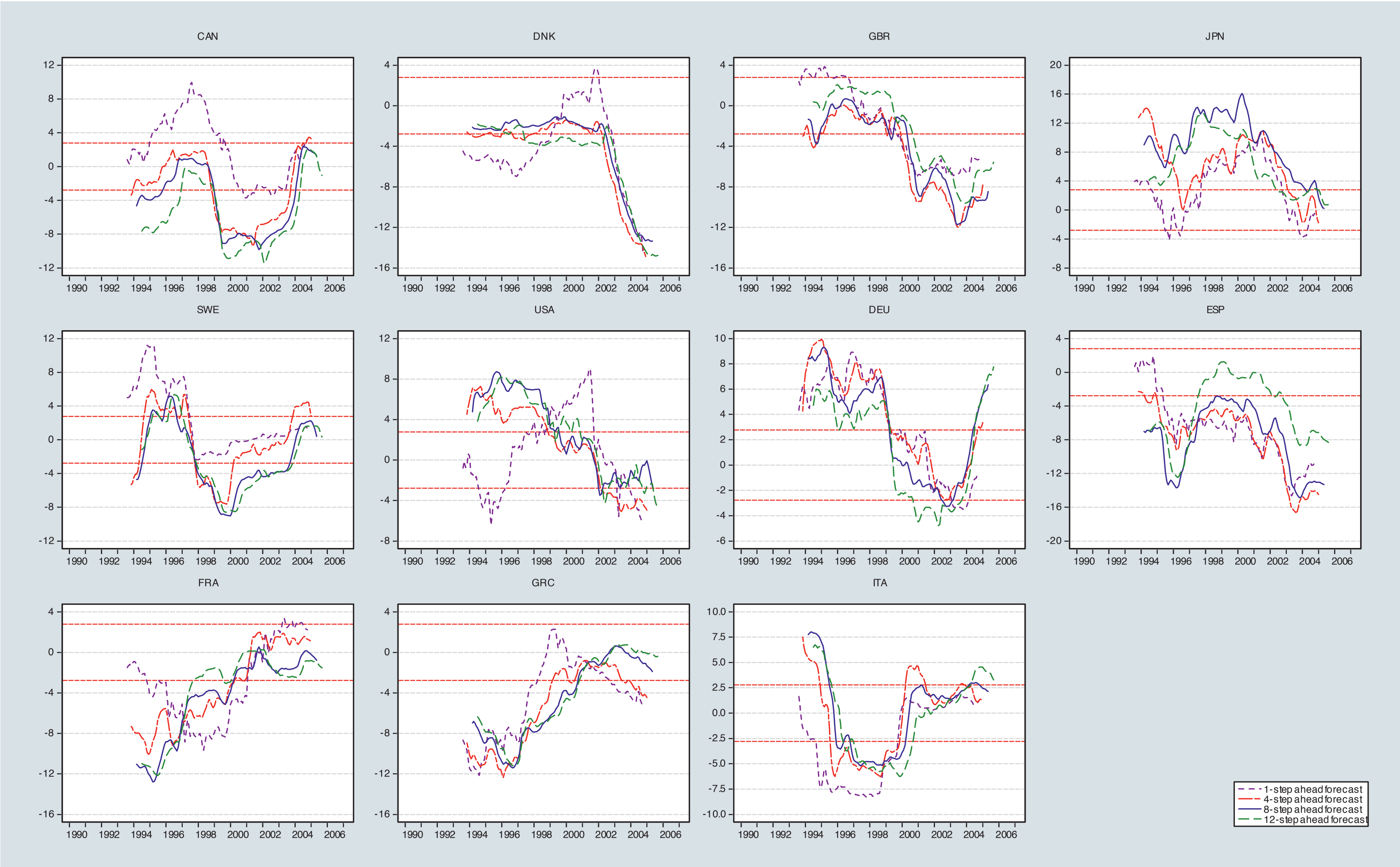

Chart 4: Forecasting performance of the COMB model relative to VEC over time.

Note: Giacomini/Rossi test statistics and critical values for the 95% significance levels (dashed lines). Negative values indicate a better performance of the COMB model compared to the VEC specification.

Similar to the point-RMSEs over the whole sample period, the results are rather ambiguous. The test statistics indicate a substantial variation of relative forecast performance over time and do not show a clear pattern of significant dominance of one of the methods under consideration. We find clear improvements over time in relative forecast performance for Denmark, Japan, Spain, the United Kingdom and the United States. While these results are mostly insignificant for Japan and the US, there is a clear trend towards relatively higher performance of the "open economy" specification, with the test statistics clearly approaching negative territory. Results are even more pronounced for Denmark, the UK and Spain, where the test statistics indicate a clear dominance of the global CLI-augmented models in recent periods.

For other countries, however, the combined forecasts fail to improve above the domestic CLI-based model. While the inclusion of the global CLI improved the forecast performance in several countries during the 1990s (France, Greece and Italy), performance gains, if any, in more recent periods are insignificant, suggesting that models based on the domestic CLI may be sufficient to forecast industrial production. This might be due to a main caveat of this analysis. In fact, there are likely to be international linkages in the series underlying the domestic CLI of some countries, which could imply that these are already responding to the international environment. This shall be addressed in future research.

6 Conclusions

This paper assessed empirically whether the ability of the country-specific leading indicators to predict the future economic situation has diminished in recent years, possibly due to rapid advances in globalisation. The analysis is based on the OECD composite leading indicator, which is one of the best-known composite indicators worldwide.

Overall, we find fairly strong out-of-sample evidence that the CLI encompasses useful information for forecasting industrial production. For most countries included in the sample and for most forecasting horizons, we observe substantial and often significant improvements of the CLI augmented VAR-based forecasts compared with standard benchmarks. The CLI-based model performs particularly well over horizon of four to eight months ahead and the results are robust to employing iterative forecasts or direct forecasts derived from horizon-specific models. Notably, accounting for cointegration between the CLI and industrial production improves the results of our forecasting exercise for most economies and horizons even further.

Turning to the temporal dimension of forecast performance over time, we find indications that the predictive accuracy of the CLI for economic activity has declined over time for several countries. Augmenting the country-specific CLI with a leading indicator of the external environment and employing forecast combination techniques tends to improve the forecast performance for several economies. Over time, we find forecast performance of the "open economy" specification to improve relative to the "closed economy" specification for some countries, indicating that the ongoing process of globalisation might increase the relevance of international dependencies for the projection of economic developments of selected countries in our sample.

Future research will turn to the underlying components of the CLI for each country in more detail to understand to what extent global information is already indirectly encompassed in these indicators.

Appendix

	IP	CLI
CAN	0.8686	0.8702
DNK	0.9660	0.9660
GBR	0.7438	0.5460
JPN	0.3447	0.2270
SWE	0.9959	0.9698
USA	0.9585	0.9749
DEU	0.9946	0.9924
ESP	0.9679	0.9473
FRA	0.9742	0.8024
GRC	0.6576	0.4913
ITA	0.7231	0.3359

Table A1: ADF test results for industrial production and composite leading indicators.
Note: The table reports the *p*-value of the null that the respective series has at least one unit root.

	$z_t = \left[\mathrm{IP}_t^k\ \mathrm{CLI}_t^k\right]'$	$z_t = \left[\mathrm{IP}_t^k\ \mathrm{CLI}_t^k\ \mathrm{CLI}_t^{\mathrm{OTO}}\right]'$	$z_t = \left[\mathrm{IP}_t^k\ \mathrm{CLI}_t^k\ \mathrm{CLI}_t^{\mathrm{EXT},k}\right]'$
CAN	1	1	1
DNK	1	1	0
GBR	1	1	1
JPN	2	1	1
SWE	1	1	1
USA	1	1	1
DEU	1	1	1
ESP	1	2	1
FRA	1	1	1
GRC	2	1	2
ITA	2	1	1

Table A2: Full sample Johansen cointegration tests for log of IP and leading indicators in different model setups.
Note: The table reports the number of cointegration relationships indicated by a trace test at the 95% level.

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