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Quantifying the probability of a recession in selected Central and Eastern European countries

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ABSTRACT

The COVID-19 pandemic simultaneously affected most economic sectors and has already caused severe worldwide social and economic damage. In response, authorities introduced social distancing measures, with an adverse impact on economic activity. If policymakers were aware of the existing vulnerabilities, including those derived from the positioning on the business cycle, resilience could have been increased. The aim of this article is to describe various methods of dating business cycles in several Central and Eastern European (C.E.E.) countries, namely Czechia, Hungary, Poland and Romania. Furthermore, a Probit model regarding the probability of a recession is estimated, confirming the adverse effects of the pandemic, in contrast with a brightening outlook given vaccination campaigns and the E.U. recovery package. However, in case of the Romanian economy, an in-sample estimation showed a high probability of negative growth rates even in a pre-pandemic world, due to the high macroeconomic imbalances.

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1. Introduction

The COVID-19 pandemic has already struck a hard blow on economies, leaving a deep mark, especially on sectors involving high social interaction. All over the world, economic growth collapsed despite efforts of both national and international authorities to counter the socio-economic impact of the pandemic. The unexpected emergence of the novel coronavirus and its high contagiousness made difficult the sanitary crisis management. In order to contain the spread of the virus, national lockdowns were introduced, with the price of an economic downturn. In this context, countries with high vulnerabilities suffered the most. While it is difficult to predict a pandemic, increasing the resilience to adverse shocks, including ones of a medical nature, is not as tough. However, in order to make a proper assessment of the measures to be implemented, one should understand the initial conditions of the economy.

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Dating business cycles represents a key interest both for economic policymakers who need to understand the pro-cyclical or counter-cyclical nature of the implemented measures and for institutions involved in macroeconomic forecasts, since understanding the initial state of the economy is an essential condition for increasing the predictive capacity. Anticipating future recessions, with a high probability, can mitigate or at least partially reduce the severity of economic crises by counteracting the negative effects of the economic downturn. A relevant example in this regard is the case of Poland, which did not experience a recession during the global financial crisis of 2008, as it implemented countercyclical, fiscal-budgetary easing measures shortly before the installation of the crisis at the European Union level.

In terms of methodology, dating business cycles involves the identification of four distinct phases in the dynamics of the economic activity: two that coexist with the formation of demand excess in the economy, namely the expansion and the slowdown phases and two that form during periods of demand deficit, the contraction and the return phases. The economic literature usually defines the demand excess and deficit depending on the positioning of the real G.D.P. relative to its potential level. The phases within each economic cycle are determined starting from the turning points identification. A complementary approach aims to identify periods of expansion – characterised by positive real G.D.P. growth rates and recession – defined by at least two consecutive quarters of negative real G.D.P. growth rates or a sharp drop in economic activity in one quarter. Knowing the positioning of the economy within the business cycle and identifying future periods when there are high probabilities of a recession are important in terms of the impact that these phenomena have both on the companies' prosperity and on the population standard of living.

Starting from the initial conditions of the economy at a given time, it is interesting to make projections for the main macroeconomic variables. This article proposes a methodology for forecasting the probability that the economy enters a new phase of the economic cycle, in particular those phases that can generate a recession. In this regard, Section 2 summarises the relevant economic literature that studies this subject from various perspectives. Furthermore, Section 3 describes the data used in the analysis, while Section 4 compares the efficiency of three methods of dating business cycles in Czechia, Hungary, Poland and Romania in the 2000–2021 period, both covering different stages of the business cycles and capturing the early stages of economic development in the context of E.U. ascension. Lastly, Section 5 provides empirical evidence on the probability of a recession in the above mentioned C.E.E. countries at the current juncture and, in case of Romania, also in the pre-pandemic environment, thus highlighting the already existing vulnerabilities.

2. Literature review

Globally, two specialised institutions conduct the business cycles analysis, namely the National Bureau of Economic Research (N.B.E.R.) in the U.S.A. and the Centre for Economic Policy Research (C.E.P.R.), which adapts the N.B.E.R. methodology to the study of the euro area (Grigoraș & Stanciu, 2014).

Broadly speaking, economic literature recognises two definitions of the business cycle, namely the so-called classic cycle and the cycle of increase or deviation. The difference between the two is relatively easy to perceive: in the case of the deviation cycle, turning points are defined in terms of deviations from the pace of the G.D.P. growth from a properly defined growth rate (e.g., potential G.D.P. growth rate), while in the case of the classical cycle the turning points are determined on the basis of a decline (or an increase) in the level of G.D.P. There is a vast specialised literature that refers to the recommended methods for determining the G.D.P. trend, such as Masi (1997) or Darvas and Vadas (2005). The G.D.P. trend defines the potential G.D.P. and it is an unobservable variable requiring different technical methods for estimation. Gălățescu et al. (2007), Altăr et al. (2010) and Grigoraș et al. (2012) are some representative papers that study the estimation of the Romanian potential G.D.P. This component of the literature is of particular importance since the past experience proved that the method used for determining the trend has major implications in the subsequent identification of turning points.

Artis et al. (2003) analyse the business cycle in the euro area, both at an aggregate level and at country-level, comparing both aforementioned concepts of the cycle. Previous work documenting the cyclical experience of the euro area economy is quite scarce, being essentially limited to Agresti and Mojon (2001), who apply the notion of increase or deviation cycle based on the use of the band-pass filter, and Harding and Pagan (2001) and Pagan (2001), focused on the classical economic cycle. Artis et al. (2003) adapt the methodology of Harding and Pagan (2001), in the context of the Markov chain approach used in Artis et al. (2004), which gives greater flexibility in imposing restrictions on the duration and the amplitude of the cycles and also makes the methodology suitable for monthly data.

More recently, Stock and Watson (2010b) use monthly data on 270 economic indicators and address the issue of business cycle. The authors point out that the results of this article must be interpreted with respect to those in the literature on forecasting based on several data series (Eickmeier & Ziegler, 2008; Fair & Shiller, 1990; Stock & Watson, 2009; 2010a). The issue of determining turning points differs from the forecast analysis, as turning points are estimated retrospectively and also because the turning point estimator is nonlinear, while the forecasts considered in the literature are predominantly linear. The authors' approach to business cycle dating follows the methodology developed by Harding and Pagan (2006) and further applied by Chauvet and Piger (2008). However, Stock and Watson (2010b) focus on the use of several disaggregated series and treat cycle dating as an estimation problem and thus confidence intervals can be determined for turning points, which is an innovation in the literature. Berger et al. (2021) propose a Bayesian stochastic factor selection approach for multilevel factor models for a panel of 60 countries in order to find evidence for the presence of a global business cycle, as well as regional international cycles.

For the case of Romania, Grigoraș and Stanciu (2014) identify the business cycles and analyse their properties. The identification of turning points is based on the B.B.Q. algorithm, as described by Harding and Pagan (2002). Caraiani (2010) estimates a Markov Switching Model for the Romanian business cycle using data on the monthly production index. The same author brings evidence to the presence of nonlinearities and chaotic patterns in the macroeconomic time series, thus supporting the endogenous business cycle theory (Caraiani, 2012). In the current juncture, evidence regarding the business cycle is scarce, papers mostly focusing on the COVID-19 pandemic economic effects and its future evolution (Albu et al., 2020; Anghel et al., 2021; Dumitru et al., 2021).

Related to the identification of business cycles is the prediction of recessions. Watson (1991) highlights various methods for the forecast of recessions, such as probit and logit models. The author also considers stochastic simulations containing 30 equations. Molnar and Kadena (2020) are rather in favour of a small, quickly updating model using financial indicators. The slope of the yield curve, as well as alternative financial variables, are also considered by Duarte et al. (2005), Miller (2019) and De Santis and Van der Veken (2020).

Nissila (2020) argues that the ability of the term spread to predict recessions in the euro area has recently diminished. Instead, confidence indicators seem to provide additional predictive power, also confirmed by Cizmesija and Skrinjaric (2021) and Ganchev and Paskaleva (2021). Other high frequency data, such as the monthly industrial production data is used by Mazur (2017). At the current juncture, given the COVID-19 pandemic, expert judgment is also used. Foroni et al. (2020) considers the forecast errors made during the financial crisis and following recovery.

3. Data

Dating business cycles involves the analysis of economic activity as a whole. From this perspective, the seasonally adjusted quarterly G.D.P. series is used in order to avoid the identification of false business cycles. Given the regularly reviews of the G.D.P., as recommended by N.B.E.R., the current analysis includes a broader set of indicators that capture economic activity both at aggregate and sectorial levels in the analysed countries, namely: (1) national accounts data: G.D.P. series and its components, according to the expenditure method, namely the actual individual consumption of households, the gross fixed capital formation, as well as the series of exports and imports of goods and services; (2) series associated with the industrial sector: the domestic industrial production and the foreign one, proxied by the industrial production in the euro area (the main trading partner of the selected economies), sales volume expressed as turnover in retail trade, except of motor vehicles and motorcycles or the one in manufacturing; (3) the index of construction works and the index of new construction works; (4) confidence indices for Czechia, Hungary, Poland and Romania, as well as for the E.U. and euro area (EA); (5) risk premium, calculated based on Option Adjusted Spread (O.A.S.) quotations (in case of the Romanian economy); (6) labour market indicators: International Labour Organization (I.L.O.) unemployment rate, employment; (7) financial market indicators: the three months interbank rate, stock exchange indices (P.X. in case of Czechia, B.U.X. in case of Hungary, W.I.G. in case of Poland and B.E.T. composite index in case of Romania); and (8) price indices: H.I.C.P., H.I.C.P. at constant taxes, C.O.R.E.2. adjusted index at constant taxes (available in case of Romania), international Brent oil price, (9) euro area G.D.P. at 2010 constant prices.

The monthly gross series were aggregated at quarterly level using the average of monthly observations. The analysed period spans from 1995Q1 to 2021Q1. The various data come from National Institutes of Statistics (N.I.S.), Central Banks and Eurostat databases. The variables were transformed to their logarithm, except for the money market interest rate series, the risk premium and the confidence indicators. Moreover, the series were seasonally adjusted using the T.R.A.M.O./ S.E.A.T.S. method.

4. Dating business cycles – methods and results

4.1. Multivariate statistical filters

Multivariate filters involve the analysis of a structural model. Thus, the estimates are enriched with economic content in comparison with the univariate filters by quantifying the existing relationships between macroeconomic variables. The Kalman filter can be adjusted to estimate the G.D.P. deviation from its potential level. According to the unobservable component approach, the G.D.P. is broken down into two unobservable component variables, corresponding to the cycle and the trend of the series, which are modelled in the form of first-order autoregressive processes:

$$y_t = \hat{y}_t + \overline{y}_t \tag{1}$$

$$\hat{y}_t = c_1 \cdot \hat{y}_{t-1} + \mu_t \tag{2}$$

$$\overline{y}_t = \overline{y}_{t-1} + \frac{c_2}{4} + \eta_t \tag{3}$$

where y_t is the G.D.P., $\hat{y}_t$ is the cyclical component, $\overline{y}_t$ illustrates the trend and μ_t, η_t are residual terms. Therefore, the G.D.P. trend was assumed to follow a random walk process with drift, while the cycle follows a first-order autoregressive process. In the equation that expresses the dynamics of the G.D.P. trend, the drift represents its long-term growth rate, identified in the literature at a potential level of approximately 3% (for example Voinea, 2019 or Brázdik et al., 2020). Regarding the cyclical component, the empirical evidence indicates its persistence placed around 0.55 (Kamber et al., 2018 or Bulir, 2013). The structural model used for Kalman filter estimation can be enriched with different theoretical macroeconomic relationships between variables of interest. Thus, a new-Keynesian, hybrid Phillips curve was introduced in the analysis:

$$\pi_t = \alpha \cdot \pi_{t-1} + (1 - \alpha) \cdot \pi_t^e + k \cdot \hat{y}_{t-1} + \varepsilon_t \tag{4}$$

where π_t is the harmonised index of consumer prices at constant taxes, π_t^e represents inflation expectations, $\hat{y}_t$ is the G.D.P. cyclical component and ε_t is the residual term.

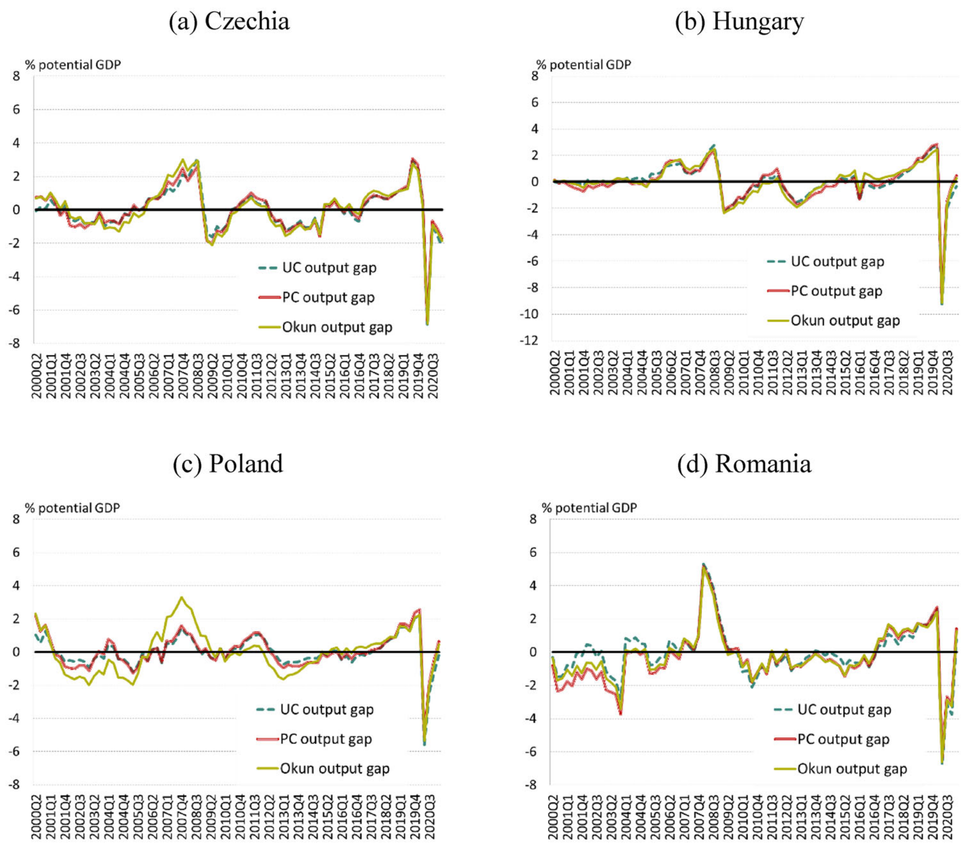

Figure 1. Extracting the cyclical component of the G.D.P. using multivariate filters U.C. represents the model described by Equations (1)–(3), P.C. represents the model that includes a hybrid Phillips curve, and Okun represents the model that includes Okun's Law in the analysis.
Source: Eurostat, authors' calculations

Given various empirical evidence,[1] inflation persistence was set at 0.5, while inflation's sensitivity to G.D.P. was set to 0.25.

In order to introduce a higher economic content in the analysis, an alternative to the models described above is the inclusion of Okun's Law:

$$\hat{u}_t = -\delta \cdot \hat{y}_{t-2} + \vartheta_t \tag{5}$$

where $\hat{u}_t$ is the cyclical component of the unemployment rate, $\hat{y}_t$ is the cyclical component of G.D.P. and ϑ_t is the residual term. In order to capture the existing rigidities in the labour market, the cyclical component of the unemployment rate responds with certain delays to the change in G.D.P. deviation, with a sensitivity coefficient set at 0.3 (suggested by simple Bayesian estimates of the model).

Therefore, three different models based on the Kalman filter were estimated for 2000Q2–2021Q1. Figure 1(a–d) shows the results of multivariate filters in case of Czechia, Hungary, Poland and Romania. The output gap generally follows a similar trajectory in all selected countries. The filters successfully captured the economic decline induced by the COVID-19 pandemic as well as the 2008 financial crisis.

However, in case of Poland, due to a countercyclical fiscal-budgetary policy implemented shortly before the outbreak of the 2008 crisis, the decline in output gap was significantly lower than in the case of the other analysed countries. The response of Poland's output gap to the COVID-19 pandemic was not as smooth, as the country experienced a significant contraction (yet at a lesser extent than the peers as shown by the multivariate filters).

In terms of expansion, empirical evidence shows a synchronised period of expansions, starting 2005 and 2016 (interrupted by the above mentioned events). Their magnitude differs according to country specific factors. For instance, in case of Romania, the accession to the E.U. in 2007 played an important role in heightening the expansionary pressures. As regards most recent data, multivariate filters show a recovery from the pandemic as the output gap is evaluated to gradually close. Robustness tests, namely replacing inflation proxied by the H.I.C.P. total index with H.I.C.P. at constant taxes, lead to similar results.

4.2. Principal component analysis

Principal Component Analysis (P.C.A.) is a method used for reducing the dimensionality of a large data set and obtaining a set of uncorrelated series, through orthogonal transformations, named principal components. Stock and Watson (2002) estimate a model based on the extraction of the main components in order to make projections of a macroeconomic variable, such as the industrial production.

The model is based on the following equation:

$$\mathrm{X}_t = \Lambda \cdot \mathrm{f}_t + \varepsilon_t \tag{6}$$

where X_t is a vector of stationary variables, f_t is a vector of common factors, Λ is a matrix of weights associated to the factors and ε_t is the residual term. In order to estimate the common factors and their corresponding weights, the model is reduced to a minimisation problem:

$$\min_{\Lambda, f_1, f_2, \ldots f_T} \sum_{t=1}^{T} (\mathrm{X}_t - \Lambda \cdot \mathrm{f}_t)' \cdot (\mathrm{X}_t - \Lambda \cdot \mathrm{f}_t) \tag{7}$$

This method is suitable for determining business cycles, considering that they involve fluctuations that take place at the aggregate level of the economic activity and consist of expansions or, as the case may be, simultaneous contractions of several sectors of the economy. Therefore, the methodology was applied to a set of macroeconomic indicators that coincides with the one previously described in Section 2. This allows the model to capture the economic activity as a whole, both at aggregate and sectorial level and, nevertheless, to include external factors which are relevant for a small open economy. The data set spans between 2001Q1 and 2021Q1. Annual growth rates were computed for most indicators, with the exception of money market interest rates, the unemployment rate and the risk premium. Starting from the

Table 1. Principal component analysis.

Czechia			Hungary		
Principal Component	Share of explained variation	Cumulative share	Principal Component	Share of explained variation	Cumulative share
PC 1	0.51	0.51	PC 1	0.50	0.50
PC 2	0.12	0.63	PC 2	0.15	0.65
PC 3	0.12	0.75	PC 3	0.10	0.76
Poland			Romania		
PC 1	0.52	0.52	PC 1	0.46	0.46
PC 2	0.13	0.65	PC 2	0.16	0.63
PC 3	0.10	0.75	PC 3	0.12	0.75

Source: authors' calculations

described data set and considering the interactions between variables, common components were extracted that represent linear combinations of the initial terms.

Table 1 describes the first three principal components, which sum up an explained variation of the initial series of more than 70%, in line with the threshold recommended by the economic literature. The selected components were used to construct the economic activity index, built as their weighted average (Figure 2a–d).

An index built on these principles has the advantage of capturing the interconnection between macroeconomic variables. The more one variable is correlated with the others in the analysis, the more weight will be assigned to it. This offers the possibility that a small deterioration of such a variable contributes more to the variation of the index, than a large deterioration of a variable that is not so correlated with the rest of the set. Unlike the initial G.D.P. series, expressed as an annual growth rate and subsequently standardised, the calculated index includes the influence of a wide range of indicators, both specific to the domestic economy and to the foreign environment. In case of Poland, the inclusion of foreign variables leads to a more pronounced decline in output than provided by the standard growth rate, yet at a lesser extent than in the other countries. Results for the Polish economy are confirmed by Burzala (2012), pointing to a deep contraction in the first quarter of 2009. Similar outcomes are obtained in case of the other countries, where the P.C.A. index shows a deeper contraction in economic activity.

Furthermore, the first principal component, the one explaining the largest share of the index variation is a proxy for the output gap (Figure 3). The index and its associated cyclical component largely replicate the evolution of economic growth. Recession periods are more pronounced when quantifying external factors. Therefore, both the decline illustrated at the beginning of the sample, corresponding to the international dot-com crisis, and the ones associated with the global financial crisis in 2008 and the COVID-19 pandemic in 2020, are more severely signalised in the P.C.A. index. Unlike statistical filters, however, recessionary periods are slightly ahead, being better correlated with the onset of the crisis in the euro area, given the inclusion of external variables in the analysis. For example, in the case of filters, the dot com crisis is estimated to have had an effect on the Romanian economy starting in 2003, but in the case of the index the G.D.P. deviation has become negative since 2001. Similar to results provided by the multivariate filters, the P.C.A. also shows a co-movement of

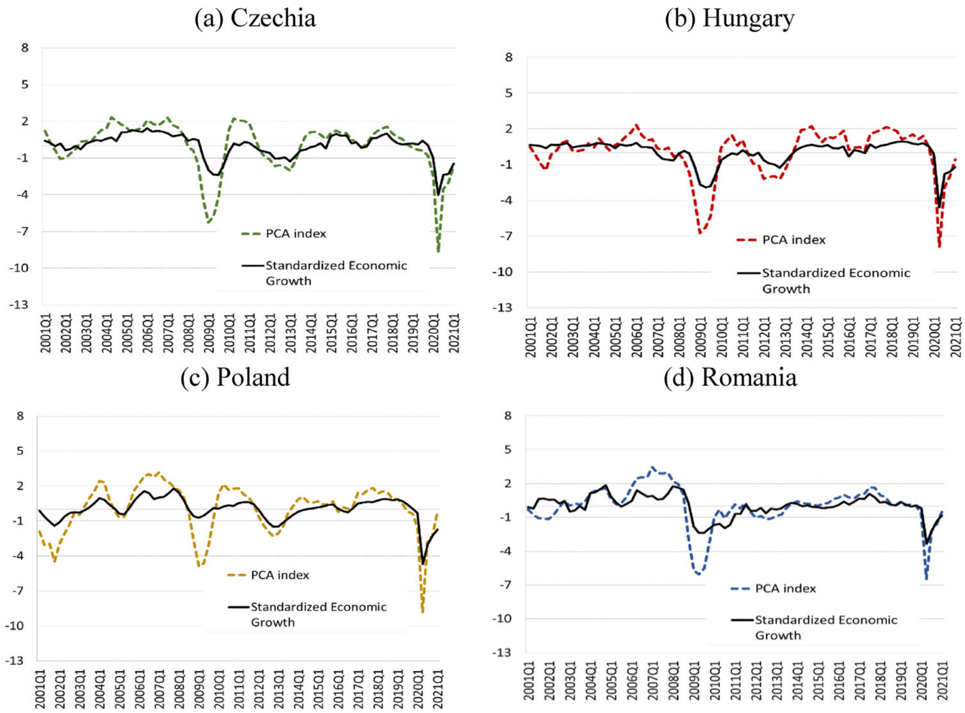

Figure 2. Economic activity index.
Source: NIS, Eurostat, authors' calculations

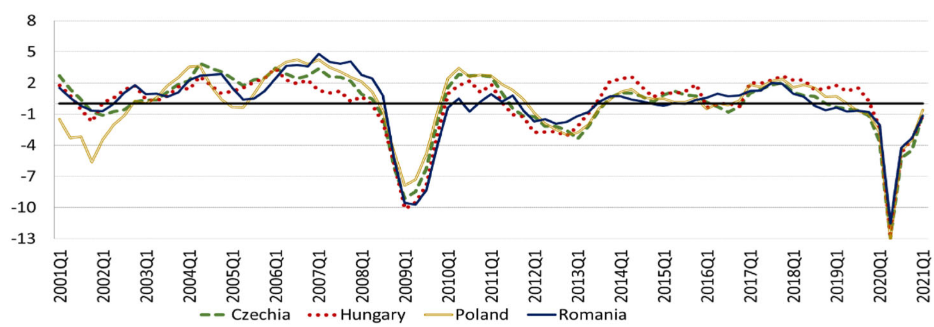

Figure 3. First principal component.
Source: NIS, Eurostat, authors' calculations

the output gap, as proxied by the first component. In case of Romania, also using the P.C.A. model, Dumitru and Dumitru (2010) finds a similar pattern for the output gap. Bandholz (2005) also highlights sluggish demand in Poland and Hungary in 2002.

4.3. Non-parametric methods for dating business cycles

A clear distinction needs to be made between two important concepts, namely dating and identifying business cycles. Although the past is, by definition, fully known, the identification of certain key points in the past, such as the turning points of a time series, involves the use of an estimation method. Many methods have been developed for the post-dating of turning points, one of the commonly used non-parametric model being developed by Bry and Boschan (1971), called the B.B. Algorithm. The version of the B.B. Algorithm that allows the analysis of quarterly time series frequency is called the B.B.Q. Algorithm (Bry and Boschan Quarterly Algorithm), developed by Harding and Pagan (2002). The model involves three steps: (1) determination of the potential turning points of the analysed series (minimum and maximum points over certain time intervals); (2) imposing conditions to ensure that these points alternate so that periods of expansion are followed by periods of decline and vice versa; (3) imposing a set of censoring rules that recombine the points identified in the first two steps so that they meet certain predetermined criteria regarding the duration of the expansion and decline phases, the minimum duration of the cycle time and the amplitude of a phase.

Through the imposed rules, this is a viable methodology for identifying as accurately as possible the turning points and, implicitly, the phases of a business cycle. The first step of the algorithm is to define a possible turning point at a certain time t whenever:

$$\{y_t > (<) y_{t\pm k}\} \tag{8}$$

where $k = \overline{1:K}$, K being the necessary number of periods for defining an expansion or a decline phase. In literature, $K = 4$ or $K = 5$ is used for monthly data, while $K = 2$ is used for quarterly data. Another censoring rule is related to the minimum duration of a complete cycle, for which, in general, a minimum duration of 15 months or at least 4–5 quarters is used.

The methodology also sets a T threshold of 10% that defines sudden changes in the phases of the financial cycle. Thus, in the situation where the quarterly dynamics of the series exceeds the threshold in absolute terms, the beginning of a new phase of the cycle is marked, regardless of the length of the previous phase. The application of the B.B.Q. algorithm on a data series allows the identification of turning points that delimit the phases of the economic cycle but also a binary series of data, which indicates by the value 0 the periods of expansion and by 1 those of decline. Using this series, we can later estimate the likelihood of a crisis in the upcoming period. The B.B.Q. methodology, also used by the International Monetary Fund (I.M.F.), analyses the data series in levels, without eliminating informational content by processing it.

The B.B.Q. algorithm can be applied univariate, using only the real G.D.P. series, or multivariate, taking into account other macroeconomic variables that reflect various aspects of the economy.

Figure 4 shows the business cycles identified in Romania, Hungary, Czechia and Poland using the quarterly historical series on real G.D.P., spanning from 1995Q1 (1996Q1 for Czechia) to 2021Q2. According to this methodology, the largest number of recession periods are identified in the case of Hungary followed by Czechia, Romania and Poland (with only two such episodes). Of course, the duration and amplitude of the recessions were different across countries and time span. Across countries, the duration and amplitude tend to be highest in Romania, followed in this order by Hungary, Czechia and Poland.

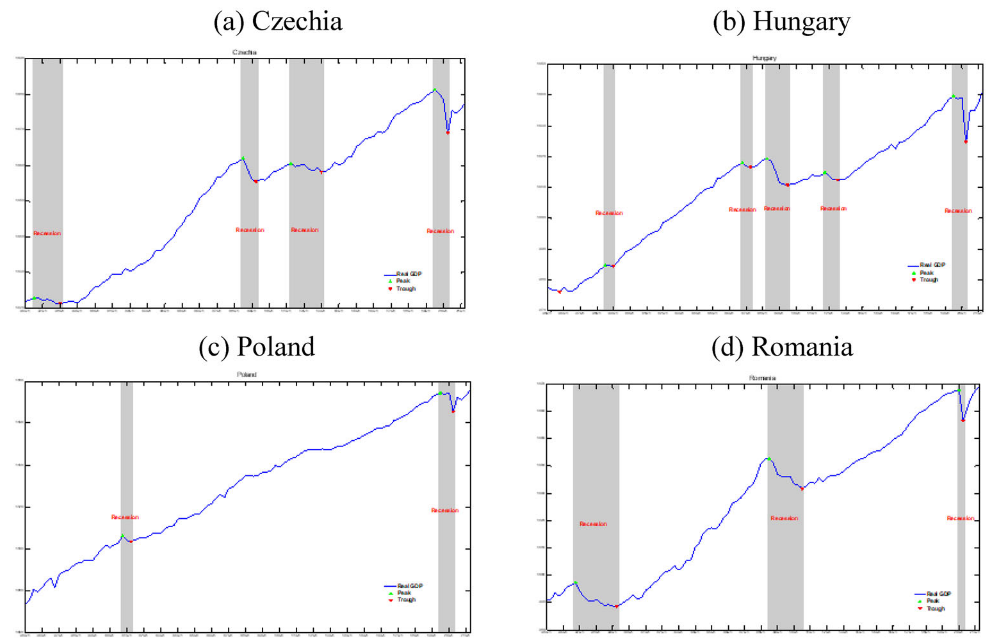

Figure 4. Dating business cycles using the univariate B.B.Q. model.
Source: Eurostat, authors' calculations

For exemplification, a more detailed analysis is provided for Romania. In this case, the first recession period is delimited by a maximum point recorded in 1996Q4 and a minimum located at 1999Q2. The recession lasted about 2 years and a half (10 quarters), an amplitude of −8.9pp and a cumulative loss of 69.7pp. The slope of the recession indicates an average decrease of 0.9% per quarter and the excess is 42%, which indicates that the actual trajectory deviates downwards from a linear recession, a number of periods, especially during 1997 and 1998, being characterised by rates of significant change in the real G.D.P. Among the factors that determined the installation of this recession episode, the lack of structural reforms in the Romanian economy superimposed on the establishment of a currency crisis in Russia during that period is the main one. Starting 1999Q3, Romania entered a period of expansion that lasted approximately six years (37 quarters), until 2008Q3 when a new maximum point of the real G.D.P. level was reached. During this period, the amplitude of economic growth was significant, being estimated at 54.3pp, which indicates that real G.D.P. has increased by more than 50% over the six years. The excess estimated at −15% shows a slower growth than the linear one in the first years after the crisis and, at the same time, a more monotonous evolution during the expansion, compared to the one during the recession detected between 1996 and 1999.

The global financial crisis, triggered in the second half of 2007 in the U.S., spread during 2008 over the euro area, Romania's main commercial and financial partner. Starting 2008Q4, the national economy also begins to feel the effects, the dynamics of real G.D.P. entering into negative territory. The installed recession lasted eight quarters and ended with a low point reached in 2010Q3. The magnitude of this recession was −11.1pp, the quarterly average loss in terms of percentage points of real G.D.P.

being 1.4. The cumulative loss during the two years of recession was 57.4pp, significantly less compared to the 873.6pp cumulative gain recorded in the previous expansion period. This shows that during the entire economic cycle the net gain was positive, summing a total of 816.2pp. The excess indicates a shift of the real G.D.P. trajectory below the linear one, its reduction rates being substantial immediately after the onset of the recession.

A new expansion period began in 2010Q4, which ended at the time of pandemic COVID-19 crisis onset in the second quarter of 2020. Within this period of expansion, real G.D.P. accumulated a gain of 656.3pp and an amplitude of 36.7pp, lower compared to similar indicators in the previous expansion period. The most recent recession triggered by COVID-19 pandemic seems to be very different from the previous ones given its duration of only one quarter, in which the amplitude, average and cumulative losses are all equal to 12.6pp, a significant figure for such a short period of time. Of course, the main reason for these findings relates to the severe measures adopted by authorities as a response to the medical crisis, which broke out at the beginning of the second quarter of 2020. Table 2 summarises the statistics related to the recessions and expansions periods identified within this analysis.

On the other hand, multivariate analysis allows the identification of business cycles based on a broader set of indicators, well correlated with the economic activity. Harding and Pagan (2006) propose the identification of turning points for each series using the B.B.Q. methodology, as described before, followed by the computation of a heatmap that indicates the time spans in which these points synchronise for several data series.

Figure 5 represents a heatmap type analysis for Romania. During the three identified recessions, colour codes signal an almost general decline in the analysed indicators. The more recent period is characterized by a wider set of increasing indicators, suggesting the high possibility of an instauration of a new expansion phase. In this context, it can be concluded that the latest available data, corresponding to 2020Q3–2021Q1, indicate that the economic activity has entered a new phase, closing the demand deficit formed in the economy, especially against the background of fiscal and monetary policy stimulus granted in the recent years.

5. Forecasting recessions using Probit models

After dating the business cycles and knowing the initial conditions that currently characterise the economy, we can estimate the probability of a new recession occurring at a certain time horizon. We use a Probit model, which can be illustrated within the following system:

$$y_i^* = x_i^{'} \cdot \beta + \varepsilon_i, \quad \text{where } \varepsilon_i \sim N(m, v)$$
$$y_i = \begin{cases} 1, & y_i^* > 0 \\ 0, & y_i^* \le 0 \end{cases} \tag{9}$$

Given that the residuals are independent and normally distributed, it can be derived:

Table 2. Descriptive analysis of the Romanian business cycles.

Indicator	Recession (1997 Q1–1999 Q2)	Expansion (1999 Q1–2008 Q2)	Recession (2008 Q1–2010 Q2)	Expansion (2010 Q1–2020 Q2)	Recession (2020 Q1–2020 Q2)	Average Values in Recessions	Average Values in Expansions
Duration (quarters)	10	37	8	38	1	6.3	37.5
Amplitude (p.p.)	−8.9	54.3	−11.1	36.7	−12.6	−10.9	45.5
Loss/Gain average (p.p.)	−0.9	1.5	−1.4	1	−12.6	−5.0	1.3
Loss/Gain cumulative (p.p.)	−69.7	873.6	−57.4	656.3	−12.6	−46.6	765.0
Excess (%)	42%	−15%	15%	−8%	0%	19%	−12%

Source: Authors' calculation

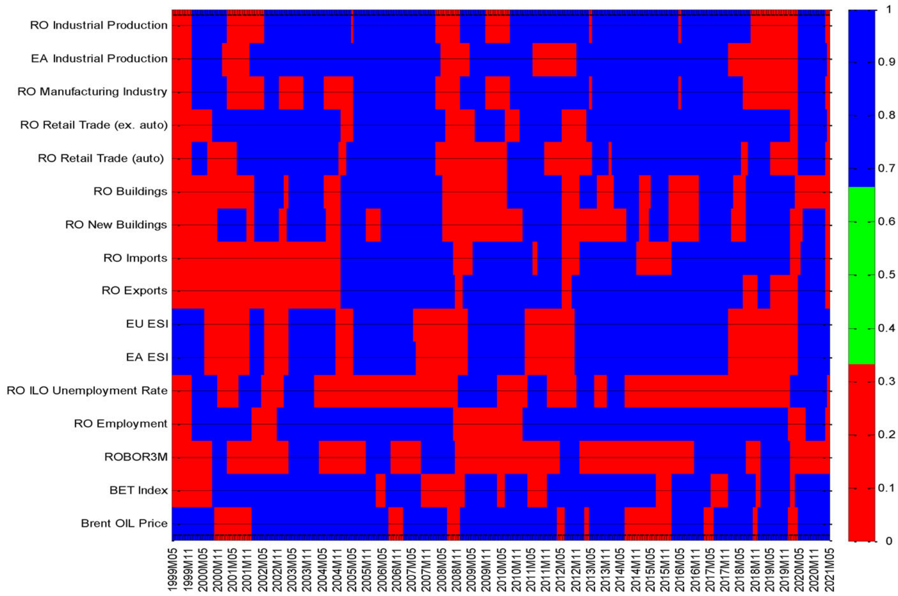

Figure 5. Heatmap obtained by applying the multivariate B.B.Q. model.
Source: NIS, authors' calculations

$$P(y_i = 1|x) = P(y_i^* > 0|x) = P\left(x_i^{'} \cdot \beta + \varepsilon_i > 0x\right) = P\left(\varepsilon_i > -x_i^{'} \cdot \beta x\right) = 1 - F(-x_i^{'} \cdot \beta) \tag{10}$$

where F is the cumulative error distribution function, which is equal to $F(x_i^{'} \cdot \beta)$, as implied by the symmetry of the normal distribution. Therefore, the probability of the onset of a crisis can also be quantified. In this context, the mix of factors that contribute to the outbreak of the crisis is the latent variable. The observable variable is the occurrence, or not, of an economic contraction. In the case of the selected C.E.E. countries, a Probit model with quarterly data was estimated, using as main explanatory variable the dynamics of seasonally adjusted real G.D.P. The reference period is 2000Q2–2021Q1. Given that Czechia, Hungary, Poland and Romania are small open economies, the confidence index for E.U. was also included in the analysis to account for the effects of the international environment:

$$r_t = \propto_0 + \propto_1 \cdot \Delta y_{t-1} + \propto_2 \cdot esi_{UE_t} + \varepsilon_t, \tag{11}$$

where r_t is the binary variable that takes value 1 for those quarters characterised by a negative quarterly G.D.P. growth rate (and 0 otherwise) and esi_{UE} is the E.U. confidence index. By estimating this model, the probabilities of identifying a negative growth rate for the next quarter can be quantified.

Firstly, the empirical evidence obtained is based on historical data. However, the analysis can be extended by including G.D.P. projections and quantifying, in these circumstances, the probability of a negative growth rate in the future. In Figure 6, the results obtained for the above-mentioned countries are illustrated. The model caught the onset of the economic crisis in 2008. Starting 2008Q2, all countries experienced a

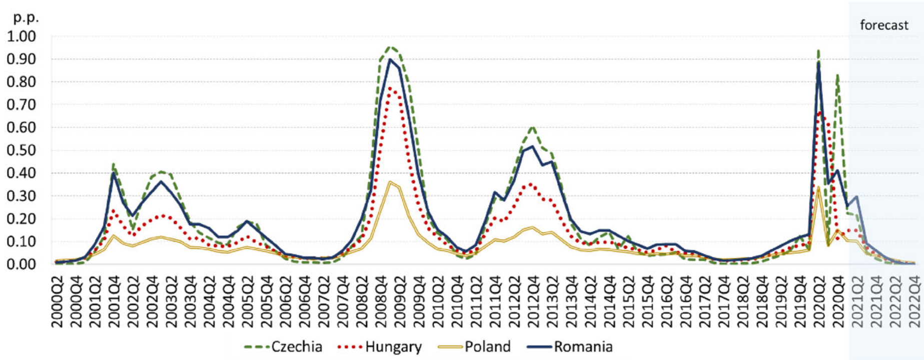

Figure 6. Estimating the probability of a negative growth rate for the next quarters.
Source: NIS, Eurostat, authors' calculations

gradual increase in the probability that a negative G.D.P. growth rate would be recorded in the next quarter. While in Czechia, Hungary and Romania this probability reached over 70% in 2009Q1, in Poland, the Probit model shows a low probability (less than 25%). After the 2008 economic crisis episode, the economies started to recover. For instance, in Romania a positive business cycle began, fuelled by numerous fiscal stimulus. The probability to record a negative growth rate gradually decreased. However, as structural vulnerabilities accumulated, more pregnant in the case of the Romanian economy, the Probit model placed this probability on an upward trajectory, slightly above the other countries. The emergence of the pandemic with the associated negative effects heightened this probability, not only for Romania, but also for Czechia, Poland and Hungary. Official N.I.S. data confirmed this empirical evidence, as there was a significant regional contraction on the back of the ongoing pandemic.

More recently, in line with the brightening global economic outlook amid the emergence of several COVID-19 vaccines coupled with impressive stimulus packages – for instance, the Next Generation E.U. (N.G.E.U.) recovery instrument or the U.S. fiscal stimulus, the likelihood of an economic contraction has begun to decrease. To quantify this probability in the coming quarters, the model can be augmented by including G.D.P. projections and confidence indicators.

In this regard, the projections of several institutions on economic growth were taken into account. First, the model was augmented with the evaluations of national institutes (for example, the National Commission for Strategy and Prognosis in case of Romania, Central Banks in case of Czechia, Hungary and Poland) The most optimistic growth projection, conditional on the available information at the moment of the projection, is that of Hungary, pointing to a growth of more than 6% in 2021. At the opposite stands Czechia, with a projected growth of only 1.2% in 2021. The confidence index series was extended starting from the moving average for the last 4 quarters recorded by it. According to the results, the index is expected to gradually increase, in line with the prospects regarding the global economic recovery, despite the current still fragile international environment.

Figure 6 illustrates the results obtained by incorporating these projections into the Probit model. Empirical evidence indicates a decrease in the probability of a negative rate of economic growth in the near future. Results reflect the expected progress of vaccination campaigns leading to a sanitary crisis easing in tandem with the absorption of E.U. funds, also of those aimed at alleviating COVID-19 negative effects. As a robustness check, the model was re-specified incorporating the projections of other financial institutions, such as the E.C. summer 2021 forecast and the I.M.F. April 2021 projections. Both forecasts account for N.G.E.U. funds. The decreasing probability of posting a negative growth rate is confirmed.

Therefore, analysing the latest economic growth data for the Czech, Hungarian, Polish and Romanian economies and corroborating the results with the E.U. confidence index, to account for influences of the external environment, it is found that the probability of posting a negative growth rate over the coming quarters is quite low. Extending the model by incorporating the official projections of I.M.F., C.E. and national institutes, the probability tends to zero, especially over the medium term. While econometric tools are not necessarily needed to confirm the decrease of the probability of registering a negative growth rate given the above-mentioned factors (vaccination campaigns becoming manifest, N.G.E.U. stimulus), the Probit model could have been useful in highlighting potential vulnerabilities in a pre-pandemic world. As an in-sample exercise, in case of Romania, the Probit model was reconstructed using 2000Q1–2019Q2 data and past projections of various institutions. At that time, there were no concerns of a contagious virus leading to social distancing measures and, finally, to national lockdowns. However, empirical evidence shows that even in a pre-pandemic world, Romania had a high probability of posting negative growth rates (Figure 7). The main reason for this finding relates to the fact that strong internal fiscal and trade imbalances marked the economy at that time. Furthermore, the external environment was already fragile at that point, amid recurring geopolitical tensions and potential intensifications of protectionist measures. Empirical models point to a probability of up to 30% for Romanian economy to start having G.D.P. negative growth rates. Should these values be known before the first pandemic wave hit the Romanian economy, authorities could have increased resilience to external shocks by implementing a balanced mix of economic policies.

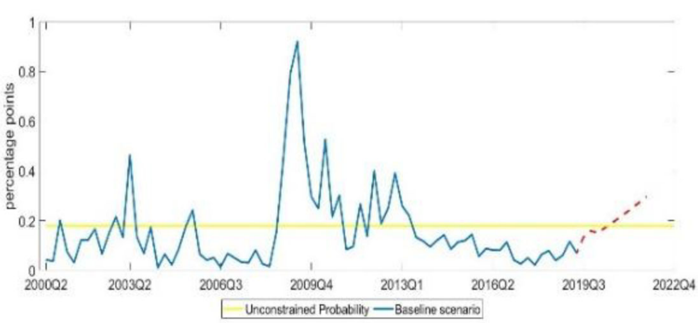

Figure 7. Estimating the probability of a negative growth rate for the next quarters in a pre-pandemic world – the case of Romania.
Source: N.C.S.P., N.I.S., Eurostat, authors' calculations

6. Concluding remarks

Anticipating the possibility of recessions in the future, with a high probability, can at least partially reduce the severity of economic crises by counteracting the negative effects of the economic downturn. A first step in achieving a quality forecast of the economic activity is to identify the position on the economic cycle and, at the same time, to date it.

The current article proposes a methodology for forecasting the probability that the economy enters a new phase of the economic cycle, in particular those phases that can generate a recession. First, analysing the G.D.P. deviation from its potential level using statistical filters, it is observed that, in case of Romania, domestic economic activity began to operate above the potential level, especially since 2007, the year marked by Romania's accession to the European Union. The peak of G.D.P. deviation was reached in 2008Q1. Subsequently, the effects of the global financial crisis significantly impacted the Romanian economy, causing large domestic macroeconomic imbalances, such as high budget deficit, strong negative current account balance and high inflation. A similar pattern is observed in Czechia and Hungary, where the 2008 international financial crisis affected their output, stopping their expansionary phase (a more prolonged one than in the case of Romania). Instead, Poland was not as affected by the 2008 financial crisis episode as countercyclical policies had been adopted shortly before the beginning of the crisis. The COVID-19 pandemic also left a deep mark on the C.E.E. economies. This time, all the analysed countries were significantly affected by the pandemic and the associated lockdown measures. The output gap entered the negative territory as shown by multivariate statistical filters. The second quarter of 2020 marked a new short-time sharp recession, followed by the shaping of a new expansion phase within the most recent periods. The P.C.A. applied to a set of 17 macroeconomic variables well correlated with the economic activity confirms the robustness of the analysis and the obtained results.

The univariate B.B.Q. non-parametric algorithm of dating business cycles, identified the largest number of recession periods in the case of Hungary followed by Czechia, Romania and Poland (with only two such episodes). In case of Romania, three significant recession periods were highlighted between 1995 and 2021: the first recession period is delimited by a point of maximum recorded in 1996Q4 and one of minimum in 1999Q2; the second one between 2008Q3 and 2010Q3; and the most recent one located in 2020Q2. In case of the Romanian economy, a more detailed analysis was conducted. The heat map constructed using the results of the multivariate B.B.Q. model on a set of macroeconomic variables, at both aggregate and sectorial levels, well correlated with the evolution of economic activity suggests several periods in which the indicators experienced a sharp decline. However, during the three recessions, an almost general decline can be observed. In the more recent quarters, a broader set of indicators suggests the high possibility of the formation of a new expansion period in economic activity.

Finally, analysing the latest economic growth data in Czechia, Hungary, Poland and Romania and corroborating the results with the E.U. confidence index, it was found that the economic outlook is brightening. The probability of a negative growth rate is evaluated on a downward trajectory starting 2021Q2. This likelihood is expected to gradually decrease to null values as indicated by Probit forecast models augmented with projections from national and international institutions, such as N.C.S.P., National Banks' forecast, E.C. and I.M.F. Given the latest E.U. recovery package and the resources European countries benefit from in order to emerge stronger from the pandemic, the empirical evidence within the Probit model is plausible. Results are in line with other evidence: Ganchev and Paskaleva (2021) confirms the temporary increased probability of a recession amid the outbreak of the COVID pandemic in the case of 11 European countries, including Czechia, Hungary, Poland and Romania. However, in a pre-pandemic world, results showed an increased likelihood in case of Romania of a negative growth rate even in the absence of the sanitary crisis. Had this information been known before the emergence of the novel coronavirus, policymakers could have implemented a balanced mix of economic policies, aiming to increase the resilience of the Romanian economy to external shocks.

Even though a simple model for forecasting recessions can be used as a quickly updating early warning system, we are aware of its limitations. Its parsimonious specification can be seen both as an advantage (amid limited resources needed) and as a disadvantage. For instance, the model could be enriched by adding other variables, increasing the predictive power. Furthermore, future research could account for effects of N.G.E.U. funds.

Note

1. For example, estimating the equation for Phillips Curve using Generalised Methods of Moments – this is available upon request.

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No potential conflict of interest was reported by the authors.

Geolocation information

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Data availability statement

The macroeconomic variables included in the study were extracted from the Eurostat database - https://ec.europa.eu/eurostat/web/main/data/database, from the Romanian National

Institute of Statistics, https://insse.ro/cms/en and the central banks websites, as follows: National Bank of Romania - https://www.bnr.ro/Interactive-database- 1107.aspx, Czech National Bank – https://www.cnb.cz/en/statistics/, Magyar Nemzeti Bank - https://www.mnb.hu/en/statistics, Narodowy Bank Polski https://www.nbp.pl/homen.aspx?f=/en/statystyka/statystyka.html; in terms of forecast, data source is the World Economic Outlook Report (IMF) - https://www.imf.org/en/Publications/WEO/Issues/2021/03/23/world-economic-outlook-april-2021 - the Summer 2021 Economic Forecast (EC) - https://ec.europa.eu/info/business-economy-euro/economic-performance-and-forecasts/economic-forecasts/summer-2021-economic-forecast_en - and the Romanian National Commission for Strategy and Prognosis, https://cnp.ro/?lang=en

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