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MAGYAR TÖRTÉNELEM ÉS EURÓPAI INTEGRÁCIÓ TANSZÉK

**BACCALAUREUSI MUNKA**

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## CONTENTS

1. INTRODUCTION.....	1
2. LITERATURE REVIEW .....	5
2.1 Definition of an economic crisis .....	5
2.2 Early Warning Systems and their application in crisis forecasting: The MIP .....	8
2.3 Time series analysis and forecasting methods .....	22
3. MATERIAL AND METHOD .....	28
3.1.1 Signal Extraction Method .....	28
3.1.2 Signal Performance evaluation.....	29
3.2 Empirical results.....	31
3.2.1 Binary Crisis Variable.....	31
3.2.2 Leading Indicators .....	33
3.3 Cross-spectral analysis .....	37
3.3.1 Empirical results .....	40
3.3.2 Criticism of the cross-correlation method.....	41
3.4 Frequency analysis of anomalous negative price fluctuations in stock market indices as a crisis forecasting tool.....	41
3.4.1 Empirical results .....	43
3.4.2 Discussion .....	47
3.4.3 Criticism of the anomalous stock price fluctuation method.....	48
4. Granger test of V4 Stock markets as leading indicators of economic growth.....	49

4.1 Stock markets' ability to predict recessions – evidence .....	49
4.2 Stock markets' inability to predict recessions – evidence .....	50
4.3 Methodology .....	51
4.4 Preparing the Data .....	57
4.5 Testing for stationarity.....	58
4.6 Testing the relationship between stock prices and the economy with an Autoregressive Distributed Lag model.....	61
4.7 Testing the time series for cointegration with Johansen cointegration test .....	67
4.8 Testing for causality with granger causality test.....	69
5.SUMMARY.....	74
REFERENCES .....	76
Internet Sources.....	83
ANNEXES.....	84
Abstract .....	88

## LIST OF FIGURES

Figure 1: Consolidated MIP data structure on the Eurostat website.....	11
Figure 2: Binary variable indicator for economic, banking and currency crises in Hungary. 32	
<i>Figure 3: Binary variable indicator for economic, banking and currency crises in Ukraine.</i> .....	32
Figure 4 Binary variable indicator for economic, banking and currency crises in Russia.....	33
Figure 5: The illustration of the forecasting window and the right tail of the window. ....	34
Figure 6: The flag of the presence of economic crises and the Hungarian sovereign debt CDS leading indicator.....	36
Figure 7 Flag of the presence of crisis and NBU currency reserves/ Bank assets - trend leading indicator. Source: authoring .....	37
Figure 8 Flag of the presence of crisis and the RTVX volatility leading indicator.....	37
Figure 9: Cross amplitude spectrum of Export and GDP.....	40
Figure 10: The algorithm for determining anomalous price fluctuations. ....	43
Figure 11: BUX time series. Source: MNB, constructed by the author.....	44
Figure 12: Frequency distribution histogram of the <b>St</b> of the BUX index. ....	45
Figure 13: RTSI Russian stock market index at -0.048 threshold. ....	46
Figure 14 Algorithm for the test .....	52

## LIST OF TABLES

Table 1: MIP scoreboard indicators (AMR 2021). .....	13
Table 2: Journal of Central Banking Theory and practice MIP scoreboard transformation. ..	14
Table 3: AMR Total Financial liabilities for V4 countries. Annual time series.....	15
Table 4: Current account imbalances for V4 countries Annual time series. ....	16
Table 5: Export market shares in volume for V4 countries annual time series. ....	17
Table 6: Gross Debt to GDP ratio of V4 countries annual time series. ....	17
Table 7: Annual house price indices in V4 countries annual data. ....	18
Table 8: Net international investment position quarterly data (% of GDP) .....	19
Table 9: Nominal Unit labour cost in V4 economies annual data (% of GDP) .....	20
Table 10: Private sector credit flow in V4 countries 3-year percentage change annual data..	21
Table 11: Real Effective Exchange rate of V4 economies 3-year change annual data .....	21
Table 12 Combination of crisis variables and signalling variables .....	29
Table 13: Table of the best leading indicators for Russia, Ukraine and Hungary. ....	35
Table 14: Cross spectrum analysis for Russian macroeconomic time series. ....	41
Table 15: Frequency of anomalous BUX price fluctuations yearly. ....	45
Table 16 Frequency of anomalies in stock indexes of Emerging and developed economies .	46
Table 17 V4 countries GDP and Stock index log-transformation .....	58
Table 18 ADF tests on time series: 1- Hungary; 2- Czechia, 3- Slovakia, 4- Poland.....	60
Table 19 KPSS tests of time series 1 - Hungary, 2- Czechia, 3- Slovakia, 4- Poland. ....	61

Table 20 OLS regression analysis for PX and PGDP. ....	63
Table 21 OLS regression analysis for BUX and HUGDP. ....	64
Table 22 OLS regression analysis for SAX and SGDP. ....	65
Table 23 OLS regression analysis for WIG and PGDP. ....	66
Table 24 Johansen cointegration Test for V4 economies' stock ick indexes and GDP growth rate.....	68
Table 25 Granger Causality test for PX and CZGDP. ....	70
Table 26 granger Causality test for BUX and HUGDP. ....	70
Table 27 Granger Causality test for WIG and PGDP. ....	71
Table 28 Granger Causality test for SAX and SGDP. ....	72

## 1. INTRODUCTION

Reflected in the cyclical nature of macroeconomic expansions and recessions, it has been determined that some periods of financial distress (or financial crises) are inherently predictable and therefore are avoidable. Evidence of a strong correlation between financial stress and recessions enforced a growing trend of policymakers allocating increasing resources to early warning systems (EWSs) (Borio and Drehmann, 2009).

Economists are confronted with the problem of creating a “general purpose indicator”, that could be applied universally for all countries. However, demonstrated by (Smets and Tsatsaronis, 1997) and reiterated by (Stock and Watson, 2003, p. 823), it is, for the time being, impossible to create a “universally applicable predictor”. In this paper we reject the to meet the claim of finding such a set of indicators, and instead focus on accepting the differences between countries and finding the right predictors or a combination of them for each economic cluster.

Further evidence of the failure of timely identification of relative macroprudential risks is in the diverging opinions of Global Financial Stability Reports from two leading financial organizations: The IMF and the FED. In the April 2007 IMF Global Financial Stability report, the writers claimed a “strong foundation for global financial stability”, omitting the exploration of short-term risks of deterioration of credit quality in the US subprime mortgage markets (IMF..., 2008). Practically, none of the identified risks were substantial to initiate government action. In the months leading up to the COVID-19 crisis, the IMF released the October 2019 issue of Global Financial Stability report. Apart from addressing the problem of stagnating economic growth, muted inflation and trade tensions, the forecasting indicators noted in the report included the yield curve, which was reported to be rapidly flattening and high asset valuations, no EWSs giving off warning signals of a coming recession were mentioned.

Empirical research on early warning indicators within EWSs is extensive. However, (Borio and Drehmann, 2009 p. 2) argued that the challenges in developing an operational framework for financial stability, presented by the early warning literature, range from adequacy of

measurement of “fuzzy<sup>1</sup>” nature, to a jointly accorded definition of a financial crisis. The two prominent methodologies used in EWS literature are the signal extraction method (sometimes referred to as the *signals* approach), panel logit models (sometimes referred to as *probit/logit* models). The third, recently developed methodology by (Davis and Karim, 2008) and (Duttagupta and Cashin, 2011), is binary recursive trees (often regarded as *classification trees*). Following (Barrel et al., 2010), binary trees and panel logit models are outperforming signal extraction in terms of type I and type II errors. More so, the reliance on cross-sections of heterogeneous markets and a common set of explanatory variables points to the paucity of respective time series variables, such as terms of trade and real credit growth for emerging markets (EMs). Such inconsistencies increase the number of infrequent financial crisis observations, thus worsening the predictive power of the model. (Barell et al., 2010) argues that since the triggers of a financial crisis depend on the type of economy and the nature of the banking system, the selection of a particular set of threshold indicators in MIPs, EWEs, which are part of EWSs, must be done with regard to the economic conditions of a given country - this was also highlighted by (Csontos and Szalay, 2013) in their review of Hungarian EWSs. Further constraints of EWS methodologies were identified by (Ward, 2014, p. 10) as: (i) the number of predictors the underlying algorithms are able to handle, (ii) the ease with which they accommodate nonlinear interaction effects, (iii) the ease with which they accommodate nonlinear effects between any single predictor and crisis risk, (iv) the degree of estimator variability.

In this paper we define the financial crisis using a multilateral literary analysis, so to, satisfy the paper’s aim of developing an accurate and up to date EWS for Eastern European Emerging markets, particularly, the V4 economies. The paper will also cover different forecasting methods, the Data Generating Process and structural Time Series Models that will allow to predict movements of time series We further investigate EWSs and identify key shortcomings of mechanistically applying EWSs in the Organization of Economic Co-operation and Development (OECD) countries through rigorous literature analysis. We demonstrate the

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<sup>1</sup> Fuzziness is referred to a measurement or a forecast of a stochastic indicator. Source: (Borio, and Drehmann, 2009)

experience of the IMF and ECB in policy response to the appearance of macroeconomic imbalances. Furthermore, the paper will cover the following three methodologies:

First, the signal extraction methodology: we will formulate the algorithm for the signal extraction method and determine its usefulness as a function  $U$ . The algorithm will then be applied to the Eastern European Emerging markets (EMs): Hungary, Ukraine and Russia. The thresholds will be compared, conclusions will be drawn.

Second, the cross-spectral analysis: we introduce the theory that the occurrence of crises is correlated with economic business cycles. Therefore, we will calculate the lag between the two time series in relation to each other.  $y_{1t}, y_{2t}, t \in \{1, 2, \dots, T\}$ . The lag between the explaining variable and the leading indicator will allow to determine the timeframe between the prediction of the crisis and its manifestation.

Third, the anomalous frequency of price fluctuations of stock market indexes indicator is inspected for its forecasting power.

The aim our study is to determine the indicators, which can correctly forecast crisis episodes in Eastern European Emerging Markets and to test them against the predetermined MIP Scoreboard indicators via a comparison. The study also investigates the MIP, briefly established in the introduction, further in the literature review to gain a better understanding of how warning signals are related to the steps of the MIP. Lastly, the paper w

The objective of this paper is to suggest an EWS that can forecast the probability of financial stress events occurring within a specified time frame in Eastern European Emerging Markets.

The method of this paper is to address the relevant aims via a literary analysis, a comparative analysis and an empirical research.

The novelty is threefold: A fresh look at crisis forecasting methods, the combination of three methodologies challenges existing EWSs proposed by the IMF for their forecasting capabilities for Eastern European EMs and finally a new method adopted from the realm of matrix theory investigates the forecasting capabilities of domestic stock market indexes.

The contribution of such a research paper would be that of an independent forecasting system that would give an estimate of the likelihood of a recession for Eastern European EMs. The

proposed EWS would meaningfully impact further researches on the topic of financial crisis forecasting, provide intrinsic information regarding the conduct of EWS in European countries by international financial institutions, and finally provide a critical comparison of the thresholds advised by the IMF and statistically derived ones. It would further alert the Hungarian economic research community on the importance of early warning indicators.

The remainder of the paper is organized as follows. In section two, we define the financial crisis, and assess the literature on the usefulness of Scoreboard indicators across European economies. Forecasting methods are introduced. Section three provides an extensive review of the signal extraction method, the cross-spectral analysis and the anomalous price fluctuation frequency distribution method with a mathematical background. Section four conducts an empirical research into which indicators serve best for forecasting crisis events in Eastern European EMs. Section five evaluates the results and draws policy implications from the findings. The Appendix contains the listing of a functional MATLAB program we used for determining the thresholds, cycles shifts and statistics.

**Key Words:** Macroeconomic Imbalance Procedure, Early Warning Systems, Early Warning Exercises, Forecasting, Banking crises, Systemic risk, Signal extraction methodology, Panel logit models, binary recursive trees, Financial Stability Index, Emerging markets, Composite Leading Indicator, Cross-Spectral analysis, Stock price fluctuations.

## 2. LITERATURE REVIEW

### 2.1 Definition of an economic crisis

The first step towards developing an efficient EWS model is to precisely and, most importantly, unanimously define what an economic crisis is, define financial distress, explain how to distinguish the noise and the actual signal within a time series. In order to do this, in this study we apply a complex literary analysis and determine the best forecasting method for each crisis.

Highlighted by (Kaminsky, Lizondo and Reinhart, 1996) there is a wide variation in how a crisis is defined. Financial distress, as defined by (Borio and Drehman, 2009 p. 4) is an event where, as a result of substantial losses at financial institutions and/or failure of these institutions cause dislocations to the real economy. Financial instability is a direct result of financial distress. In this empirical study, we use the database of (Laeven and Valencia, 2018) to identify and date economic crises. In the period between 1970 and 2017 three types of crises were identified: systemic banking crises, sovereign debt crises and currency crises. While (Laeven and Valencia, 2018) identify a systemic banking crisis based on two criteria, that are required to be met: signs of financial distress in the banking system – losses, bank runs, bank liquidations, and policy measures being taken as a counteract to the risen distress. Laeven and Valencia build on previous work by (Caprio et al., 2005). The EWSs are mainly used specifically for systemic banking crisis prediction. The signal extraction approach, further discussed in section 3, is generally applied for forecasting systemic banking crises. According to (Laeven and Valencia, 2018 p.3) there were 151 banking crises from 1970 until 2017. Meanwhile (Thomson and Ergungor, 2005) raise the question of how big of a default and how many banks need to fail before the government is required to intervene? Researchers have examined the statements and actions of central bankers and concluded that “...when central bankers think that a particular shock to the financial system could develop into a systemwide problem, the problem is considered systemic” (Caprio and Klingebiel, 1997). Following (Demirguc-Kunt A and Detragiache, 2005) a banking crisis is defined as the ratio of non-performing loans (NPLs) to the total assets of the bank, denoted as  $P_b = \frac{D}{A} 100\%$ , where  $P_b$  is the banking crisis indicator,  $D$  is the number of non-performing loans and  $A$  is the assets. If  $P_b$  exceeds 10%, a banking crisis is considered to have occurred. Systemic banking crises are more likely to occur during cycles of expansionary monetary and fiscal policy, and they almost often involve a kind of financial liberalization. Governments, for example, lift interest rate caps on

deposits as part of growth policies, or enable banks to participate in previously limited practices such as international borrowing. In general, amendments broaden the range of operations that depositories will do.

Following (Boysen-Hogrefe et al., 2015 p. 9) and building on (Laeven and Valencia, 2018), a sovereign debt crisis is defined based on the information of sovereign defaults to private creditors and debt rescheduling. (Manasse et al., 2003) argue that a priori there is no single empirical definition of what should constitute a sovereign debt crisis (sometimes referred to as sovereign default). While (Detragiache and Spilimbergo, 2001) define a sovereign debt crisis quantitatively, as when a country has arrears on external obligations toward commercial creditors in excess of 5% commercial debt outstanding. Sovereign debt crises are predicted among other methodologies, with the help of probit/logit regression models or signal extraction models. (Manasse et al., 2003, p.7) concludes that the determinants analysed in former studies are insufficient to determine a quantitative approach and defining an empirical model to predict sovereign debt crises. In their later work (Manasse and Roubini, 2009) in the introduction they state that: “We find that not all crises are equal: they differ depending on whether the government faced insolvency, illiquidity, or various macroeconomic weaknesses and risks.” The authors finally point out that “A country is defined to be in debt crisis if it is classified as being in default by Standard & Poor’s.” Unlike systemic banking and currency crises, sovereign debt crises tend to last long and be persistent. (Fuertes and Kalotychou, 2007) state that there is proof that nation credit ratings can forecast sovereign debt crises and can trigger Granger-cause<sup>2</sup> sovereign bond spreads. (Laeven and Valencia, 2018) state that there have been 74 sovereign debt crises globally from 1970 to 2017.

As with sovereign debt crises, a large number of studies have stated that it seems unlikely to systematically predict currency crises. A currency crisis is defined as an event of depreciation of the currency to the U.S dollar of at least 30 percent (some researchers inter alia (Kaminsky, Lizondo and Reinhart, 1998), (Xu, Kinkyo and Hamori, 2018), (Eichengreen, Rose and Wyplosz, 1995) estimate the value at 25 percent), which is simultaneously 10 percentage points higher, than the rate of depreciation in the year before (Boysen-Hogrefe et al., 2015 p. 9).

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<sup>2</sup> A Granger cause implies that if a signal  $x$  “granger-causes” a signal  $y$ , then the past values of  $x$  should contain information that predict  $y$ . For more information, see Anil Seth (2007), Granger causality, Scholarpedia, doi:10.4249/scholarpedia.1667

(Wilett and Wihlborg, 2013) draw our attention to an EU-specific definition of a currency crisis (also called as balance-of-payments crisis). In a recent study by (Xu, Kinkyo and Hamori, 2018) it is pointed out that in addition to the definitions in seminal works of (Frankel and Rose, 1996) and (Kaminsky, Lizondo and Reinhart, 1998) an identification of a currency crisis can be in terms of low output growth, rapid increase in domestic credit growth, and high foreign interest levels. A useful quantitative definition of a currency crisis was proposed by (Eichengreen, Rose and Wyplosz, 1995), where, as a result of introducing an exchange market pressure index (EMP) more accurate forecasting models, such as the multinomial logistic model were developed. Adopting the notation of (Xu, Kinkyo and Hamori, 2018, p. 4), a currency crisis is characterized as a situation in which a country's currency is under attack the end result of which is sharp depreciation of exchange rates and loss in exchange reserves. The EMP consists of a sum of standardised change in the exchange rate and standardised change in reserves. Since neither of the afore mentioned parameters have any dimensions, their addition, therefore, is straightforward. The modified version of the EMP proposed by (Bussiere and Fratzscher, 2006) is the weighted average of the annual changes of real exchange rates and foreign exchange reserves given by  $EMP_{i,t} = \omega_{exr} \left( \frac{rexr_{i,t} - rexr_{i,t-1}}{rexr_{i,t-}} \right) - \omega_{resr} \left( \frac{res_{i,t} - res_{i,t-1}}{res_{i,t-}} \right)$  where  $rexr_{i,t}$  is the real exchange rate,  $res_{i,t}$  is the foreign exchange reserves,  $\omega_{exr}$  is the inverse of the variance of change rates in exchange rates,  $\omega_{resr}$  is the change in rates in exchange reserves. While (Kaminsky, Lizondo and Reinhart, 1998) propose the signal extraction approach to forecast crises (in retrospect, they have found that exports, real exchange rate overvaluation, GDP growth, foreign exchange reserves, and equity prices are the most reliable predictors of crises), .Within an extensive comparative research framework, (Berg and Patillo, 1999, p. 584) concluded that the bivariate probit models seemed to have been the most efficient in crisis forecasting, resulting in successful predictions at 51 percent of the time. (Laeven and Valencia, 2018) identified over 236 currency crises globally from 1970 to 2017.

The assessment of risks to financial stability is one of the primary objectives of modern central banks. While earlier the evaluation of financial stability was conducted by a panel of experts, in the 1990's a quantitative approach has been introduced. Financial markets are inherently forward-looking (Kliesen et al., 2012, p. 371), and therefore are also predictable. Financial conditions indices (FCIs) are statistically derived indicators encompassing a large set of financial variables summarizing the information about the future state of the economy. They measure financial shocks that predict future economic activity (Hatzius et al, 2010, p. 1). There

are seven well-established FCIs that are closely followed by economists. These are: Bloomberg FCI – a weighted sum of standardized money, equity and bond market indicators available from 1991 (Rosenberg, 2009; Hatzius, 2010); Citi FCI – a weighted sum of six financial variables available from 1983; Deutsche Bank FCI, determined as a percentage point drag or boost to GDP, available from 1983; Goldman Sachs FCI – a weighted sum of short-term bond yield, a long-term corporate yield, the exchange rate, and the stock market variables (Dudley et al, 2000; Hatzius et al., 2010); Federal Reserve Bank of Kansas City FCI – a weighted average of 11 standardized indicators divided by yields spread and asset price behavior available from 1990 on a monthly basis; Macroeconomic Advisers Monetary FCI – based on the “surface impulse response” methodology available from 1982; OECD FCI – a weighted normalized sum of six financial variables available from 1995. Even so the specific variables included in the FCIs differ, commonalities still exist. FCIs, given their design, assume a correlation between financial sector and a macroeconomic element, hence they are expected to be better predictors of real economic activity (Kliesen et al., 2012, p. 373).

## **2.2 Early Warning Systems and their application in crisis forecasting: The MIP**

Adopted in the late '90s by international financial institutions such as the IMF, ECB, World Bank, EWSs are closely monitored, assessed, and stress-tested through regular early warning exercises (EWEs), improving their ability to spot risks and vulnerabilities that could lead to further systemic shocks (Ghosh et al., 2009). Taking heed of the NBERs extensive research on the explanatory capabilities of EWSs during the 2008-09 crisis summed up in the work of (Frankel and Saravelos, 2010), economists have gained valuable experience from the conduct of EWEs. Namely: (i) crises are a direct result from the collision of vulnerabilities with specific trigger events, (ii) while failing to predict crises based on triggers, EWSs have been found good in identifying vulnerabilities, (iii) fragmented<sup>3</sup> analysis underestimate risks, (iv) scattered warnings fail to spur concrete policy action (Mühleisen et al., 2010, pp: 10-13). EWEs are jointly conducted by the IMF and the Financial Stability Board (FSB). The two independent international bodies guide analytical work and prepare documents in consultation with management. The execution of the EWE is a three-month process that starts with a qualitative and quantitative analysis of financial and macroeconomic vulnerabilities jointly identified by

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<sup>3</sup> Fragmented is referred to the jointly conducted early warning exercise by the International Monetary Fund - Financial Stability Board through two fifteen-minute presentations. Source: (Mühleisen et al., pp: 10-13., 2010)

the two bodies. The analysis is summarized in the Early Warning List (EWL), which documents the common understanding of risks and vulnerabilities between the IMF and FSB staff. The EWE is finalized in two separate presentations based on the EWL given by IMF and FSB staff and followed by a detailed discussion. The two fifteen-minute presentations include the examination of: (i) external sector risks; (ii) fiscal risks and vulnerabilities; (iii) corporate sector risks and vulnerabilities; (iv) asset prices and market valuations. The presentation further covers the estimation of systemic tail risks in real and financial sectors measured in GDP-at-Risk (GDPaR) and Financial System-at-Risk (FSaR) indicators and provides crisis duration models given by the Index of Capital Account Crises (IKAC). GDPaR, and FSaR are defined by (Nicolò and Lucchetta, 2010, pp: 6-9) as the worst predicted realization of quarterly growth in real GDP at 5% probability and the worst predicted realization of the market-adjusted return of large portfolios of financial firms at 5% probability, respectively and are modeled by a version of the Dynamic Factor Model (DFM) detailed in (Stock and Watson, 2005). The impulse responses to the structural shocks, defined as the sum of GDPaR and FSaR, are identified through the Factor-Augmented Vector Autoregressive (FAVAR), which is interpreted as a stress test of systemic risk indicators to structural shocks akin to that adopted by (Bernanke et al., 2005). Finally, the EWE presentation is concluded with policy response propositions. As an additional part of the post-presentation discussion, crisis exit patterns are identified and evaluated. Senior country officials, academics, and market analysts all take part in the panel discussion. Results of EWEs frequently appear in flagship publications including the World Economic Outlook, Global Financial Stability Report, and Fiscal Monitor (Mühleisen et al., 2010, p. 17). Notwithstanding the seemingly complicated process of the exercise and the sophistication of the tools described, EWEs not only provide an insight to the viability of a given EWS model, but also facilitate the improvement of the IMF's analytical toolkit.

The Macroeconomic Imbalance Procedure (MIP) is an EWS directed by the European Commission. Since 2011 it identifies and prevents potential macroeconomic risks and imbalances. The MIP is integrated into the annual cycle of the EU's monitoring of the European Semester (Milana, 2020 p. 4). Aimed at assessing risks in both the financial and in real sectors, the MIP is the most prominent EWS that is used today. The commission examines 14

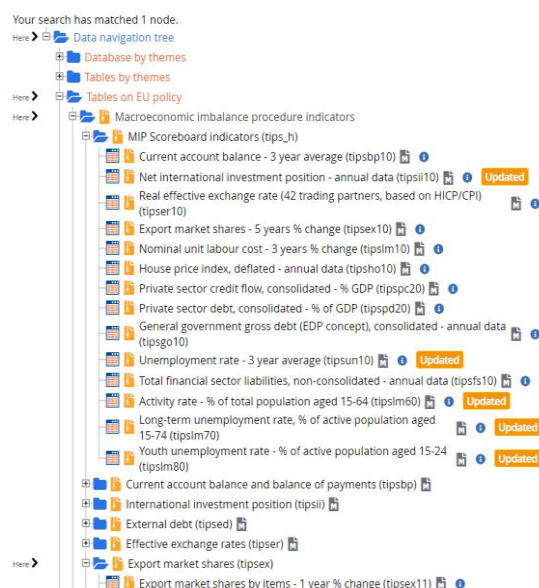
scoreboards<sup>4</sup> indicators identified in critically acknowledged literature Table 1. The annually updated table is provided in the Alert Mechanism Report (AMR), which is a document issued by the Commission towards the end of a calendar year. Based on the statistically determined scoreboard indicators' thresholds, macroeconomic imbalances within European member states are identified. The third step of the MIP is the In-Depth Review – an investigation of a member states' macroeconomic imbalances, where correction and preventive measures are proposed. The values for the thresholds in Table 1 are calculated via the signal extraction method (further discussed in chapter 3), which uses indicators and thresholds for forecasting crisis events. The procedure for its determination is as follows: a given economic indicator is statistically normalized<sup>5</sup>, then arbitrary thresholds are selected based on the number of standard deviations from the mean. The, now, signalling threshold indicator is monitored, and when its value exceeds the thresholds, a signal is produced and interpreted as a warning stipulating the presence of an imbalance. Howbeit the MIP is, at the moment, the most prominent macroeconomic surveillance mechanism in Europe, as a result of multiple intrinsic multilateral assessments in empirical works like (Boysen-Hogrefe et al., 2015 pp: 5-13; Csontos and Szalay, 2013; Arahetes and Gómez, 2018; Erhart et al., 2018), considerable flaws were identified in implementation. As of writing this paper, the usefulness of the Scoreboard in identifying macroeconomic imbalances at a reasonable early stage and how it is related to the outcomes of the MIP, is yet undetermined. Furthermore, an inconsistency in the signal extraction method resulting in many Type II errors<sup>6</sup> could affect the threshold levels in the Scoreboards, as false warning signals could provoke misguided policy measures, which involve high economic costs. Since the Scoreboard is not meant to provide warning signals for specific events, but rather for broadly defined imbalances, the evaluation of its usefulness becomes complicated. In the work of (Knedlik, 2014 p. 157) it has also been determined that "...the thresholds of the Commission's Scoreboard are rather tight (resulting in more alarm signals), as compared to a neutral stand", this the usefulness of official thresholds is negative for all indicators – which can have political and economic consequences

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<sup>4</sup> The scoreboard captures relevant internal and external aspects of macroeconomic imbalances through a limited set of relevant indicators of high statistical quality. Source: (European..., 2021).

<sup>5</sup> Statistical normalization is a procedure, when the values of an indicator are adjusted to a common scale, often between 0 and 1.

<sup>6</sup> A Type II error is a statistical term used in the Signal Extraction method, when the indicator provides a false signal when a certain threshold value is exceeded. Source: see (Boysen-Hogrefe et al., 2015 p. 6).



**Figure 1: Consolidated MIP data structure on the Eurostat website.**

Source: Own compilation based on ec.europa.eu

. In a report by (Erhart et al., 2018 p. 9) it is argued that the lack of two-sided thresholds in case of some indicators raise doubts about the consistency and optimality of thresholds. On page 14 of the same report, the goal of achieving duality in prevention and protection is highlighted, as a means of supporting the need for two-sided thresholds. For example, in Table 1, we can see the current threshold for house prices, which is +6% - a one-sided threshold that could be interpreted as an early warning threshold, but no lower threshold exists for house price declines, which could signal a bust period and serve monitoring purposes. (Erhart et. al 2018) argued that stock variables are better for ex-post monitoring of fading away imbalances, while flow variables, such as the current account deficit or the credit flow, could serve better as EWS. Figure 1 demonstrates the consolidated data structure within which all of the hereinafter scoreboard indicators can be found.

	<b>Indicator</b>	<b>Unit</b>	<b>Data source</b>	<b>Statistical domain</b>	<b>Threshold (2021)</b>	<b>Threshold (2012)</b>
External	Current account balance (% of GDP)	3-year average	Eurostat	BoP/NA	+6%/-4%	+6%/-4%
	Net international	% of GDP	Eurostat	BoP/NA	-35%	-35%

	investment position					
	Real effective exchange rate (42 trading partners, HICP deflator)	3-year % change	DG ECFIN	-	±5% (EA)*/±11% (NEA)**	±5% (EA)*/±11% (NEA)**
	Export market share (% of world exports)	5-year % change	Eurostat	IMF BoP	-6%	-6%
	Nominal unit labour cost index (2010=100)	3- year % change	Eurostat	NA	+9% (EA)*/+12% (NEA)**	+9% (EA)*/+12% (NEA)**
Internal Imbalance Indicators	House price index (2015=100) deflated	1-year % change	Eurostat	Price statistics/NA	+6%	+6%
	Private sector credit flow, consolidated	% of GDP	Eurostat	NA (FA)	+14%	+15%
	Private sector debt, consolidated	% of GDP	Eurostat	NA (FA)	+133%	+160%
	General government gross debt	% of GDP	Eurostat	EDP/GFS	+60%	+60%
	Unemployment rate	3-year average	Eurostat	EU-LFS	+10%	+10%
	Total financial sector liabilities, nonconsolidated	1-year % change	Eurostat	NA (FA)	+15.5%	+16.5%
Unemploy	Activity rate (% of total population aged 15- 64)	3-year change in pp	Eurostat	EU-LFS	-0.2%	-

	Long-term unemployment rate (% of active population aged 15-74)	3-year change in pp	Eurostat	EU-LFS	+0.5%	-
	Youth unemployment rate (% of active population aged 15-24)	3-year change in pp	Eurostat	EU-LFS	+2%	-
<p>Note: NA – National Accounts; BoP – Balance of Payments; FA – Financial Accounts; EDP – Excessive Deficit Procedure Statistics / GFS – Government Finance Statistics; and LFS – Labour Force Survey/Labour Market Statistics; pp – percentage points/ EA- Euro Area Member countries/ NEA- Non- Euro Area Member countries</p>						

*Table 1: MIP scoreboard indicators (AMR 2021).*

Source: Own compilation based on

[https://ec.europa.eu/eurostat/documents/16624/9862137/2021\\_statistical\\_annex\\_en.pdf](https://ec.europa.eu/eurostat/documents/16624/9862137/2021_statistical_annex_en.pdf)

The formulas for determining the individual aggregate leading indicators of the scoreboard can also be found on the Eurostat, further proving its transparency and ease of access.

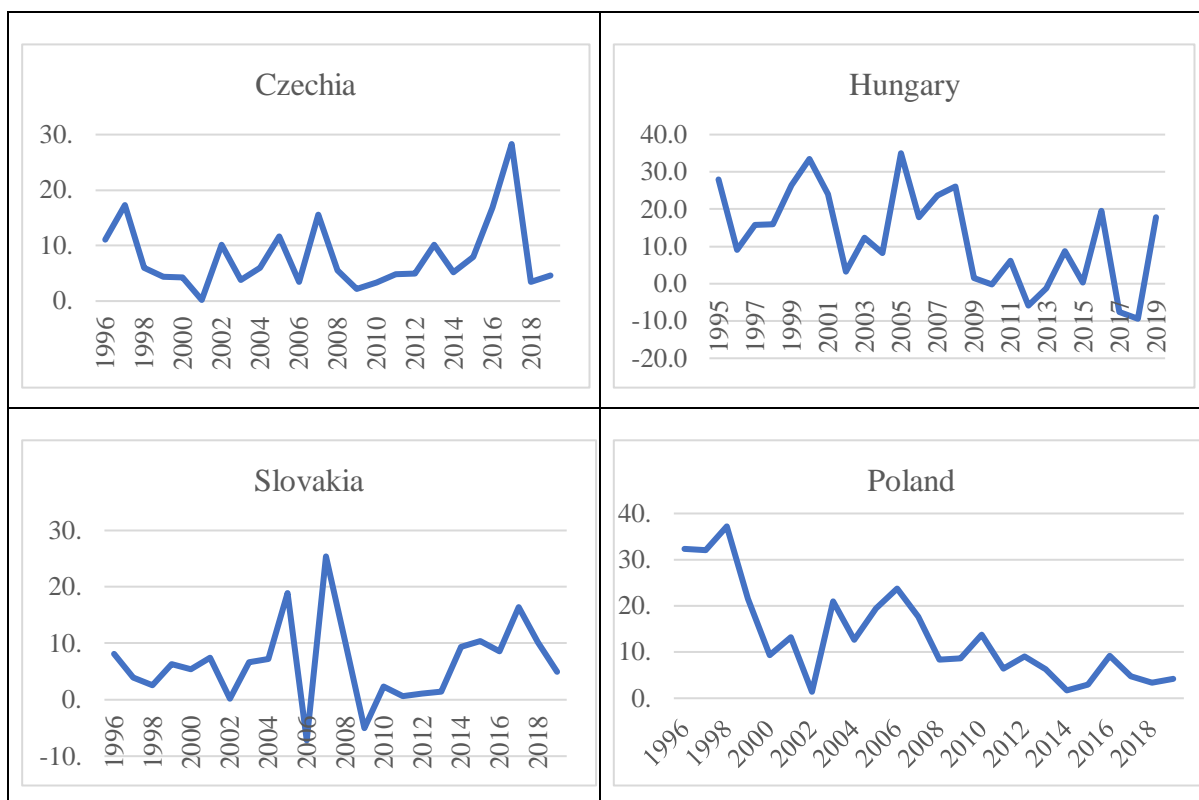
3 year backward moving average of CURRENT ACCOUNT BALANCE as % of GDP	$\frac{\left(\frac{CA}{GDP}\right)_t + \left(\frac{CA}{GDP}\right)_{t-1} + \left(\frac{CA}{GDP}\right)_{t-2}}{3} \cdot 100$
NET INTERNATIONAL INVESTMENT POSITION as % of GDP	$\left(\frac{NIIP_t}{GDP_t} \cdot 100\right)$
% change (3 years) of REAL EFFECTIVE EXCHANGE RATE with HICP deflators relative to 42 other industrial countries	$\frac{(REER\_HICP\_42)_t - (REER\_HICP\_42)_{t-3}}{(REER\_HICP\_42)_{t-3}}$

% change (5 years) in Export Market Shares	$\frac{\left(\frac{EXP_c}{EXP_{world}}\right)_t - \left(\frac{EXP_c}{EXP_{world}}\right)_{t-5}}{\left(\frac{EXP_c}{EXP_{world}}\right)_{t-5}} \cdot 100$
% change (3 years) in Nominal Unit Labour Cost	$\frac{(ULC)_t - (ULC)_{t-3}}{(ULC)_{t-3}} \cdot 100$
YoY % change in Deflated House Prices	$\frac{\frac{HPI_t}{DEFL_t} - \frac{HPI_{t-1}}{DEFL_{t-1}}}{\frac{HPI_{t-1}}{DEFL_{t-1}}} \cdot 100$
Private sector credit flow as % of GDP	$\frac{PSCF_t}{GDP_t} \cdot 100$
Private sector debt as % of GDP	$\frac{PSD_t}{GDP_t} \cdot 100$
General government debt as % of GDP	$\frac{GGD_t}{GDP_t} \cdot 100$
3 year backward moving average of UNEMPLOYMENT RATE	$\frac{(UR)_t + (UR)_{t-1} + (UR)_{t-2}}{3}$

*Table 2: Journal of Central Banking Theory and practice MIP scoreboard transformation.*

Source: Own compilation based on [https://cbcg.me/slike\\_i\\_fajlovi/fajlovi/journal/vol2/no1/the\\_new\\_eu\\_macro-economic\\_imbalances.pdf](https://cbcg.me/slike_i_fajlovi/fajlovi/journal/vol2/no1/the_new_eu_macro-economic_imbalances.pdf)

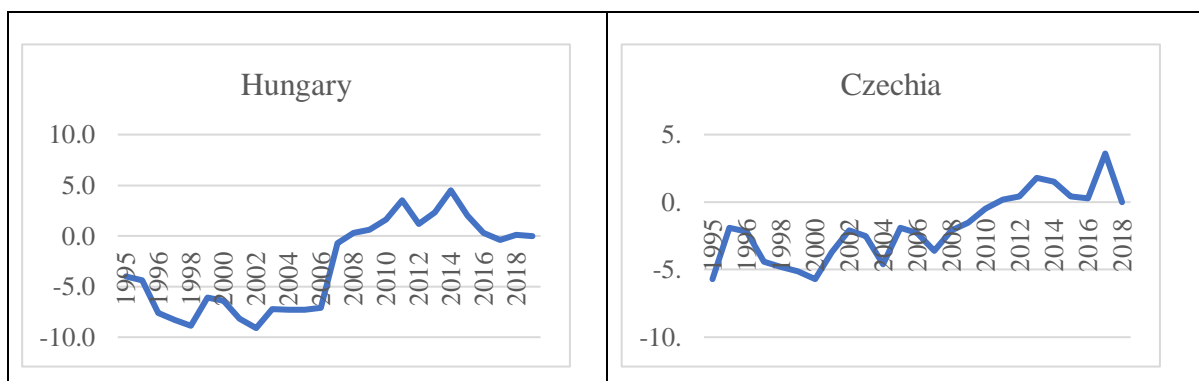
It is evident that a critical advantage of the MIP process and the scoreboard indicators themselves is their wide accessibility and incredible transparency. The data is easily available from the Eurostat website consolidated database structure. The tables below feature the MIP scoreboard indicators for V4 countries. The graphs were constructed from the data provided on the website. Commentary regarding the evolution of the indicators during and after the 2008 global financial crisis and leading up to the current recession were added as to elucidate the vector of development of the indicators.

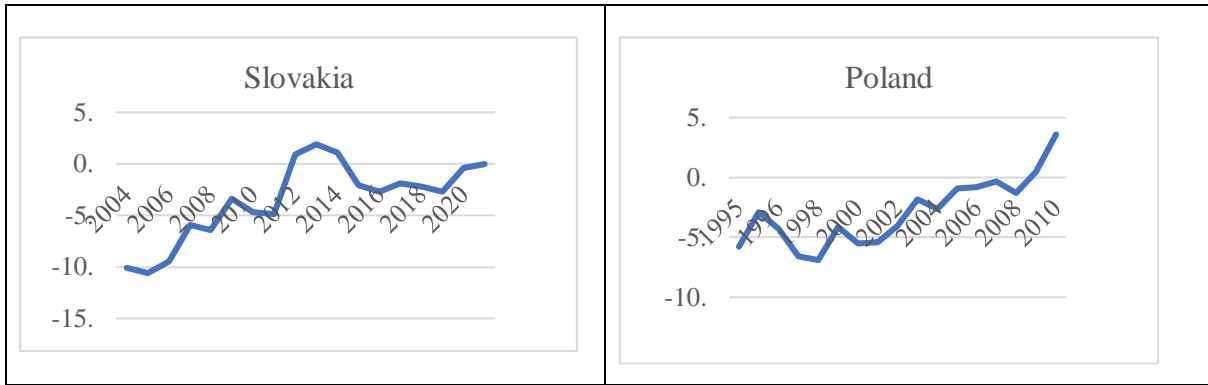


**Table 3: AMR Total Financial liabilities for V4 countries. Annual time series.**

Source: Own compilation based on the data from Eurostat

The total financial corporations sector liabilities measure the evolution of a composite of liabilities including currency, deposits, loans, equity and so on. The time frequency of the data is annual. The data presented in Table 3 are in percentage change on previous period. At a quick glance, we can notice similarities in the increase of volatility of the indicator at around the timeframe of the Great Recession, particularly well in the Slovakian time series, whereas in Hungary, for example a distinct negative trendline can be observed. The latest In-depth-review to feature Hungary as its subject was in 2016.

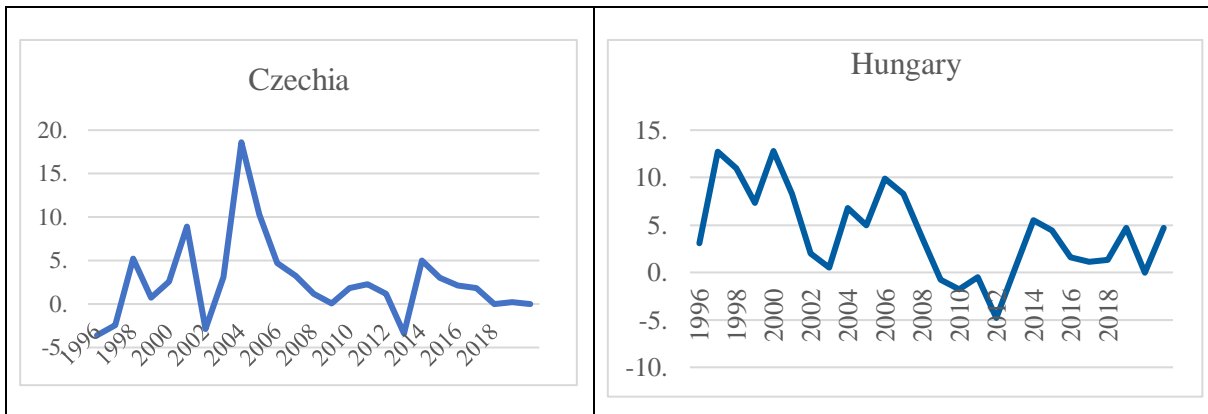


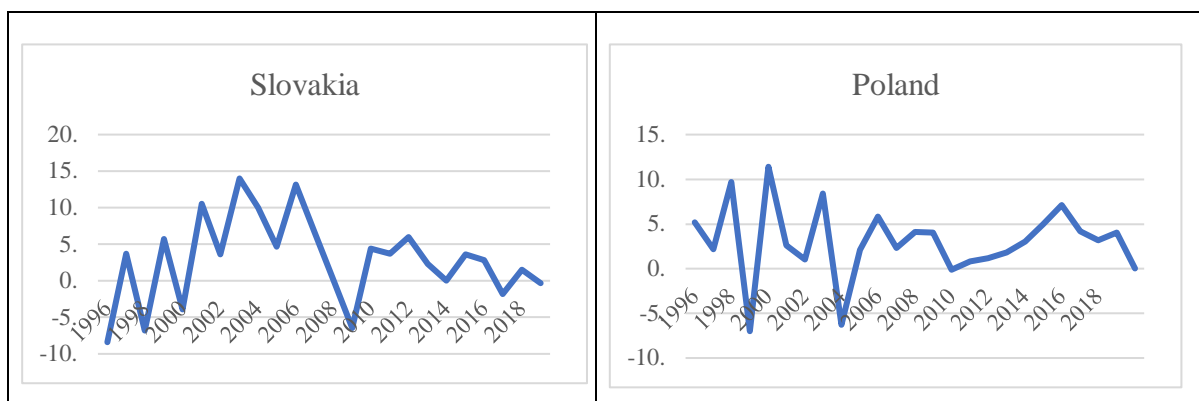


**Table 4: Current account imbalances for V4 countries Annual time series.**

Source: Own compilation based on the data from Eurostat

The Current account imbalances indicator gives the insight into the Balance of Payments (BoP) of a country with the rest of the world. The indicator measures the imports, exports, exchange of goods and services and the general financial flows marked as credit or a debit. The data is measured in percentage of GDP. A negative current account balance usually means that the country is a net borrower and generally has the trust of foreign investors. Usually, it is within these periods that economic growth happens. On the contrary, a positive current account balance indicates that the country is a net lender. The current account balance is strongly affected by interest rates and the currency, therefore valuable forecasting information could be drawn from the correlation of the two.

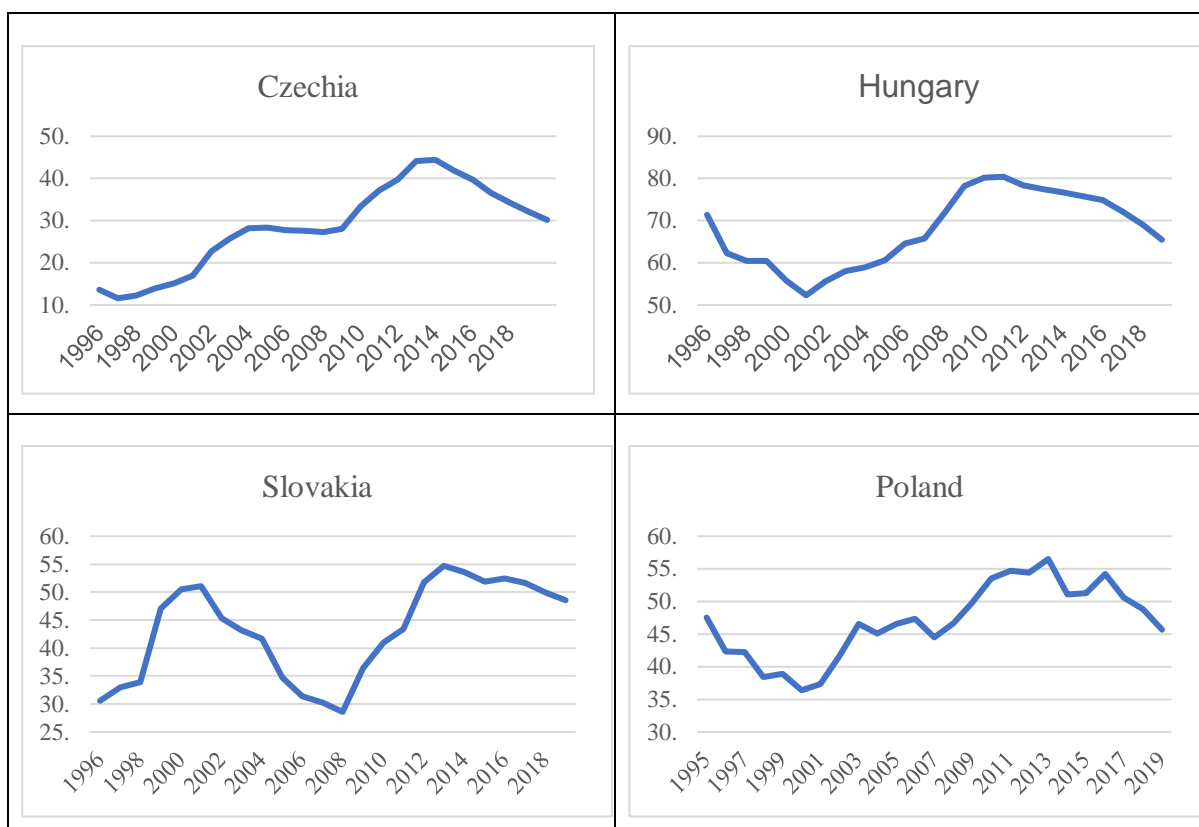




**Table 5: Export market shares in volume for V4 countries annual time series.**

Source: Own compilation based on the data from Eurostat

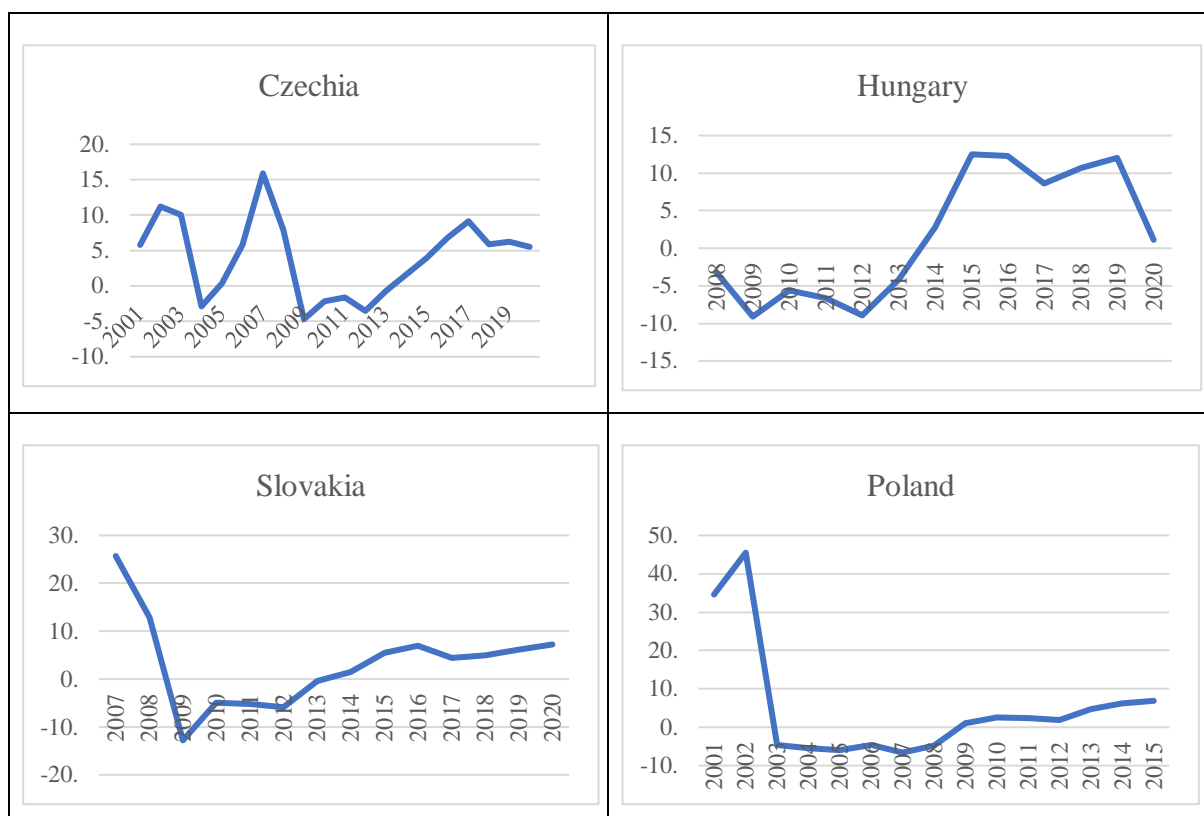
Explanatory variables for the export market share indicator include global value chains. A higher value indicates that the country operates ‘upstream’ in the global value chain specializing in research and development as well as raw materials, whereas a lower value indicates that a country operates ‘downstream’, meaning in the final assembly process. The unit of measurement is percentage change on previous period.



**Table 6: Gross Debt to GDP ratio of V4 countries annual time series.**

Source: Own compilation based on the data from Eurostat

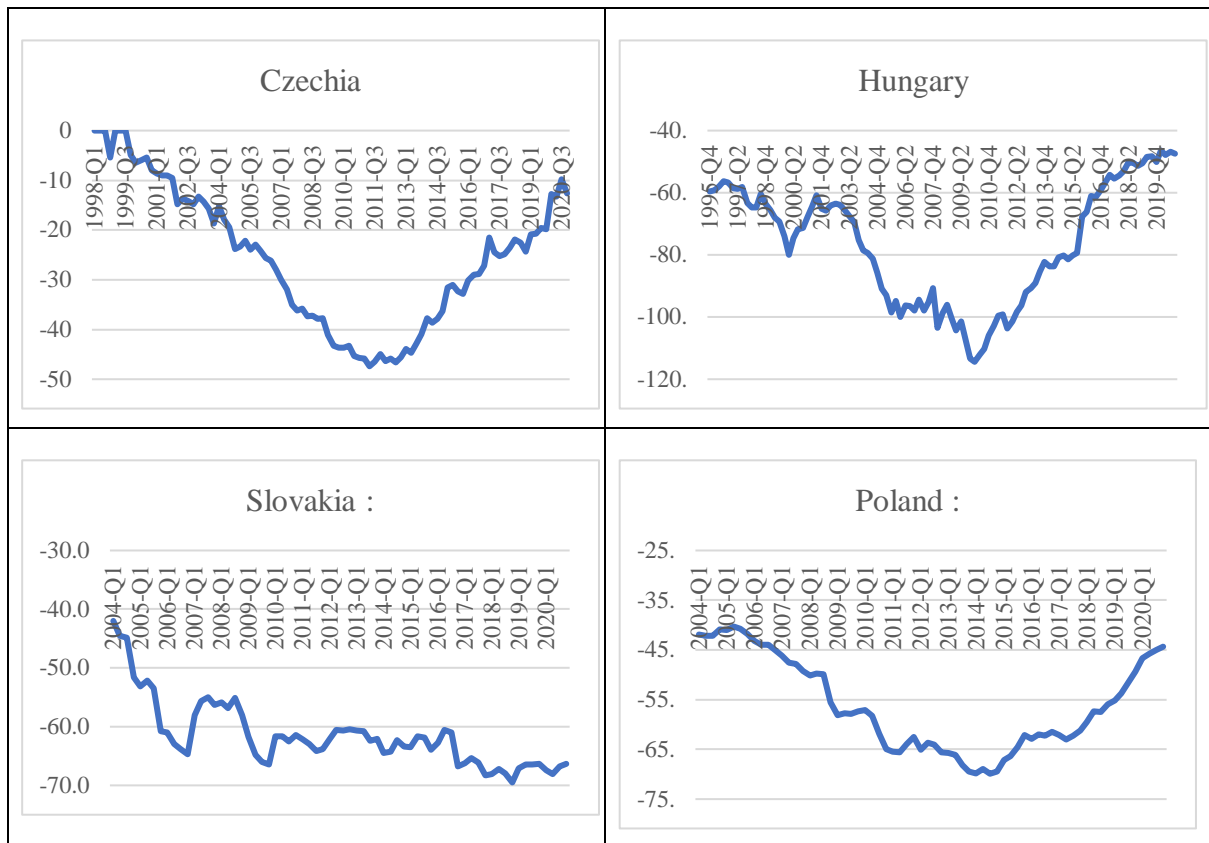
The general government debt-to-GDP ratio is one of the main indicators of government finance sustainability. It is also often referred to as public debt, national or sovereign debt. It is defined as gross debt at nominal (face) value outstanding at the end of the year and consolidated between and within the sectors of general government. Government debt is calculated as the sum of currency and deposits, debt securities, loans, insurance, pensions and other accounts payable. (OECD..., 2021). The unit of measurement is percentage of GDP. Modern Monetary Theory states that as long as the economy can continue growing at a higher rate than the public debt growth rate, high levels of general gross public debt can be maintained. In the last years, based on the graphs above, a clear trend can be outlined of a gradual reduction in public debt.



**Table 7: Annual house price indices in V4 countries annual data.**

Source: Own compilation based on the data from Eurostat

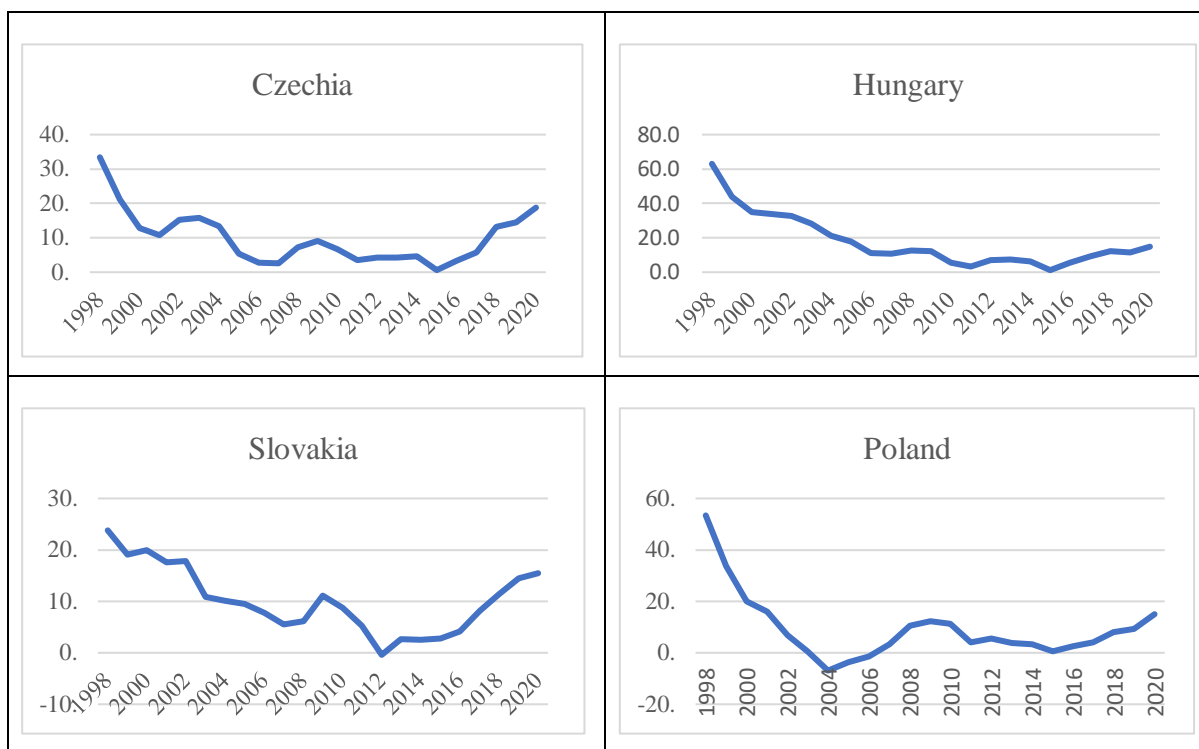
The house price index is a valuable estimator of inflation of house prices relative to the inflation in the final consumption expenditure of households. The indicator captures residential properties purchased by households like flats, detached houses, terraced houses. The reason why it is an important measure is that it is able to capture more complex events such as mortgage defaults, housing affordability, number of units sold. The unit of measure is annual average rate of change.



**Table 8: Net international investment position quarterly data (% of GDP)**

Source: Own compilation based on the data from Eurostat

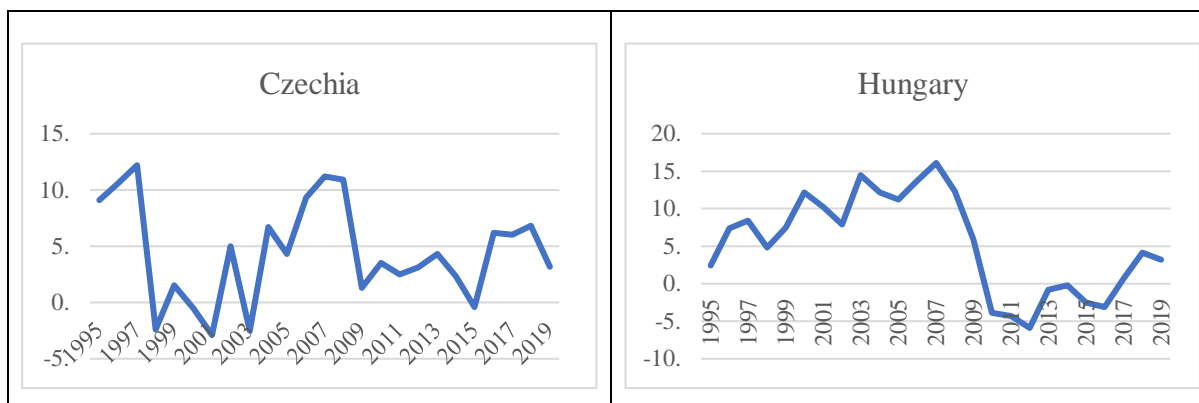
The Net International Investment position is used to indicate the creditworthiness of an economy. A nation with a positive Net International Investment position is a creditor nation, whereas a negative NIIP is a debtor nation. It can be viewed separately, but it complements the BoP and the current account balance of the country. In case of all of the 4 economies we see that they all are debtor nations. Mathematically it is given by subtracting assets owned by foreign nations from assets owned by the domestic nation. The indicator is released on a quarterly basis and is measured in percentage of GDP.

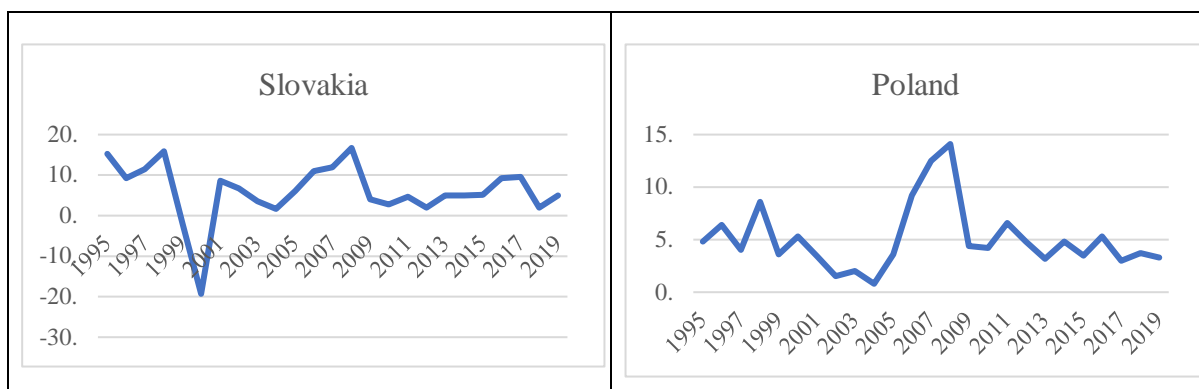


**Table 9: Nominal Unit labour cost in V4 economies annual data (% of GDP)**

Source: Own compilation based on the data from Eurostat

The nominal unit labour cost is measured as the 3-year backwards moving percentage change. The indicative threshold is 95 for the euro area and 12% for non-euro area. The data is released on an annual basis.

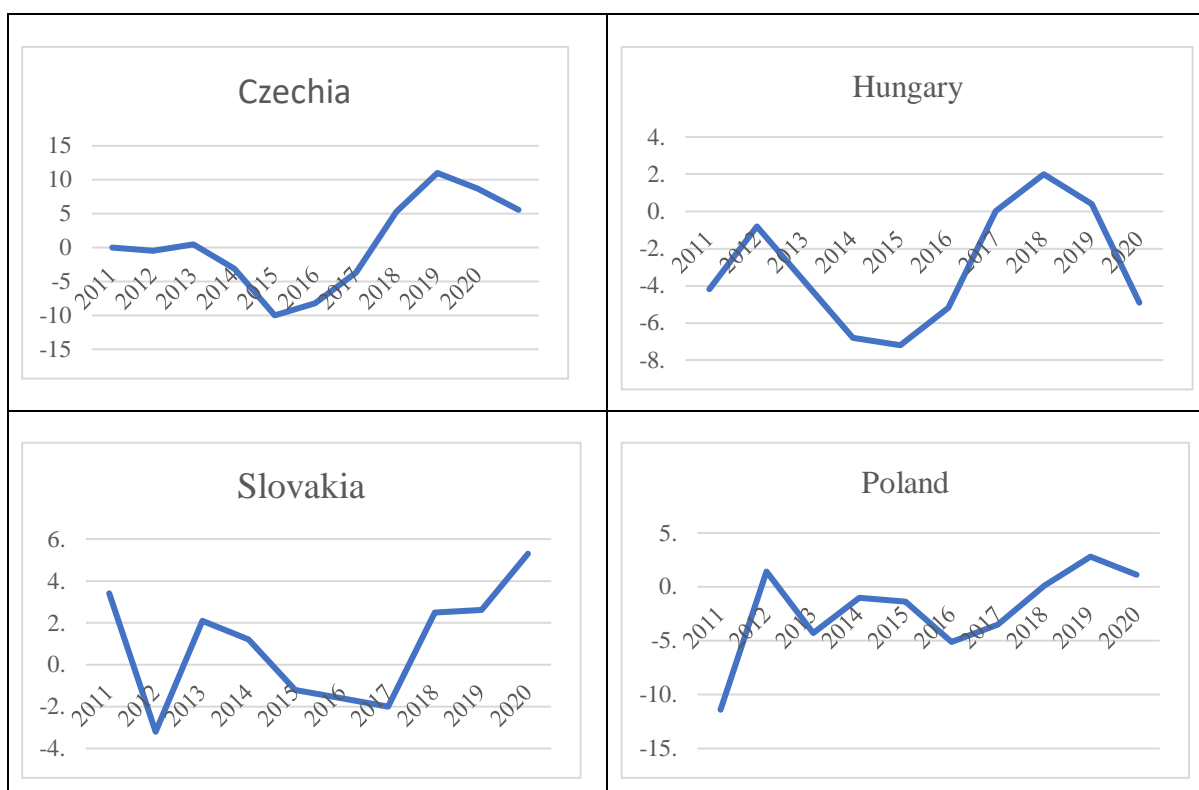




**Table 10: Private sector credit flow in V4 countries 3-year percentage change annual data**

Source: Own compilation based on the data from Eurostat

The private sector credit flow represents the net amount of liabilities in which the sectors Non-Financial corporations, Households and Non-Profit institutions serving households have incurred along the year. The data is measured in percentage of GDP and is published at an annual basis.



**Table 11: Real Effective Exchange rate of V4 economies 3-year change annual data**

Source: Own compilation based on the data from Eurostat

The real effective exchange rate is one of the main leading indicators, which is also further discussed in the paper. It is defined as a weighted average of a country's currency in relation

to a basket of foreign currencies. The weights of the REER are placed strategically depending on the trade relationships between the domestic and foreign country. When the REER is negative, the economy gains competitiveness compared to its trading partners and vice versa. The REER is measured as a 3-year backwards moving percentage change and the time frequency is annually.

Based on the tables above, the In-depth-review is created, where the macroeconomic imbalances of a country are assessed multilaterally, and policy measures are advised for prevention and correction purposes.

### **2.3 Time series analysis and forecasting methods**

The building block of any forecasting is the time series. Following (Montgomery et al., 2015, pp: 2-6), “A time series is a time-oriented or chronological sequence of observations on a variable of interest.” Time series plots reveal patterns, random, trends, level shifts. A forecast consists of a point estimate, or a point forecast and a forecast error. Together they form the prediction interval (PI). Forecasts vary in time forecast horizons (sometimes called the forecast lead time) and forecast intervals – which is the frequency with which new forecasts are prepared. There exist three timeframe classifications of forecasts: (a) short-term, (b) medium-term and (c) long-term. (a) forecasts – are usually done days, weeks and months into the future. (b) forecasts – are forecasts, which extend from 1 to 2 years into the future. (c) forecasts extend beyond by many years. (Montgomery et al, 2015, p. 13) further defines the activities in the forecasting process (i) Problem definition, (ii) Data collection, (iii) Data analysis, (iv) Model selection and fitting, (v) Model validation, (vi) Forecasting model deployment, (vii) Monitoring forecasting model performance. There are stationary and non-stationary time series. Stationarity implies that the time series has a constant mean, constant variance over time and has no seasonality. In practice o

The earliest economic time series forecasting methods were developed in the 1920s (which were then regarded as ‘business barometers’). Yet arguments against the possibility of business and economic forecasting were adopted by many prominent economists and statisticians of that time, some of the arguments are reiterated even today. The, then widely held belief was that economic forecasting could not rely on probability reasoning, because economic data are inhomogeneous and are not distributed independently as required by statistical theory (Morgan, 1990). Economic forecasts were also stressed with self-fulfilling expectations, which was an

issue that concerned many business-cycle analysts of the time – this was a problem raised by (Morgenstern, 1928) and later reaffirmed in (Lucas, 1976). Economic theories were tested against the data via statistical methods like standard Error and multiple correlation coefficients (Clements and Hendry, 1998, p. 6). Up until 1944, forecasting was treated as a probability statement about the location of a sample point not yet observed. (Clements and Hendry, 1998, p. 8) further adopt the concept of the data generating process (DGP), which, as asserted by (Haavelmo, 1944), is an inherently stochastic process parameter vector. “If the DGP were to be known to the observer, the future of the time series could be forecasted perfectly. In reality, the DGP is completely unknowable due to the inherently stochastic nature of economic indicators” (Molnár, 2020, p. 51). In this study we deal with forecasting with unobserved components time series models.

Following (Clements and Hendry, 1998, p. 8), since at its core any forecasting involves a certain prediction interval, we define the probability distribution of the observed time series as  $D_{(Y_2|Y_1)}(y_{T+1}, \dots, y_{T+H} | y_1, \dots, y_T)$ , where, we are given  $T$  ( $y_1, \dots, y_T$ ) observable values on the random variable of  $Y$ , from which the future values, indicated by  $H$  ( $y_{T+1}, \dots, y_{T+H}$ ) are to be predicted. Bayesian forecasting allows for the generation of interval forecasts by combining the sources of uncertainty into a probability distribution function (p.d.f). Through integrating the information given by the observed results, Bayes theorem is used to update a prior distribution (probabilities defined prior to data analysis) into a posterior distribution (probabilities following data analysis). Adapting the notation of (Lütkepohl, 2005 p. 1) let  $y_t$  denote the value of a variable of interest in period  $t$ , signified by  $y_t$ ,  $t = 1, 2, \dots, T$  with the entire sample from  $t = 1$  to  $t = T + H$ . The forecast for period  $T + H$  will therefore be of the form  $\hat{y}_{T+H}$ . The history of the sequence at time  $t$  is given by  $Y_t$ . The sample space for  $y_t$  is  $\psi_t$  upholding the criteria that  $\psi_0 \neq \emptyset$ .  $\theta \in \Theta \subseteq R^k$ , where the parameter vector includes not only parameters as usually conceived, but also latent variables convenient in model formulation. This extension immediately accommodates non-standard distributions, time varying parameters, and heterogeneity across observations (Carter and Kohn, 1994), therefore it is a shorthand for the DGP parameter vector. The pre-sample information,  $Y_0$ , is denoted by  $Y_{T-1} = (Y_0, Y_{T-1}^1)$ , so that  $Y_{T-1}^1 = (y_1 \dots y_{T-1})$ . The joint density of  $y_t$  at time  $t$  is therefore given as  $D_{y_t}(y_t | Y_{T-1}, \theta)$ . (Clements and Hendry, 1998, p. 35) explore the conditional expectation as the main predictive function. this paper the conditional expectation is the workhorse predictor. In their research, they further argue that in  $\hat{y}_{T+H} =$

$E(y_{T+H}|Y_T)$ , where  $Y_T = (... y_1 ... y_T)$  The joint density function can be sequentially factorized as  $p(Y_T|A, \theta) = \prod_{t=1}^T p(Y_t|Y_{T-1}, \theta, A)$ , where  $A$  specifies a corresponding sequence of probability density functions. Understanding the basis of mathematical denotation of the forecasting procedure is thus important to establish the logic of the three methodological frameworks discussed in the introduction.

Structural time series models (STMs) incorporate a time series model for forecasting that provides a way of weighting data that is determined by the properties of time series. Taking heed of (Montgomery et al., 2015, p. 331) "...STMs are formulated in terms of unobserved components, such as trends and cycles, that have a direct interpretation. Thus, they are designed to focus on the salient features of the series and to project these into the future. They also provide a way of weighting the observations for signal extraction, so providing a description of the series". STMs differ from other statistical models like Bayesian forecasting, as they are developed from *ad hoc* procedures<sup>7</sup>. The exponentially weighted moving average (EWMA) procedure developed by (Holt, 1957) is an example of the early development of STMs, where adhering to its requirements, the model captures both the random walk plus noise and seasonality of a time series. Thanks to its simplicity and transparency this method is widely used today as well. The Kalman filter (Kalman, 1960), first applied in the trajectory estimation of the Apollo program<sup>8</sup> at NASA, has also found application in econometrics. The Kalman filter is able to handle unobserved components models, time-varying parameters (Rosenberg, 1973). In the 1980s the application of the Kalman filter methodology in works like (Young, 1984) and (Harvey, 1989) reached its peak. The state space form (SSF) adopts the Kalman filter to virtually any linear time series model. The advantages of the SSF become more notable when it is applied to more complex problems, the method further offers enormous flexibility in dealing with data irregularities, such as missing observations. A notable research conducted to compare the forecasting performance of STMs with other time series methods on a wide range of data sets was conducted by (Andrews, 1994 p. 237 ) where the following conclusion has been drawn: "The structural approach appears to perform quite well on annual, quarterly, and monthly data, especially for long forecasting horizons and seasonal data. Of the more

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<sup>7</sup> Ad hoc procedures are not based on statistical models

<sup>8</sup> Source:: Paul Zarchan; Howard Musoff (2000). *Fundamentals of Kalman Filtering: A Practical Approach*. American Institute of Aeronautics and Astronautics, Incorporated. ISBN 978-1-56347-455-2.

complex forecasting methods, structural models appear to be the most accurate”. Similar *ad hoc* forecasting methods were explored in (Assimakopoulos and Nikolopoulos, 2020).

Adhering to the forecasting process, the individual components of an economic time series are subject to direct decomposition. The individual components of a time series are usually identified as the trend, cycle, seasonality and error. In theory, to form a forecast, these individual components have to be projected separately into the future and then recombined to form a forecast. In practice, difficulties arise in successfully isolating the error component and producing correct forecasts for the trend component. Whereas seasonally adjusted forecasting developed by (Holt, 1957) is successful at predictions and is nowadays used in manufacturing planning, it is insufficient in economic forecasting. A relatively newly developed Theta-model ( $\theta$  – *coefficient*), based on the concept of modifying local curvatures of time series, thereby minimizing the fluctuations of the time series. If the local curvatures decrease, the time series is deflated. The larger the  $\theta$  – *coefficient*, the smaller is the degree of deflation. At  $\theta = 0$  the time series is a linear regression line. Following the tests made on empirical data by (Assimakopoulos and Nikolopoulos, 2020, p. 524), the decomposition approach to forecasting through the  $\theta$ - model is conducted in 6 steps: (i) seasonality testing – where time series are tested for statistically significant seasonal behaviour with the *t*-*statistic*, (ii) ‘deseasonalisation’ – where the time series are decomposed, via:  $Y''_{new}(\theta) = \theta \cdot Y''_{data}$ , where  $Y''_{data} = Y_t - 2Y_{t-1} + Y_{t-2}$  at time  $t$ , (iii) decomposition – the two  $\theta$  – values are set equal to  $\theta = 0$  (for the linear regression line) and  $\theta = 2$ , magnifying short-term behaviour, (iv) extrapolation of the two  $\theta$  – lines is performed on the original time series, an exponential smoothing, (v) combination – where the forecasts produced through extrapolation are combined with equal weights, (vi) ‘reseasonalisation’. In the abstract it was concluded that:”...as adopted in order to produce forecasts for the 3003 series of the M3 competition. The method performed well, particularly for monthly series and for microeconomic data”

Further adopting the notation of (Graham and Timmerman, 2015 p. 335), STMs are made up of a stochastic trend component, denoted as  $\mu_1$  and a random irregular term. The most basic STM model is the exponentially weighted moving average (EWMA), commonly regarded as simple exponential smoothing, the function is denoted as  $S(\lambda) = \sum \hat{v}_t^2$ , where  $\hat{v}_t = y_t - \hat{y}(t|t-1)$ . The logic behind the derivation of the equation stems from the assumption that we want to estimate the current level of a series of observation, the simplest way of doing which

would be by using the sample mean. Weights of  $w_j$  are added to the model, where  $0 < w_j < 1$  (the set of which sums to unity). The estimate of the current level of the series is therefore:

$m_t = \sum_{j=0}^{T-1} w_j y_{T-j}$ . As a means of putting more weight on the most recent observations, the  $\lambda$  smoothing constant is introduced, where  $0 < \lambda < 1$ . The formula can be rewritten as:  $m_t = \lambda \sum_{j=0}^{T-1} (1 - \lambda)^j y_{T-j}$ . If the former expression is defined for any value of  $t$  from  $t = 1$  to  $t = T$ ,  $m_t = (1 - \lambda)m_{t-1} + \lambda y_t$ . Since  $m_t$  denotes the forecast, the expression can be rewritten in terms of  $\hat{y}_{(t+1|t)}$ . The smoothing constant  $\lambda$  can be chosen so as to minimize the sum of squares of the predicted errors, that is  $\hat{y}_{(t+1|t)} = \hat{y}_{(t|t-1)} + \lambda \hat{v}_t = S(\lambda)$ . More recent evidence on the effectiveness of EWMA models in economic time series prediction was found in the research of (Yu et al., 2020, p. 13), where the authors examined 18 real time series datasets ranging from Unemployment rate in the USA (duration time of the time series 2000. 01.- 2019. 01; monthly timescale) to the S&P 500 stock index (2009.01-2019.01; monthly timescale) and USA M2 supply (1890-1974; yearly). Addressing the drawback of traditional EWMA models, a two-stage EWMA (double exponential smoothing) was applied to the datasets. "...It has been found that both two- and one- stage EWMA's showed unsatisfactory performance in that this model can't accommodate the nonstationary time series encountered in real situations." The seasonal factors are poorly estimated when the initial time series observations are not sufficient.

Expanding the prediction intervals and probability distributions defined by (Clements and Hendry, 1998), the local level model (LLM) consists of a random walk plus noise  $y_t = \mu_t + \varepsilon_t$ , where  $\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$  – irregular level disturbance independently distributed with mean 0 and variance  $\sigma_\varepsilon^2$ , and  $\mu_t = \mu_{t-1} + \eta_t$  with  $\eta_t \sim NID(0, \sigma_\eta^2)$ . The signal-to-noise ratio given by  $q = \frac{\sigma_\eta^2}{\sigma_\varepsilon^2}$ . The autocorrelation function (ACF) is written as  $\rho_1 = -\frac{1}{q+2}$ , where  $-1/2 < \rho_1 < 0$ . The properties of LLM allow for the following assumptions to be made: since  $\Delta y_t = \Delta \mu_t + \Delta \varepsilon_t$  and  $E(\Delta y_t) = 0$ ,  $y_t$  can be represented in an autoregressive integrated moving average (ARIMA) with parameters (0,1,1), we can rewrite the forecast expression of  $y_t$  in terms of  $\Delta y_t = \xi_t + \theta \xi_{t-1}$ , where  $\xi \sim NID(0, \sigma^2)$ . The autocorrelation function would be  $\rho_1 = \frac{\theta}{(1+\theta)^2}$ , where  $-1 < \theta < 0$ .  $\theta$ -can be expressed as a function of  $q$ , where  $\theta = \frac{\sqrt{q^2+4q}-2-q}{2}$ . A recent review of the literature on this area by (Scott and Varian, 2013) approaches to variable

selection categorising them in 4 groups: significance testing, information criteria, principle component and factor models and regression models.

### 3. MATERIAL AND METHOD

#### 3.1.1 Signal Extraction Method

In their work (Borio and Drehman, 2009) argued that the signalling method (the signal extraction method) as a so-called ‘fuzzy’ measurement is the most suitable one for the assessment of the economy in terms of financial balance, since not only the method is simple in execution (which is the main reason why it is used in the MIP scoreboard), but additionally it takes into account the time requirement of the transmission of monetary policy (Csontos and Szalay, 2013 p. 15). The signal extraction method was developed by (Kaminsky, Lizondo, Reinhart, 1998). Adhering to (Erhart et al., 2018), the signals approach can be easily applied for the MIP scoreboard. Adopting the notation of (El-Shagi, Knedlik and Scweinitz, 2013 p.79), let  $C$  denote the binary crisis variable, that is the crisis in a given period.  $\bar{C}_t$  is a matrix that denotes periods where indicators produce a signal. The expression is as follows:

$$\bar{C}_t = \begin{cases} 1, & \text{if } \exists k \in \{0, \dots, h\}: C_{t+k} = 1 \\ 0, & \text{else} \end{cases} \quad (1)$$

where  $t \in \{1, \dots, T\}$  is the time period,  $h$  is the forecasting horizon. The indicator signals the beginning of an economic crisis in a forecast horizon when it exceeds or falls below a statistically determined threshold. Empirical literature assumes the relationship between the  $\bar{C}_t$  variable and the indicator to be non-linear, rather probabilistic. Therefore, the threshold  $\Pi_0$  for the indicator  $I$  is determined at first arbitrarily and as the procedure is reiterated a statistically significant number of times, the threshold that is found becomes more and more accurate. Using the threshold, every indicator is translated to the binary signal variable  $S_I$ :

where the expression is as follows:

$$S_I = 1_{I_t > \Pi_0} \quad (2)$$

The combination of the afore mentioned  $\bar{C}_t$  and  $S_I$  variables creates a 2x2 matrix of observations detailed in two separate representations below:

	Crisis occurs	No crisis occurs		$\bar{C}_t$	
			$S_t$	1	0
Signal	A	B	1	A	B
No signal	C	D	0	C	D

*Table 12 Combination of crisis variables and signaling variables*

Source: (Kaminsky, Lizondo, Reinhart, 1998)

Note that both representations can be used in the signalling method and their utility is down to preference.  $N$  observations are made, where with the larger the  $N$  (number of observations), the better the final threshold estimate will be.

The four logically derived results of the observations in the table above are summed up below:

- A-  $N$  of times the signal issued a warning and the crisis occurred
- B-  $N$  of times the signal issued a warning and the crisis did not occur
- C-  $N$  of times the signal did not issue a warning and the crisis occurred
- D-  $N$  of times the signal did not issue a warning and the crisis did not occur

If the former conditions are true, the following expression must hold:  $N = A + B + C + D$

### 3.1.2 Signal Performance evaluation

It is evident that the less binding the  $\Pi_0$  thresholds are, the more crises are correctly predicted (A), but simultaneously, the number of type II errors in (B) increases. A higher  $\Pi_0$  threshold, however, increases the number of cases, in which the absence of crises is correctly predicted (D), concurrently, type I errors in (C) increases. An optimally chosen  $\Pi_0$  threshold rectifies the numbers of false alarms and significant delays in signals.

To test the quality of the indicator, it is statistically compared to the binary crisis variable. Following (Kaminsky, Lizondo, Reinhart, 1998), we calculate the probability of the crisis occurring in a defined timeframe.

$$P(F) = \frac{A + C}{N} \tag{3}$$

The probability of a crisis occurring given that the indicator issued a warning – in our research we denote as  $S$ .

$$P(F/S) = \frac{A}{A + B} \quad (4)$$

A key problem with much of the literature in relation to the further steps in the signal extraction method is in the obscurity of the threshold estimation. The main pitfall of empirical literature is the absence of a reasoning as to how and why a particular  $\Pi_0$  threshold is determined. Contrary to the contemporary papers on the signal extraction method, this research paper adds an additional step expressed in the equation below:

$$P(F/S) > P(F) \quad (5)$$

The above expression asserts the relationship of correct signals to the probability of the crisis occurring. If the indicator sends mostly good signals, meaning that the crisis periods confirm the predictions of the indicator, then it can be expected that the probability of a signal produced as a result of the indicator crossing a certain threshold will be more than the unconditional probability of the crisis occurring in a given period of time (Molnár, 2020). If the expression fails, a new  $\Pi_0$  threshold is selected. As long as the expression holds true, the subsequent steps can be executed.

Type II errors are defined by the substituting  $B$  and  $D$  in the expression below:

$$P(G/S) = \frac{B}{B + D} \quad (6)$$

The noise-to-signal ratio, calculated as the share of incorrectly signaled crises in a number of years in this study is defined by a  $K$ - coefficient, where

$$K = \frac{P(G/S)}{P(F/S)} \quad (7)$$

To find the optimum threshold, the procedure is reiterated a statistically significant number of times. The final usefulness, denoted as  $U$  is defined in the expression below:

$$U = 1 - K \quad (8)$$

Several other authors, like (Boysen-Hogrefe et al., 2015) also introduce a loss function to the above expression, where weights of K and U are assigned to the share of type I errors and type II errors. The leading indicator is more useful the lower the noise-to-signal ration and the higher the value of U.

## **3.2 Empirical results**

### *3.2.1 Binary Crisis Variable*

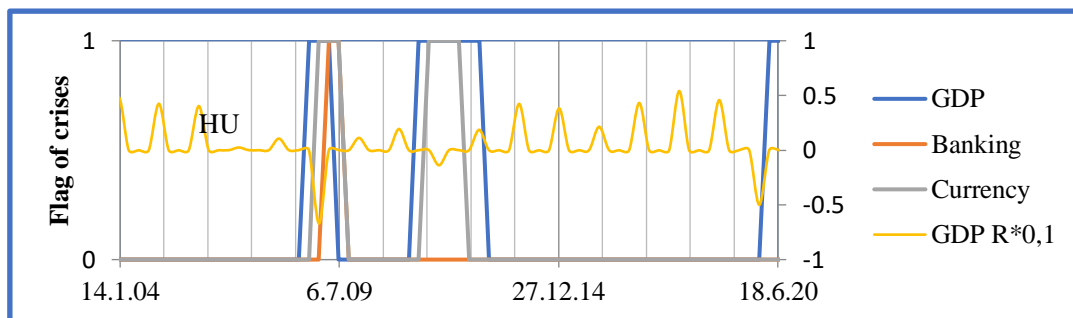
We tested the binary crisis variable on three crises in three Eastern European countries - Hungary, Ukraine and Russia. The definitions of economic, banking and currency crises were based on the outlined details mentioned in Chapter II. Economic crises, denoted as “GDP” in Figures 2-4 were identified as periods, of two consecutive months of quarterly negative GDP growth, following (Abberger, Nierhaus, 2008, p. 75). In Hungary, periods of economic crises resulting in recessions were identified between 2008q3-2009q2, and 2011q3-2013q1 and the latest ongoing recession, which started in 2020q1. In Ukraine, economic crises were identified between 2004q1-2004q4, 2009q1-2010q1, 2013q4-2015q3 and the current ongoing recession, which started in 2020q1. In Russia three periods of economic crises were pinpointed from 2005 to 2020. Namely: 2008q3-2010q1, 2014q3-2015q2 and the current ongoing recession, which started in 2020q1.

Banking crises in the three countries, denoted in the graph below as “Banking” were identified in accordance to the ratio of non-performing loans to the banks’ total assets, denoted in Chapter II as  $P_b = \frac{D}{A} 100\%$ . Whenever the value exceeded the 10% threshold, discovered by (Demirguc-Kunt A and Detragiache, 2005), we interpret it as a 1- value in the binary crisis variable graph. Thus, in Hungary banking crises were between 2009q2-2009q4. In Ukraine, there were 2 instances of banking crises in the observed timeframe: between 2009q2-2010q3 and 2013q3-2016q1. In Russia during the same period the same number of banking crisis occurrences were identified: between 2009q1-2010q2 and 2013q3-2015q1.

In this paper it was decided that the best procedure for determining a currency crisis in case of the three emerging markets is to abstain from using the traditional EMP index, and adhere to the definition of the currency crisis as the rapid devaluation of a domestic countries currency

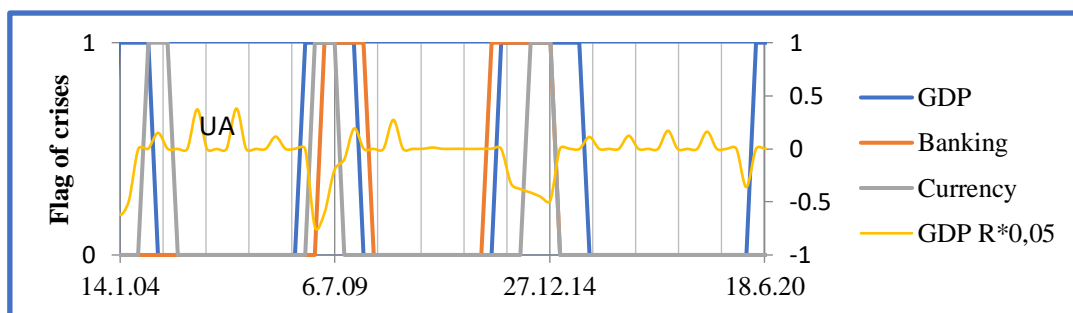
in respect to the USD. Taking advantage of the nominal effective exchange rate (NEER) indicator- as the weighted rate at which the domestic currency is exchanged with a basket of foreign currency, for the sake of simplicity, it was used to determine whether a country is in a currency crisis or not. The empirical results of this research highlighted in the subsequent discussion segment, showed that the NEER it is just as, if not more effective in determining currency crisis episodes as the EMP index. As a result, the obtained binary crisis variable graph for the Hungary denoted as “currency” encompasses two periods: 2009q1-2009q3 and 2011q4-2012q3. In Ukraine currency crises were observed in 2004q4-2005q2, 2009q2-2010q2, 2014q2-2015q1. In Russia currency crises occurred in 2009q1-2009q3 and 2012q4 as well as 2015q1.

Lastly, Figures 2-4 also feature a GDP R\*0.1 indicator denoted as “GDP R\*0.1”, which shows the GDP QoQ percentage change. It is normalized, so it moves between the values of 0 and 1, to indicate that the above identified banking, currency, and economic crises truly correlate to the drops in the GDP quarterly growth rate.



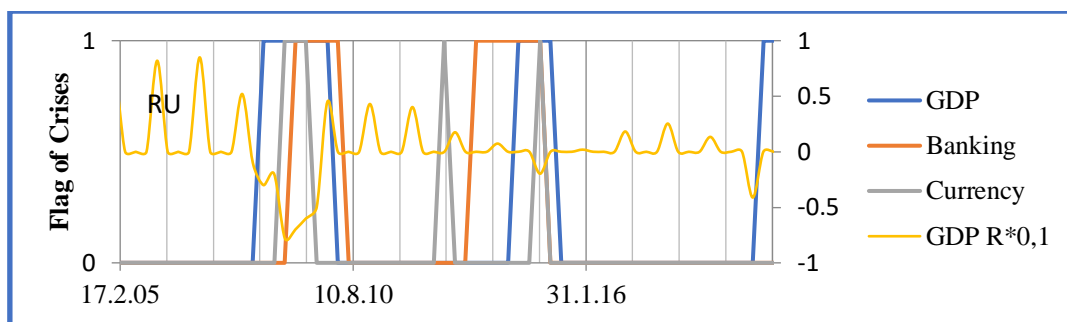
**Figure 2: Binary variable indicator for economic, banking and currency crises in Hungary.**

Source: own compilation



**Figure 3: Binary variable indicator for economic, banking and currency crises in Ukraine.**

Source: own compilation

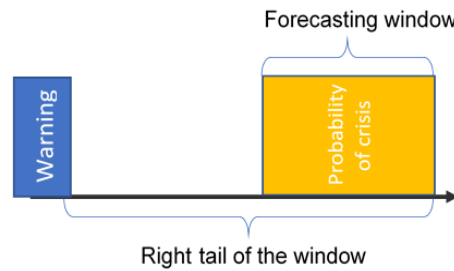


*Figure 4 Binary variable indicator for economic, banking and currency crises in Russia.*

*Source: own compilation*

### 3.2.2 Leading Indicators

After the identification of leading indicators, the best 3-4 were each assigned to a given country. Following the two main criteria we consider the leading indicator for – the highest usefulness (U) and best economic interpretation. The leading indicators are divided into short and long-term indicators- short-term being: .An additional methodological weakness of many research papers in leading indicators within the signal extraction method is that they fail to identify the forecasting window and the forecasting horizon. The afore mentioned parameters are found in Table 13. The forecasting window width indicates the timeframe between which there is a probability for the crisis occurrence  $P(F/S)$ . The right ‘tail’ of the window is defined as the timeframe between the indicator issuing a warning and the rightmost limit of the forecasting window. The right ‘tail’ of the window includes the forecast window and excludes the timeframe between which the indicator issued the warning. For more clarity, Figure 5 illustrates the concept. The calculation of the forecasting window and right tail of the window is performed via empirical analysis and standard statistical procedures alike the afore mentioned. Additionally, it must be noted that no operations of missing value treatment were performed during the calculation of the usefulness of the indicator. The data availability column shows the timeframe in which the data sampling was available from.



**Figure 5: The illustration of the forecasting window and the right tail of the window.**

Source: Own compilation based on above described methodology

Lastly, a critical pitfall in much of the contemporary literature is the ambiguity of the definition of a one-sided threshold. Several authors, inter alia (Csontos, Szalay, 2013; Erhart et al., 2015) expressed doubts about one sided threshold shown in the MIP Scoreboard. The absence of a clearly defined direction that would show that the leading indicator exceeded or dropped below the determined threshold inclined me to add the parameter of direction in Table 13 , as to elucidate whether the indicator approaches the threshold from up or bottom.

What’s more the study consciously omitted indicators, which had a right tail window of greater than 8 months, since according to empirical literature, they prove to be less effective than leading indicators of shorter right tail windows.

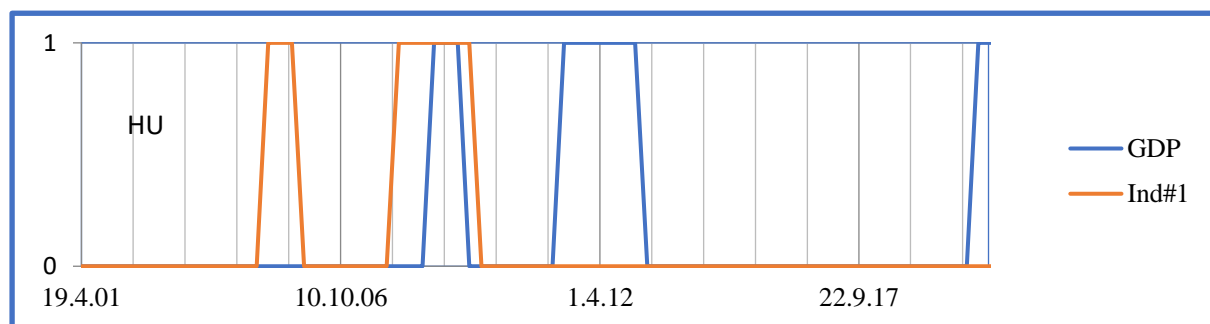
	<b>Leading Indicator</b>	<b>Data availability</b>	<b>Forecast window width (1.-4. q.)</b>	<b>Right tail of the</b>	<b>Threshold</b>	<b>Direction</b>	<b>U=1-K</b>	<b>P(F)</b>	<b>P(F/S)</b>
<b>RRU</b>									
11	5 year sovereign CDS Eurobonds	06q1- 19q4	3	4	78%	1	0,4	0,5	0,73
22	RTSVX -stock market volatility index	06q1- 19q4	1	2	32	1	0,32	0,5	0,63
33	Export of Oild and Gas products	06q1- 19q4	2	1	- 0,03	0	0,28	0,25	0,68

	YoY% change in USD								
44	Money supply YoY% change	06q1- 18q4	1	7	0,02	1	0,24	0,75	0,57
55	Household debt/disposable income	06q1- 18q4	2	6	0,14	1	0,15	0,5	0,85
UUA									
11	NBU currency reserves/ Bank assets - trend	03q1-19q4	2	7	0,01	0	0,52	0,5	0,84
22	Export YoY% change without trend & cycle	03q1-19q4	2	4	0,05	1	0,48	0,5	0,74
33	Import YoY% change without trend & cycle	03q1-19q4	3	5	0,07	1	0,32	0,5	0,52
44	M2 monetary aggregate/ bank loans to households	03q1- 19q4	3	5	-0,06	0	0,25	0,75	0,58
55	Difference btw. Household deposits and loans, minus trend	03q1- 19q4	2	6	0,4 %	0	0,28	0,5	0,48
HHU									
11	Hungarian sovereign debt CDS 5-year change	05q1- 15q4	5	6	0,1	1	0,12	0,5	0,56
12	International reserves/sovereign debt x multiplier	05q1- 15q4	5	6	0,2	0	0,10	0,5	0,48

*Table 13: Table of the best leading indicators for Russia, Ukraine and Hungary.*

Source: Own compilation

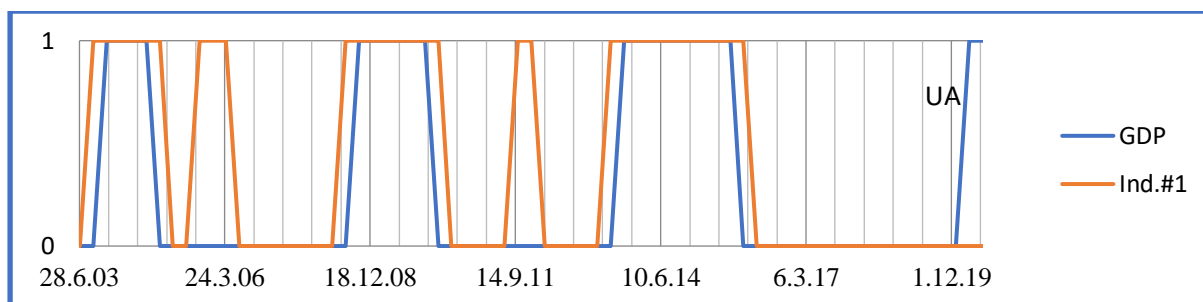
For the graphical interpretation of the above table, this study highlighted the best leading indicator and its predictive power relative to the economic crisis binary variable for the three countries. In case of Hungary, we chose the Hungarian sovereign debt CDS leading indicator, since it had the largest P(F/S) value and also the largest utility of 0,12. The 0 in the direction column indicates, that whenever the leading indicator drops below the threshold level of 0,2, a crisis can be expected 1 quarter after the issue of the warning up to the 6<sup>th</sup> quarter from the moment of the issue. In practice, we can see that while the “Hungarian sovereign debt CDS 5-year change” leading indicator issued two separate warnings before the onset of the 2008 global financial crisis, it failed to predict the economic turbulence of 2011-2013 and, naturally, did not issue any warning before the current ongoing COVID-recession.



**Figure 6: The flag of the presence of economic crises and the Hungarian sovereign debt CDS leading indicator.**

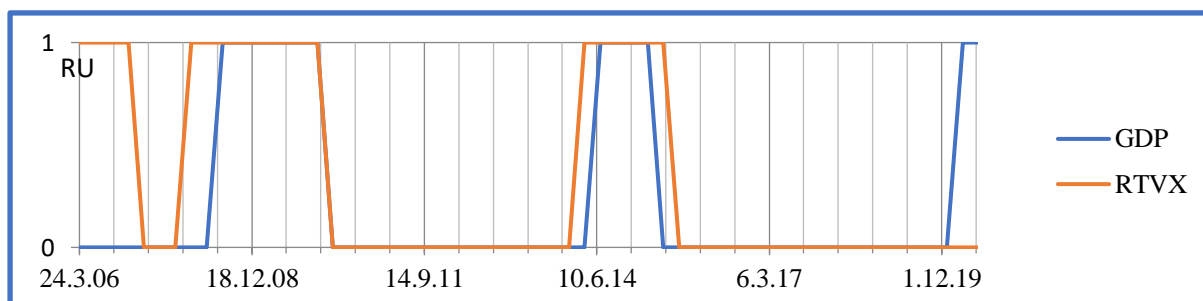
Source: own compilation

As for Ukraine, NBU (National Bank of Ukraine) currency reserves to bank assets ratio was used as the leading indicator. Because there were more periods of economic crises in Ukraine in a similar observed timeframe, there were more opportunities for the leading indicators to demonstrate their warnings. The NBU currency reserves / bank assets leading indicator has one of the highest predictive powers out of the list of 0,84. Whenever the indicator drops below the threshold level of 0,01, a warning is issued that in 5 quarters, the probability of an economic crisis occurrence rises. The leading indicator correctly predicted the economic crisis from economic imbalances formed during the political turmoil of 2003-2004. It also correctly predicted the 2008 global financial crisis in Ukraine. While the spike at the point of 14.9.11, is misleading and it did not predict any crisis event, it can be argued, that the macroeconomic imbalances formed during the post-recession years were the prerequisites of the subsequent economic and political crisis in 2013-2015. The indicator failed to predict the current ongoing recession.



**Figure 7** Flag of the presence of crisis and NBU currency reserves/ Bank assets - trend leading indicator.  
Source: own compilation

The RTVX measures volatility in Russian financial markets and was applied in Figure 8. Again, since the direction parameter in Table 13 is defined as 1, it is implied that once the indicator exceeds the threshold of 32, an economic crisis will be expected in the following 2 quarters. It is trivial that both the forecasting window and the right tail are narrow. Financial markets are inherently forward looking and reflect investor sentiment in the near future. The leading indicator successfully predicted 2 out of the three economic crises in the past 2 decades. Notwithstanding, its successful predicting capabilities its narrow forecasting window doesn't benefit policy makers in the implementation of counteraction.



**Figure 8** Flag of the presence of crisis and the RTVX volatility leading indicator.

Source: own compilation based on table of leading indicators

### 3.3 Cross-spectral analysis

As it was demonstrated in the previous section, long-term indicators that have a well-defined cyclical characteristic present issued correct warning signals before the crisis event in the economy. Following the logical framework of (Andreev, 2016), the relationship between the leading indicator and the binary crisis variable inclines that there is a correlation between the occurrence of economic crisis and economic business cycles. (Andreev, 2016) further argues

that the predictive capabilities of leading indicators with 5-8 quarter right tail forecasting windows are disputed among researchers, since usually the right tail forecasting window doesn't surpass the timeframe of 1-2 quarters. To find an answer to this question of whether a given leading indicator correlates with the business cycles in the economy the cross-correlation analysis is applied.

The method enables to determine the magnitude of the delay of cyclic series relative to each other. Adopting the notation of (Molnár, 2020) the cross-correlation determination algorithm is given by the following:

Suppose there are two time series with a random  $\varepsilon_t$  component. They are given by  $X(t_i), Y(t_i)$ , where  $i = 0, 1, 2, 3, \dots, N$ . The sample acquisition is done at equidistant points, meaning the time series have the same dimensions and the same DGP interval measured in a timeframe. The correlation coefficient- which is the degree of statistical connectivity of two random variables is given by the following expressions:

$$\bar{Y} = \frac{1}{N+1} \cdot \sum_{i=0}^N Y(t_i) \quad (9)$$

$$\bar{X} = \frac{1}{N+1} \cdot \sum_{i=0}^N X(t_i) \quad (10)$$

$$\sigma_x = \frac{1}{N+1} \cdot \sum_{i=0}^N \sqrt{(X(t_i) - \bar{X})^2} \quad (11)$$

$$\sigma_y = \frac{1}{N+1} \cdot \sum_{i=0}^N \sqrt{(Y(t_i) - \bar{Y})^2} \quad (12)$$

$$cov_{xy} = \frac{1}{N+1} \cdot \sum_{i=0}^N (X(t_i) - \bar{X}) \cdot (Y(t_i + \Delta t) - \bar{Y}), \quad (13)$$

$$r_{XY} = \frac{cov_{xy}}{\sigma_x \sigma_y} \quad (14)$$

To determine the phase shift between the time series we consider the digital Fourier transform (DFT) (15).

$$f_{xy}(\omega) = \frac{1}{2\pi} \sum_{i=-N}^{i=N} \left(1 - \frac{|i|}{N}\right) \cdot r_{xy}(i \cdot \Delta t) \cdot e^{-j\omega i \Delta t} \quad (15)$$

The density function (16) is defined below:

$$f_{xy}(\omega) = c_{xy}(\omega) + jq_{xy}(\omega), \quad (16)$$

From (16) the estimation of the amplitude becomes trivial:

$$A(\omega) = \sqrt{c_{xy}^2(\omega) + q_{xy}^2(\omega)} \quad (16)$$

The phase of the spectra comes from (117):

$$\varphi_{xy}(\omega) = \arctg\left(-\frac{q_{xy}(\omega)}{c_{xy}(\omega)}\right). \quad (17)$$

The absolute value, or the amplitude (17) shows to what extent is the covariance of a function similar to that of a harmonic with frequency  $\omega$ . Respectively, the maximum of the amplitude can determine the harmonic frequency  $\omega^*$ , which has the most similar covariance. Then both series together are as similar as possible to vibrations with a frequency of  $\omega^*$ . It is at this frequency  $\omega^*$  that we will determine the phase shift  $\varphi_{xy}(\omega^*)$  between the rows and, accordingly, the amount of delay in quarters.

The phase shift is defined by

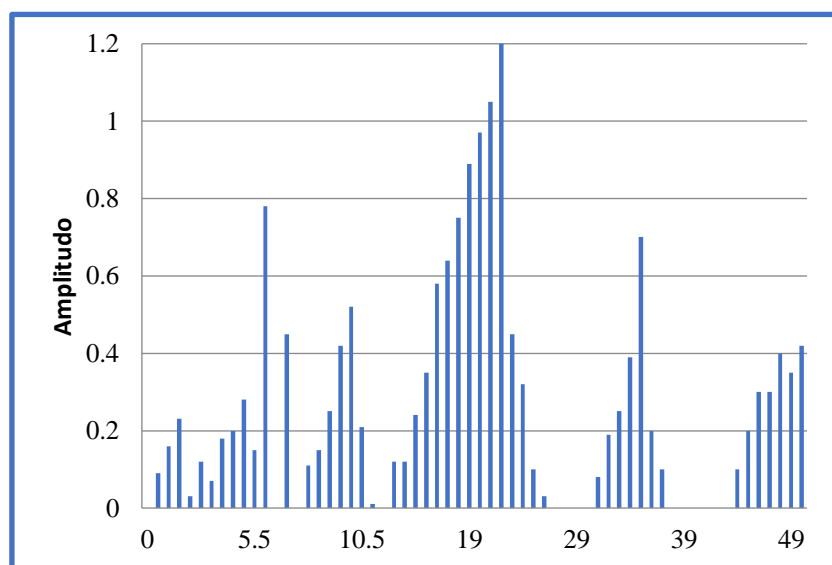
$$\varphi(\omega^*) = k \cdot 2\pi f^* \Delta t, \quad (18)$$

We define the time lag (i.e., the time interval)  $k$  between highs measured in quarters.

The program for performing calculations is given in the Appendix. The program was tested on a set of data created artificially as a sum of the cycle trend and a random component.

### 3.3.1 Empirical results

To demonstrate the effectiveness of the method, the cross-correlation analysis was conducted for the Russian export time series relative to GDP.



*Figure 9: Cross amplitude spectrum of Export and GDP.*

Source: National Bank of Russia, graph created by author

From the graph above we can visually determine the phase corresponding to the highest amplitude. As a result of the calculation procedure outlined in the previous section the following results were obtained.

<b>Index</b>	<b>Time series, Russia</b>	<b>Data availability</b>	<b>Cross-periodicity of real spectrum with real GDP, quarters</b>	<b>Time series precedes GDP time series (&gt; 0) or lags behind (&lt;0), quarters</b>
1	Export	95q1-18q2	25	3
2	Import	95q1-18q2	22	-1

3	Household retail bank investment	00q1 – 18q4	26	-6,5
4	Unemployment rate	00q1 – 18q4	23	-0,6
5	The debt burden of the population relative to its income	00q1 – 18q4	26	2,5

*Table 14: Cross spectrum analysis for Russian macroeconomic time series.*

Source: National Bank of Russia, table compiled by author

In Figure 9 it was exemplified that during the 19<sup>th</sup> quarter of observations- during the 2008 global financial crisis the correlation of the Export and GDP time series was the highest. As we graph the correlation in a wider timescale a pattern emerges, where the correlation of the leading indicator and the GDP gradually rises QoQ up to the peak of the crisis, after which there is a major drop. The GDP time series lags behind the Export time series on average by 3 quarters. This is enough timeframe for policy action to be implemented to prevent the spread of macroeconomic imbalances.

### *3.3.2 Criticism of the cross-correlation method*

It is hard to analyse the topic of financial crises with cross-market correlations – without even mentioning the contagions. This is a strong conceptual weakness in the paper and it prepares the secondary problem, that it misses the whole concept of heteroscedasticity which can bias any linear correlation – this is why people are using GARCH models and conditional variance-covariance matrices (like DCC-GARCH) in the last twenty years.

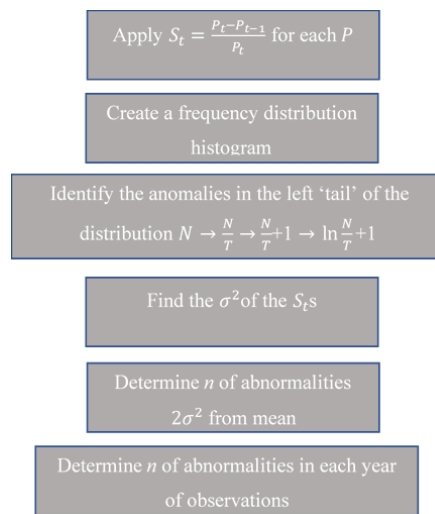
## **3.4 Frequency analysis of anomalous negative price fluctuations in stock market indices as a crisis forecasting tool**

The efficient market hypothesis (EMH) proposed by (Fama, 1965) is the central argument in explaining the behavior of composite stock market indices and their DGP. The processes of dissemination and interpretation of these signals by market participants may be distorted by market anomalies, questioning the postulates of the EMH. Among the key anomalies, (Plastun, Makarenko, 2018) draw our attention to spikes in volatility, seasonal anomalies and an

unpredictable change in profitability under the influence of a range of market variables. Anomalous price fluctuations of indices on the stock market can be used as a separate block of leading indicators for forecasting economic crises on the line with traditional macroeconomic indicators summarized in the previous sections of this study. Notwithstanding the significant diversity of warning signals on the stock market, the search for new methods continues to this day. The role of traditional macroeconomic indicators such as GDP growth, industrial production indices, inflation, unemployment rate in forecasting economic crises is often neglected, due to their general low predictive capabilities, and a significant lag in their publication. However, there is an array of economic indicators, devoid of these shortcomings, the access to which is available in real time for all users. Among these indicators, the most prominent are composite stock market indices containing a weighted basket of stocks, others are variables that characterize the condition of the stock market, for instance the RTVX- which in itself is a volatility index. In this context, forecasting of crisis phenomena in the economy can be done using various parameters and indicators of the stock market: volatility, correlation of stock market assets, its long-term memory (persistence), frequencies of abnormal price fluctuations (overreactions and underreactions). Empirical studies on stock market price fluctuations inter alia (Sandoval, Franca, 2012; Stefanescu, Costel, 2012) outline that a sudden increase of the number of anomalous negative fluctuations in the stock market could indicate that the economy of the country is about to enter a recession. The hypothesis put forward by (Plastun, Makarenko, 2018, p. 74) states that the increase in the frequency of anomalous negative fluctuations of the stock index indicates the intensification of crisis phenomena. Accordingly, the phases of crisis development correlate with the dynamics of changes in the frequency of anomalous negative fluctuations. Adopting the notation of (Sandoval and Franca, 2012), it becomes evident that the goal of the method is the creation of a visual graph that displays the frequency of anomalous variable fluctuations on a monthly, quarterly or yearly interval. The variables of the stock indicator are normalized, so they are between -1 and 1 – this makes it easier to compare variations of the time indices. The expression for the log-returns are given by the following expression:

$S_t = \frac{P_t - P_{t-1}}{P_t}$ , also expressed as  $S_t = \ln(P_t) - \ln(P_{t-1})$ . The log-density distribution function is graphed, and a certain number of the leftmost outliers are counted for each given time period.

To simplify the above described algorithm, Figure 10 illustrates the procedure on a step-by-step basis. The explanations of the expression above is detailed in the empirical results.

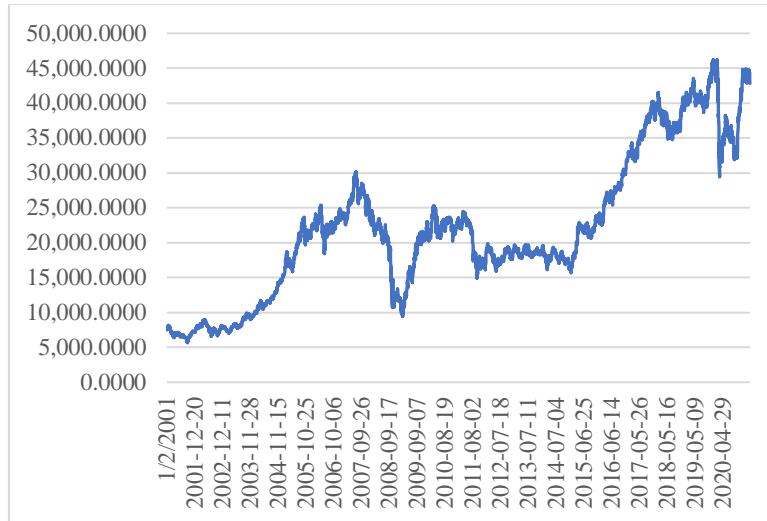


**Figure 10: The algorithm for determining anomalous price fluctuations.**

Source: Own compilation

### 3.4.1 Empirical results

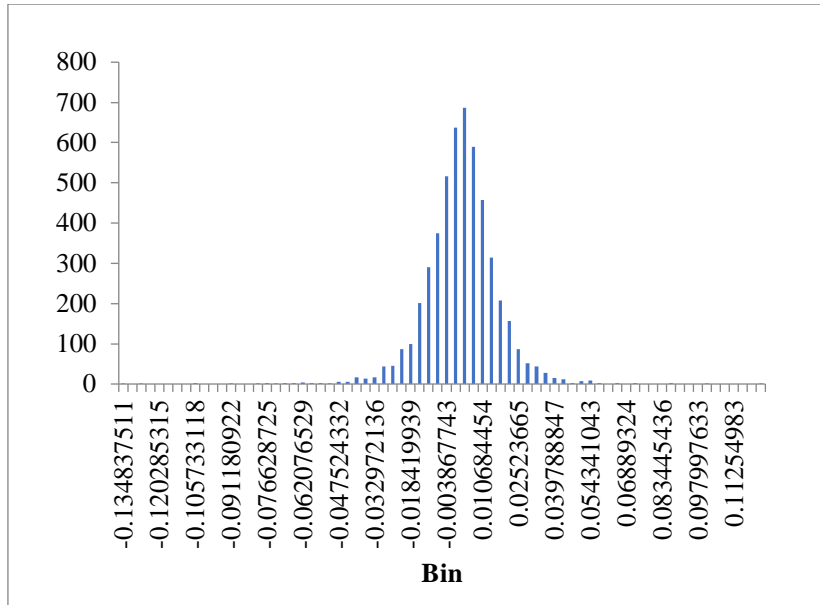
As to demonstrate the effectiveness of the method on Hungarian financial markets, the BUX stock market index was analyzed within the anomalous fluctuation frequency analysis framework. In this research we looked at the daily closing price of the index from 2001 until 2021 as seen in Figure 11. The data was gathered from the MNB (Hungarian National Bank). Altogether, about 5056 values were obtained. The expression:  $S_t = \frac{P_t - P_{t-1}}{P_t}$  states that for each subsequent days' closing price, the value of the previous days' closing price was subtracted and divided by the subsequent days' closing price, where  $P_t$  is the closing price value of the index.  $t$  – denotes the moment when the value of closing price of the index was recorded and  $P_{t-1}$  is the previous days' closing price.



**Figure 11: BUX time series.**

Source: MNB, constructed by the author

When we compute  $S_t$  for every  $P$ , we use a frequency histogram to visualize the optimal binning of the intervals and determine the outliers in the leftmost tail of the distribution. In order to smoothen the curve, a logarithmic transformation can be applied given by  $\ln(\frac{N}{T}+1)$ , where  $N$  is the frequency of the observed values in a bin, and  $T$  is the total number of observations, which in our case is 5056. This step can be omitted, as it doesn't add nor subtract any valuable information from the process. The subsequent steps of defining the left tail threshold can be executed using the histogram. In Figure 12 the frequency histogram for the BUX index is graphed. Empirical studies point out that the log-density function  $t$  is used to visualize the most extreme points better. Although in case of our research, it smoothed them out. The purpose of the visualization of the histogram or the log-density function is to visually determine the position of the threshold relative to the mean. The equations given in (Sandoval and Franca, 2012) and (Plastun, Makarenko, 2018) define the threshold level as “the 10 most negative variations”, which means that the leftmost 10 bars are used for further measurements. No statistical, or logical background as to the choice of the threshold have been offered by either of the authors – this is a major pitfall in the methodologies. In this research paper, instead of giving a constant for determination of the threshold, we instead use the threshold value of  $2\sigma^2$  from the mean. The logical reasoning behind this decision is that only 2.5% of the observed data will be featured in the final frequency graph.



**Figure 12: Frequency distribution histogram of the  $S_t$  of the BUX index.**

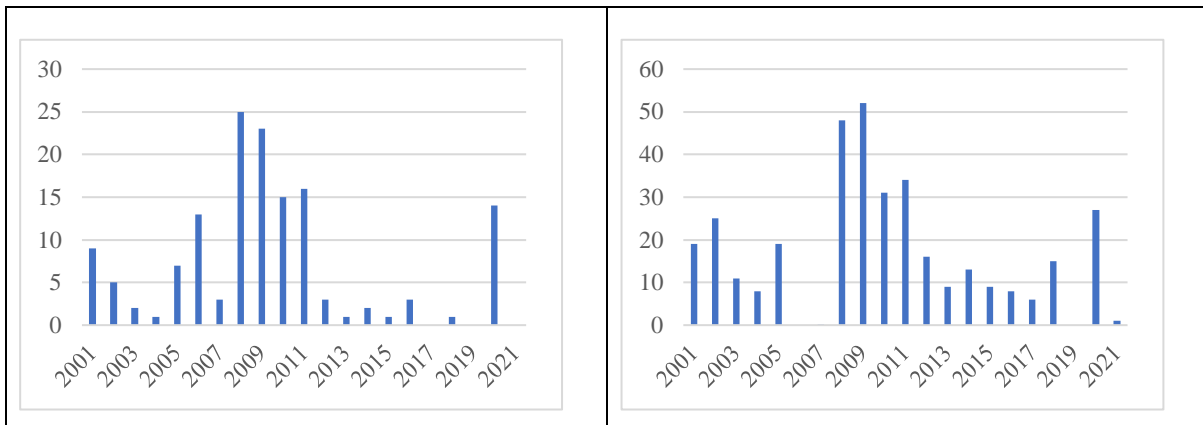
Source: Own compilation, based on calculations of normalization

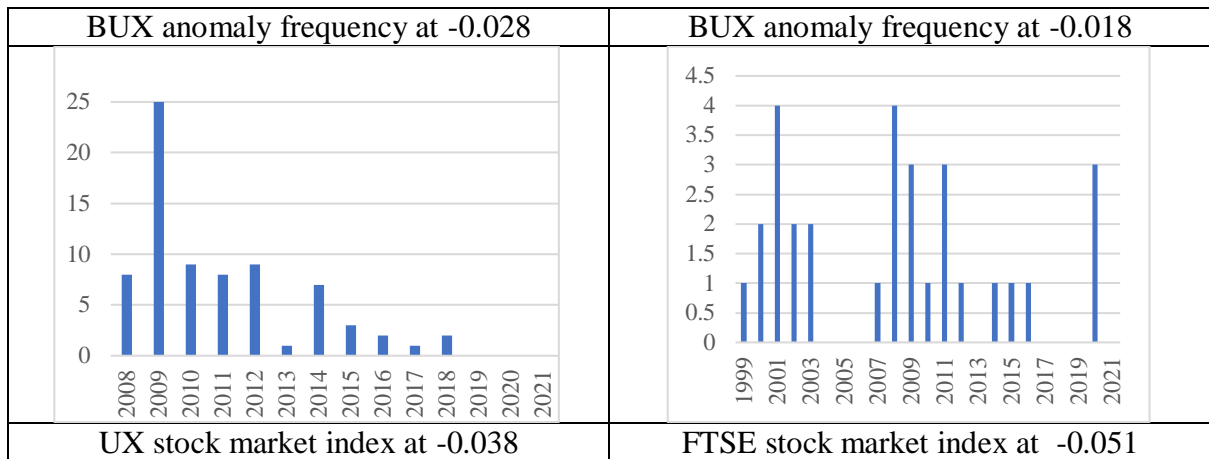
To calculate the standard deviation, we used an Excel function the result of which was 0.014. In the final frequency graph, we therefore included all of the outliers below -0.028 and determined how many of these anomalies occurred in a given year of observations Table 15. In Table 16 the results were graphed.

2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
9	5	2	1	7	13	3	25	23	15	16	3	1	2	1	3	0	1	0	14	0

**Table 15: Frequency of anomalous BUX price fluctuations yearly.**

Source: Own compilation



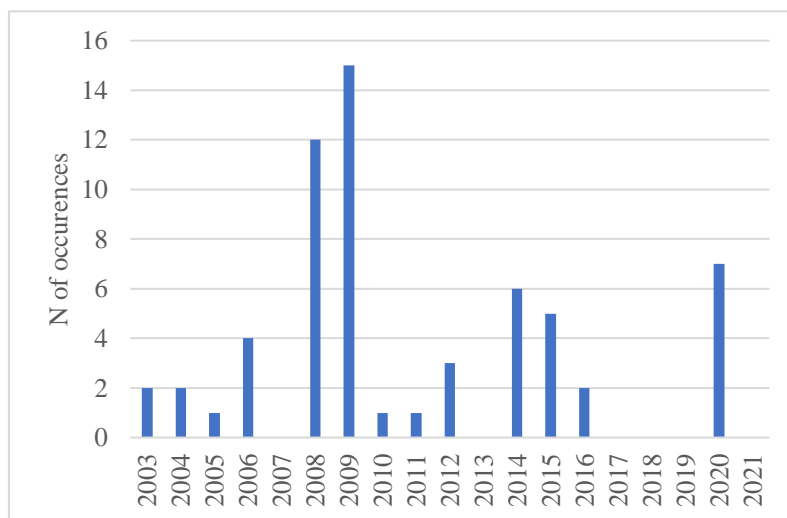


**Table 16 Frequency of anomalies in stock indexes of Emerging and developed economies**

Source: MNB, graph created by author

We also tested the claim by (Plastun and Makarenko, 2018 p 74) that the threshold point must be in the lower 2-3% of the observed data – the threshold was -0.018. If we turn to the histogram, we can observe that the binning value of -0.018 also corresponds to the 10<sup>th</sup> bar of most negative variations, following (Sandoval and Franca, 2012).

To test whether the method provides a reasonable crisis forecasting alternative, the above-described procedure was conducted for the Ukrainian stock market index (UX) at -0.038 threshold, the British Financial Times Stock Exchange (FTSE) at -0.051 threshold and the Russian stock market index (RTSI) at -0.048.



**Figure 13: RTSI Russian stock market index at -0.048 threshold.**

Source: Stock exchange, graph created by author

### *3.4.2 Discussion*

The conducted study on the effectiveness of the method in three EMs and one developed economy showed, that frequency analysis of negative overreactions in the stock market generates important information about the future state of the economic system and has predictive properties for the emergence of crisis phenomena in the economy. In contrast to traditional macroeconomic indicators - GDP, inflation index, etc., among stock market indicators, anomalous price fluctuations have a high predictive capacity and predictive properties. Their application was tested both to identify the economic crisis in Hungary, Ukraine, Russia and Great Britain in 2007-2009, as a consequence of the global financial crisis and the crisis in the economy of Ukraine and Russia in 2013-2015 and the mild recession in Hungary in 2011-2013.

Based on the frequency analysis of the BUX index from 2001 to 2021, it has been determined that a rapid increase in the frequency of anomalous negative fluctuations can provide warning signals for forthcoming economic crises. The spike in the frequency of observed fluctuations in 2006 can relate to the increase of macroeconomic imbalances leading up to the 2008 currency, banking, and economic crises. While no anomalies below the -0.28 threshold were recorded in 2019 (in the year leading up to the 2020 COVID crisis), it can be argued that the spike of anomalous fluctuations in 2018 could have been a warning for rising macroeconomic imbalances.

As for the RTSI spikes in price fluctuations in 2006 and 2012 could be interpreted as warning signals for the growth of economic imbalances and the subsequent 2008-2009 and 2014-2015 crises.

On the basis of the frequency analysis of the UX index between 2008-2021, as a consequence of a smaller data sample, the relevant conclusions can't be made. The increase of negative price fluctuations in 2010-2012 leading up to the 2013-2015 crises, however, proved to be correct in crisis forecasting. However, alike the BUX, a spike can be seen in 2018, that, again, can be interpreted as a warning for rising economic imbalances.

The same case can't be made for the FTSE index. No significant spikes were identified, which were leading up to the 2008, 2012 and 2020 recessions. A, yet, dubious conclusion can be

therefore made, that the anomalous stock price fluctuation indicator works best for EMs, however this claim must be tested in further research papers.

### *3.4.3 Criticism of the anomalous stock price fluctuation method*

The hypothesis tested in this section was whether the increase in the frequency of abnormal negative fluctuation in stock indexes indicates a forthcoming crisis or its intensification. While it has been determined that the phases of the crisis development correlate with the dynamics of changes in the frequency of anomalous negative fluctuations, the results of the yearly fluctuation distribution graphs of the analysed stock market indexes do not provide sufficient evidence to make them reliable crisis forecasting alternatives for developed economies such as Great Britain.

The case whether the method provides a viable forecasting alternative for EMs must be tested on a larger data sample to provide statistically meaningful evidence. Furthermore, contrary to the opinion of contemporary literature on the method, it is believed that there is reasonable evidence to suggest that the time intervals for the final anomaly frequency tables should be in quarters, preferably in months, rather than years.

The research on the methodology since its introduction in 2012 is still being developed.

## **4. Granger test of V4 Stock markets as leading indicators of economic growth**

### **4.1 Stock markets' ability to predict recessions – evidence**

Stock markets are closely related to economic cycles, which is a long-term pattern of alternating periods of economic expansions and declines – known as the business cycle. Stock prices reflect investor' expectations about profitability, and since economic activity is driven by profitability, it is believed that investors will anticipate a recession by selling stocks and rotating into safer assets. In the traditional stock price valuation model, the price of the stock is its present value of expected future returns. Following this logic, stock prices fall as soon as the near-term expectations of corporate profits decline, and comparatively, a higher rate used to discount future earnings results in stock prices going lower. A higher discount rate usually means the rise of uncertainty and volatility in markets. Leading macroeconomic indicators, such as consumer sentiments, housing construction starts, industrial production tend to move ahead of the economy. Investment strategies are rarely based on market behavior in the past. Instead, investment strategies are built around thorough company performance research, the analysis of valuations and predicting future earnings.

The question of the stock market's ability to predict recessions has been examined since the early 60's. Nobel-Prize winning economist Paul Samuelson was the first to publish his findings – 5 out of the 9 recessions that occurred up until 1966 were predicted by bear markets. According to a recent article Samuelson's remark was right on. In the postwar period, there have been 13 bear markets. Out of the 13 bear markets 7 led to recessions within a year (Liesman, 2016). Chen et. al. (2015) provides further evidence of the predictive power of the stock market through analyzing illiquidity – the measure of how easily a security is exchanged on the market. They have found that the annual change in stock market illiquidity is a strong predictor of the economy. The dynamic probit models classify 70% of the recessions.

In early 70's financial literature, the stock market has been studied for its effect on consumer demand. Bosworth (1975) links the stock markets macroeconomic forecasting ability to a number of mechanisms: (1) investor optimism pessimism, also known as consumer sentiment, and (2) the life-cycle model of consumer behavior. To determine whether the stock market is a good leading indicator, Bosworth proposes examining the nature of the correlation between

changes in stock prices and consumption to find whether monetary policy affects stock prices. This correlation could represent a wealth effect or a proxy for consumer sentiment.

The wealth effect is also regarded as a major supporting argument for the forecasting ability of stock markets. Following the definition provided by the national bureau of economic research, the wealth effect is the idea that as asset values grow, such as company stock prices or home values, households would spend more and stimulate the economy – thus creating a positively reinforcement loop. Pearce (1983) defined the wealth effect in terms of a consumer sentiment. Again, adopting the element of risk into the theoretical framework, Pearce points out that when investors are optimistic, this is reflected in a higher level of confidence in markets, lower volatility, higher returns and eventual economic expansion. On the other hand, if stock prices are declining, investors are less optimistic, less wealthy and more likely to put their money into ‘safer’ assets.

#### **4.2 Stock markets’ inability to predict recessions – evidence**

Practical evidence, however, shows that the stock market is a poor indicator of future economic activity. Since the stock market generates many “false signals” that are usually hard to interpret. Comincioli (1995) mentions the 1987 “Black Monday” stock market crash, that triggered a global selloff, as one of these events, when stock prices falsely predicted the economy. In a publication by Kaverman (2020) it is established that markets are generally irrational – this is expressed in market anomalies, such as Dot-com bubble, the housing bubble and even the latest cryptocurrency bubble. Irrational market behavior isn’t only induced by endogenous factors involving the fear of missing out, speculation and panic, but also by exogenous factors, independent of the sentiment or action of market participants. Injection of stimulus into the banking system, lowering interest rates, quantitative easing – all of these exogenous factors contribute to the markets becoming more irrational.

Another key reason why the stock markets’ recession forecasting abilities are subject to criticism is connected with investors’ expectations. Often investors’ expectations about future economic activity are inherently flawed, biased and simply incorrect. Human error, after all, plays a great deal in both price discovery and making predictions on future corporate earnings. The ability to make well-informed predictions and investment decisions is often hindered by the level of optimism or pessimism in the market – hence, Keynes’ (1936) definition of investors as “spirit animals”. Neither optimism nor pessimism can be identified in market

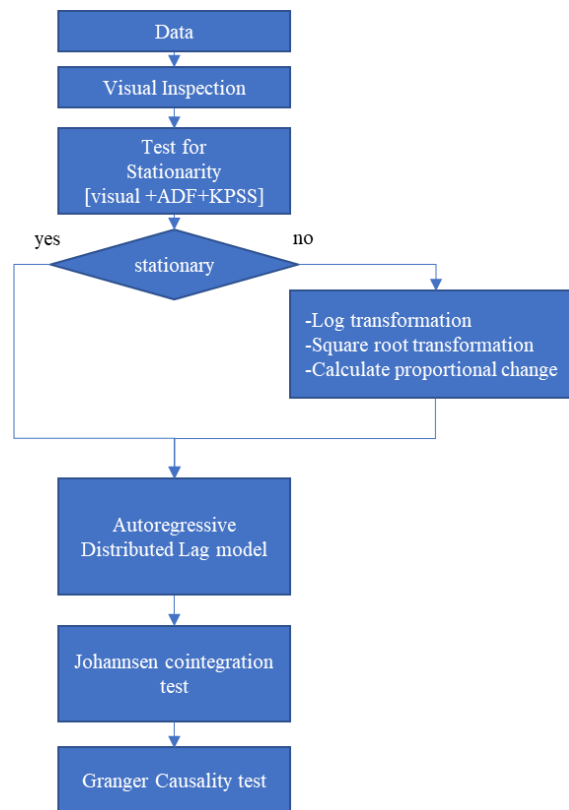
momentum as a good predictor of the economy. Stock prices rise or fall due to the reinforcement of the expectations of investors. The perceived state of confidence or distrust in the system will drive investors to either take up more risk by investing in high-yielding assets like stocks and derivatives or save their money by investing in low-yielding assets, like government bonds. As a result, the argument of anticipation of higher or lower corporate earnings doesn't hold any longer in the process of price discovery – thereby the market becomes irrational, unpredictable, and the stock market will not be a useful leading indicator (Pearce, 1983).

### **4.3 Methodology**

This study evaluates the composite stock market indexes of the Visegrád group countries by empirically testing for causality and cointegration, similarly to Sayed (2016), Ikoku (2010), and Comincioli (1995). The literature review has put forward the idea that even though the flow of information is unpredictable, and hence, so are market movements, nonetheless, anomalies exist, and they can be defined within a statistical framework. The analysis of evidence and counterevidence to stock markets' ability to predict recession has shown that stock markets do not always cause changes in the real economy, and the extent of their impact and influence on the economy is often determined by the state of the domestic markets and development of the country's financial system. In order to ascertain if there exists a relationship between stock prices and the economy the Granger-causality test is implemented.

In Figure 1 we define the complete algorithm for determining the relationship between the stock market and the economy including all of the necessary tests and statistical inferences and assumptions we make along the way. The data on the variables have been collected over a period of 26 years, totaling 86-104 observations depending on the availability of data. Most of the empirical works on economic data have been conducted under the assumption that the time series are stationary. For all intents and purposes in this research we consider a stationary stochastic process, whereby the time series will tend to revert to its mean as time progresses. To determine whether the time series are stationary, we compute the Augmented Dickey Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test as a means of getting two independent answers. A more detailed explanation of stationarity and its testing methodologies is provided in the subsequent chapters of this research.

In case the time series is found to be nonstationary, most of the literature recommends transforming the data by differencing processes. In this study, however, we consider the log-transformation process, as we believe that it is more efficient in removing skewness and hence, making the time series stationary – mean reverting (Hassler and Wolters, 2005).



**Figure 14 Algorithm for the test**

Source: Compiled by author

In our research we suggest that there is a relationship between the economy and the stock market. The autoregressive distributed lag model (ARDL), which is a model based on the ordinary least square regression applicable for both stationary and nonstationary data. The model is useful for separating long-run relationships from short-run between two time series. The ARDL is also significantly less vulnerable to spurious regression, according to Pearsan and Smith (1998), it provides a flexible method for incorporating different lag structures.

Making statistical inferences based on the results of the Granger causality test without proving that the time series are integrated would not be ample in econometrics, therefore we regress the

GDP percentage change for every member state in the V4 group to the composite stock indexes of the countries back 4 quarters. The chosen number of lags, in our case 4, has been chosen because choosing fewer lags will lead to the omission of relevant variable bias. Choosing any more would result in inclusion of irrelevant variable bias. The Akaike information criterion computed in Python provides the optimum number of lags.

$$GDP = \alpha + \beta_0 StockMarket_t + \beta_1 StockMarket_{t-1} + \dots + \beta_4 StockMarket_{t-4} \quad (19)$$

According Weierstrass' theorem, on a finite closed interval any continuous function may be approximated uniformly by a polynomial of a suitable degree. After running the regression based on equation 19, we may find, for instance, that  $\beta_1$  is statistically significant, while  $\beta_2$  isn't. In this case we assume that the first degree polynomial provides a reasonable approximation.

Having determined the coefficients of the regression and having asserted their significance, we move further along the algorithm and proceed to the Johansen cointegration test. The Johansen test, otherwise referred to the maximum eigenvalue or the trace test is a likelihood ratio test. It enables us to determine the relationships between two or more nonstationary time series. Regressing nonstationary time series on other nonstationary time series results in a spurious regression. Within the scope of our research cointegration refers to the following: (i) there exists a long-term equilibrium between the GDPs and the V4's stock markets, (ii) the V4 GDP's and the corresponding stock indexes move in a way so that their linear combination results in stationarity, and (iii) the time series share a common stochastic trend. In line with the above defined theoretical framework, we investigate the forecasting ability of the stock indexes and the GDP's.

As it was mentioned before, the Johansen cointegration test outputs two statistics: the trace statistic, which is a likelihood ratio function that sequentially tests the null hypothesis that the  $\Pi$  matrix, which is the number of cointegrating vectors, is equal to its rank  $r$  (Equation 20).

$$\begin{aligned} 1. H_0: r_0 = (\Pi); H_a: r_0 < (\Pi) \\ 2. H_0: r_0 + 1 = (\Pi); H_a: r_0 + 1 < (\Pi) \\ \vdots \end{aligned} \quad (20)$$

⋮

$$N. H_0: r_0 + N = (\Pi); \quad H_a: r_0 + N < (\Pi)$$

The trace test is thereby calculated by the following likelihood ratio:

$$LR(r_0, n) = -T \sum_{i=r_0+1}^n \ln(1 - \lambda_i) \quad (21)$$

where  $T$  is the sample size  $\lambda$  is the largest eigenvalue.

A non-zero vector, that, when subjected to a linear transformation, changes by a scalar factor is an eigenvalue. The maximum eigenvalue test evaluates if there is a cointegration between the time series. For this, we define the following two hypotheses and their corresponding alternatives:

$$1. H_0: (\Pi) = 0; \quad H_a: (\Pi) = 1 \quad (22)$$

If the null hypothesis is confirmed, meaning the rank of the  $\Pi$  matrix is zero, therefore we conclude that the largest eigenvalue is zero, hence we conclude that no cointegration exists between the time series whatsoever. Conversely, if the alternative hypothesis is confirmed, meaning that the largest eigenvalue  $\lambda_1$  is nonzero, and the rank of the  $\Pi$  matrix is equal to or more than one, we conclude that there is at least one cointegrating vector, and hence the second null hypothesis can be further defined. We test the following set of hypotheses:

$$1. H_0: \lambda_2 = 0; \quad H_a: \lambda_2 > 0)$$

⋮

(23)

⋮

$$N. H_0: \lambda_n = 0; \quad H_a: \lambda_n > 0$$

$$N. H_0: \lambda_n = 0; \quad H_a: \lambda_n > 0$$

If the first largest eigenvalue  $\lambda_1$  is nonzero, we further test whether  $\lambda_2$  is nonzero up until  $\lambda_n$ , where we will be able to confirm the null hypothesis.

The eigenvalue test is a likelihood ratio test denoted as follows:

$$LR(r_o, r_o + 1) = -T \ln(1 - \lambda_{r_o+1}) \quad (24)$$

It is important to note that neither of the test statistics follow a chi square distribution. In case the time series contain a unit root, or in other words, is stationary, the critical values of the maximum eigenvalue and the trace test will be incorrect (Hjalmarsson and Österholm, 2007, p. 5). However, since the appropriate tests for stationarity are already predefined in the model, we are free to neglect the statement.

From the “statsmodels.tsa.vector\_ar.vecm” python library we import the “coint\_johansen” test to ease the burden of calculations and to produce more assertive results. The results are detailed in the

The idea of causality has been introduced by Norbert Wiener in 1956, who inferred that a time series is causal if the ability to predict another time series is improved by the incorporation of information about the former (Wiener, 1956). In his seminal work Granger (1969, p. 428) dissects the two-variable feedback mechanism into causal relations. Granger defines causality as the predictability of some series. If information contained in the past values of  $Y_t$  time series effectively predicts values of  $X_t$  time series and the extent of this predictability can be measured, then  $Y_t$  is said to cause  $X_t$ . A purely nonstationary deterministic time series can't have causal influences other than autocorrelation or autocovariance. This is the reason why stochasticity is important in the Granger-causality test. Instead of measuring causality as a positive relationship between an event and an outcome, Granger views them as precedents of information. Diebold's (2001) asserts that the Granger-causality test is a test for predictive causality. Following Granger's notation, if  $U$  is all of the information accumulated since time

$t - 1$ , causality is defined as  $\sigma^2(X|U) < \sigma^2(X|\overline{U - Y})$ , where  $Y$  is causing  $X$ . The Granger-causality test further ascertains if adding the lagged values of  $X_t$  would improve the predictive power of the  $Y_t$  time series. Further description of the Granger causality test and its interpretation can be found in the Granger causality section of this research.

In this study we shall examine the question if the stock markets of V4 emerging markets actually cause the GDP changes (Stock market  $\rightarrow$  GDP), where the arrow points to the causality's direction.

$$GDP = \sum_{i=1}^n \alpha_i StockMarket_{t-i} + \sum_{i=1}^n \beta_j GDP_{t-i} + u_{1t} \quad (25)$$

$$StockMarket = \sum_{i=1}^n \lambda_i GDP_{t-i} + \sum_{i=1}^n \delta_j StockMarket_{t-i} + u_{2t} \quad (26)$$

To perform the Granger Causality test it is necessary to estimate the regression defined in equations 25 and 26. Both equations state that the time series are related to the past values of themselves in addition to being related to the past values of the other time series. Gujarati (1995) defines three different cases based on the results of the test: (i) unidirectional causality – when the values of the lagged *StockMarket* variable are not zero, and when the values of the lagged *GDP* variable are zero; (ii) bilateral causality – an outcome, when the coefficients in equations 25 and 26 are not zero; (iii) independence – suggested when the coefficients in equations 25 and 26 are statistically insignificant.

Before we define the algorithm of the Granger causality test, we must first list the prerequisites and make some assumptions, namely: (i) the time series are stationary; (ii) the choice of the number of lags is defined by the Akaike information criterion; (iii) The error terms are uncorrelated.

To test the causality between the *StockMarket* and *GDP* time series as well as the direction of the causality equations 25 and 26 have been specified. Following (Gujarati, 1995, pp. 696-700) the steps in testing if the stock market causes changes in the economy are the following:

1. A restricted regression is performed solely on the *GDP* time series, where we regress the current *GDP* on its own lagged values excluding lagged *StockMarket* variables in

the regression. From the results of the regression, we obtain the restricted residual sum of squares  $RSS_R$

2. We perform an unrestricted regression, where we include the lagged *StockMarket* variables. From the results of the regression, we obtain the unrestricted residual sum of squares  $RSS_{UR}$
3. We declare the null hypothesis, which is the following:  $H_0 : \sum \alpha_i = 0$ . The hypothesis states that lagged *StockMarket* variables do not belong in the regression, and therefore are unsuitable to predict the economy
4. To test the hypothesis, we perform the  $F$  test given by equation 27, where  $m$  is the number of lagged *StockMarket* terms, and  $n - k$  refers to the degrees of freedom.

$$F = \frac{\frac{(RSS_R - RSS_{UR})}{m}}{\frac{RSS_{UR}}{n - k}} \quad (27)$$

5. Finally, having obtained the value of the  $F$ - statistic, we compare it to the critical value at the 95% significance level. If the  $F$ - statistic is greater than the critical value, we reject  $H_0$ .

#### 4.4 Preparing the Data

The macroeconomic data for the research have been obtained from three large data libraries: the imf.data.org, the European central bank statistical warehouse, and the Eurostat database. The stock indexes time series were retrieved from the MarketWatch and Yahoo Finance databases. While retrieving the data, we paid special attention to seasonal and trend adjustment. Further analysis of non-transformed data would have resulted in spurious statistical inferences. Taking into account the ramifications of unadjusted stock index data, we applied the following transformation :  $S_t = \frac{P_t - P_{t-1}}{P_t}$ . A log-transformation expressed as  $S_t = \ln(P_t) - \ln(P_{t-1})$  yields similar results, and it removes the skewness of the data. A log transformation, however, must be conducted keeping in mind that it also makes the interpretation of the results of a multiple regression more complicated. Among other advantages log transformation reduces the variability of data and makes patterns more visible (Changyong et. al., 2014). We used the

quarterly percentage change of the Gross Domestic Product (GDP) as the variable measuring changes in real economic activity.

In the below table we have illustrated the normalized values of GDPs (HUGDP – Hungary; CZGDP – Czechia; SGDP – Slovakia; PGDP – Poland) and stock index log returns (BUX – Hungary; PX – Czechia; SAX – Slovakia; WIG – Poland) of V4 countries.

	HUGDP	BUX	CZGDP	PX	SAX	SGDP	WIG	PGDP
<b>0</b>	-0.001281	0.191267	0.020982	0.054894	0.031469	-0.059193	0.017757	-0.110927
<b>1</b>	0.000307	0.092816	0.005068	-0.042772	0.047787	0.199275	0.032951	0.419053
<b>2</b>	-0.004319	-0.042006	0.020715	0.274216	0.031946	0.147646	0.001477	0.179744
<b>3</b>	0.005388	0.600587	0.020311	-0.204992	0.023218	-0.066891	0.016482	0.051390
<b>4</b>	-0.005563	0.343715	0.011196	-0.045214	0.024655	-0.133749	0.010994	-0.050974
...	...	...	...	...	...	...	...	...
<b>82</b>	-0.006414	0.105782	-0.085951	0.150316	0.003203	-0.039529	0.009316	-0.131982
<b>83</b>	0.014172	-0.004742	0.071900	-0.055626	0.002759	-0.010737	0.002938	-0.023803
<b>84</b>	0.004675	0.050850	0.014928	0.167962	0.009699	0.029207	0.009922	0.130555
<b>85</b>	0.008833	0.156838	0.005785	0.059858	0.011873	-0.043826	0.002687	0.110708
<b>86</b>	0.014700	-0.011523	0.024109	0.055601	0.012512	0.075555	0.022319	0.055352

*Table 17 V4 countries GDP and Stock index log-transformation*

Source: Compiled by author

In order to perform the Granger causality test, both of the time series need to be of the same frequency. Since the GDP data are released on a quarterly basis, the stock prices needed to be adjusted to the corresponding frequency. As a result, we have filtered the stock data by quarters and extracted the closing values. Most of the data span from 1995Q3 to 2021Q2 totalling around 84 – 100 observations. All of the stock indexes are value-weighted

#### **4.5 Testing for stationarity**

Following the definition of Gujarati (1995, pp. 797- 800) a stochastic time series is considered stationary if its mean and variance are constant, and its covariance depends solely on the lag between the observations. If a time series would be nonstationary, any statistical inferences made about the time series would only be correct for the studied time period. It would be impossible to generalize the findings and therefore the model would be of little use.

Making statistical inferences on data containing trend, random walk or seasonality will result in faulty conclusions. The time series must therefore be tested for the presence of a unit root that makes it nonstationary. Phillips (1987) notes that errors present in the univariate time series can't be reliably modelled by independence or homoskedasticity and therefore, can't be characterized as random walk. In a stationary time series, the mean, variance and autocorrelation don't change over time.

For the sake of simplicity, in this paper we will be testing the time series for stationarity with the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. If the aforementioned tests yield the same results, we will be confident enough to proceed with the next steps of the algorithm. Each test has its own specific advantage and field of application. The augmented dickey-fuller test removes autocorrelation from the series and tests for stationarity similarly to the dickey-fuller test, first proposed in the seminal work of Dickey and Fuller (1979). The unit root test is carried out under the null hypothesis  $H_0$  = the series has a unit root. The dickey fuller test creates a t-statistic, which is compared to critical values, allowing us to affirm or reject the null hypothesis. Following (Chumacero, 2001) the ADF is based on:  $y_t = \alpha + \rho y_{t-1} + \sum_{i=1}^p \delta_i \Delta y_{t-i} + e_t$ , where  $\alpha$  is a constant,  $\beta$  is the time coefficient and  $p$  is the lag order of the autoregressive process, and  $e_t$  is noise. If  $\rho = 1$ , then the null hypothesis holds which means the time series contains a unit root. To reject the null hypothesis and declare the time series stationary, the p-value must be less than the significance level. The ADF test is able to handle complex models, however, it does have a high Type I error rate.

In the program listing, following the syntax defined in 'statsmodels.tsa.stattools' we set the regression to constant and trend, set the auto lag to the Aikaike information criterion (AIC) and run the test.

```
result = adfuller(series, regression='ct', autolag='AIC')
```

(1) ADF Statistic: -9.603763 p-value: 0.000000 Critical Values: 1%: -4.049 5%: -3.454 10%: -3.153 Reject Ho - Time Series is Stationary	ADF Statistic: -11.508826 p-value: 0.000000 Critical Values: 1%: -4.050 5%: -3.454 10%: -3.153 Reject Ho - Time Series is Stationary	(2) ADF Statistic: -8.572425 p-value: 0.000000 Critical Values: 1%: -4.067 5%: -3.462 10%: -3.157 Reject Ho - Time Series is Stationary	ADF Statistic: -9.461101 p-value: 0.000000 Critical Values: 1%: -4.068 5%: -3.463 10%: -3.158 Reject Ho - Time Series is Stationary
---	--	---	---

(1) Hungary BUX log returns and GDP		(2) Czechia PX log returns and GDP	
(3) ADF Statistic: -7.917281 p-value: 0.000000 Critical Values: 1%: -4.049 5%: -3.454 10%: -3.153 Reject Ho - Time Series is Stationary	ADP Statistic: -7.825711 p-value: 0.000000 Critical Values: 1%: -4.049 5%: -3.454 10%: -3.153 Reject Ho - Time Series is Stationary	(4) ADF Statistic: -9.783205 p-value: 0.000000 Critical Values: 1%: -4.049 5%: -3.462 10%: -3.157 Reject Ho - Time Series is Stationary	ADP Statistic: -8.892660 p-value: 0.000000 Critical Values: 1%: -4.067 5%: -3.462 10%: -3.157 Reject Ho - Time Series is Stationary
(3) Slovakia SAX log returns and GDP		(4) Poland WIG log returns and GDP	

**Table 18 ADF tests on time series: 1- Hungary; 2- Czechia, 3- Slovakia, 4- Poland.**

Source: Compiled by author

Table 2 displays the results of the ADF test conducted on log returns of the composite stock indexes of the V4 countries. In all of the cases the log-returns of the stock indexes have proven to be successful in eliminating stationarity and thereby enabling us to proceed with the analysis. The ADF statistic in all of the cases is lower than all of the critical values – this further strengthens the decision of rejecting the null-hypothesis. Furthermore, the rejection of the null hypothesis is also justified by the extremely small p-value.

However, in order to confirm our findings, we should perform an alternative test - the KPSS test. The null hypothesis in the KPSS test is that the data is stationary, while the alternative hypothesis is that the time series is not stationary. By rejecting the alternative hypothesis, we can't assume the time series is stationary, we must also consider trend-stationarity. The data of our research were tuned for the KPSS test, so that the no exponential trends would interfere with the results.

(1) KPSS Statistic: 0.3622484501988779 p-value: 0.09342739215565607 num lags: 2 Critical Values: 10% : 0.347 5% : 0.463 2.5% : 0.574 1% : 0.739 Result: The series is stationary	KPSS Statistic: 0.11436010799191071 p-value: 0.1 num lags: 4 Critical Values: 10% : 0.347 5% : 0.463 2.5% : 0.574 1% : 0.739 Result: The series is stationary	(2) KPSS Statistic: 0.10222623455544386 p-value: 0.1 num lags: 3 Critical Values: 10% : 0.347 5% : 0.463 2.5% : 0.574 1% : 0.739 Result: The series is stationary	KPSS Statistic: 0.2787832590461547 p-value: 0.1 num lags: 1 Critical Values: 10% : 0.347 5% : 0.463 2.5% : 0.574 1% : 0.739 Result: The series is stationary
(2) Hungary BUX log returns and GDP		(2) Czechia PX log returns and GDP	
KPSS Statistic: 0.2787832590461547 p-value: 0.1	KPSS Statistic: 0.5155400898580037	(1) KPSS Statistic: 0.10281641482077652	KPSS Statistic: 0.3921942922366165

num lags: 1 Critical Values: 10% : 0.347 5% : 0.463 2.5% : 0.574 1% : 0.739 Result: The series is stationary	p-value: 0.038166646428377 55 num lags: 3 Critical Values: 10% : 0.347 5% : 0.463 2.5% : 0.574 1% : 0.739 Result: The series is not stationary	p-value: 0.1 num lags: 1 Critical Values: 10% : 0.347 5% : 0.463 2.5% : 0.574 1% : 0.739 Result: The series is stationary	p-value: 0.080519701622148 05 num lags: 3 Critical Values: 10% : 0.347 5% : 0.463 2.5% : 0.574 1% : 0.739 Result: The series is stationary
(3) Slovakia SAX log returns and GDP		(4) Poland WIG log returns and GDP	

*Table 19 KPSS tests of time series 1 - Hungary, 2- Czechia, 3- Slovakia, 4- Poland.*

Source: Compiled by author

In their pioneering paper Kwiatkowski et . al. (1992) used parametrization to represent the stationary and nonstationary variables. The KPSS test are intended to compliment Dickey-Fuller tests and is amongst the most commonly used stationarity tests in applied statistics.

Applying the below listed code, we have been able to obtain the results presented in Table 19.

```
def kpss_test(GDP, **kw):
```

```
    statistic, p_value, n_lags, critical_values = kpss(GDP, **kw)
```

```
    for key, value in critical_values.items():
```

```
        print(f' {key} : {value}')
```

Table 19 reaffirms the findings of Table 1 for the tested time series. The data manipulation involving normalization and log-transformation turned out to be successful and we have managed to make the data stationary.

#### **4.6 Testing the relationship between stock prices and the economy with an Autoregressive Distributed Lag model**

To determine whether there is a relationship between the stock indexes of V4 countries and the GDP percentage change, we build a model by regressing the GDP percentage change on the past values of stock index log returns of V4 countries. By analysing the statistical significance of the coefficients corresponding to each lag, we evaluate the null hypothesis, which states that

the stock indexes effect on the GDP is zero and determine the effect of the lagged stock market variable on the dependant GDP variable.

Importing the “statsmodels.formula.api” library in Python, before running the regression, we specify the model:

```
mod_L1_est = smf.ols(formula = 'GDP ~ 1 + lag(Stockmarket, 0) + lag(Stockmarket, 1) + lag(Stockmarket, 2) + lag(Stockmarket, 3) + lag(SP500, 4)', data = data)
```

```
mod_L4_fit = mod_L4_est.fit()
```

```
print(mod_L4_fit.summary())
```

Listed below are the tables containing the complete OLS regression analysis summary of the paired stock market and GDP time series. The top table of the summary outputs the name of the dependant variable, number of observations, degrees of freedom (Df Residuals), date and time of the program’s execution. One of the key outputs in the top table is the R-squared value, which shows what percentage of the change in the dependant variable can be explained by the lagged variable. The adjusted R-squared adds independent variables and measures the reliability of the correlation. The F-statistic shows if the Stock market variable is significant in explaining the variance in the GDP variable. The larger the F-statistic is, the greater its statistical significance. The probability F-statistic should be interpreted as the probability that the null hypothesis, which states that all of the regression coefficients are zero, is true. The closer it is to zero, the better the model is. Both the AIC and Bayesian Information Criteria (BIC) are measures of goodness of fit, the sign of the statistic is irrelevant, as far as the absolute values are considered.

The model is specified in the bottom table. The intercept indicates the result of the equation 1 if all of the constants would be zero and returns only the value of  $\alpha$ . Following the intercept, the program outputs the specified lags row by row, and for each of the variables the program further outputs the values of the coefficients, the standard error, the t statistic, the the p-value and the 95% confidence interval. The standard error is the measure of heteroscedasticity of the coefficient. The lower the standard error is the better the estimated coefficient, the higher the significance of the coefficient. The p-value denoted as “P>|t|” shows the chance that the stock market has no effect on the GDP. Similarly to the probability F-statistic, the lower the p-value

is, the better the model's fit, the higher the predictive capability of the stock market. The [0.025 and 0.975] column indicates the range within two standard deviations, outside of which the coefficient is unlikely to be found.

Lastly, the bottommost table contains some additional information regarding the model, namely, the omnibus, which describes the skewness and kurtosis of the distribution of residuals, followed by the prob(Omnibus), which indicates the probability the residuals being normally distributed. The Durbin-Watson statistic measures the homoscedasticity of data, ideally a value between 1 and 2.

OLS Regression Results						
=====						
Dep. Variable:	CZGDP	R-squared:	0.231			
Model:	OLS	Adj. R-squared:	0.181			
Method:	Least Squares	F-statistic:	4.622			
Date:	Tue, 23 Nov 2021	Prob (F-statistic):	0.00096			
7						
Time:	12:24:35	Log-Likelihood:	232.61			
No. Observations:	83	AIC:	-453.2			
Df Residuals:	77	BIC:	-438.7			
Df Model:	5					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
Intercept	0.0102	0.002	6.045	0.000	0.007	0.014
lag(PX, 0)	-0.0028	0.015	-0.181	0.857	-0.034	0.028
lag(PX, 1)	0.0588	0.015	3.871	0.000	0.029	0.089
lag(PX, 2)	-0.0114	0.015	-0.775	0.441	-0.041	0.018
lag(PX, 3)	0.0253	0.015	1.714	0.091	-0.004	0.055
lag(PX, 4)	0.0262	0.015	1.775	0.080	-0.003	0.056
=====						
Omnibus:	35.482	Durbin-Watson:	2.047			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	187.184			
Skew:	-1.094	Prob(JB):	2.26e-41			
Kurtosis:	10.024	Cond. No.	9.98			

**Table 20 OLS regression analysis for PX and PGDP.**

Source: Compiled by author

The change in the log returns of the PX Czech stock index can explain 23.1% of the change in the GDP. The PX has been found to be positively related to the Czech GDP when lagged back as much as three quarters. Judging by the p-value, the PX lagged back one quarter is statistically significant at the 0.01 level, since  $P > |t|_{PX,1} = 0.000$ . The values of the third and fourth quarters are both statistically significant at the 0.1 level.

Another statistic of interest would be the Durbin-Watson statistic, indicating the value of 2.047, which means that there was no autocorrelation detected in the sample.

Thus, we are able to define the equation for the Czech GDP, expressed as:

$$CZGDP = 0.010 - 0.002PX_t + 0.058PX_{t-1} - 0.011PX_{t-2} + 0.025PX_{t-3} + 0.026PX_{t-4}$$

The above equation's interpretation is given by the following assessments:

1. An increase in the Czech GDP will result in an immediate increase of PX by 1%, and, other things equal,
2. An increase in the PX by 5.8 percent in the next quarter.

OLS Regression Results						
=====						
Dep. Variable:	HUGDP	R-squared:	0.106			
Model:	OLS	Adj. R-squared:	0.059			
Method:	Least Squares	F-statistic:	2.232			
Date:	Tue, 23 Nov 2021	Prob (F-statistic):	0.0574			
Time:	12:20:30	Log-Likelihood:	254.99			
No. Observations:	100	AIC:	-498.0			
Df Residuals:	94	BIC:	-482.3			
Df Model:	5					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
Intercept	0.0053	0.002	2.617	0.010	0.001	0.009
lag(BUX, 0)	0.0078	0.013	0.614	0.541	-0.017	0.033
lag(BUX, 1)	0.0357	0.012	2.875	0.005	0.011	0.060
lag(BUX, 2)	-0.0107	0.012	-0.855	0.395	-0.035	0.014
lag(BUX, 3)	0.0116	0.012	0.925	0.357	-0.013	0.036
lag(BUX, 4)	0.0061	0.012	0.487	0.627	-0.019	0.031
=====						
Omnibus:	102.702	Durbin-Watson:	2.317			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3255.351			
Skew:	-2.889	Prob(JB):	0.00			
Kurtosis:	30.348	Cond. No.	6.94			

**Table 21 OLS regression analysis for BUX and HUGDP.**

Source: Compiled by author

In case of Hungary the change of BUX log returns is only able to explain around 10.6% of the change in GDP, which is significantly less than the PX's predictive capability. Again, the BUX has also been found to be positively correlated to the GDP, specifically when lagged back up to 1 quarter, as the p-value indicates statistical significance at that specific timeframe. The coefficients at two, three and four lags, therefore, have little statistical significance, and

therefore, a lesser relationship to the economy. Considering the Durbin-Watson statistic, the time series have no autocorrelation, as the 2.317 value is close to 2.

We define the Hungarian GDP model as follows:

$$HUGDP = 0.005 + 0.007BUX_t + 0.035BUX_{t-1} - 0.010BUX_{t-2} + 0.0116BUX_{t-3} + 0.0061BUX_{t-4}$$

The conclusions drawn from the coefficient values are the following:

1. An Increase in the percentage change of the Hungarian GDP would result in an immediate increase of the BUX stock index by 0.005, corresponding to 0.5%, and
2. An increase in the BUX stock index by 3.5% in four months, other things equal.

OLS Regression Results						
Dep. Variable:	SGDP	R-squared:	0.084			
Model:	OLS	Adj. R-squared:	0.035			
Method:	Least Squares	F-statistic:	1.717			
Date:	Tue, 23 Nov 2021	Prob (F-statistic):	0.138			
Time:	12:45:09	Log-Likelihood:	223.32			
No. Observations:	99	AIC:	-434.6			
Df Residuals:	93	BIC:	-419.1			
Df Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.0166	0.003	6.267	0.000	0.011	0.022
lag(SAX, 0)	0.0321	0.028	1.165	0.247	-0.023	0.087
lag(SAX, 1)	0.0459	0.028	1.641	0.104	-0.010	0.101
lag(SAX, 2)	0.0111	0.027	0.406	0.686	-0.043	0.065
lag(SAX, 3)	0.0240	0.027	0.879	0.382	-0.030	0.078
lag(SAX, 4)	0.0045	0.027	0.168	0.867	-0.048	0.057
Omnibus:	12.374	Durbin-Watson:	1.545			
Prob(Omnibus):	0.002	Jarque-Bera (JB):	2.406			
Skew:	-0.265	Prob(JB):	9.19e-08			
Kurtosis:	5.752	Cond. No.	12.5			

**Table 22 OLS regression analysis for SAX and SGDP.**

Source: Compiled by author

The SAX Slovak stock market index was found to have one of the weakest correlations with the economy, with the SAX only being able to explain less than 8.4% of the change in Slovak GDP. The probability that the coefficients determined in the table below have a zero effect on

the model is 13.8%, which is higher compared to Czechia and Hungary. The coefficient corresponding to the 1-quarter lag was barely statistically significant at the 0.1 percent level, with  $P > |t|_{PX,1} = 0.104$  the rest of the coefficients have little to no statistical significance in the model. The Durbin Watson statistic shows 1.545, indicating little to no autocorrelation. The Slovak GDP model is expressed as follows:

$$SGDP = 0.016 + 0.032SAX_t + 0.045SAX_{t-1} + 0.111SAX_{t-2} + 0.024SAX_{t-3} + 0.0045SAX_{t-4}$$

There was hardly a coefficient to be found in the output that was of a statistical significance in the model. This implies that the Statistical inferences based on this model are weaker than the others, nevertheless, since stock prices are positively related to the economy, we proceed with the examination of this particular model. We therefore conclude the following:

1. An increase in the percentage change of the Slovak GDP will immediately result in an increase of SAX by 1.6%, and
2. An increase of the SAX index by 4.5% in the following quarter

OLS Regression Results						
=====						
Dep. Variable:	SGDP	R-squared:	0.081			
Model:	OLS	Adj. R-squared:	0.032			
Method:	Least Squares	F-statistic:	1.646			
Date:	Tue, 23 Nov 2021	Prob (F-statistic):	0.155			
Time:	21:16:48	Log-Likelihood:	263.82			
No. Observations:	99	AIC:	-515.6			
Df Residuals:	93	BIC:	-500.1			
Df Model:	5					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
Intercept	0.0088	0.002	5.009	0.000	0.005	0.012
lag(SAX, 0)	0.0013	0.014	0.090	0.928	-0.027	0.030
lag(SAX, 1)	0.0366	0.014	2.555	0.012	0.008	0.065
lag(SAX, 2)	-0.0016	0.014	-0.111	0.912	-0.030	0.027
lag(SAX, 3)	0.0075	0.014	0.555	0.580	-0.019	0.034
lag(SAX, 4)	0.0162	0.014	1.197	0.234	-0.011	0.043
=====						
Omnibus:	49.272	Durbin-Watson:	2.692			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	525.524			
Skew:	-1.170	Prob(JB):	7.65e-115			
Kurtosis:	14.042	Cond. No.	8.45			
=====						

**Table 23 OLS regression analysis for WIG and PGDP.**

Source: Compiled by author

The WIG log returns have shown the weakest explanatory capabilities in the variation of the PGDP dependent variable from the perspective of the R-squared statistic – an 8.1% value. There is an 84.5% chance that the effect of the coefficients on the model is nonzero, given by the Probability F-statistic. The coefficient corresponding to the 1-quarter lag was the only one to have been found to be statistically significant at the 0.05 level, with the p-value being 0.012.

The Durbin-Watson statistic shows a value of 2.69 indicating some negative autocorrelation. We define the Poland GDP model as follows:

$$PGDP = 0.088 + 0.001WIG_t + 0.036WIG_{t-1} - 0.0016WIG_{t-2} + 0.007WIG_{t-3} + 0.016WIG_{t-4}$$

We interpret the findings as follows:

1. An increase in Poland's GDP will result in an immediate 8.8% increase of WIG, and, other things equal
2. An increase of WIG by 3.6% in the following quarter

#### **4.7 Testing the time series for cointegration with Johansen cointegration test**

Extending the research on relationships between stock prices and the economy, we implement a cointegration analysis that sheds light on potential long-run equilibrium relationships between the GDP and the stock market indexes of V4 countries. Many empirical works (Cominicoli, 19995; Ikoku, 2010) omit this step in the Granger causality testing framework, and as of yet, it is unclear why. In this research we justify the importance of cointegration testing through the basic definition of the Granger causality test. In order for variable Y to Granger cause X or vice-versa, it is essential for the time series to be cointegrated.

To perform the Johansen cointegration test in python, we import the “coint\_johansen” function from the “statsmodels.tsa.vector\_ar.vecm” library. The data are

We specify the statistics in the following lines of code and identify the trend, which in our case is -1, meaning no constant and no deterministic trend:

```
def joh_output(res):
    output = pd.DataFrame([res.lr2,res.lr1],
                          index=['max_eig_stat',"trace_stat"])
```

```

print(output.T,\n')
print("Critical values(90%, 95%, 99%) of max_eig_stat\n",res.cvm,\n')
print("Critical values(90%, 95%, 99%) of trace_stat\n",res.cvt,\n')

```

We call the `coint_johansen` function and run the test :

```

joh_model1 = coint_johansen(data,-1,2) # k_ar_diff +1 = K
joh_output(joh_model1)

```

The output of the test detailed below consists of trace statistics and eigenvalue statistics. In the output they are represented in a two-by-two matrix with the variables 0 and 1. The `max_eig_stat` column shows the maximum eigenvalue score. The eigenvalue statistic shows how strongly cointegrated the series are and how likely their mean reversion is. If the test-statistic (rank of the matrix) is greater than the confidence value at the 95 percent level for the corresponding test, we reject the null hypothesis. We run the program on the stock market indexes and the corresponding GDPs of V4 economies. It should be remarked, that “cv” stands for critical value in the table below:

<pre> max_eig_stat  trace_stat 0      23.954102  42.137038 1      18.182935  18.182935  CV(90%, 95%, 99%) of max_eig_stat [[ 9.4748 11.2246 15.0923]  [ 2.9762  4.1296  6.9406]]  CV(90%, 95%, 99%) of trace_stat [[10.4741 12.3212 16.364 ]  [ 2.9762  4.1296  6.9406]] </pre>	<pre> max_eig_stat  trace_stat 0      25.305611  33.369268 1       8.063657   8.063657  CV(90%, 95%, 99%) of max_eig_stat [[ 9.4748 11.2246 15.0923]  [ 2.9762  4.1296  6.9406]]  CV(90%, 95%, 99%) of trace_stat [[10.4741 12.3212 16.364 ]  [ 2.9762  4.1296  6.9406]] </pre>
<b>Hungary BUX log returns and GDP</b>	<b>(2) Czechia PX log returns and GDP</b>
<pre> max_eig_stat  trace_stat 0      18.543911  28.282130 1       9.738219   9.738219  CV(90%, 95%, 99%) of max_eig_stat [[ 9.4748 11.2246 15.0923]  [ 2.9762  4.1296  6.9406]]  CV(90%, 95%, 99%) of trace_stat [[10.4741 12.3212 16.364 ]  [ 2.9762  4.1296  6.9406]] </pre>	<pre> max_eig_stat  trace_stat 0      33.273549  48.053206 1      14.779656  14.779656  CV(90%, 95%, 99%) of max_eig_stat [[ 9.4748 11.2246 15.0923]  [ 2.9762  4.1296  6.9406]]  CV(90%, 95%, 99%) of trace_stat [[10.4741 12.3212 16.364 ]  [ 2.9762  4.1296  6.9406]] </pre>
<b>(3) Slovakia SAX log returns and GDP</b>	<b>(4) Poland WIG log returns and GDP</b>

**Table 24 Johansen cointegration Test for V4 economies' stock ick indexes and GDP growth rate.**

Source: Compiled by author

In case of Hungary, we observe the trace statistic to be 42.137, therefore we reject the null hypothesis, meaning that the sum of the eigenvalues is 0. This implies that the BUX and HUGDP time series are cointegrated. We similarly reject the null hypothesis of the trace statistic for the PX and CZGDP time series and assert that they are cointegrated as well. At 28.28, the Slovak SAX index exceeds the 99% critical value, allowing us to assert that SAX log-returns and SGDP percentage change are cointegrated. The case is the same for WIG log-returns and PGDP - the time series are cointegrated, based on the trace statistic.

#### 4.8 Testing for causality with granger causality test

The null hypothesis under inspection states that the stock indexes do not Granger cause the GDP. The stock market causes GDP, if past values of the Stock market help in predicting the future values of the GDP, therefore we lag the *StockMarket* variable by 1 quarter. To test the hypothesis, we import the “grangercausalitytests” from “statsmodels.tsa.stattools” library. We define the number of lag, and run the test as follows:

```
gc_res = grangercausalitytests(ts_df, 5)
```

The tables below show the number of lags used in finding causality, the F-test shows if the lagged values of the *StockMarket* variable improve the forecast of *GDP*.

```
number of lags (no zero) 1
ssr based F test:          F=0.0312 , p=0.8602 , df_denom=82, df_num=1
ssr based chi2 test:      chi2=0.0324 , p=0.8572 , df=1
likelihood ratio test:    chi2=0.0324 , p=0.8572 , df=1
parameter F test:        F=0.0312 , p=0.8602 , df_denom=82, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:          F=7.3769 , p=0.0012 , df_denom=79, df_num=2
ssr based chi2 test:      chi2=15.6877 , p=0.0004 , df=2
likelihood ratio test:    chi2=14.3829 , p=0.0008 , df=2
parameter F test:        F=7.3769 , p=0.0012 , df_denom=79, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:          F=5.7609 , p=0.0013 , df_denom=76, df_num=3
ssr based chi2 test:      chi2=18.8746 , p=0.0003 , df=3
likelihood ratio test:    chi2=17.0069 , p=0.0007 , df=3
parameter F test:        F=5.7609 , p=0.0013 , df_denom=76, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:          F=5.3591 , p=0.0008 , df_denom=73, df_num=4
ssr based chi2 test:      chi2=24.0793 , p=0.0001 , df=4
likelihood ratio test:    chi2=21.1123 , p=0.0003 , df=4
parameter F test:        F=5.3591 , p=0.0008 , df_denom=73, df_num=4
```

Granger Causality			
number of lags (no zero) 5			
ssr based F test:	F=4.8066	, p=0.0008	, df_denom=70, df_num=5
ssr based chi2 test:	chi2=27.8094	, p=0.0000	, df=5
likelihood ratio test:	chi2=23.9071	, p=0.0002	, df=5
parameter F test:	F=4.8066	, p=0.0008	, df_denom=70, df_num=5

**Table 25 Granger Causality test for PX and CZGDP.**

Source: Compiled by author

As it can be observed in the above table, in case of the Czech time series, the F-statistics are significant for lagged quarters 2 – 5. Therefore, for these lags we reject the null hypothesis that PX does not Granger cause CZGDP. For lag 1 we accept the null hypothesis. Lag 2 is associated with the highest F-statistic.

Granger Causality			
number of lags (no zero) 1			
ssr based F test:	F=0.3950	, p=0.5311	, df_denom=98, df_num=1
ssr based chi2 test:	chi2=0.4071	, p=0.5234	, df=1
likelihood ratio test:	chi2=0.4063	, p=0.5239	, df=1
parameter F test:	F=0.3950	, p=0.5311	, df_denom=98, df_num=1
Granger Causality			
number of lags (no zero) 2			
ssr based F test:	F=2.3299	, p=0.1028	, df_denom=95, df_num=2
ssr based chi2 test:	chi2=4.9051	, p=0.0861	, df=2
likelihood ratio test:	chi2=4.7886	, p=0.0912	, df=2
parameter F test:	F=2.3299	, p=0.1028	, df_denom=95, df_num=2
Granger Causality			
number of lags (no zero) 3			
ssr based F test:	F=2.9073	, p=0.0388	, df_denom=92, df_num=3
ssr based chi2 test:	chi2=9.3856	, p=0.0246	, df=3
likelihood ratio test:	chi2=8.9670	, p=0.0297	, df=3
parameter F test:	F=2.9073	, p=0.0388	, df_denom=92, df_num=3
Granger Causality			
number of lags (no zero) 4			
ssr based F test:	F=2.3496	, p=0.0603	, df_denom=89, df_num=4
ssr based chi2 test:	chi2=10.3488	, p=0.0349	, df=4
likelihood ratio test:	chi2=9.8381	, p=0.0432	, df=4
parameter F test:	F=2.3496	, p=0.0603	, df_denom=89, df_num=4
Granger Causality			
number of lags (no zero) 5			
ssr based F test:	F=2.7448	, p=0.0238	, df_denom=86, df_num=5
ssr based chi2 test:	chi2=15.4795	, p=0.0085	, df=5
likelihood ratio test:	chi2=14.3618	, p=0.0135	, df=5
parameter F test:	F=2.7448	, p=0.0238	, df_denom=86, df_num=5

**Table 26 granger Causality test for BUX and HUGDP.**

Source: Compiled by author

For Hungary we can observe that the smallest p-value corresponds to the largest F-statistic value – an implication that the BUX preceding the HUGDP. At lag 3 all of the p-values are less than the 0.05 significance level, and therefore we can reject the null hypothesis again.

Granger Causality			
number of lags (no zero) 1			
ssr based F test:	F=1.1463	, p=0.2869	, df_denom=99, df_num=1
ssr based chi2 test:	chi2=1.1811	, p=0.2771	, df=1
likelihood ratio test:	chi2=1.1743	, p=0.2785	, df=1
parameter F test:	F=1.1463	, p=0.2869	, df_denom=99, df_num=1
Granger Causality			
number of lags (no zero) 2			
ssr based F test:	F=0.2789	, p=0.7572	, df_denom=96, df_num=2
ssr based chi2 test:	chi2=0.5869	, p=0.7457	, df=2
likelihood ratio test:	chi2=0.5852	, p=0.7463	, df=2
parameter F test:	F=0.2789	, p=0.7572	, df_denom=96, df_num=2
Granger Causality			
number of lags (no zero) 3			
ssr based F test:	F=1.7401	, p=0.1642	, df_denom=93, df_num=3
ssr based chi2 test:	chi2=5.6132	, p=0.1320	, df=3
likelihood ratio test:	chi2=5.4613	, p=0.1410	, df=3
parameter F test:	F=1.7401	, p=0.1642	, df_denom=93, df_num=3
Granger Causality			
number of lags (no zero) 4			
ssr based F test:	F=2.0134	, p=0.0993	, df_denom=90, df_num=4
ssr based chi2 test:	chi2=8.8592	, p=0.0647	, df=4
likelihood ratio test:	chi2=8.4849	, p=0.0753	, df=4
parameter F test:	F=2.0134	, p=0.0993	, df_denom=90, df_num=4
Granger Causality			
number of lags (no zero) 5			
ssr based F test:	F=3.2334	, p=0.0100	, df_denom=87, df_num=5
ssr based chi2 test:	chi2=18.2109	, p=0.0027	, df=5
likelihood ratio test:	chi2=16.7030	, p=0.0051	, df=5
parameter F test:	F=3.2334	, p=0.0100	, df_denom=87, df_num=5

**Table 27 Granger Causality test for WIG and PGDP.**

Source: Compiled by author

As for the WIG's and the PGDP's Granger causality test, we can observe that the p-values are statistically significant only at 5 lags. If more lags were added, the influence of WIG on the GDP would increase.

Granger Causality			
number of lags (no zero) 1			
ssr based F test:	F=3.7945	, p=0.0543	, df_denom=99, df_num=1
ssr based chi2 test:	chi2=3.9095	, p=0.0480	, df=1
likelihood ratio test:	chi2=3.8364	, p=0.0502	, df=1
parameter F test:	F=3.7945	, p=0.0543	, df_denom=99, df_num=1

Granger Causality			
number of lags (no zero) 2			
ssr based F test:	F=2.8040	, p=0.0655	, df_denom=96, df_num=2
ssr based chi2 test:	chi2=5.9002	, p=0.0523	, df=2
likelihood ratio test:	chi2=5.7343	, p=0.0569	, df=2
parameter F test:	F=2.8040	, p=0.0655	, df_denom=96, df_num=2
Granger Causality			
number of lags (no zero) 3			
ssr based F test:	F=1.6900	, p=0.1745	, df_denom=93, df_num=3
ssr based chi2 test:	chi2=5.4517	, p=0.1416	, df=3
likelihood ratio test:	chi2=5.3083	, p=0.1506	, df=3
parameter F test:	F=1.6900	, p=0.1745	, df_denom=93, df_num=3
Granger Causality			
number of lags (no zero) 4			
ssr based F test:	F=1.3185	, p=0.2692	, df_denom=90, df_num=4
ssr based chi2 test:	chi2=5.8015	, p=0.2145	, df=4
likelihood ratio test:	chi2=5.6379	, p=0.2279	, df=4
parameter F test:	F=1.3185	, p=0.2692	, df_denom=90, df_num=4
Granger Causality			
number of lags (no zero) 5			
ssr based F test:	F=1.0599	, p=0.3882	, df_denom=87, df_num=5
ssr based chi2 test:	chi2=5.9695	, p=0.3092	, df=5
likelihood ratio test:	chi2=5.7948	, p=0.3267	, df=5
parameter F test:	F=1.0599	, p=0.3882	, df_denom=87, df_num=5

*Table 28 Granger Causality test for SAX and SGDP.*

Source: Compiled by author

At 2 lags a statistical significance exists between the causal relationship of the SAX and SGDP at the 0.1 level, with the p-value being 0.0655.

## 4.9 Discussion

The goal of this research was to examine if it is possible to predict the economy through an intrinsic assertive algorithm involving a stationarity test, a distributed lag analysis, a cointegration test, and finally, and a granger causality test. The lags were chosen based on the AIC, and the results were computed in the Python environment.

We have asserted the pro and counterevidence of stock markets' ability of predicting recessions through an interpretive literature analysis. This allowed us to create a theoretical framework on which we can base the research. The data was retrieved from reliable statistical warehouses and databases. We employed the ADF and the KPSS tests to test whether the data were

stationary and applied log-transformation and normalization to make the data mean-reverting. In the next steps with an OLS regression summary in the framework of an autoregressive distributed lag analysis, we have built the models for the individual countries' stock index to GDP relationships. It has been found that the lagged coefficients of WIG were the least reliable in explaining the changes in the PGDP, nonetheless, based on the t-statistic, it was concluded that a relationship does exist.

From the Johansen cointegration test we can assert that there exists a long-run relationship between the composite stock indexes and the GDPs of V4 economies. From the ADL regression, based on the constructed models, it was determined that past values of stock prices do in fact lead economic growth, but this does not mean that stock prices Granger cause the economy. The Granger causality tests showed that there exists a causality between the composite stock indexes and the GDPs of the V4 countries.

There are several issues, however, that haven't been addressed in this section. It is possible that the lack of statistical significance in the coefficients can be attributed to the individual GDP time series of V4 countries. The previous statistical alterations of the GDP data, in particular, seasonal adjustment, could have contributed to a less deterministic model. The fact that the GDP was obtained in the country's domestic currency could also have contributed to weak R-squared values. Furthermore, the reason the causal relationship can be attributed to the individual composite stock indexes and the GDPs is unclear. What is the role of the forward-looking aspect and the wealth effect on the stock market's relationship with the economy.

## 5.SUMMARY

Outlined in Section 2, there is reason to suggest that the Scoreboard general purpose indicators recommended by the IMF MIP should not be applied mechanically for EMs. Reiterating (Csontos, Szalay, 2013), different levels of development of countries justify the application of different thresholds and different indicators. In the literature review pitfalls of the Scoreboard and the subsequent in-depth-review procedures were identified. Empirical literature was found to be lacking a theoretical background as to justify the choice of the indicators, except for the argument that they have a high utility. While the statistical determination methodology and formulas for calculation were found to be useful, examples as the calculation algorithm was absent in all the reviewed literature. Notwithstanding the advantages of the Scoreboard indicators' transparency, ease of accessibility and simplicity in interpretation, the choice of the particular set of 14 indicators was not justified. Understanding the major downsides of the MIP EWSs, this research paper introduced ways to identify three different crisis episodes on corresponding market segments of Hungarian, Ukrainian and Russian financial markets.

Section 3 introduced the signal extraction method and in detail outlined the aspects of the binary crisis variable, its construction and application. It was tested for currency, banking and economic crises for Hungary, Ukraine and Russia. Based on the binary crisis variable, a table of indicators was introduced for each of the afore mentioned EMs. Table 13 further featured the utility and predictive power of the listed indicators. The concepts of forecasting window width and the right 'tail' of the window were explained in detail. For Hungary the Hungarian sovereign debt CDS 5-year change indicator was tested for forecasting power. It was determined that if the indicator exceeded 0.1 threshold, within the forecasting window of 5 quarters a recession could be expected. The results were visualized for the best leading indicators of Ukraine and Russia as well. Long-term signaling indicators were tested for their correlation with economic business cycles. The cross-correlation model was further explored on sample data from the National Bank of Russia. The amplitude of the correlation of the Russian GDP and Exports in the timeframe between 1995 to 2018 were visually determined, hence it was possible to determine the frequency and the phase shifts between the time series. It was found that for Russian markets the GDP lagged behind exports data by 3 quarters, which is objectively enough for the implementation of policy action. Nonetheless, the problem of linear trends and heteroskedasticity was not elucidated in the work.

Finally, a relatively new method – anomalous stock index price fluctuations frequency was tested for its predictive power. On the example of the BUX index, the threshold for the leftmost tail of the distribution was statistically determined and a year-by-year anomalous price fluctuation occurrence graph was illustrated to determine the predictive power as a forecasting indicator. The hypothesis was put forward that for EMs this could serve as a useful indicator if it showed the price fluctuations in months rather than years, but it needs to be proved in subsequent works on the topic.

In general, according to the results of the application of the signal extraction method, the cross-spectrum analysis and the price fluctuations analysis, the best results in explaining economic crises in Eastern European EMs are provided by indicators based on data on external monetary situation, like monetary aggregates, current bank accounts, real exports.

The research paper achieved all of its tasks and objectives and aims to notify the Hungarian economic research community of the importance of the development of EWSs in Hungary.

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## ANNEXES

### Matlab Program Listing:

```
%Preparation of test signals
Period=30; chastota=1/30; time=(1:150);N=length(time);

%Meandr
XPostijnaSkladova=0.5;
XTrend=1+0.005*time;
XPersaHarmonika=(4/(1*pi))*sin(2*pi*(1/Period)*time);
XTretyaHarmonika=(4/(3*pi))*sin(2*pi*(3/Period)*time);
XPjataHarmonika=(4/(5*pi))*sin(2*pi*(5/Period)*time);
XSyomaHarmonika=(4/(7*pi))*sin(2*pi*(7/Period)*time);
AnX=.1;NoiseX=AnX*randn(1,length(time));

RjadX=NoiseX+XPostijnaSkladova+XTrend+XPersaHarmonika+XTr
etyaHarmonika+XPjataHarmonika+XSyomaHarmonika;

%Shaw
YPostijnaSkladova=0.5;
YTrend=1-0.005*time;
YPersaHarmonika=(1/(1*pi))*sin(2*pi*(1/Period)*time);
YDrugaHarmonika=(1/(2*pi))*sin(2*pi*(2/Period)*time);
YTretyaHarmonika=(1/(3*pi))*sin(2*pi*(3/Period)*time);
YChetvertaHarmonika=(1/(4*pi))*sin(2*pi*(4/Period)*time);
YPjataHarmonika=(1/(5*pi))*sin(2*pi*(5/Period)*time);
YShostaHarmonika=(1/(6*pi))*sin(2*pi*(6/Period)*time);
YSyomaHarmonika=(1/(7*pi))*sin(2*pi*(7/Period)*time);
AnY=.1;NoiseY=AnY*randn(1,length(time));
```

```

RjadY=NoiseY+YPostijnaSkladova+(YTrend) -YPersaHarmonika-
YDrugaHarmonika-YTretyaHarmonika-YChetvertaHarmonika-
YPjataHarmonika-YShostaHarmonika-YSyomaHarmonika;

X=fft(RjadX);

X1=abs(X);

[maxX1, indexX]=max(X1);

for i=1:150

    if abs(real(X(i)))*abs(imag(X(i)))< maxX1/20

        FiX(i)=0;

    else FiX(i)=atan(-imag(X(i))/real(X(i)));

    end

end

FiX;

Y=fft(RjadY);

Y1=abs(Y);

[maxY1, indexY]=max(X1);

for i=1:150

    if abs(real(Y(i)))*abs(imag(Y(i)))< maxY1/20

        FiY(i)=0;

    else FiY(i)=atan(-imag(Y(i))/real(Y(i)));

    end

end

FiY;

subplot(4,2,1);plot(time,RjadX);

subplot(4,2,3); stem(X1);

subplot(4,2,5); stem(FiX);

```

```

subplot(4,2,2);plot(time,RjadY);
subplot(4,2,4); stem(Y1);
subplot(4,2,6); stem(FiY);

%clear all

%1 point of the Algorithm .input of data for X and Y from
an Excell file

%2 point of the Algorithm. Calculating arithmetic mean
values

MeanX=mean(RjadX); MeanY=mean(RjadY);

%3 point of the Algorithm. Calculating Deviation

DX=std(RjadX); DY=std(RjadY);

%4 point of the Algorithm. kovariation indicator
calculation

for k=1:length(time)
    RjadY(N+k)=RjadY(k);%condition of cycling
end

for k=1:length(time)
    covxy(k)=0;
    for i=1:N
        covxy(k)=covxy(k)+(1/N)*(RjadX(i)-MeanX)*(RjadY(i+k)-
MeanY);
    end
end

rxy=(1/(DX*DY))*covxy;

%fft on covxy

Fouriercovxy=fft(rxy);

ModulFouriercovxy=abs(Fouriercovxy);[MaxModulFouriercovxy
,indexFouriercovxy]=max(ModulFouriercovxy);

```

```
for i=1:150
    if ModulFouriercovxy(i) < MaxModulFouriercovxy/20
        FiFouriercovxy(i)=0;
    else FiFouriercovxy(i)=atan(-
imag(Fouriercovxy(i))/real(Fouriercovxy(i)));
    end
end

subplot(4,2,7); stem(ModulFouriercovxy);
subplot(4,2,8); stem(FiFouriercovxy);
```

## **Abstract**

On their missions to save the domestic countries' economy, central banks all around the world have gone to unprecedented measures with monetary and fiscal stimuli. Through lowering interest rates, buying up corporate debt, issuing helicopter money, and quantitative easing programs, central banks have bloated their balance sheets, thereby increasing systemic risk. In the period between 1970-2017, there were 151 banking crises 236 currency crises, and 74 sovereign crises globally (Laeven and Valencia, p-3, 2018). Cumulative losses from banking and twin crises are notoriously higher in OECD countries than in emerging economies (Davis and Dilruba, 2008). The many economic imbalances created by the two recent global crises: The Great Recession and the COVID-19 Recession have, yet again alerted economists and experts of the importance of measures of financial condition and early warning systems (EWSs).

The postulates of the research paper infer that since expansions and recessions move in a cyclical manner, their further movements are inherently predictable, therefore there exists a set of macroeconomic indicators that shows that the economy is heading into a recession before it is evident on the broader market. An extensive literature on EWSs presented methods ranging from panel logit to binary recursive trees' estimators, all of which have been successful in predicting crises in terms of type I and type II errors. This research paper aims to find a list of indicators capable of predicting crisis episodes in Eastern European Emerging markets, particularly in the V4 countries. The objective of the research paper is to identify the disadvantages of a mechanistic approach of EWSs provided by the ECB, update the literature on EWSs with contributors analyzing predictability of crises in developed economies and post-soviet countries and examine the methods of signal extraction, cross-spectral analysis, composite leading indicators, thereby, expanding the scope of previously conducted researches. We will apply them for a pre-determined set of indicators to evaluate their predictive power. The methodology of the work involves a qualitative and quantitative approach to determining the best economic indicators capable of forecasting crises. In addition to an algorithm for the three main methods of EWS estimation, a MATLAB program will enhance the predictive capabilities via applying machine learning and neural networks. The contribution of such a research paper would be that of an independent forecasting system that would give an estimate of the likelihood of a recession.