Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

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To cite this article: Filip Bašić & Tomislav Globan (2023) Early bird catches the worm: finding the most effective early warning indicators of recessions, Economic Research-Ekonomska Istraživanja, 36:1, 2120040, DOI: 10.1080/1331677X.2022.2120040

To link to this article: https://doi.org/10.1080/1331677X.2022.2120040

Published online: 16 Sep 2022.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2023, VOL. 36, NO. 1, 2120040
https://doi.org/10.1080/1331677X.2022.2120040

Early bird catches the worm: finding the most effective early warning indicators of recessions

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ABSTRACT
The paper examines whether certain macrofinancial indicators can be used for early detection of recessions. Analysing a sample of small open economies from Central and Eastern European Union, we first identify the most important indicators used for early detection of recessions, and then test the validity of the selection by using the signal method and multivariate probit regressions. Our results imply that the most effective predictors of upcoming recessions are the slope of the yield curve, current account balance to GDP ratio, real estate price index, self-financing ratio of commercial banks, nominal effective exchange rate, global exports and LIBOR rate. Using the Mann-Whitney U Test, we also find that foreign indicators emit earlier signals of incoming recessions in analysed countries than domestic ones. This type of research is important because of the various stakeholders that base their decisions on the signals provided by these indicators. Primarily, these are various government agencies that participate in monetary and fiscal policy making. Early warning of an impending recession allows economic policy makers to take corrective action to avoid a recession or to significantly mitigate its effects, while unreliable indicators may lead to adoption of unnecessary measures with adverse effects on the economy.

ARTICLE HISTORY
Received 17 November 2021
Accepted 25 August 2022

KEYWORDS
Early warning signals; Mann-Whitney U Test; recession forecasting; Central and Eastern EU; signal method; yield curve

JEL CODES
F40; F44; F47

1. Introduction

By recognizing an impending recession early, policy makers may be in a better position to shorten its duration and mitigate its effects by using monetary and fiscal policies in a timely manner. Numerous researchers have thus recently focused on discovering various indicators that could be used for early signalling of incoming recessions. These often include complex ratios of specific economic variables, but also some simpler indicators based on the monitoring of individual financial and macroeconomic variables, such as the analysis of monetary aggregates. For an indicator to be effective in early recession signalling, it is necessary that in a certain period before

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the onset of a recession it signals the possibility of an impending recession. This period is called the 'signal horizon' and can vary from one to two years before the onset of the recession (Ahec-Šonje, 1999).

Given that the last several decades have witnessed various financial crises and recessions in developed and developing countries, international financial institutions have begun to develop early warning systems to identify the weaknesses in economies on time and anticipate such events (Bussiere & Fratzscher, 2006). Caggiano et al. (2014) defined early warning systems as models that warn of the risk of a recession or a financial crisis by using specific theoretical and empirical analyses. Early warning systems may differ in the definition of a recession, the frequency of model updates, the statistical methods used, the selection and the number of indicators (Lestano et al., 2003), as well as the purpose of their use. For example, Babecky et al. (2012) note that there are models for predicting recessions, currency crises, banking crises, and public debt crises. The International Monetary Fund and the Financial Stability Board use the Early Warning Exercise (EWE) indicator to identify macrofinancial weaknesses and risks in global systems (International Monetary Fund, 2010; Momani et al., 2013). The U.S. Fed uses the Recession Probability Model (RPM) to estimate the likelihood of a recession occurring in the United States over the next twelve months (FED, 2019). Similar forecasting models are used by the UK Ministry of Finance, London Business School, National Institute of Economic and Social Research (NIESR), National Association for Business Economics (NABE), Bloomberg, etc. (Altshuler et al., 2016; National Association for Business Economics [NABE], 2019; Pickert et al., 2019).

Analysing a sample of small open economies of Central and Eastern European Union (the so-called 'New Europe', or CEEU), this research aims to answer the question of whether certain macrofinancial indicators can be used for early detection of recessions, and if so which. We also aim to measure the relative importance of domestic versus foreign indicators in predicting recessions and compare the obtained results with existing analyses that focused on more developed economies. Looking into this problem is important because of the various stakeholders whose decision-making process may be influenced by the existence of early warning signals emitted by some indicators. These include various policy makers, central banks, government agencies and institutions that can mitigate the effects of a recession by adopting various counter-cyclical measures. On the other hand, unreliable indicators can lead to wrong decisions that may adversely affect the economy as a whole. Also, the use of indicators for early detection of recessions is important for companies in the business sector, especially for the creation of medium-term plans and strategies.

Despite the progress and development of research in this area, prompted by numerous theoretical and empirical studies, the global recession of 2008-09 showed that there is significant room for further development (Babecky et al., 2012). In this paper we aim to identify the most important financial and macroeconomic indicators that may serve for early detection of recessions and aim to determine the level of their validity. The analysis is conducted on a sample of 11 small open CEEU countries (Bulgaria, Croatia, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovakia, and Slovenia).

The paper also compares the effectiveness of specific groups of indicators, i.e. we test whether domestic or foreign variables are the ones that generate signals more accurate or earlier than the other group. This is especially important for small open economies like the ones in our sample, given that their macroeconomic dynamics are very often primarily affected by foreign variables out of their control (Globan, 2015). We also aim to precisely determine the turning points of business cycles and date the occurrence and duration of recessions in the analysed group of countries. Due to its extraordinary nature and unprecedented abruptness, the period of the most recent recession caused by the coronavirus pandemic and consequential world-wide lockdown measures is not included in the analysis. These types of recessions can be viewed as exogenous shocks to the economy, not characterised by the emission of early warning signals by macrofinancial indicators.

The vast majority of the existing literature has focused on the performance of indicators in the most developed countries, mainly the United States (Mastromarco et al., 2021), primarily due to the availability of financial and macroeconomic data for a longer period of time. Some authors decided to analyse the indicators on the sample of one country or on a small sample of similar countries from a particular region. On the other hand, several papers dealing with a large number of countries from around the world are most often characterised by a relatively small number of indicators included, due to the data availability issues. Small open CEEU economies have mostly been overlooked in these types of analyses, probably due to data availability issues. However, enough time has now passed to collect longer, more robust datasets to perform econometric analysis for this group of countries as well. This paper aims to fill this gap and contribute by investigating whether the economic specificities and idiosyncrasies of countries in question affect the predictive power of individual indicators, as well as whether certain indicators signal incoming recessions better or worse than in developed countries. Also, the existing research has not focused particularly on how early certain indicators emit the initial recession signals, nor if there are differences between specific groups of indicators. Thus, the important contribution of this paper is reflected in the analysis of the relative effectiveness of domestic vs. foreign indicators in early recognition of recessions.

The paper is structured as follows. The following chapter focuses on the methodology used to measure the effectiveness of indicators to predict recessions – the signal method and multivariate probit regressions. The third chapter focuses on the data, variable selection and determining business cycle turning points. Chapter 4 reports the results obtained by econometric analysis and identifies key macrofinancial indicators that are most effective in early signalling of recessions. The final chapter discusses the policy implications as well as the limitations of the study and offers concluding remarks.

2. Methodology

Following Krznar (2004) and Manasse et al. (2003) we combine two main methods in our empirical approach: the signal method and probit regressions. First, we use the signal method to determine the accuracy of all analysed indicators that may signal an impending recession. Then we single out several of the most accurate indicators and include them into the probit model to test their validity. Both methods will be explained in this section.

2.1. The signal method

The signal method is based on the notion that recessions usually do not occur suddenly 'out of thin air', but are rather preceded by certain disturbances in the economy (Brüggemann & Linne, 1999). The signal method is a non-parametric method that analyses the movement of an individual indicator before and during a recession. If the value of a certain indicator exceeds the critical value, it is considered it has emitted a signal. Similarly, if the critical value is not exceeded, it is considered that the indicator has not emitted a signal (Kaminsky et al., 1998). A signal is considered correct if it occurs in the period from one to two years before the onset of a recession. Assume that X is a specific indicator for predicting recessions. According to Edison (2003), we say that X emitted a signal in period t if in that period its value exceeded the critical value of X^*. The state with an emitted signal is defined as:

$$(St = 1) \;\; if \;\; (|X_t| > |X^*|) \tag{1}$$

If X has not exceeded the critical value X^*, it is considered that a signal has not been emitted:

$$(St = 0) \;\; if \;\; (|X_t| \leq |X^*|). \tag{2}$$

It should be noted that for some indicators it is considered that a signal was emitted if the critical value is exceeded, while for others the situation is reversed, i.e. the signalling occurs if it falls below the critical value. Therefore, the above conditions are expressed in absolute values.

In order to determine the accuracy of an individual indicator, it is necessary to determine (Kaminsky et al., 1998; Kaminsky & Reinhart, 1999): A - the number of months in which the signal appeared before the onset of a recession; B - number of months in which the signal appeared and no recession occurred; C - number of months in which no signal appeared before the onset of a recession; D - number of months in which no signal appeared and no recession occurred.

It is possible to calculate several measures to determine the performance of an indicator. For instance, it is possible to calculate indicator's recall, i.e. the ratio of accurate signals in the event of a recession in the total number of predictions in periods ending in a recession, using the formula $A/(A+C)$ (Wang et al., 2022). Applying this formula, the most effective indicator would be the one that emits signals of an impending recession each month within the signal horizon, so that: $A/(A+C)=1$ or $C=0$.

Similarly, it is possible to calculate the ratio of false signals in the total number of predictions in periods that do not end in a recession, expressed as $B/(B+D)$. In this case, the indicator would be of better quality if the ratio of false signals is as low as possible because it would mean that it produced fewer false signals in periods that do not end in a recession (Ahec-Šonje & Babić, 2002).

The key measure used to determine the accuracy of an indicator in the signal method, which will also be used in this paper, is the noise-to-signal ratio or the measure of signal error (ω). It is calculated using the previously mentioned measures, i.e. as the ratio of the share of incorrect signals and the share of correct signals (Padhan & Prabheesh, 2019):

$$\omega = \frac{B/(B+D)}{A/(A+C)}. \tag{3}$$

A particular indicator is thought to be more accurate the lower its signal error is (Kaminsky et al., 1998). A perfect indicator would only lead to situations A and D and its measure of signal error would be zero. In case the share of false signals in normal periods (periods not followed by a recession) is higher than the share of correct signals within the signal horizon, the measure of signal error becomes greater than one and should be discarded (Boonman et al., 2019). Building on the signal error, Alessi and Detken (2011) suggest minimizing the loss function of the government:

$$\mathrm{L} = \theta \frac{C}{A+C} + (1-\theta) \frac{B}{B+D} \tag{4}$$

By determining the parameter θ, which represents a relative risk aversion between type one errors (signal not emitted before a recession) and type two errors (signal emitted without the onset of a recession), identification of the optimal critical value of an indicator can be made by making a trade-off between type one and type two errors (Ferrari & Pirovano, 2015). If θ has a value higher than 0.5, this means that the government is more averse towards missing a signal which could predict a recession than towards receiving a false signal which would lead to unnecessary corrective actions, and vice versa (Alessi & Detken, 2011). If we assume that the government may always record a minimal loss of {(1 - θ); θ} without using the early warning indicators (the government either expects that a signal always appears or that it never appears), an indicator's utility may be defined as (Duca & Peltonen, 2013):

$$U = \min\{(1-\theta); \theta\} - \mathrm{L}(\theta) \tag{5}$$

If the utility is positive, it can be concluded that there is a good reason to use the proposed measure for early detection of recessions.

Wang et al. (2022) propose three additional measures for calculating the performance of indicators. Thus, the precision can also be assessed by comparing a signal-induced recession, $A/(A+B)$, while accuracy can be calculated as:

$$Accuracy = \frac{A+D}{A+B+C+D}. \tag{6}$$

The third measure, the F1 Score which works better in an uneven class distribution like the recession, allows calculating the harmonic average between the precision and the previously mentioned recall of an indicator:

$$F1\ \ Score = 2\ X\frac{\left(\frac{A}{A+C}\right)X\ \left(\frac{A}{A+B}\right)}{\left(\frac{A}{A+C}\right)+\ \left(\frac{A}{A+B}\right)}. \tag{7}$$

Another approach is to use a measure of signal stability (Ahec-Šonje & Babić, 2002), which is basically the inverse of the measure of signal error given in (3). For higher signal stability in pre-recession periods, it is assumed that the indicator is of better quality, i.e. that it anticipates the incoming recession better. On the other hand, Kaminsky et al. (1998) note that when determining the effectiveness of an indicator, it is desirable to calculate the percentage of correctly predicted recessions, i.e. the share of the number of recessions for which the indicator emitted at least one signal within the signal horizon in the total number of recessions.

Since it does not matter whether a particular indicator emits the first signals 18 months or only two to three months before the onset of a recession, the quality of a particular indicator can also be assessed using the forecast period. This measure determines how many months before the outbreak of a recession a certain indicator has generated the first signal. An indicator that emitted an earlier signal is considered better than those that emitted signals later on (Ahec-Šonje & Babić, 2002).

To know whether an indicator generated a signal at a certain moment, it is necessary to determine its critical value. Determining critical values depends on three different factors. The first factor is based on the probabilities of type one and type two errors. By setting a higher critical value that needs to be exceeded to generate a signal, there is a higher probability for a type one error and a lower probability for a type two error (and vice versa). The second factor is based on the unconditional probability of a recession, i.e. if recessions occur frequently, the probability for a type one error will be high (and vice versa). The last factor focuses on government agencies and compares the cost of taking preventive measures versus the cost of failing to predict a recession. Thus, government agencies that overestimate the cost of preventive measures or underestimate the cost of a recession will decide to set a higher critical value that needs to be exceeded in order to generate a signal (Demirgüç-Kunt & Detragiache, 2000).

In the literature, three methods are most often used to determine critical values in the signal method: the use of percentile measures (Ahec-Šonje & Babić, 2002), minimization of the signal error (Edison, 2003; Krznar, 2004; Schardax, 2002) and the use of standard deviations (Edison, 2003). These procedures are relatively simple when used on a single country. However, if a critical value is determined for a set of multiple countries, as is the case in this paper, then it is necessary to determine the range of critical values to take into account the specifics of individual countries. Brüggemann and Linne (1999) solved this problem by determining the critical values of a particular indicator separately for each country. A different approach mentioned in Edison (2003) is to determine the critical values relative to the percentile of distribution for each country. For example, if the optimal value for a given indicator is the tenth percentile, then the tenth percentile of distribution is taken for each country.

Thus, the actual critical values differ between countries, but the percentiles are identical.

The signal horizon is the period before the onset of a recession within which the indicator should emit its signal of an impending recession. There is no one-size-fits-all solution to how long the signal horizon period should be, but it most often depends on the researcher's own assessment. According to empirical results of other papers, Kaminsky et al. (1998) concluded that signals most commonly occur between 12 and 24 months before the onset of a recession. If signals are generated too early, there is a question of their actual connection to the incoming recession. On the other hand, if they appear too late, their usefulness decreases because it makes more difficult for the government to take adequate pre-emptive corrective action (Schardax, 2002).

Since most authors use signal horizons from one to two years long, in this paper the cut-off is set at six quarters, i.e. 18 months before the outbreak of a recession. One of the justifications for the use of 18 months is the work of Fendel et al. (2018) who analysed the indicators for early detection of recessions in the Eurozone and found that the signal horizon of 18 months shows a certain decline in the precision of indicators based on industrial data when compared to the signal horizon of 12 months. However, the financial indicators achieve excellent results with the horizon of 18 months. On the other hand, with a 24-month signal horizon, most of the analysed indicators proved to be too unreliable due to the large number of false signals. Therefore, the signal horizon will be set at 18 months because there is no significant degradation of results compared to 12 months, and a longer period significantly helps the policy makers to be more effective in preventing possible recessions (Brüggemann & Linne, 1999). This adequately balances the trade-off between proving the connection between an indicator and the recession and the need for the policy makers to act counter-cyclically early enough before the actual recession hits.

2.2. Probit regressions

Probit, together with logit models are often used to estimate the probability of a discrete dependent variable's connection to an independent variable. The dependent variable assumes a value of one (recession) or zero (no recession). At the same time, the model tells us which independent variables have sufficient power to predict the onset of future recessions (Bucevska, 2011). They also allow for testing of their significance while taking into account their cross-correlations (Bruns & Poghosyan, 2018).

According to Hyden and Porath (2011), these models assume a latent variable y^* of the following form:

$$y_i^* = \beta' \cdot \mathrm{x_i} + \mathrm{u_i}. \tag{8}$$

The variable y_i^* is metrically scaled and takes the value of the binary variable y_i:

$$yi = \begin{Bmatrix} 1, & if\ \ yi_{\mathrm{i}}^{\Theta} > 0 \\ 0, & otherwise \end{Bmatrix}. \tag{9}$$

This means that an event has occurred when the latent variable exceeds the threshold of zero. Therefore, the possibility of a given event occurring is equal to:

$$P(y_i = 1) = P\left(u_i > -\ \beta' \cdot x_i\right) = 1 - \mathrm{F}\left(-\ \beta' \cdot \mathrm{x_i}\right) = \mathrm{F}(\beta' \cdot \mathrm{x_i}) \tag{10}$$

where F(.) denotes an (unknown) distribution function that is assumed to have a symmetric density around zero. The choice of the distribution function F(.) depends on the assumptions of the distribution of the residual u_i. If a normal distribution is assumed, a probit model will be used:

$$\mathrm{F}\ (\beta'\ \cdot\ x_i) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\beta'\ \cdot\ x_i} e^{\frac{-t^2}{2}} dt. \tag{11}$$

Typically, probit and logit models used to predict recessions employ lagged variables because it is assumed that it takes some time for adverse dynamics in key parts of the economy to manifest in the form of a recession. Also, without using the lagged variables, it would be difficult to determine causality, that is, whether adverse effects in key parts of the economy led to a recession or vice versa (Brüggemann & Linne, 1999).

In this paper we use a multivariate probit model in which the dependent variable assumes a value of 1 if a recession occurs in the following 18 months, and −1 otherwise. This approach follows the work of Berg and Pattillo (1999) and Chu (2021), but differs in the length of the signal period. However, a value of −1 was used instead of 0 for periods without a recession occurring to enable the employment of the Pesaran-Timmermann test and to give a clear threshold for moving from one state to another. If the dependent variable has a positive value, then a recession is expected in the following 18 months, and vice-versa if it has a negative value. Given that the logit model is more practical for larger samples (over 500), we employ a probit model, more commonly used for smaller samples (Cakmakyapan & Goktas, 2013).

Furthermore, to determine if foreign indicators emit earlier recession signals, the Mann-Whitney U Test will be used. This is a non-parametric test without a predetermined structure of the model, but is rather determined according to the data. The term non-parametric does not imply the absence of parameters but the fact that the parameters are flexible and not predetermined. This test was independently developed by Mann and Whitney (1947) and Wilcoxon (1945).

The null hypothesis of the Mann-Whitney U test claims that two independent sets are homogeneous and have identical distributions (Nachar, 2008), while the alternative is that variables have stochastically higher values in one of the sets. To reject the null hypothesis, the calculated z-value (z^*) must be greater than the critical z-value (z_α) at the 1% significance level:

$$\begin{aligned} \mathrm{H_0} &: \ \mathrm{p}(\mathrm{x_i} > \ \mathrm{y_i}) \ = \ 1/2 \rightarrow \mathrm{z}* \ \leq \ \mathrm{z}_\alpha \\ \mathrm{H_1} &: \ \mathrm{p}(\mathrm{x_i} > \ \mathrm{y_i}) > 1/2 \rightarrow \mathrm{z}* \ > \mathrm{z}_\alpha \end{aligned} \tag{12}$$

where x_i represents a variable from the first set and y_i from the second set.

3. Data

3.1. Variable selection

To determine which indicators can be used in the analysis, it is necessary to first determine the availability of data. The analysis is conducted on a sample of 11 small open CEEU countries (Bulgaria, Croatia, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovakia, and Slovenia). The data are taken from the databases of national statistical offices, central banks and international organizations such as the Eurostat, the International Monetary Fund (International Financial Statistics database), the OECD or specialised web services such as Investing.com (2021).

A significant limiting factor was the relatively short time period for most of the required variables. For the successful implementation of the research, it is necessary that the data cover at least the year 2006 in order to be able to analyse the signal period before the global recession in 2008. Murgasova (2005) also highlights the issue of short time series for macroeconomic variables in the new members of the European Union, which prevents the implementation of more in-depth analyses.

All variables included in our analysis are listed in the online Appendix in Table A1. Variables that were reported in domestic currencies were converted to euros using the average monthly exchange rates of a particular local currency against the euro.

Variables that were available only on a quarterly basis were converted to monthly frequencies using the cubic spline interpolation method. Numerous economists have used it to convert quarterly data to monthly, especially GDP (e.g. Coorey et al., 2005; Stuart, 2018). Additionally, the interpolated quarterly values for GDP and gross national savings were divided by three to obtain the corresponding monthly values.

Certain indicators could not be included in the model because there is no available data at all, or the time series are not long enough to cover the period just before the 2008-09 global recession. One of the main criteria used in the selection of indicators is their frequency of occurrence in the literature. Repetition of relatively similar indicators was avoided. Considering the above criteria, 44 indicators were selected for the analysis, of which the equal number of financial and macroeconomic indicators. Selected indicators are shown in Table A1 in the online Appendix, together with a description of their calculation and an indication of whether they belong to the group of domestic (34) or foreign (10) indicators.

3.2. Identifying recession periods

Data on seasonally adjusted real GDP (2010 prices) taken from the Eurostat (2021) database were used to determine the periods of recessions in analysed countries. Quarterly data for the period from 1995:Q1 to 2019:Q4 were taken, except for the Czech Republic and Croatia, where the data start from 1996:Q1 and 2000:Q1, respectively. In the analysed group of countries, the total of 28 recessions occurred in the observed period, with an average duration of five and a half quarters. At the same time, several countries experienced the shortest duration of only two quarters, while

Table 1. Recession periods in CEEU economies.

Country	Analysed period	Quarterly CAGR	Recession periods	No. of quarters in a recession
Bulgaria	Q2 1995 – Q4 2019	0.69%	Q2 1996 – Q4 1999 Q1 2009 – Q4 2009 Q2 2012 – Q4 2012	22
Czech Republic	Q1 1996 – Q4 2019	0.62%	Q1 1997 – Q4 1997 Q4 2008 – Q2 2009 Q1 2012 – Q1 2013	12
Estonia	Q2 1995 – Q4 2019	0.98%	Q2 1995 – Q3 1995 Q2 1998 – Q1 1999 Q4 2007 – Q1 2008 Q4 2008 – Q3 2009 Q2 2013 – Q4 2013	15
Croatia	Q2 2000 – Q4 2019	0.46%	Q3 2008 – Q4 2012 Q3 2013 – Q3 2014	23
Latvia	Q2 1995 – Q4 2019	0.93%	Q1 1996 – Q2 1996 Q2 1998 – Q2 1999 Q2 2008 – Q3 2010	17
Lithuania	Q2 1995 – Q4 2019	1.03%	Q3 2008 – Q4 2009	6
Hungary	Q2 1995 – Q4 2019	0.63%	Q2 1996 – Q3 1996 Q1 2007 – Q2 2007 Q3 2008 – Q1 2010 Q1 2012 – Q2 2012	13
Poland	Q2 1995 – Q4 2019	1.01%	Q1 2001 – Q2 2001	2
Romania	Q2 1995 – Q4 2019	0.77%	Q1 1997 – Q2 1999 Q4 2008 – Q3 2010	18
Slovakia	Q2 1995 – Q4 2019	0.92%	Q1 1999 – Q4 1999 Q4 2012 – Q1 2013	6
Slovenia	Q2 1995 – Q4 2019	0.66%	Q3 2008 – Q1 2010 Q2 2011 – Q4 2012	14

Source: authors' calculations.

the longest recession was recorded in Croatia, lasting 18 quarters. The analysis also showed that in the whole sample, recession occurred in 13.9% of the observed quarters.

Table 1 shows the identified periods of recessions in the analysed group of countries. The third column shows the average quarterly growth rate (CAGR) for each country. The highest average quarterly growth rates were achieved by Lithuania (1.03%), Poland (1.01%), Estonia (0.98%), Latvia (0.93%) and Slovakia (0.92%), while the lowest growth rate was in Croatia (0.46%). This can be attributed to the fact that Croatia was in a recession for the largest number of quarters (23), which is particularly worrying given that that country had the shortest time period included in the analysis. Periods of recession have been identified using the conventional method, according to which the economy is in a recession if GDP falls in two consecutive quarters (Hansen, 2022).

4. Results

4.1. Macrofinancial indicators as predictors of recessions

The signal method is first used to determine the accuracy of each indicator in the model. The approach used by Edison (2003), and Schardax (2002) to minimise measures of signal error of indicators in each individual country will be used to determine the critical values. The measure of the signal error will be calculated for the whole set of values for each country and the percentile where the measure of the signal error is the lowest will be selected as the critical one. It should be noted that for indicators with an upper limit (signal is generated when the indicator exceeds the critical value), values above the 90th percentile will be ignored because in that case the indicator generates too few signals. For the same reason, for indicator with a lower limit (signal is generated when the indicator falls below the critical value), values below the 10th percentile will be ignored. The implementation of this procedure for each country will determine the specific percentile for each indicator, which will represent the critical value at which the signal error measure is minimised.

Also, if in a given country the indicator values cover only a period that does not include a signal period (contains only situations B and D), then that country will be excluded from the analysis because it would not be possible to calculate an adequate signal error measure. Analysis for each selected indicator with the shares of correct and false signals, as well as the measures of signal errors is available upon request and is not included in the paper due to its voluminous output.

Using the signal method, we find that 11 indicators had a measure of signal error not higher than 0.4. These 11 indicators may be viewed as the most accurate (effective) ones in early prediction of impending recessions in the small open CEEU economies. These include (measures of signal error in brackets):

- slope of the yield curve on euro bonds (0.158)
- current account balance to GDP ratio (%) (0.198)
- real estate price index (0.307)
- yield on two-year treasury bills (0.339)
- self-financing ratio of commercial banks (0.352)
- money market interest rate (0.354)
- nominal effective exchange rate (0.374)
- ratio of bank deposits to GDP (%) (0.381)
- global exports (0.400)
- LIBOR (0.400)
- slope of the yield curve on treasury bills (0.402)

In the second part of the analysis, we test whether the identified most accurate indicators from the signal method are sufficiently reliable in early detection of recessions in the analysed group of EU countries. The multivariate probit regression and the Pesaran-Timmermann test will be used to that end. The test is used to estimate the direction of the changes in the observed dependent variable (Pesaran & Timmermann, 1992). For this reason, the dependent variable in the probit model will take the value of either −1 (no recession) or 1 (recession).

Given that data are not available for all analysed countries for some indicators, namely the yield on 2-year treasury bills, money market interest rate, bank deposit to GDP ratio, and slope of the yield curve on treasury bills, they will be omitted from the model. The model will thus include the remaining seven indicators from the list above.

Table 2. Results of the multivariate probit regression for seven selected indicators.

Dependent variable: Generated signal

Variable	Coefficient	p-value
constant	−3.351323	(0.0000)
Slope of the yield curve on euro bonds	0.081818	(0.0019)
Current account balance to GDP ratio (%)	−0.713593	(0.0000)
Real estate price index	0.006725	(0.0000)
Self-financing ratio of commercial banks	−2.455174	(0.0000)
Nominal effective exchange rate	0.020390	(0.0000)
Global exports	−0.000461	(0.7848)
LIBOR	0.100974	(0.000)
Number of observations	1,481	
Number of countries	11	
Number of periods	160	
R^2	0.167297	
F-test *p-value*	0.0000	

Source: authors' calculations.

Table 2 reports the results of the multivariate probit regression with seven selected indicators, using the least squares method. The obtained coefficient signs are in line with expectations, given that the indicators with an upper limit for signal generation have a positive sign, and those with a lower limit have a negative sign. The only exception is the indicator of the slope of the yield curve on euro bonds, but this is acceptable because its sign is not ex-ante theoretically determined. A certain problem occurs with a high p-value for the global exports indicator as it indicates that it is not significant at usual levels of significance. However, when we remove global exports from the model, there is no change in the significance of other variables nor a significant decrease in the value of R^2.

To test whether the used probit model is well identified, it is necessary to determine its prognostic power. One of the best ways is to compare the estimated values of the dependent variable with the actual value. Therefore, the Pesaran-Timmermann test will be used, which evaluates the prognostic success of a certain model against the null hypothesis that model estimates are not better than random guessing. For more technical details on the Pesaran-Timmermann test see Pesaran and Timmermann (1992).

Using the estimated coefficients from Table 2, the estimated value of the dependent variable is calculated for all 1,481 observations. These values are then compared to the actual value of the dependent variable (-1 or 1). We obtain a Pesaran-Timmermann test value of 14.0534 that is greater than the critical value of the chi-square distribution for one degree of freedom (6.6349), at the 1% level of significance. Therefore, we can reject the null hypothesis and accept the assumption that our model is useful for early detection of recessions, i.e. that there is an interdependence in the movements of the selected macrofinancial indicators and the emergence of recessions.

As mentioned earlier, in the estimated probit model the global exports indicator is statistically insignificant. Therefore, a probit model without the specified indicator was estimated for additional robustness testing, and the main hypothesis was tested by re-applying the Pesaran-Timmermann test, but the results, available upon request, remain unchanged.

Table 3. Comparison of the signalling moment in foreign vs. domestic indicators.

Type of indicator	Number of indicators	Number of observations	Min	Max	Average	Standard deviation
Foreign	10	252	0	18	13.48809	6.339959
Domestic	34	675	0	18	11.83111	7.524515

Source: authors' calculations.

4.2. Accuracy of domestic vs. foreign indicators

In this part we compare and test the accuracy of domestic versus foreign indicators as predictors of recessions in a selected group of countries. Given that the CEEU countries are largely dependent on their trading partners and that many of their recessions have occurred as a result of serious disturbances in the global or European market, the initial hypothesis is that foreign indicators detect global disturbances before they become manifested in domestic indicators. Foreign indicators include various variables related to a particular region (for example Europe) or the world as a whole, while the domestic indicators include only country-specific variables.

To test this hypothesis, each indicator was analysed separately and for the signal periods of all countries (if there are data) it was determined how many months before the onset of the recession the first signal was generated. Only the recession in Estonia between Q2 and Q3 of 1995 was left out of the analysis because it was at the very beginning of the analysed period and there was no signal period captured before it started. Table 3 shows that the group of domestic indicators consists of 34 variables and 675 observations (signal generation time), while the group of foreign indicators consists of 10 variables and 252 observations. In both groups there were signal periods where signals were absent, but also those in which the signal was generated immediately at the beginning of the signal horizon. It is also evident that, on average, the moment of the first signalling comes slightly earlier with foreign indicators (13.488) than with domestic ones (11.831) and that the dispersion of results is slightly lower for the former group (6.340 vs. 7.525, respectively).

The hypothesis of foreign indicators emitting earlier recession signals can also be tested by using the one-way Mann-Whitney U Test. This test has been chosen because it has superior power compared to similar tests for heavy tailed distributions (Blair & Higgins, 1980), which is the case here where a large number of observations have values of 0 or 18. The Mann-Whitney U Test was performed on two previously mentioned datasets, one for domestic indicators which consists of 675 observations (signal generation time) and the other for foreign indicators which consists of 252 observations. The null hypothesis of the Mann-Whitney U test is that an observation (signal generation time) from the set of foreign indicators is equally likely to have a higher or lower rank than an observation from the set of domestic indicators. The alternative is that observation (signal generation time) ranks are stochastically higher in the set of foreign indicators.

Since the calculated z-value was 2.380, which is greater than the critical z-value (2.326), at the significance level of 1%, the null hypothesis can be rejected and the alternative hypothesis that foreign indicators generate earlier signals of impending recessions than domestic indicators can be accepted. The same conclusion about the rejection of the null hypothesis is indicated by the empirical level of significance (0.00865), which is lower than the theoretical level of significance at 1% ($\alpha = 0.01$).

5. Discussion and conclusions

The results presented in this study confirm that a number of macrofinancial indicators may be effectively used as early warning signals of impending recessions. Using the signal method, multivariate probit regressions and a number of additional tests on a sample of 11 small open EU economies, we find that the most important predictors of upcoming recessions are the slope of the yield curve, current account balance to GDP ratio, real estate price index, self-financing ratio of commercial banks, nominal effective exchange rate, global exports and LIBOR rate. This offers a wider set of variables with a high prediction power than obtained in previous research (e.g. Babecky et al., 2012). The finding that foreign indicators are more effective in catching early signals of recessions than domestic ones are consistent with the findings of Alessi and Detken (2011) and Babecky et al. (2012), who emphasize the importance of careful monitoring of foreign indicators to identify global risk factors in a timely manner, which provides the opportunity for the policy makers to take appropriate preventive counter-cyclical measures.

Given the policy makers' need to anticipate future economic conditions (Hasse & Lajaunie, 2022), our results may be of use to government agencies, central banks, and other policy makers in small open economies, who can use the results presented in this paper to focus their attention on a specific set of indicators that proved most effective in early detection of recessions. This may help them significantly mitigate the adverse effects of recessions. Closely monitoring the selected group of indicators may be of use for the business sector as well, to better anticipate future macroeconomic events and consequently adjust their medium-term plans and strategies. For example, for institutional investors, recognizing the turning points in business cycles is of paramount importance. By shifting investment from stocks to short-term bonds before the recession begins and back to stocks before the end of the recession, significant returns can be made. It is therefore not surprising that various economic agents invest significant resources in developing business cycle turning points models (Siegel, 2014).

As pointed out by Babecky et al. (2012), even belated signals can be useful to economic policy makers. Economic policy makers should use all available opportunities to identify vulnerabilities in the economy that can lead to recessions and, if possible, improve their tools to mitigate their effects (Abiad, 2003). As pointed out by Basu et al. (2017), it is possible even to use the models like those presented in this study to determine which sectors have historically been most responsible for increasing the vulnerability of the economy and, consequently, which sectors may need to be affected by certain preventive measures to reduce the risk of an onset of a recession.

The usefulness of indicators in early detection of recessions depends to a large extent on the preferences of economic policy makers in the trade-off between the possibility to fail to predict a recession and to act unnecessarily based on false signals. Alessi and Detken (2011) point out that central banks, as monetary policy makers, are more likely to miss a number of recessions than to react unnecessarily to possible false signals. In doing so, Abiad (2003) notes that the effectiveness of an early warning system can be significantly improved, regardless of the indicators used, if data for countries with similar characteristics are used in its creation, which is what we have done in this study. Berge (2015) points out the differences in signalling of different indicators in different periods before a recession starts may pose a problem in the application of early detection indicators in economic policy, which makes it difficult for the policy makers to create a relevant early warning system. This problem has been addressed to some extent in our study, by proving that foreign indicators generate earlier recession signals than domestic indicators.

Results obtained in this study offer another temporal dimension in the use of indicators for early detection of recessions because the initial signals from foreign indicators can be either further confirmed by later signals of domestic indicators, or, if they have not occurred, indicate isolated disturbances in the global market with little effect on the domestic economy. It should be noted that there is no single fully accurate early-warning indicator and it would be wrong to base the policy decision making on signals from only one or two foreign indicators, accompanied by signals from a small number of domestic indicators. For more robust predictions, it is necessary to monitor the signals of a larger number of foreign and domestic indicators, while giving greater importance to indicators that have proven to be more reliable (with a lower value of signal error) in studies like ours.

Also, our analysis indicates the need to modify the existing early warning systems for small open economies that are mostly based on the simultaneous analysis of a selected set of indicators. Instead, to achieve better results, we propose that it is necessary to consider the possibility of performing the analysis in two phases. The first would focus on foreign indicators, and the detected disturbances would be further confirmed by analysing domestic indicators in the second phase.

One of the limitations of this study is that it cannot be used to predict recessions of extraordinary nature like the most recent one, caused by the abrupt spread of the coronavirus pandemic and consequential world-wide lockdown measures. These types of recessions do not emit early warning signals that would be visible in macrofinancial indicators, but can rather be viewed as exogenous shocks to the economy.

In addition, some authors believe that it is not possible to effectively predict the turning points in business cycles given that a large number of models, which are updated and analysed every month, have failed to predict some recessions in a timely fashion (An et al., 2018). This applies equally to public and private sector models. The main reasons for the failure of the models are the lack of information to reliably predict recessions; insufficient incentives to warn the public of an impending recession given that false warnings can lead to higher costs (e.g. reputational damage) than benefits of accurate predictions; behavioural reasons such as too slow revision of the model and inadequate handling of the information obtained (An et al., 2018).

Despite the fact that the results of some existing predictive models have not proven overly accurate, the application of indicators for early detection of recessions still offers great potential for improving economic policy making and the economic outcomes in the economy as a whole.

This paper primarily focuses on small open CEEU economies, characterized by a relatively high degree of democracy and financial openness. Whether similar results would be obtained in developing countries in other geographic areas of the world, with different institutional, economic and socio-political settings is an interesting and potentially fruitful topic for future research. Furthermore, future research could follow up the work done in this paper and analyse the similar sample of indicators by using different methods like the Bayesian model averaging (Babecky et al., 2012), Binary Recursive Trees (Ghosh & Ghosh, 2003), Artifical neural networks (Hosseini et al., 2018), etc.

Disclosure statement

Authors declare they do not have any competing financial, professional, or personal interests from other parties.

Funding

This work was supported by the Croatian Science Foundation under project no. UIP-2017-05-6785.

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