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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.

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 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 “fuzzy¹” 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

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

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. (Barrell 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 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. (^bManasse et al., 2003) argue that a prior 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. (^bManasse 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 (^aManasse 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-cause² 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). (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,

² 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

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 $EMP_{i,t} = \omega_{exr} \left(\frac{rexr_{i,t} - rexr_{i,t-1}}{rexr_{i,t-1}} \right) - \omega_{resr} \left(\frac{res_{i,t} - res_{i,t-1}}{res_{i,t-1}} \right)$ where $rexr_{i,t}$ is the real exchange rate, $res_{i,t}$ is the foreign exchange reserves, ω_{exr} is the inverse of the variance of change rates in exchange rates, ω_{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) fragmented³ 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 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

³ 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)

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 scoreboards⁴ 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

⁴ 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).

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 normalized⁵, 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. However, 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; Arahuetes 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 errors⁶ 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", thus the usefulness of official thresholds is negative for all indicators – which can have political and economic consequences. 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

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

⁶ 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).

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.

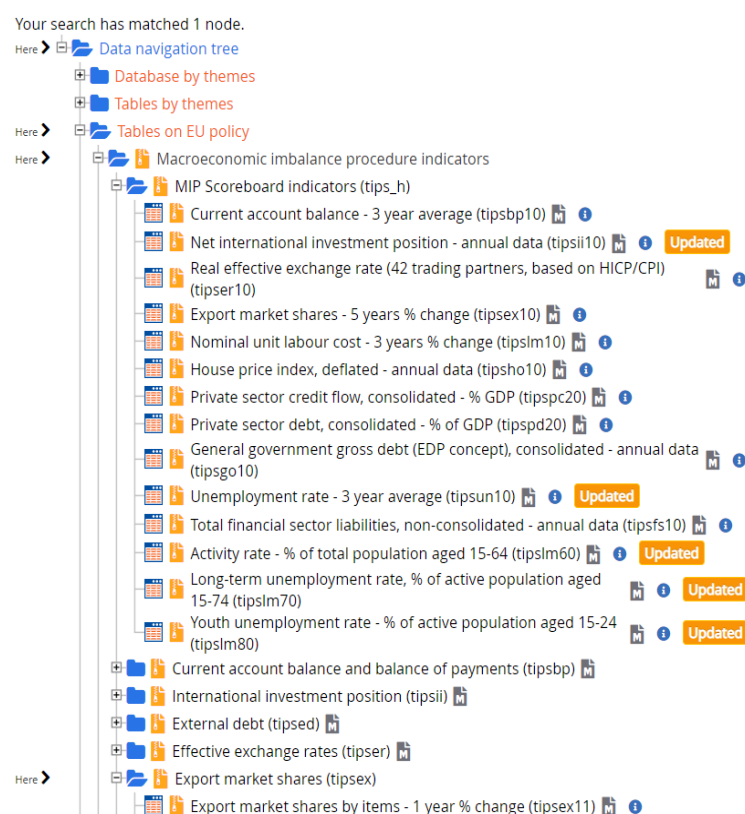


Figure 1: Consolidated MIP data structure on the Eurostat website. Source: own compilation

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

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

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:
https://cbcg.me/slike_i_fajlovi/fajlovi/journal/vol2/no1/the_new_eu_macroeconomic_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.

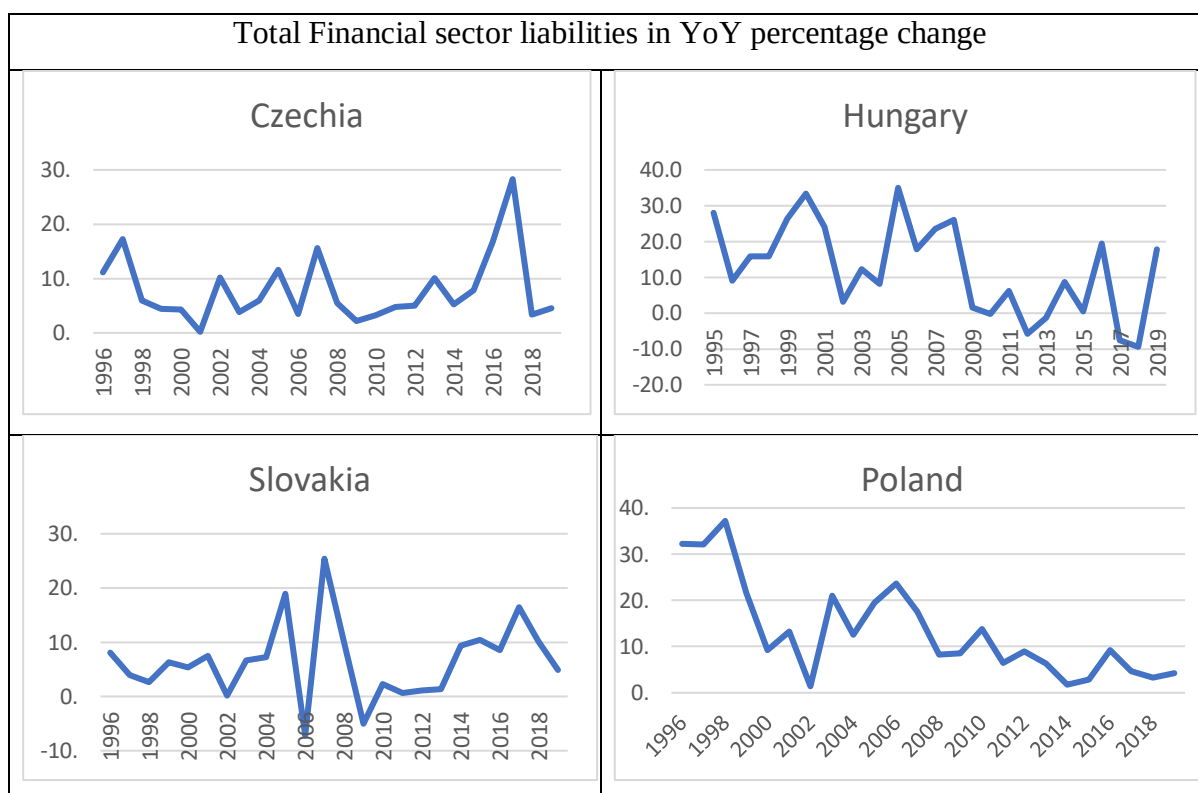
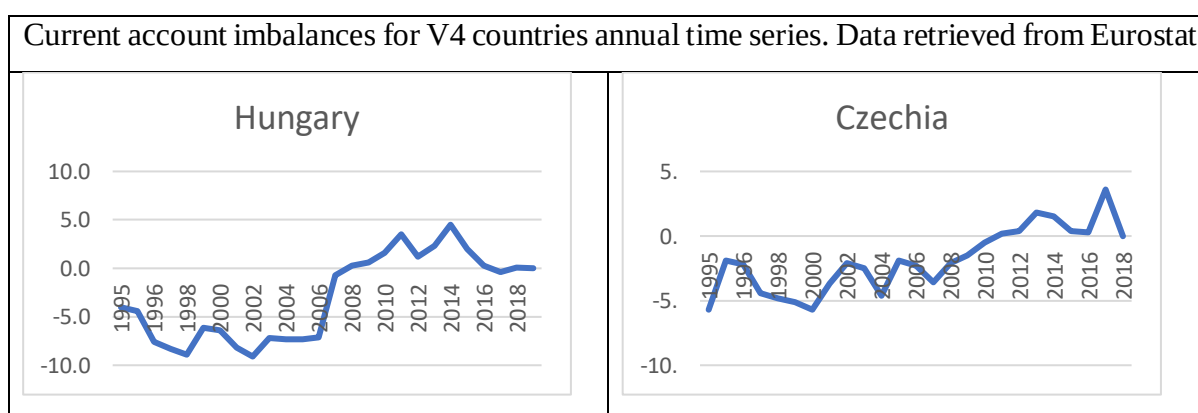


Table 3: AMR Total Financial liabilities for V4 countries. Annual time series. Source: own compilation based on the data from Eurostat

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.



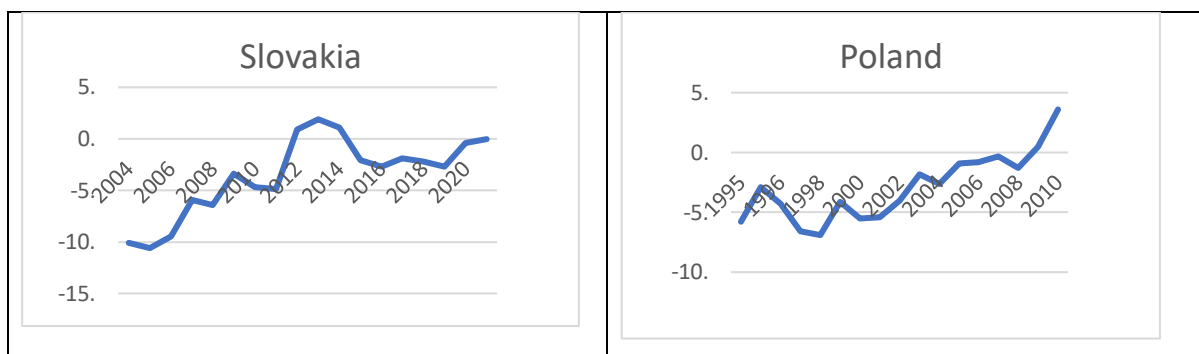


Table 4: Current account imbalances for V4 countries Annual time series. Source: own compilation based on the data from Eurostat

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.

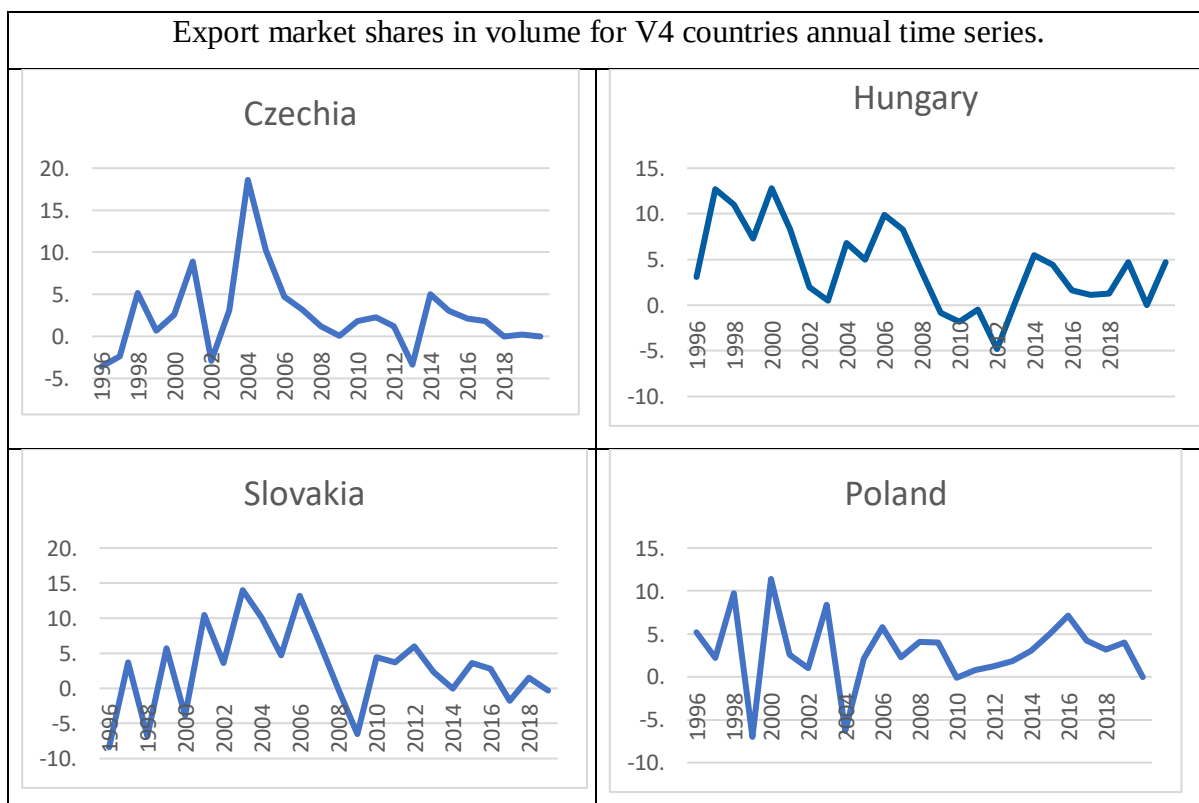


Table 5: Export market shares in volume for V4 countries annual time series. Source: own compilation based on the data from Eurostat

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.

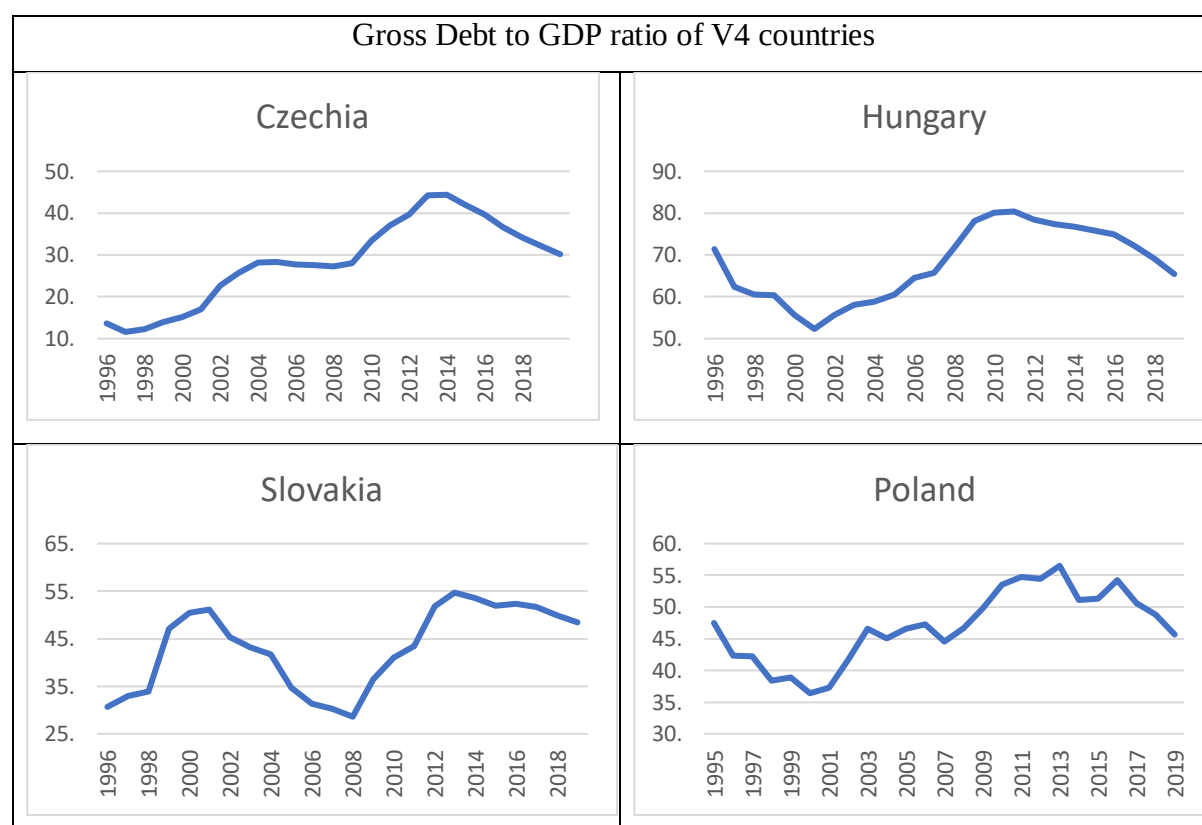


Table 6: Gross Debt to GDP ratio of V4 countries annual time series. Source: own compilation based on the data from Eurostat

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.

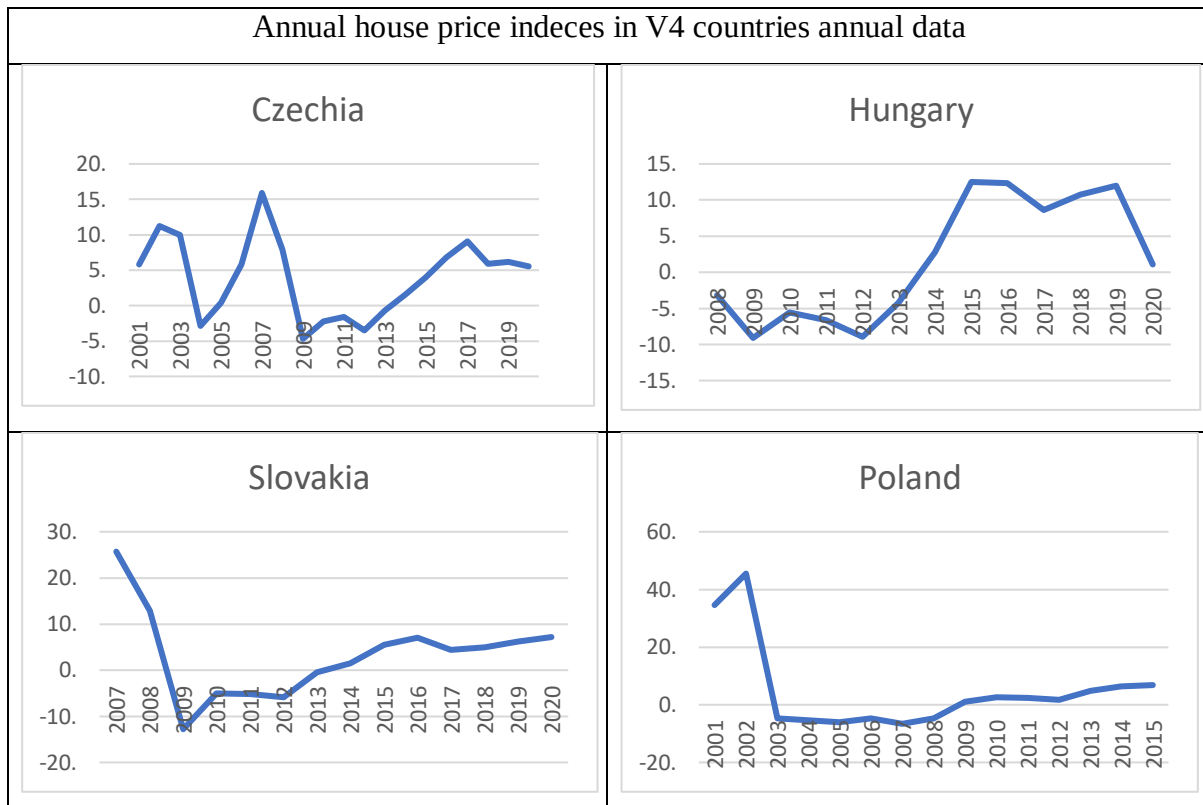
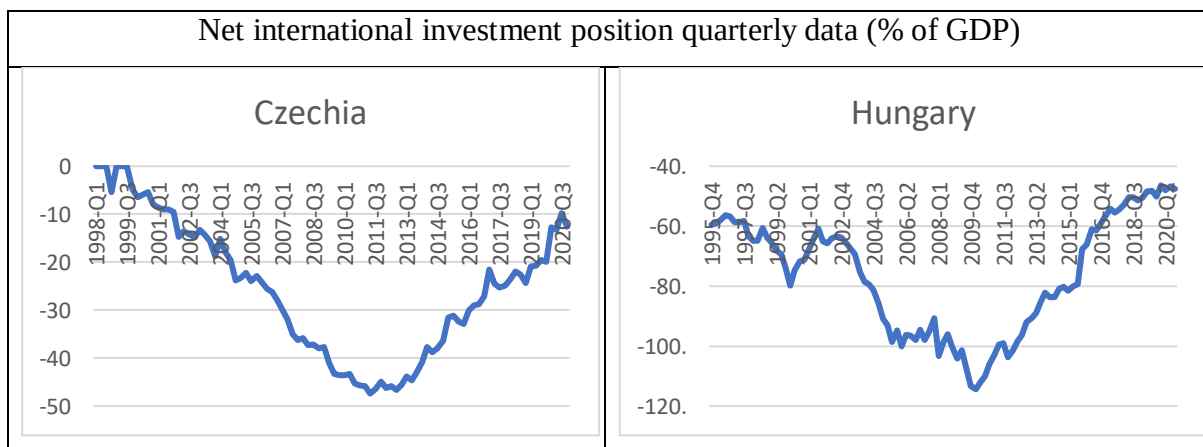


Table 7: Annual house price indices in V4 countries annual data. Source: own compilation based on the data from Eurostat

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.



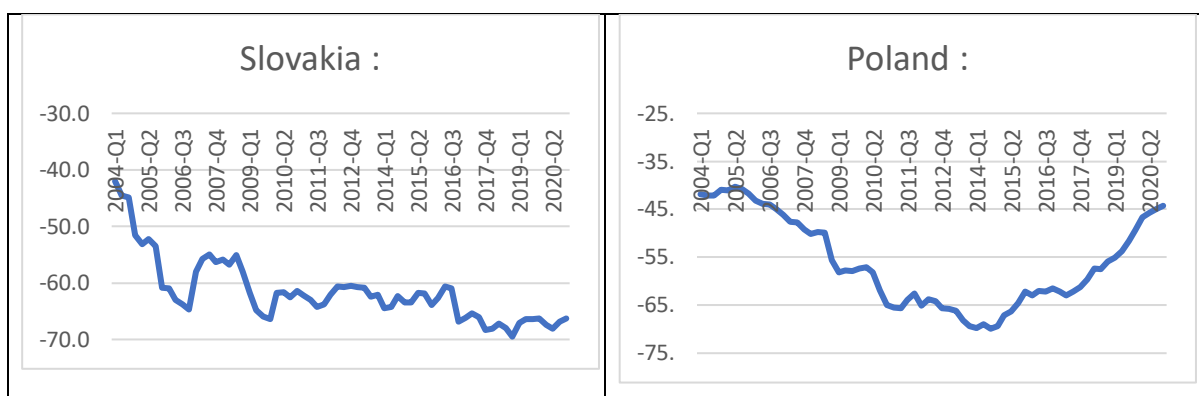


Table 8: Net international investment position quarterly data (% of GDP) Source: own compilation based on the data from Eurostat

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 compliments 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.

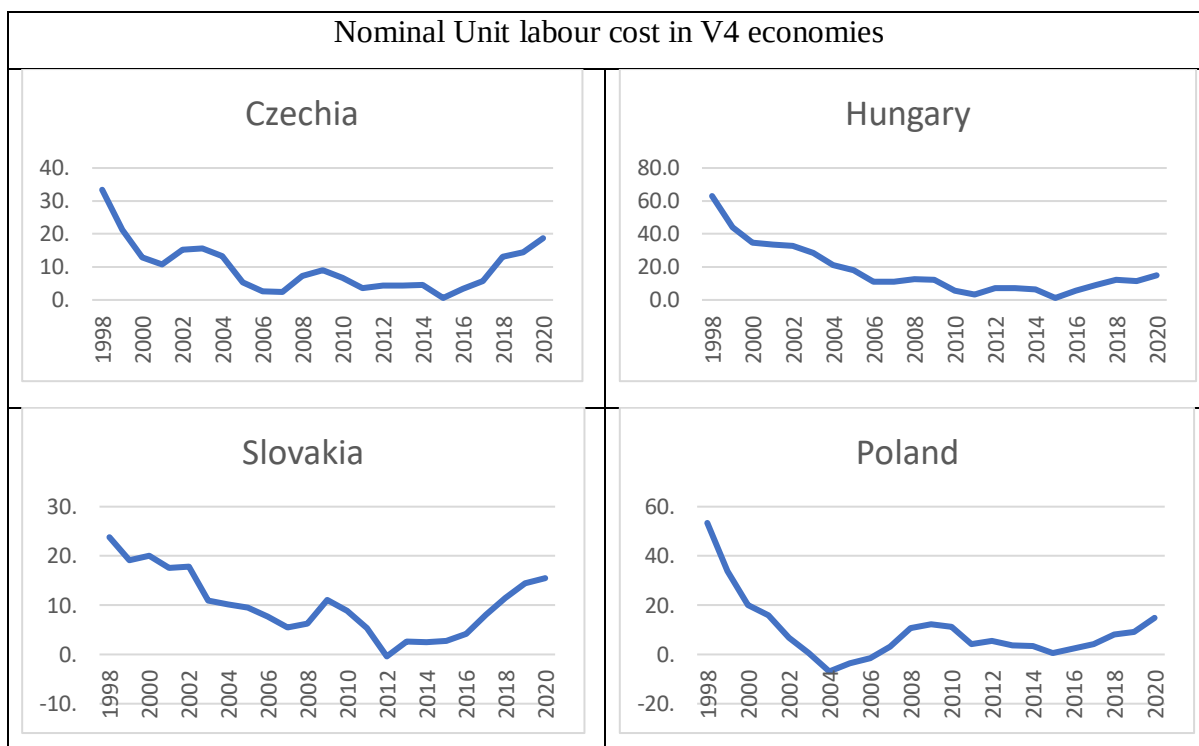


Table 9: Nominal Unit labour cost in V4 economies annual data (% of GDP) Source: own compilation based on the data from Eurostat

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.

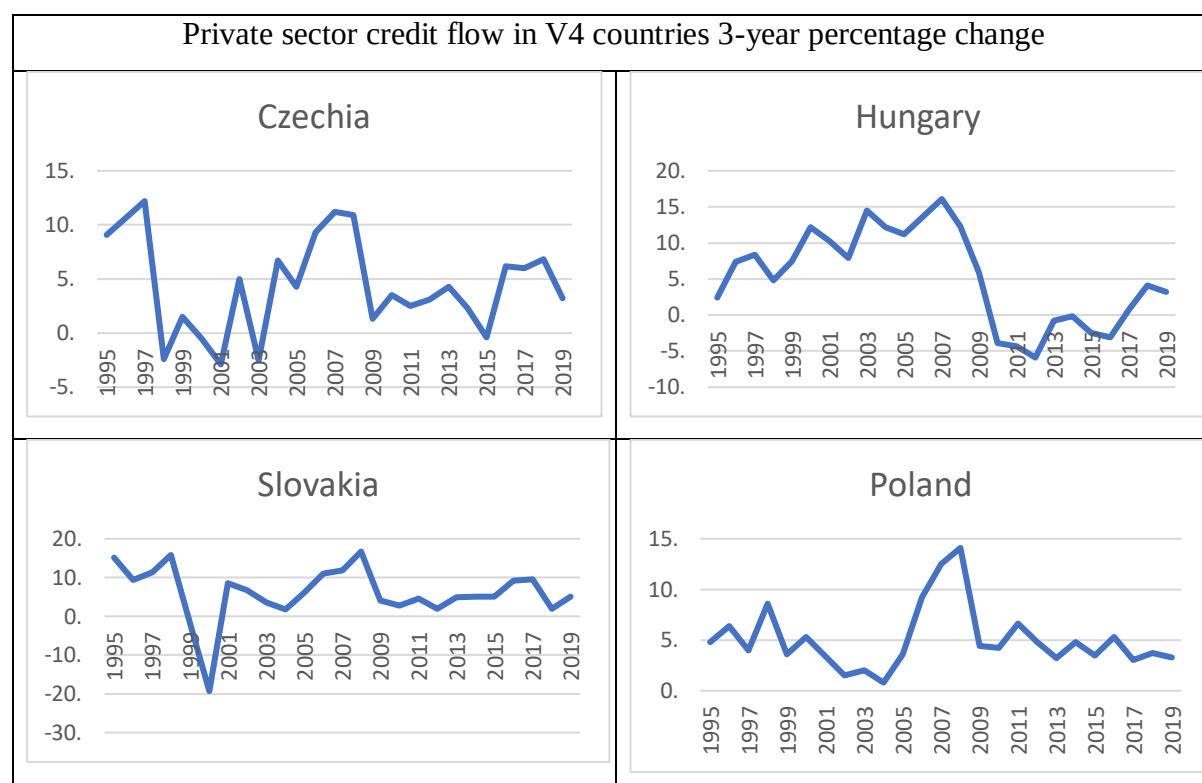
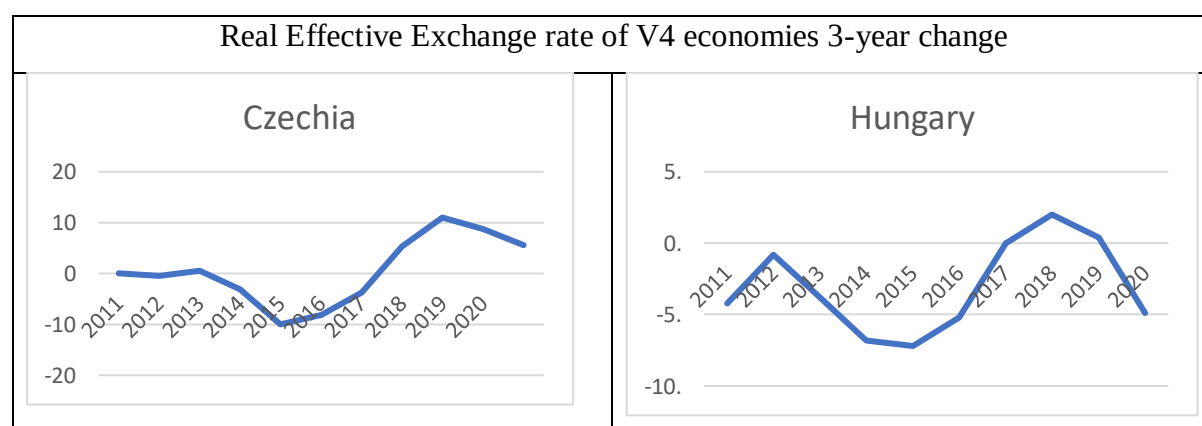


Table 10: Private sector credit flow in V4 countries 3-year percentage change annual data Source: own compilation based on the data from Eurostat

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.



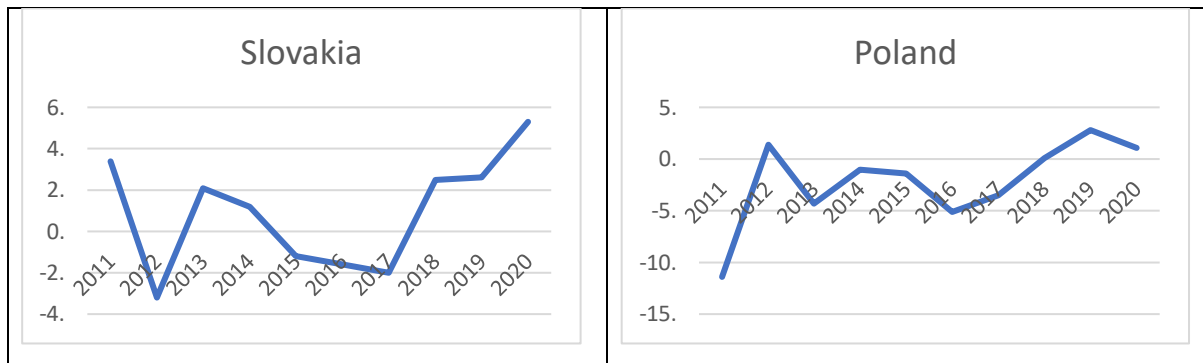


Table 11: Real Effective Exchange rate of V4 economies 3-year change annual data Source: own compilation based on the data from Eurostat

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. These 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 ψ_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 $Y_T = (\dots y_1 \dots y_T)$ 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* procedures⁷. 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 program⁸ 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

⁷ Ad hoc procedures are not based on statistical models

⁸ 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.

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 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 (θ – *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 θ – *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 θ - 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 θ –values are set equal to $\theta = 0$ (for the linear regression line) and $\theta = 2$, magnifying short-term behaviour, (iv) extrapolation of the two θ – 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 μ_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 λ 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 λ 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 σ^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 $-1 < \theta < 0$. θ -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 Schweinitz, 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 Π_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_I	1	0
Signal	A	B	1	A	B
No signal	C	D	0	C	D

Table 12 Combination of crisis variables and signalling variables

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 Π_0 thresholds are, the more crises are correctly predicted (A), but simultaneously, the number of type II errors in (B) increases. A higher Π_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 Π_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.

$$P(F) = \frac{A + C}{N} \quad (1)$$

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

$$P(F/S) = \frac{A}{A + B} \quad (2)$$

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 Π_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:

$$P(F/S) > P(F) \quad (3)$$

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 Π_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:

$$P(G/S) = \frac{B}{B + D} \quad (4)$$

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

$$K = \frac{P(G/S)}{P(F/S)} \quad (5)$$

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:

$$U = 1 - K \quad (6)$$

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.

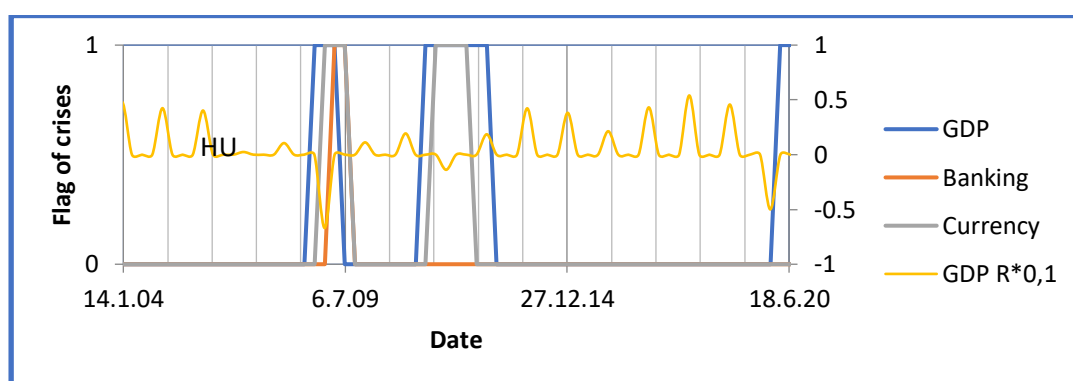


Figure 2: Binary variable indicator for economic, banking and currency crises in Hungary. Source: authoring

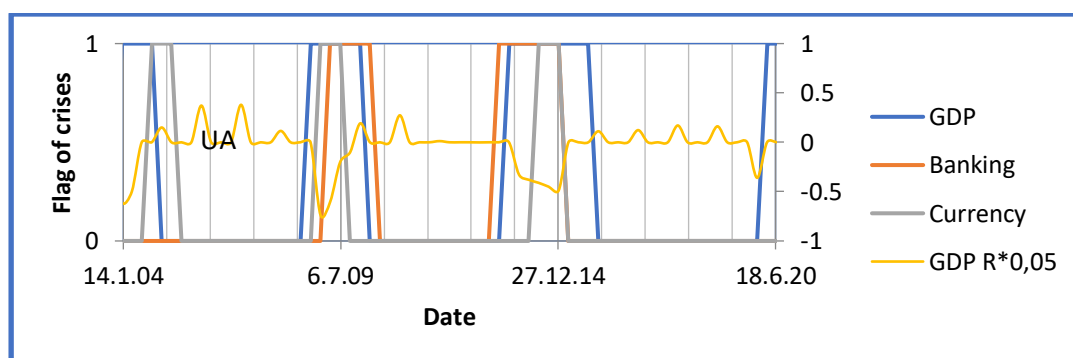


Figure 3: Binary variable indicator for economic, banking and currency crises in Ukraine. Source: authoring

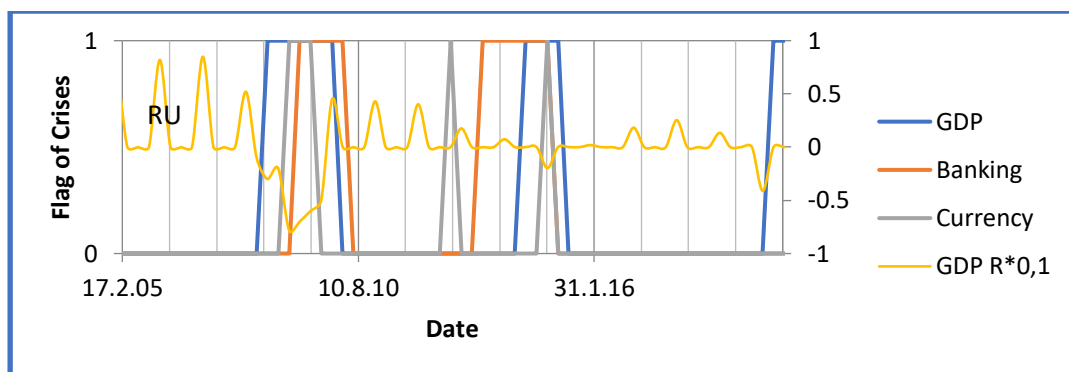


Figure 4 Binary variable indicator for economic, banking and currency crises in Russia. Source: authoring

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.

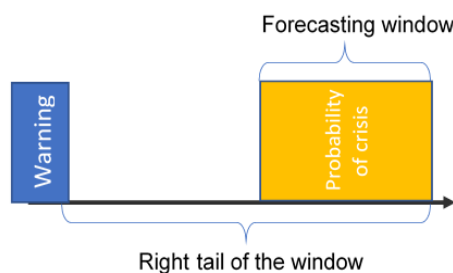


Figure 5: The illustration of the forecasting window and the right tail of the window. Source: authoring

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.

	Leading Indicator	Data availability	Forecast window width (1.-4. q.)	Right tail of the window (0.-8. q)	Threshold	Direction	U=1-K	P(F)	P(F/S)
RU									
1	5 year sovereign CDS Eurobonds	06q1- 19q4	3	4	78%	1	0,4	0,5	0,73
2	RTSVX -stock market volatility index	06q1- 19q4	1	2	32	1	0,32	0,5	0,63
3	Export of Oil and Gas products YoY% change in USD	06q1- 19q4	2	1	- 0,03	0	0,28	0,25	0,68
4	Money supply YoY% change	06q1- 18q4	1	7	0,02	1	0,24	0,75	0,57
5	Household debt/disposable income	06q1- 18q4	2	6	0,14	1	0,15	0,5	0,85
UA									
1	NBU currency reserves/ Bank assets - trend	03q1-19q4	2	7	0,01	0	0,52	0,5	0,84
2	Export YoY% change without trend & cycle	03q1-19q4	2	4	0,05	1	0,48	0,5	0,74

3	Import YoY% change without trend & cycle	03q1-19q4	3	5	0,07	1	0,32	0,5	0,52
4	M2 monetary aggregate/ bank loans to households	03q1- 19q4	3	5	- 0,06	0	0,25	0,75	0,58
5	Difference btw. Household deposits and loans, minus trend	03q1- 19q4	2	6	0,4 %	0	0,28	0,5	0,48
HU									
1	Hungarian sovereign debt CDS 5-year change	05q1- 15q4	5	6	0,1	1	0,12	0,5	0,56
2	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: authoring

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 6th 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.

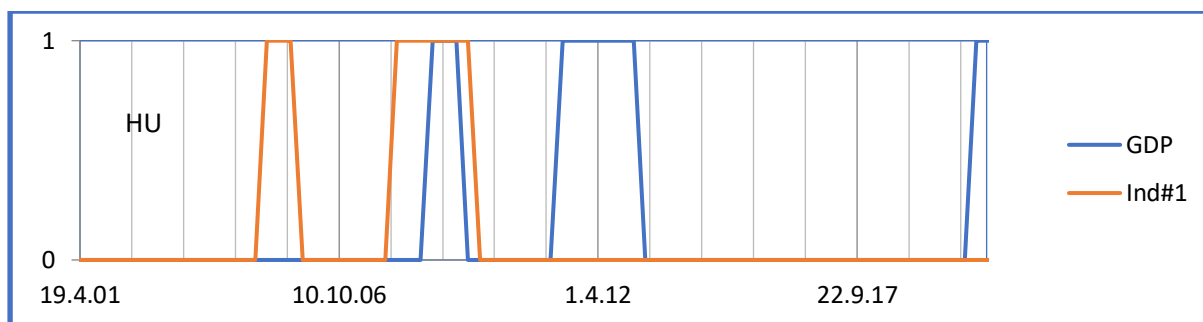


Figure 6: The flag of the presence of economic crises and the Hungarian sovereign debt CDS leading indicator. Source: authoring

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.

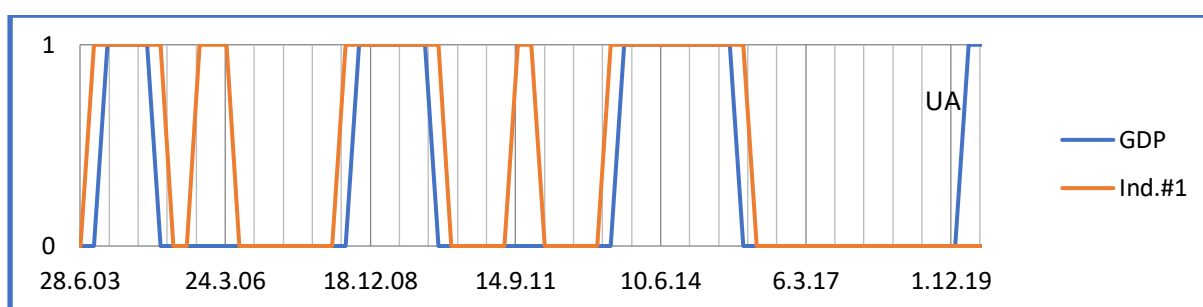


Figure 7 Flag of the presence of crisis and NBU currency reserves/ Bank assets - trend leading indicator. Source: authoring

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.

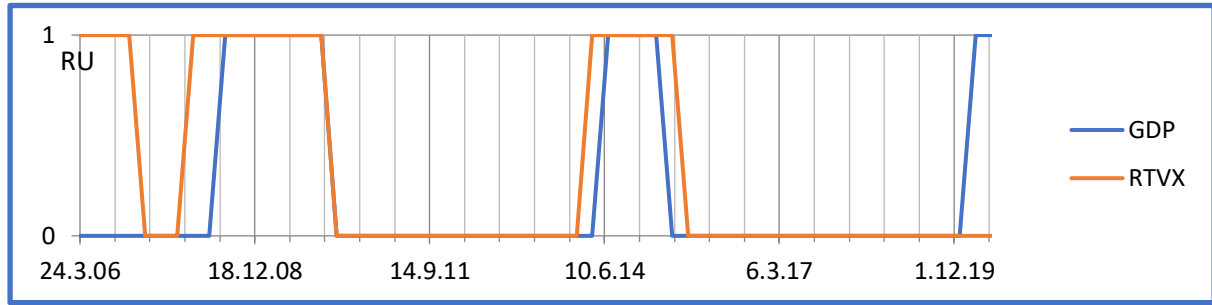


Figure 8 Flag of the presence of crisis and the RTVX volatility leading indicator. Source: authoring

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 ε_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:

$$\bar{Y} = \frac{1}{N+1} \cdot \sum_{i=0}^N Y(t_i) \quad (7)$$

$$\bar{X} = \frac{1}{N+1} \cdot \sum_{i=0}^N X(t_i) \quad (8)$$

$$\sigma_x = \frac{1}{N+1} \cdot \sum_{i=0}^N \sqrt{(X(t_i) - \bar{X})^2} \quad (9)$$

$$\sigma_y = \frac{1}{N+1} \cdot \sum_{i=0}^N \sqrt{(Y(t_i) - \bar{Y})^2} \quad (10)$$

$$cov_{xy} = \frac{1}{N+1} \cdot \sum_{i=0}^N (X(t_i) - \bar{X}) \cdot (Y(t_i + \Delta t) - \bar{Y}), \quad (11)$$

$$r_{XY} = \frac{cov_{xy}}{\sigma_x \sigma_y} \quad (12)$$

To determine the phase shift between the time series we consider the digital Fourier transform (DFT) (13).

$$f_{xy}(\omega) = \frac{1}{2\pi} \sum_{i=-N}^{i=N} \left(1 - \frac{|i|}{N}\right) \cdot r_{xy}(i \cdot \Delta t) \cdot e^{-j\omega i \Delta t} \quad (13)$$

The density function (14) is defined below:

$$f_{xy}(\omega) = c_{xy}(\omega) + jq_{xy}(\omega), \quad (14)$$

From (14) the estimation of the amplitude becomes trivial:

$$A(\omega) = \sqrt{c_{xy}^2(\omega) + q_{xy}^2(\omega)} \quad (15)$$

The phase of the spectra comes from (15):

$$\varphi_{xy}(\omega) = \arctg\left(-\frac{q_{xy}(\omega)}{c_{xy}(\omega)}\right). \quad (15)$$

The absolute value, or the amplitude (15) shows to what extent is the covariance of a function similar to that of a harmonic with frequency ω . Respectively, the maximum of the amplitude can determine the harmonic frequency ω^* , which has the most similar covariance. Then both series together are as similar as possible to vibrations with a frequency of ω^* . It is at this frequency ω^* 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

$$\varphi(\omega^*) = k \cdot 2\pi f^* \Delta t, \quad (16)$$

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.

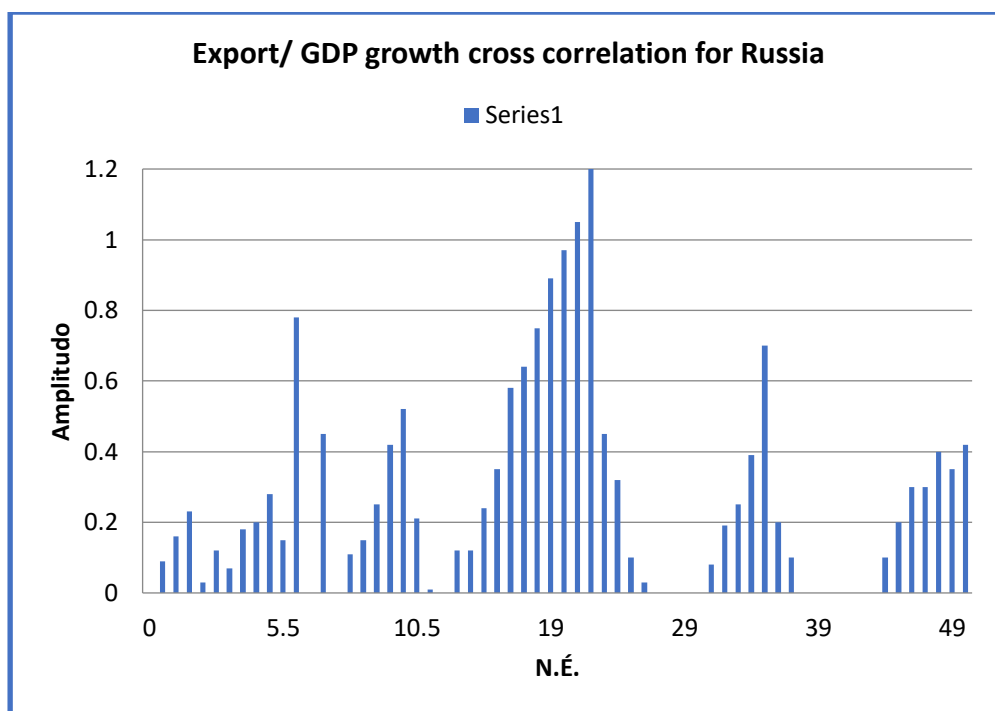


Figure 9: Cross amplitude spectrum of Export and GDP. Source: National Bank of Russia, graph created by author

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.

Index	Time series, Russia	Data availability	Cross-periodicity of real spectrum with real GDP, quarters	Time series precedes GDP time series (> 0) or lags behind (<0), quarters
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 19th 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.

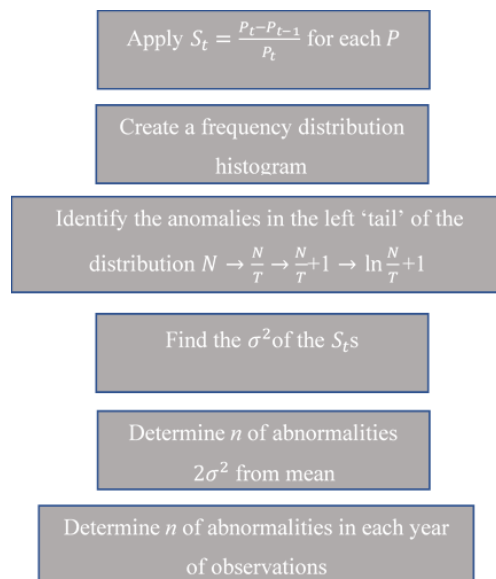


Figure 10: The algorithm for determining anomalous price fluctuations. Source: authoring

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. Figure 13 features the log-density distribution function. 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.

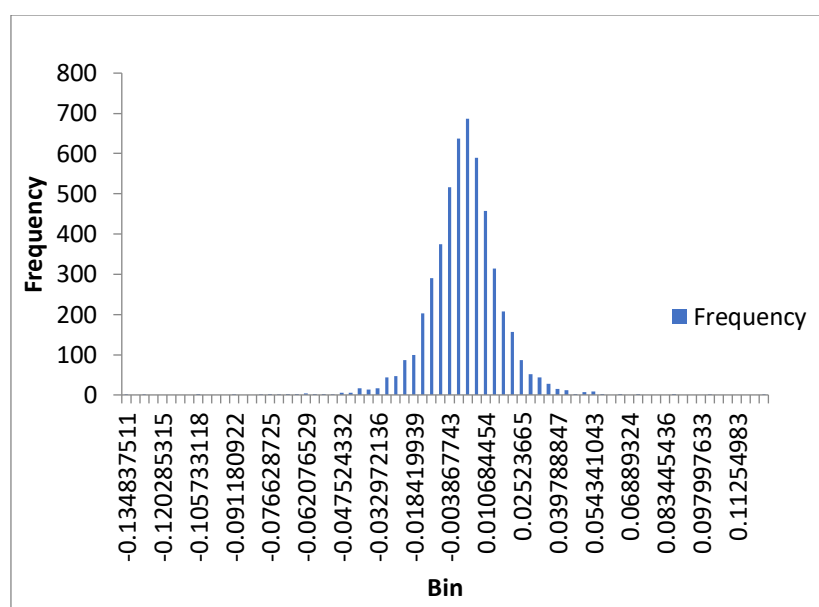


Figure 12: Frequency distribution histogram of the S_t of the BUX index. Source: authoring, graph created by author

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 Figure 14 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: authoring

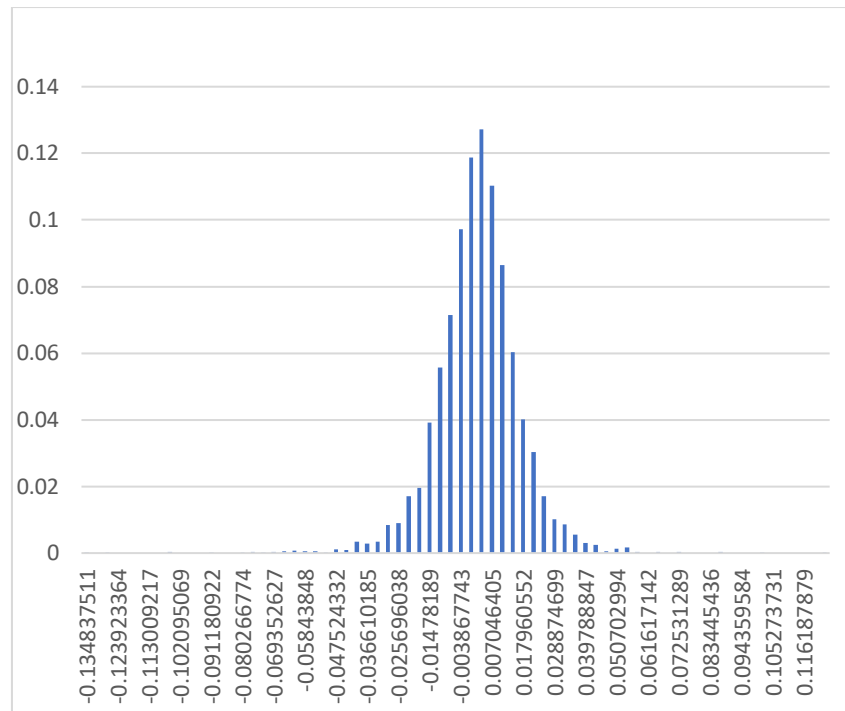


Figure 13: Log-density function of S_t of the BUX index. Source: authoring, graph created by author

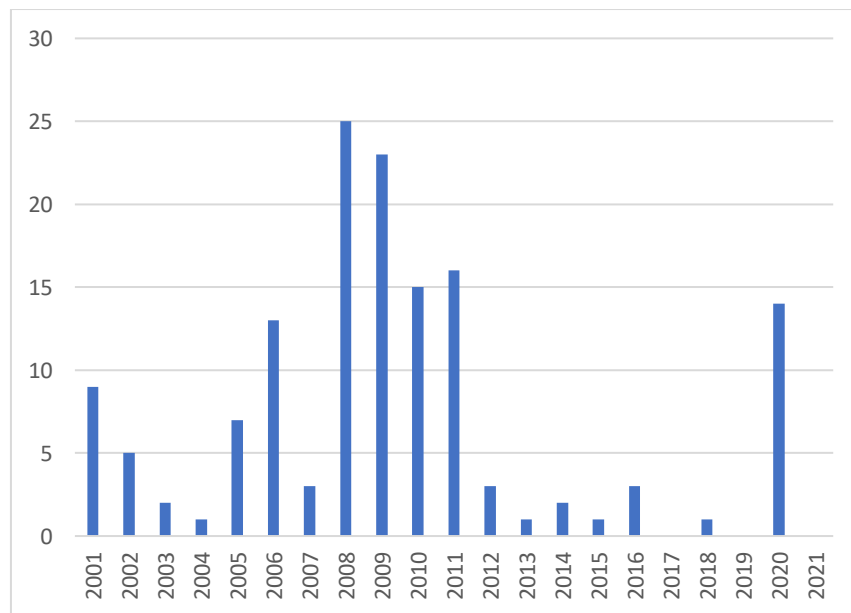


Figure 14: BUX anomaly frequency chart at -0.028 threshold. Source: MNB, graph created by author

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 in Figure 15 was -0.018. If we turn to the histogram in Figure 12, we can observe that the binning value of -0.018 also corresponds to the 10th bar of most negative variations, following (Sandoval and Franca, 2012).

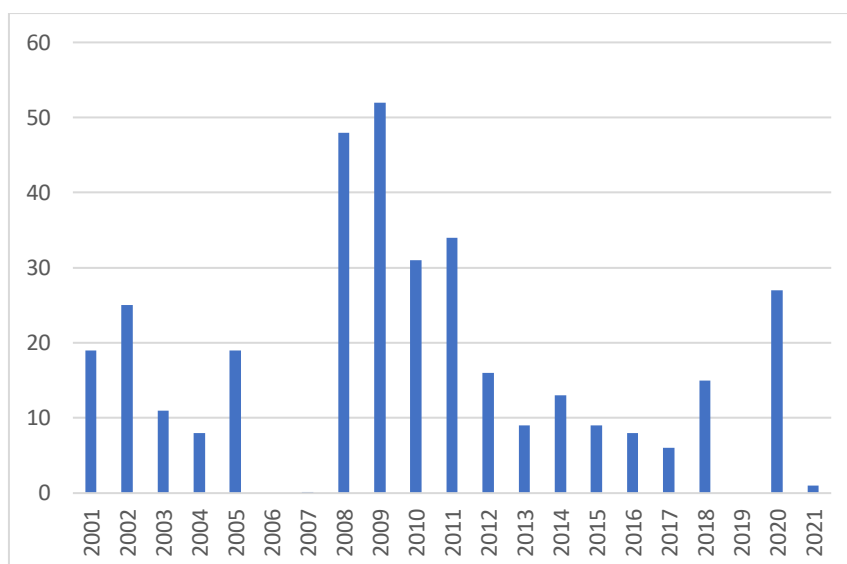


Figure 15: BUX anomaly frequency chart at -0.018 threshold. Source: MNB, graph created by author

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 (Figure 16), the British Financial Times Stock Exchange (FTSE) at -0.051 threshold (Figure 17) and the Russian stock market index (RTSI) at -0.048 (Figure 18).

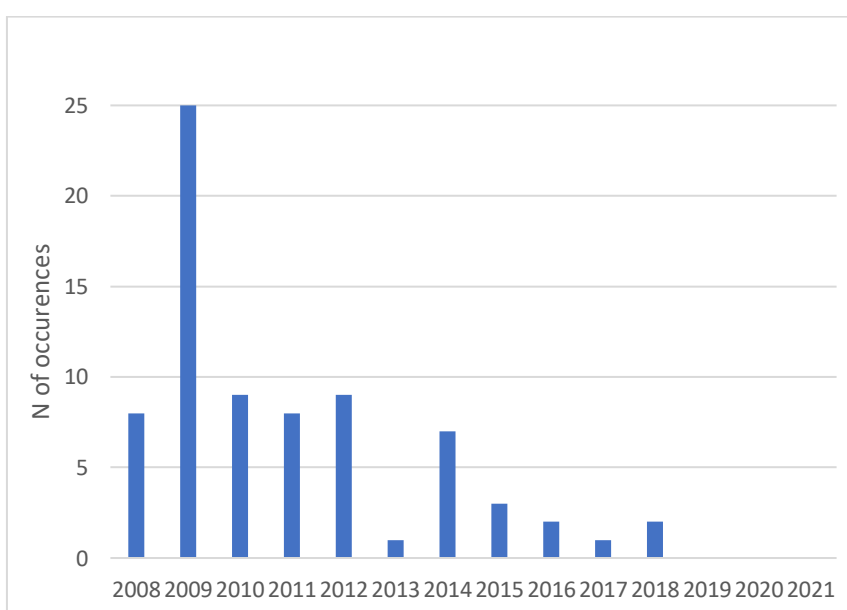


Figure 16: UX stock market index at -0.038 threshold Source: NBU statistics, graph created by author

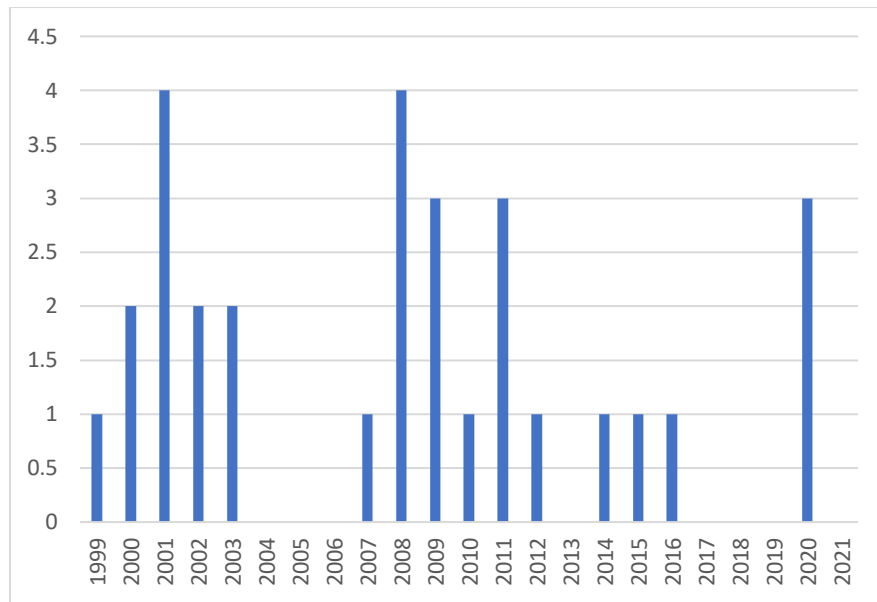


Figure 17 FTSE stock market index at -0.051 threshold. Source: Yahoo Finance, graph created by author

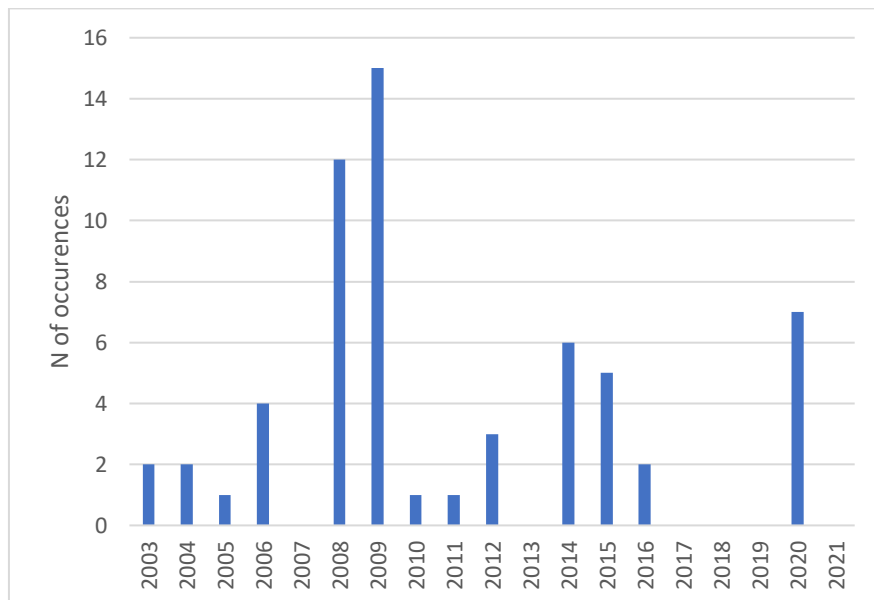


Figure 18: RTSI Russian stock market index at -0.048 threshold. Source: Moscow Stock exchange, graph created by author

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. Conclusion

Outlined in Section 2, there is reason to suggest that the Scoreboard general purpose indicators recommended by the IMF MIP should not be applied mechanistically 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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Appendix

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

```