Evaluating OECD’s main economic indicators at anticipating recessions*

Máximo Camacho+
Universidad de Murcia
mcamacho@um.es

Gonzalo Palmieri
Universidad de Murcia
gd.palmierileon@um.es

ABSTRACT

Using Receiver Operating Characteristic (ROC) techniques, we evaluate the predictive content of the monthly OECD's main economic indicators for predicting both growth-cycle and business-cycle recessions at different horizons. From a sample that covers the 35 OECD countries as well as for Brazil, China, India, Indonesia, Russian Federation and South Africa, our results suggest that the indicators perform better at anticipating business cycles than growth cycles. Although the performance for OECD and non OECD members is similar in terms of timeliness, the indicators are more accurate to anticipating recessions for OECD members. Finally, we find that single indicators, such as interest rates, spreads and credit indicators, perform better than the composite leading indicators.

Key words: Business cycles, Growth cycles, income inequality, receiver operating curve

Classification JEL: C22, C53, E32, F44.

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+ Corresponding Author: Universidad de Murcia, Facultad de Economía y Empresa, Departamento de Métodos Cuantitativos para la Economía, 30100, Murcia, Spain. E-mail: mcamacho@um.es

1. Introduction

A decade from the beginning of the Great Recession, leading indicators have weakened around the world and start pointing towards increasing concerns about the health of the global economy. Among others, the external factors that contribute to the global fragility are the deceleration in world trade, the slowdown in emerging markets, the increasing concerns about the sovereign-bank loop and debt sustainability in some euro area countries, and the doubts around the total effects of Brexit.

Anticipating whether the economic downturn is likely to turn to a new change in the economic cycle phase is crucial for households, investors and policymakers in order to be prepared for the potential impacts of the adverse circumstances that characterize recessions. However, contrary to what one might think, recognizing economic cycle turning points in real time is not easy. Among others, Stock and Watson (2003) and Hamilton (2011) review the difficulties in foreseeing the economic downturns.

With the aim of giving advance warnings of turning points, the Organization for Economic Co-operation and Development (OECD) compiles a set of monthly statistical publications presenting a wide range of Main Economic Indicators (MEI) for the 35 OECD countries as well as for Brazil, China, India, Indonesia, Russian Federation and South Africa. In addition, OECD develops Composite Leading Indicators (CLIs) that are designed to provide early signals of turning points in economic cycles through qualitative rather than quantitative information on short-term economic movements.

The CLIs are computed by combining a set of selected single indicators for each country, which, at least from a theoretical point of view, is done in order to reduce the risk of false signals and to provide the composite indicators with better forecasting and tracking qualities than any of its individual components. However, monitoring the ongoing development of the economic activity from economic indicators is rather complex because each cycle has its unique characteristics as well as features in common with other cycles. This implies that some indicators will perform better in one cycle and others in a different cycle. Thus, the relative performance of the single indicators with respect to CLIs at classifying the state of economy between expansionary and recessionary periods will ultimately be a matter of practice.

The main purpose of this paper is evaluating the usefulness of the OECD's main economic indicators for predicting recessions by focusing on identifying the relevant predictors and on whether they perform better than the composite leading indexes. In particular, we screen lots of potential predictors, evaluate their relevance performance for anticipating phase changes in a large set of counties, and check whether they are able to produce more accurate warnings of ongoing recessions than the composite aggregates. Thus, we aim to identify which are the more reliable OECD's indicators when searching for potential turning points at different forecasting horizons in a country. In line with, among others, Drehmann and Juselius (2014), we evaluate the indicators in terms of its timeliness and its accuracy at forecasting both business cycles and growth cycles.

To this end, the methods that we use in this paper to measure the recession/expansion classification ability of the OECD's leading indicators belongs to the Receiver Operating Characteristic (ROC) framework. With this nonparametric method, that addresses the tradeoff in signal detection between true and false positive rates, we evaluate the performance of the OECD's leading indicators at predicting the distinct phases of the economic cycles. While not claiming to be exhaustive, examples of recent contributions that use ROC methods to business and financial cycle analyses are Berge and Jorda (2011), Jorda, Schularick and Taylor (2011), Berge (2015), and Camacho, Perez-Quiros and Poncela (2018).[1]

Using the ROC analysis, we examine the timeliness, or relative classification ability of the cycle phases of each OECD's leading indicator over horizons ranging from 0 to 20 months in advance. In addition, we also examine the accuracy and the stability of these indicators by checking whether they provide significantly better classifications than a coin-toss classifier within more than one year in advance.

The main findings of our study are summarized in the following lines. First, the OECD's MEI show a high overall performance in providing early signals of economic downturns worldwide. Although many indicators achieve its maximum classification ability at horizons very close to zero, they perform much better than a random classifier at horizons up to 20 months into the future.

Second, we find a significantly better performance of MEI to anticipating recessions in OECD members than in non-OECD members in terms of classification accuracy, although the timeliness tends to be similar. Third, MEI tend to perform better at anticipating business cycles than growth cycles, especially in terms of accuracy.

Fourth, we detect that the composite leading indicators perform worse than some of their single component indicators. In particular, our results show that measures of short-term

[1] Examples of other recent economic applications are Cohen, Garman, and Gorr (2009), Gorr and Schneider (2011).

interest rates, term spreads and credit indicators are very good classifiers of both growth cycles and business cycles.

Our paper is structured as follows. Section 2 outlines the ROC framework and describes our measures of accuracy and timeliness. Section 3 develops the empirical evaluation of OECD's MEI as classifiers of the distinct phases of the economic cycles. Section 4 concludes.

2. Methodology

2.1 Receiver Operating Curve analysis

The Receiver Operating Characteristic (ROC) curve approach dates back to Peterson and Birdsall (1954), although it has recently been adopted into business cycle analysis by Berge and Jorda (2011).

Let s_{it} be a dichotomous variable denoting the true state of the economic activity of country *i* at time *t*, with $s_{it} = 0$ when *t* is an expansion and $s_{it} = 1$ when *t* is a recession. When the focus is on growth cycles, we assume that OECD can determine the value of this variable and we compute s_{it} from the reference cycle chronology provided by the OECD's dating committee for each country of the sample. In particular, they determine the turning points as the deviation-from-trend series of national GDP for all countries, except for China for which the OECD relies on the value added of industry at 1995 prices.

When the focus is on business cycles, we determine s_{it} by using the business cycle reference chronologies provided by the Economic Cycle Research Institute (ECRI). In this case, the turning point identification relies on the Burns and Mitchel (1946) view of business cycles as alternating fluctuations of periods of recession and recovery in the aggregate economic activity, observed simultaneously in many economic activities.

We denote Y_{jit} as the *j*-th observable indicator for country *i* that is used to computing inferences on the phase of the economic cycle at time *t* in that country. Given a threshold c_{ji} and assuming that the indicators are procyclical, a recession is called when $Y_{jit} < c_{ji}$ whereas an expansion is called when $Y_{jit} \geq c_{ji}$. This allows us to generate a binary indicator that takes the value of 1 when a recession is called ($Y_{jit} < c_{ji}$) and 0 when an expansion is called ($Y_{jit} \geq c_{ji}$).

Besides these variables, we can define the following True Positive ($TP(c_{ji})$) rate and False Positive ($FP(c_{ji})$) rate as

$$TP(c_{ji}) = p\left(Y_{jit} < c_{ji} \mid S_{jit} = 1\right), \tag{1}$$

$$FP(c_{ji}) = p\left(Y_{jit} < c_{ji} \mid S_{jit} = 0\right). \tag{2}$$

Now, we can define the ROC curve as a probability curve, usually displayed graphically, that represents the trade-off set of different outcomes of $TP(c_{ji})$ and $FP(c_{ji})$ obtained as a result of varying c_{ji} between -∞ and ∞. As c_{ji} tends to -∞, both $FP(c_{ji})$ and $TP(c_{ji})$ tend to zero, while as c_{ji} tends to ∞, both $FP(c_{ji})$ and $TP(c_{ji})$ tend to one. Thus, the ROC curve is usually represented as the plot of $TP(FP(c_{ji}))$ on the first quadrant of the coordinate plane with $FP(c_{ji})$ in the x-axis and $TP(c_{ji})$ in the y-axis.

When the indicator is an uninformative classifier with respect to the phase cycle, $FP(c_{ji}) = TP(c_{ji})$ for all c_{ji}, which implies that the ROC curve coincides with the 45 degrees line connecting the origin to (1,1). A perfect classifier will provide a ROC curve placed on the left and upper part of the unit quadrant. In practice, the ROC curve of OECD's indicators generate ROC curves between these two extremes located above the diagonal.[2]

A standard measure of overall classification ability is the Area Under the ROC (*AUROC*) curve. For a perfect classifier of the phase cycle, *AUROC*=1 whereas any deviation from this perfect classification decreases the *AUROC* until 0.5, which is the expected *AUROC* for a random classification. The improvements of OECD's indicators over a random classification results in an ROC curve at least partially above the straight line, which will take values between 0.5 and 1. Therefore, *AUROC* is closely related to the ranking quality of the classification and becomes a natural non-parametric statistic for evaluating the performance of OECD's economic indicators as predictors of phase changes.

Formally, the area under the ROC curve is given by

$$AUROC = \int_0^1 TP(FP(c_{ji}))dFP(c_{ji}). \tag{3}$$

[2] For countercyclical classifiers, which would generate ROC curves below the diagonal, we just multiply the indicators by minus one.

Let Z_{jit} be the observations of the *j*-th OECD's indicator for country *i*, Y_{jit}, for which $S_{it}=1$. Let X_{jit} be the observations of the same indicator for which $S_{it}=0$. Let n_{i1} and n_{i0} be the total number of recessionary and expansionary periods in country *i*, respectively. Finally, let $I(\cdot)$ be a binary indicator that takes on a value of one when the condition is true and of zero otherwise. Green and Swets (1966) proposed a simple nonparametric estimate of *AUROC* as

$$AU\hat{R}OC=\frac{1}{n_0 n_1}\sum_{\tau'=1}^{n_0}\sum_{\tau=1}^{n_1}\left\{I\left(Z_{ji\tau}<X_{ji\tau'}\right)+\frac{1}{2}I\left(Z_{ji\tau}=X_{ji\tau'}\right)\right\}. \qquad (4)$$

Since the last term rarely occurs, this statistic can be viewed as an estimate of the probability $p\left(Z_{ji}<X_{ji}\right)$ that the *j*-th OECD's indicator for country *i* ranks a randomly chosen within-recession figure lower than a within-expansion value.

There exist a number of methods that have been proposed to approximate the distribution of the AUROC. In this paper, we rely on the approach developed by Hsieh and Turnbull (1996), who show that, under standard regularity conditions the estimator is asymptotically normally distributed

$$\sqrt{n_1}\left(AU\hat{R}OC-p\left(Z_{ji}<X_{ji}\right)\right)\rightarrow N\left(0,\sigma^2\right), \qquad (5)$$

where

$$\hat{\sigma}^2=\frac{AU\hat{R}OC\left(1-AU\hat{R}OC\right)+\left(n_1-1\right)\left(Q_1-AU\hat{R}OC^2\right)+\left(n_0-1\right)\left(Q_2-AU\hat{R}OC^2\right)}{n_1 n_0}, \qquad (6)$$

where $Q_1=\dfrac{AU\hat{R}OC}{2-AU\hat{R}OC}$ and $Q_1=\dfrac{2AU\hat{R}OC^2}{1+AU\hat{R}OC}$.

2.2. Timeliness and Accuracy

Although the ROC approach can be used to rank the OECD's leading indicators according to their relative performances at classifying the two phases of the cycle, evaluating the usefulness of its leading properties may crucially depend on both their timeliness and accuracy.

Early symptoms of deteriorations in economic conditions should be given to economic agents with sufficient time in advance to let them react against its adverse situations, although the warnings cannot come too early because there are costs associated to these reactions. To assess the relative classification ability of an OECD's indicator Y_{ji} to predict future recessions, we estimate the ROC curves of the indicators dated at t and the recessionary indicators dated at $t+h_{ji}$, with h_{ji} ranging from 0 to 20, which are denoted as $AUROC(Y_{ji},h_{ji})$. Then, we approximate the timeliness of the indicator as the value of the leading month h_{ji} for which $AUROC(Y_{ji},h_{ji})$ achieves its maximum. To approximate the timeliness of a group of indicators G, we compute three statistics: (i) the percentage of indicators whose $AUROC(Y_{ji},h_{ji})$ maximize at $h_{ji}>0$, with $i,j \in G$; (ii) the average over G of the leading months; and (iii) the average of the *AUROC* maxima.

Besides timeliness, an OECD's is required to provide accurate signals of ongoing recessions. In this paper, we consider that an indicator is a good (accurate) classifier of economic cycles when it anticipates the phase changes for at least one year. This implies that it should reject the null of $AUROC(Y_{ji},h_{ji})=0.5$ against the alternative of $AUROC(Y_{ji},h_{ji})>0.5$ for more than 12 values of h_{ji} out of its 20 possible values. As in the case of timeliness, we approximate the accuracy of a group of indicators by using the percentage of indicators achieving this condition.

3. Empirical results

3.1. Preliminary data analysis

Our dataset, which go back at least 20 years and in many cases back to 1960, covers the monthly OECD's main economic indicators for the 35 OECD countries as well as for Brazil, China, India, Indonesia, Russian Federation and South Africa. We use a sample of 150 single indicators, including national business tendency and consumer opinion surveys, financial indicators, international trade indicators, labour indicators, national accounts, monetary aggregates and production and sales variables.

The database also includes composite leading indicators, which are designed to provide early signals of short-term economic movements. According to Nilsson and Gyomai (2011), the OECD's composite leading indicators are composed by business tendency surveys (39%), real quantitative variables (30%), financial variables (24%) and consumer surveys (7%).

Table 1 describes the two classifications that we use to analyze both timeliness and accuracy of OECD's indicators. According to Classification 1, we classify the single indicators according to the OECD groups Monetary and Financial Indicators, Real Quantitative Indicators, and Business and Consumer Survey Indicators. For a deeper analysis, we also perform a more detailed classification, that we call Classification 2. In the first group, we distinguish indicators of Inflation, Monetary Aggregates, Asset Prices, Interest Rates, Credit, and Interest Rate Spreads. The second group is divided into indicators of Trade, Demand, Production and Employment. Finally, the third group is divided into surveys indicators related to Economic Situation Expectations, Employment Expectations, Demand Expectations, Production Expectations, Consumer Confidence, Inflation Expectations and Trade Expectations.

3.2 Growth cycle chronology: total sample

In this section, we evaluate the performance of OECD's main economic indicators to anticipate the OECD growth cycle chronology. These reference cycle dates are calculated according to the growth cycle spirit, in the sense that the turning points occur when the deviation-from-trend of national GDP data reached a local maximum (peak) or a local minimum (trough). Thus, growth cycle peaks (end of expansion) occur when activity is furthest above its trend level, whereas growth cycle troughs (end of recession) occur when activity is furthest below its trend level.

According to Classification 1, Table 2 provides insight into the timeliness of OECD's main economic indicators by showing the percentage of indicators of each group for which $AUROC(Y_{ji}, h_{ji})$ maximizes at $h_{ji}>0$ (columns labelled as Time), along with the average lead period and the average of the maximum *AUROC* achieved. The figures of the table suggest that only a few indicators (24%) achieve *AUROC* maxima at horizons $h_{ji}>0$.

However, Figure 1, which displays the percentage of leading indicators for which the null of *AUROC*=0.5 is rejected against the alternative of *AUROC*>0.5 across horizons $h_{ji}=0,1,\ldots,20$, suggests that many of the indicators have valuable information to forecast growth-cycle recessions at distant horizons.

To be precise, almost half of the Monetary and Financial Indicators are leading indicators of growth cycle recessions. In fact, this is the group evidencing the highest leading behaviour, followed by Real Quantitative Indicators (35%) and, to a lesser extent by Business and Consumer Surveys (20%).

Moving to Classification 2, Table 3 shows that Interest Rates and Spreads contain the highest timeliness proportions (92% and 75%, respectively). Employment (72%), Inflation (70%) and Credit (50%) also show relevant leading classification abilities. In addition, these indicators present the highest anticipated signals. Interest Rates, leading the growth-cycle recessions by 17 months on average, is the group of indicators with higher leading properties.

The good performance of financial indicators, especially those related to interest rates and spreads, as promptly indicators of phase changes is in line with some results obtained in the related literature. Among others, Davis and Fagan (1997), Estrella and Mishkin (1998), Stock and Watson (2003), and Marcellino (2006) also find this leading behaviour of financial indicators. As a potential explanation of this result, Marcellino (2006) points out the short publication delay of final financial data.

Interestingly, we find that Confidence Indicators (8%), Trade Expectations (10%), Asset Prices (10%), Demand Expectations (11%) and Economic Situation Expectations (12%) tend to behave most as coincident indicators of the growth-cycle recessions.

Focusing on accuracy, Tables 2 and 3 reveal that the composite indicators tend to present the highest proportions of variables with significant signals of recession in more than one year of the periods prior to the beginning of a growth-cycle recession. Among the single leading indicators, those with highest degree of accuracy are the Real Quantitative Indicators, especially the indicators related to trade, demand and employment.

Within the group of Monetary and Financial indicators, variables related to credit provide the most consistent and accurate classifications of the growth cycle. Among others, Gourinchas and Obstfeld (2012) and Gersl and Jasova (2017) also find that credit variables provide accurate signals at anticipating banking and financial crisis.

It is worth pointing out the lack of relevance of Monetary Aggregates as leading indicators of growth-cycle recessions. In line with the results of Estrella and Mishkin (1998) and Berge (2015), we find that only 17% of these indicators lead the recessions with an average lead time of only 2 months. In addition, we fail to find a good performance of asset prices as leading indicators of expansions and recessions, which is in line with the results of Burgstaller (2002).

Let us make one final remark on the relative performance of the composite leading indicators with respect to the single indicators. In terms of accuracy, we find that composite indicators tend to be more accurate than most single indicators. In line with this finding, the Conference Board´s Business Cycle Indicators Handbook (2001) find that the composite indicators provide a better summary of the information of the economic development than the single indicators because they provide less volatile signals. In addition, Marcellino (2006) also find that the different features and sources of economic recessions can be better captured by composite indexes.

However, the composite leading indicators achieve their highest *AUROC* values either contemporaneously or within the first few months. In particular, only the trend-restored composite leading indicator's *AUROC* holds a relatively noticeable percentage of maximum AUROCs achieved at h_{ji}>0 with an average lead time different from 0 (average of 6 months). Therefore, although OECD Composite Leading Indicators behave accurately, they do not provide their most intensive signals at leading time horizons relative to some of their single components.

In terms of timeliness, this result agrees with the findings of other studies. Estrella and Mishkin (1998) find that spread yields provide better in-sample and out of sample forecasts than the Conference Board Composite Leading Indicator (CBCLI) and the composed index developed by Stock and Watson (1989). Dueker (1997) find similar insights regarding the forecasting performance of the US yield slope over CBCLI. Finally, Qi (2001) finds that although CBCLI outperforms interest spreads at one-quarter-ahead forecast horizon, the latter does it better from two-quarter-ahead to six-quarter-ahead horizons.

3.3. Growth cycle chronology: OECD vs non-OECD countries

In this section, we develop a comparative assessment of the classification performance of OECD's main economic indicators for OECD members with respect to non OECD members, with the help of Tables 4 to 7. Regarding timeliness, the leading indicators of OECD countries exhibit the same leading properties than non-OECD countries. By contrast, their accuracy at anticipating growth cycles falls from 77% for OECD members to 62% for non-OECD members.

This result is mainly driven by the poor performance of indicators based on surveys, whose accuracy falls from 76% in OECD countries to 53% in non-OECD countries. As pointed out by Curtin (2004), despite the efforts undertaken by OECD to improve the sentiment indexes in non-OECD countries, it seems that there are still ways of improvements in computing their surveys-expectations indicators.

Another significant difference between the relative performance of the main economic indicators in OECD versus non-OECD countries, besides the higher accuracy of variables in the formers, is that all groups (Classification 1) present lower degrees of timeliness, with the exception of monetary variables.

3.3. Business cycle chronology: total sample

In the business cycle analysis, we are precluded from using the large sample of countries of the growth cycle analysis because the ECRI´s business cycle chronology is not available for most of these countries. In particular, this section focuses on Australia, Austria, Brazil, Canada, France, Germany, Italy, Japan, Korea, Mexico, New Zealand, Russia, South Africa, Spain, Sweden, Switzerland, the UK and the US.[3]

On average, OECD's leading economic indicators generate more timely and more accurate predictions of the business cycle than of the growth cycle. According to Table 2, as in the case of growth cycles, the indicators with higher timeliness are Monetary and Financial variables, being interest rates, spreads and credit the indicators on the top of the ranking. As in the case of the growth cycle analysis, Figure 2 suggests that many of the indicators contain valuable information to forecast business-cycle recessions at distant horizons.

Monetary and Financial ones register a slightly decreasing pattern as the forecasting horizon increases but the percentage of variables with *AUROCs* significantly higher than 0.5 start to steadily rise at one-year forecasting horizon. This is in line with previous studies that highlight the relevance of financial variables for predicting business cycle recessions at long horizons, such as Berge (2015) and Drechsel and Scheufele (2010).

In terms of accuracy, Real Quantitative Indicators exhibit again the larger percentages of variables providing *AUROCs* significantly greater than 0.5 for more than one year. However, there are two remarkably differences in business cycle analysis. The first difference is the much better performance of the indicators based on surveys (from 73% to 82%). This result is in line with the increasing role of survey indicators in forecasting the future economic developments. Some examples are as in Levanon (2010), García-Ferrer and Bujosa (2010), Christiansen, Eriksen and Möller (2014). This remarkably increase in accuracy percentages also holds for Monetary and Financial variables.

The second difference with respect to the growth cycle analysis is the much higher timeliness (keeping similar accuracy) of composite leading indicators at performing business cycle classifications. However, the composite leading indicators again fail to outperform some of their single components both in terms of accuracy and timeliness.

4. Conclusions

[3] Although ECRI develops the business cycle chronology in China, there is only one recession in the sample. India was also excluded from the business cycle analysis due to data availability restrictions. Data restrictions also precludes us from separating OECD and non-OECD countries.

There has been a recent upswing interest of using leading indicators for forecasting potential phase changes of the economic cycles. With the help of Receiver Operating Characteristic (ROC) techniques, this paper explores the effectiveness of the monthly OECD's Main Economic Indicators, which is one of the most important sources of worldwide comparable key economic statistics in providing early warning signals of recessions.

Our empirical results suggest that the OECD’s indicators show a high overall performance in providing early signals of economic downturns worldwide. However, our results also suggest some lines of improvements in the way OECD elaborates the leading indicators. First, despite the effort of OECD in the development of economic indicators in non-OECD members, the leading indicators perform worse in these countries, especially in terms of providing accurate signals of phase changes.

Second, we find that the composite leading indicators perform worse than some of their single component indicators, especially in the case of financial indicators, such as short-term interest rates, the term spreads and credit indicators.

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Table 1. Variable grouping.

Classification 1	Classification 2
Monetary and Financial Indicators	Inflation Monetary Aggregates Asset Prices Interest Rates Credit Trade Interest Rates Spreads
Real Quantitative Indicators	Trade Demand Production Employment
Surveys Indicators (BTS or CS)	Surveys-Economic Situation Expectations Surveys-Employment Expectations Surveys-Demand Expectations Surveys-Production Expectations Surveys-Confidence Indicator Surveys-Inflation Expectations Surveys-Trade Expectations

Notes. This table contains the two different divisions made in this paper

Table 2. Total sample, classification 1

	Growth cycles				Business cycles			
	Accuracy	Time	Lead	Max AUROC	Accuracy	Time	Lead	Max AUROC
CLI	84	17	2	0.70	81	31	1	0.76
Monetary and Financial	69	49	7	0.60	87	51	6	0.63
Real Quantitative	84	35	5	0.58	89	39	4	0.68
Surveys	73	20	3	0.65	82	20	2	0.77
Total Sample	75	24	3	0.64	83	27	3	0.75

Notes. For each group, accuracy shows the percentage of indicators with AUROC>0.5 for more than 12 out of the 20 months prior to the start of recessions. Time evaluates the timeliness as the percentage of indicators for which the AUROC maximizes a positive lead time, whose average is reported in column labelled as Lead. The averages of the maximum ROC curves appear in columns labelled as Max AUROC.

Table 3. Total sample, classification 2

	Growth cycles				Business cycles			
	Accuracy	Time	Lead	Max AUROC	Accuracy	Time	Lead	Max AUROC
y-o-y change CLI	84	21	0	0.78	94	50	1	0.91
Amplitude adjusted CLI	100	5	0	0.75	83	22	0	0.83
Normalized CLI	100	5	0	0.74	83	22	0	0.83
Trend-restored CLI	50	37	6	0.54	61	28	4	0.50
Inflation	81	70	12	0.56	90	40	8	0.64
Monetary aggregates	58	17	2	0.56	50	50	4	0.60
Asset prices	63	10	1	0.63	85	15	1	0.63
Interest rates	65	92	17	0.55	86	86	16	0.50
Credit	100	50	9	0.54	100	100	20	0.66
Spreads	75	75	3	0.72	93	86	6	0.82
Trade	84	43	5	0.58	100	60	7	0.61
Demand	84	16	2	0.59	91	17	0	0.72
Production	79	42	6	0.56	88	47	6	0.61
Employment	83	72	11	0.61	82	55	6	0.72
Economic situation	75	12	1	0.66	89	17	1	0.80
Employment expectation	72	18	2	0.64	82	18	2	0.77
Demand expectation	74	11	1	0.67	78	12	0	0.81
Production expectation	73	43	6	0.65	88	47	6	0.61
Confidence	70	8	1	0.67	87	9	0	0.81
Inflation expectation	74	31	5	0.56	71	23	3	0.60
Trade expectation	74	10	2	0.67	72	17	0	0.65
Total Sample	75	24	3	0.64	83	27	3	0.75

Notes. See notes of Table 2.

Table 4. OECD countries, classification 1

	Growth cycles			
	Accuracy	Time	Lead	Max AUROC
CLI	84	18	2	0.71
Monetary and Financial	69	49	7	0.60
Real Quantitative	84	36	5	0.59
Surveys	76	20	3	0.65
Total Sample	77	24	3	0.65

Notes. See notes of Table 2.

Table 5. OECD countries, classification 2

	Growth cycles			
	Accuracy	Time	Lead	Max AUROC
y-o-y change CLI	81	19	0	0.77
Amplitude adjusted CLI	100	6	0	0.76
Normalized CLI	63	6	0	0.75
Trend-restored CLI	83	41	6	0.54
Inflation	65	75	13	0.56
Monetary aggregates	75	20	2	0.56
Asset prices	77	10	1	0.63
Interest rates	60	90	16	0.55
Credit	100	50	9	0.53
Spreads	100	71	4	0.71
Trade	76	35	3	0.58
Demand	85	18	2	0.59
Production	53	46	6	0.57
Employment	83	72	11	0.61
Economic situation	84	13	1	0.66
Employment expectation	78	18	2	0.64
Demand expectation	76	10	1	0.67
Production expectation	53	46	6	0.57
Confidence	75	6	1	0.67
Inflation expectation	75	31	5	0.57
Trade expectation	71	9	1	0.68
Total Sample	77	24	3	0.65

Notes. See notes of Table 2.

Table 6. Non OECD countries, classification 1

	Growth cycles			
	Accuracy	Time	Lead	Max AUROC
CLI	83	13	1	0.69
Monetary and Financial	70	52	9	0.62
Real Quantitative	86	29	4	0.55
Surveys	53	19	2	0.65
Total Sample	62	24	3	0.64

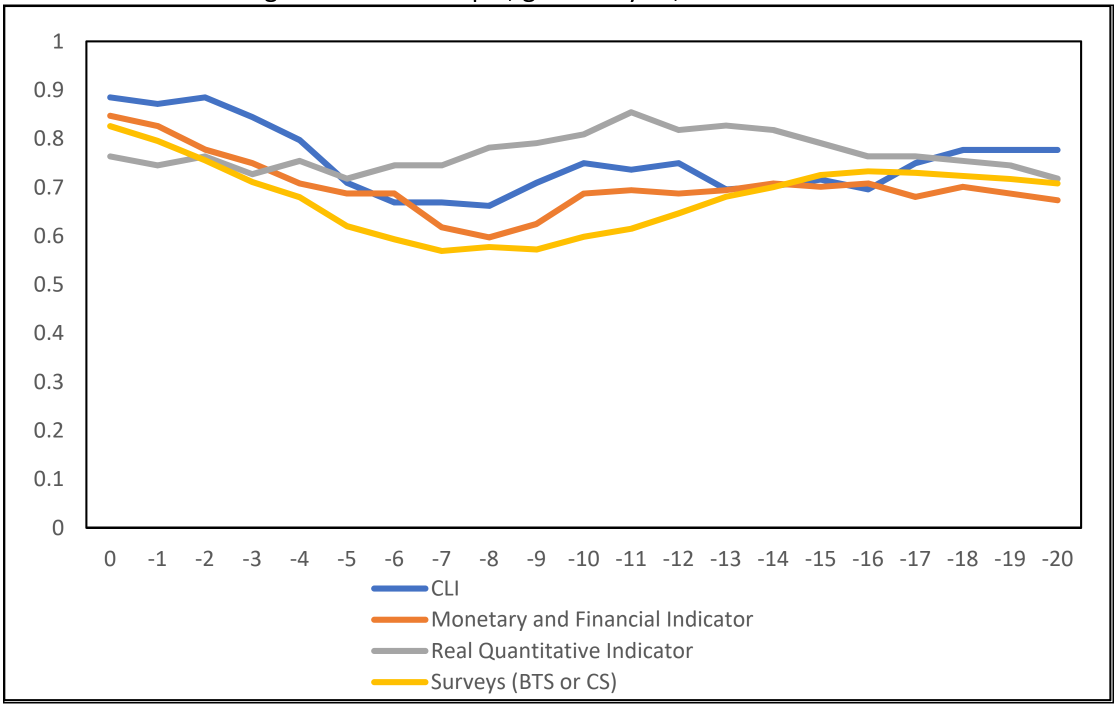
Notes. See notes of Table 2.

Table 7. Non OECD countries, classification 2

	Growth cycles			
	Accuracy	Time	Lead	Max AUROC
y-o-y change CLI	100	33	1	0.80
Amplitude adjusted CLI	100	0	0	0.71
Normalized CLI	100	0	0	0.71
Trend-restored CLI	33	17	3	0.53
Inflation	67	33	6	0.63
Monetary aggregates	50	0	0	0.54
Asset prices	63	13	3	0.68
Interest rates	67	100	19	0.56
Credit	-	-	-	-
Spreads	100	100	3	0.81
Trade	83	83	13	0.54
Demand	80	0	0	0.62
Production	100	20	4	0.50
Employment	-	-	-	-
Economic situation	56	6	0	0.57
Employment expectation	46	23	2	0.63
Demand expectation	47	18	1	0.69
Production expectation	52	30	2	0.64
Confidence	44	15	1	0.68
Inflation expectation	100	29	3	0.50
Trade expectation	60	20	4	0.58
Total Sample	62	24	3	0.64

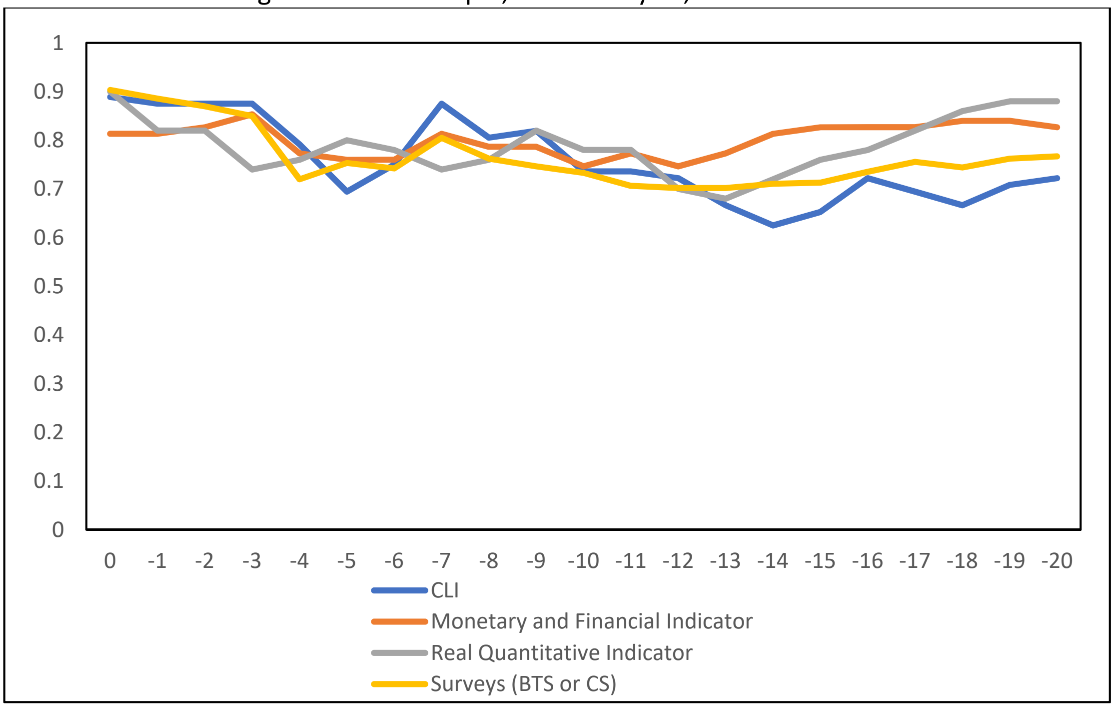
Notes. See notes of Table 2.

Figure 1. Total Sample, growth cycle, Classification 1.



Notes. The figure plots the percentage leading indicators for which the null of AUROC=0.5 is rejected against the alternative of AUROC>0.5 across horizons 0,1,...,20.

Figure 2. Total Sample, business cycle, classification 1.



Notes. The figure plots the percentage leading indicators for which the null of AUROC=0.5 is rejected against the alternative of AUROC>0.5 across horizons 0,1,...,20.