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„An Early Warning System for new challenges“

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Abstract

The novel economic circumstances and shocks, which are apparent from the end of 2019 since the presence of the COVID-19 global pandemic, provided many new challenges for policy makers, governments, and also market participants. The current master thesis considers an Early Warning System (EWS) for the recently observed novel economic downturns. The thesis aims to identify whether the existing framework of EWS methods expanded with further relevant variables to incorporate the recent changes in the market environments and global economies could reliably forecast recessions and crisis events. Given that a statistically meaningful model can be established, the applied model is capable of introducing the essential underlying relationships. Therefore, the presented model attempts also to determine variables, i.e. indicators that play a decisive role in signaling possible economic recession periods. The results of the current master thesis suggest that the novel challenges are addressed by the presented economic models. Currency crisis episodes may be forecasted and signaled with existing EWS frameworks, by expanding the list of independent variables which drive the present prominent changes in macroeconomic indicators and introducing a new independent variable to EWS, the Pandemic Misery Index (PMI). Crisis signals are perceived for the quarters of 2022.

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1. Introduction

Financial crises are impactful events influenced by the characteristics, setup, applied restrictions, and movements of specific markets, market participants and sectors and negatively affect the economy of involved countries. They are most often defined by the sudden value loss of financial institutions or financial assets. This may affect the nominal value of stocks, real estate and oil, and such crises further ripple through other types of markets, possibly even to different countries. The most common types of crises are banking crises (for example, when bank runs occur), currency crises (foreign exchange markets are most commonly afflicted), speculative bubbles, or systemic crises (Honkapohja, 2009). The essence of the crisis may also be defined as the reduction of economic activity in a given period, which is noticeable from the downfall of GDP, individual incomes, employment rate, consumption, and industrial rates (Percic et al., 2019). Currency crises specifically affect fixed exchange rate regimes and potentially not formally fixed currencies or other currencies that are allowed to float freely (Vlaar, 2000).

However, all financial crises share one aspect, they have long-lasting impacts and cause economic disruptions. IMF found persistent output losses even a decade after the global financial crisis in 2008, published in the 2018 World Economic Outlook. Among other findings and approaches, IMF analyzed the recovery of the countries ten years after the global financial crisis in 2007-2008 (IMF, 2018). It is no surprise that economists and researchers have been looking for means, regulations, and scientific methods to alleviate and minimize the impact of such events and set up economic frameworks and methodologies to identify, project and estimate the probability and severity of crises. One relevant approach for this is the method of Early Warning Systems (EWS).

The recent years of the COVID-19 pandemic provided many new challenges for all market participants and forced them to adapt to new solutions, standards. This includes governments, which had to interfere in several, unusual ways, concerning the financial system as well. The unexpected occurrence of a global pandemic undoubtedly led to new sanctions, laws to abide by, and was disruptive for economies.

The current master thesis analyzes and challenges the framework of EWS under new circumstances. Posing the question of whether EWS are of use and have a crisis forecasting power even in the novel situation of the recent years. Furthermore examining whether macroeconomic indexes are a proper reference to capture and validate the signal of a crisis in the framework of EWS for new, upcoming time periods.

The structure of the thesis is set in the following way. The next section will provide an overview of the existing literature about EWS and crises, while also introducing the effects and relevance of the global pandemic. Section 3 will summarize the scope of study, applied methodology and outline research questions, expectations. Ultimately, the last two sections will evaluate the results and conclude this paper.

2. Overview of literature

Percic et al. (2019) define Early Warning Systems as economic forecasting systems, which are able to define crises in a precise way and predict them. EWS incorporate economic variables and indicators which could alert policy makers of prospective vulnerabilities of the financial systems or unsustainable exchange rates. Such models may be adjusted for different types of crises, e.g. currency, fiscal and banking crises.

The method of EWS primarily relies on economic theory and principles, while it requires empirical analysis in a significant part. The crisis dates are defined in terms of the processed data for currency crises. The main evaluation perspective for EWS models is whether they are able to provide both economically and statistically significant predictions of crisis events. This also implies in some way that such models have the ability to exceed the 'innate' prediction power of the market upon experiencing exchange rate shocks and changes. To ensure a better fit and meaningful conclusions for the specified models, out-of-sample performance estimation is also necessary (Berg et al., 2004).

EWS consist of different approaches; one focuses on the leading indicators approach, where the vulnerability of indicators is considered and afterward transformed into a binary sign. By setting up a certain threshold, it can be determined whether the given indicator surpasses the set threshold. The other commonly used EWS methodology is based on a discrete-dependent-variable approach, such as binomial or multivariate/multinomial regression approach, mainly logit and probit models (Bussiere and Fratzscher, 2006). The topic of the overall effects, consequences of a financial crisis under global pandemic times is a very recent question and a field of research to be yet well-analyzed. Some of the most recent research papers have been published, in which the direct and indirect effects of the pandemic and economic, political interventions enforced were considered.

Feng et al. (2021) reflected on the relationship between exchange rate volatility and government interventions after the worldwide spread of the novel coronavirus disease in 2020. By applying a system of Generalized Method of Moments (GMM) estimation, they show that confirmed virus cases caused a significant rise in the exchange rate volatility. Exchange rate volatility is depicted in Figure 1 for the four main currencies: euro, Chinese yuan, English pound, and Japanese yen. It shows a highly volatile period at the end of 2019 and during 2020. The authors indicated that their research result is similar to Sharif et al. (2020). The result in the previously mentioned research paper presents a rise in the volatility of U.S. financial markets in close parallel response to the increase of confirmed virus cases, indicating the same core finding as Feng et al. (2021).

Likewise, the effects of government shutdowns on the exchange rate volatility have been researched by Sharma et al. (2019). Their regression model estimation found that government shutdowns affected the volatility of exchange rate returns and that the volatility of exchange rate is more influenced, impacted than the exchange rate returns. They concluded that regardless of pooled data or individual country data, the effect of shutdowns on the exchange rate volatility disappears in five days.

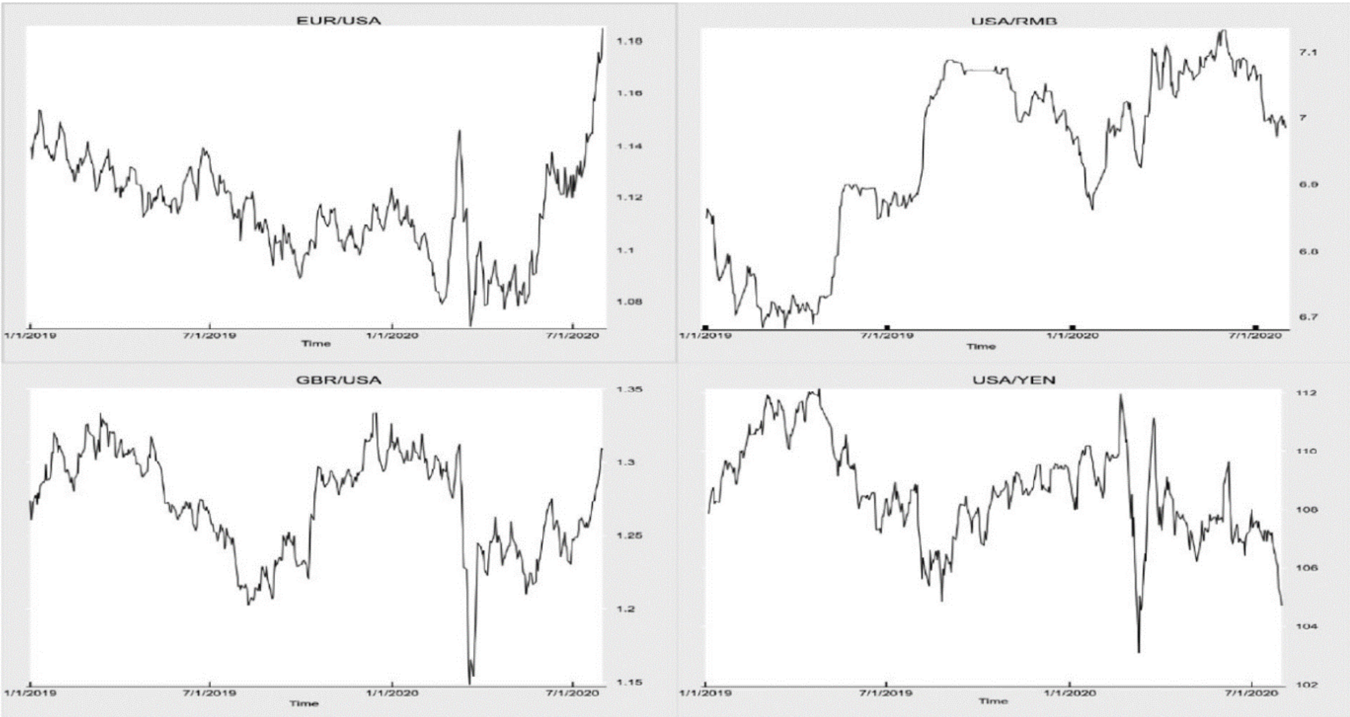

Figure 1: Exchange rate changes in euro, yuan, pound and yen from Jan 1, 2019, and Jul 31, 2020. [1]

Kutlar et al. (2021) used clustering analyses to measure and compare the effect of COVID-19 on macroeconomic indicators across countries. They concluded that the indicator of foreign trade suffered the adverse effects of the pandemic the most, although unemployment rates steadily increased, but were less severe in countries with employment protection packages.

Indeed, a lot of regular workers have lost their job during the first year of the pandemic. The International Labor Organization (ILO) (2021) made estimations and presented the recent global labor market situation, focusing on the COVID-19 induced effects. For the three quarters of 2021, they estimated a stagnation of the fall short of working hours compared to previous, virus-struck quarter years. However, compared to the last pre-crisis quarter of 2019, the global working hours still remained in a 4.7% deficit, which equals the loss of 137 million full-time jobs. The change of the worldwide working hours for the last two years is depicted in Figure 2. These findings imply that the globally increased rate of unemployment is closely tied to global events.

[1] *Source: Feng et al. (2021)*

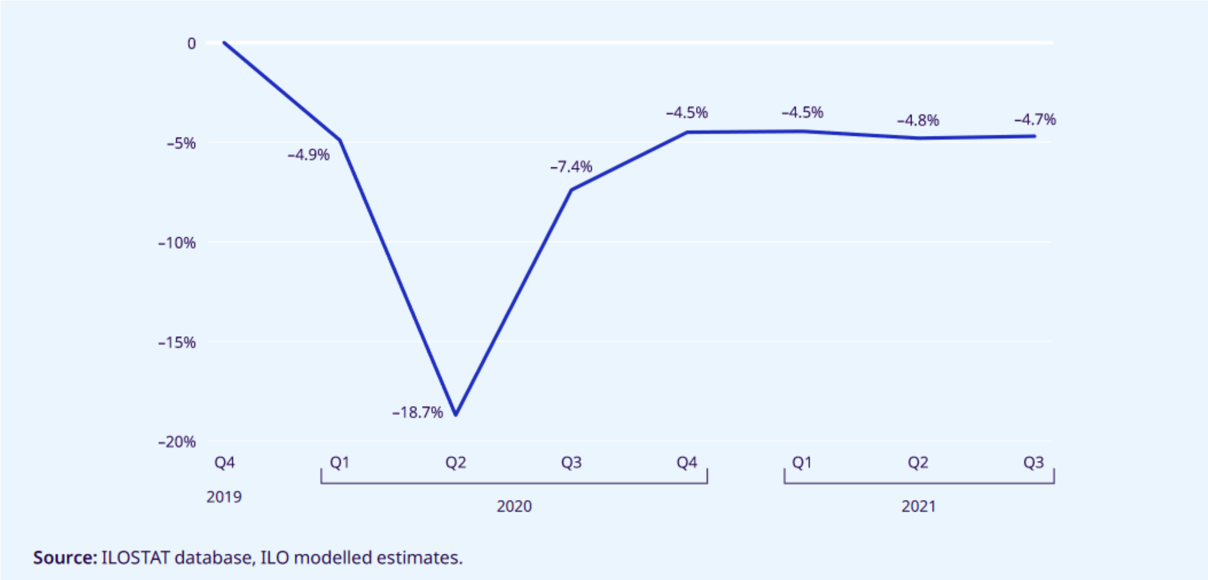

Figure 2: The shortfall of working hours compared to the pre-crisis period of 2019 Q4.[2]

Not only exchange rates and some of the leading economic indicators such as the unemployment rate have suffered from the negative consequences of the global pandemic outbreak. Understandably, stock markets did not remain unaffected, as has been shown by Baker et al. (2020), specifically for the U.S. stock markets. The authors found that the novel virus-induced stock market effects are unprecedented compared to other historical pandemic-struck times. While some of the stock market volatility was directly influenced by the news of the disease and case numbers, the later observed stock market jumps can be attributed to the responses to the government and institution-inflicted policies, including actual and prospectively announced actions.

To conclude, the research results with the most recent data analyzing the effects of the global virus event suggest that a possible crisis scenario is about to evolve. Since the global financial crisis in 2007-2008, some research have been conducted to try and interpret the signals post-crisis and analyze whether these models could have predicted economic downfalls with the aim of improving EWS frameworks.

In the case of developing countries, Abdelsalam et al. (2020) show that logit and probit models performed superiorly concerning the Average of Forecast Squared Errors (AFSE) and Squared Root of Average of Forecast Squared Errors (RAFSE). The authors evaluated different model for developing countries, specifically for Egypt, on a dataset from 1995 to 2018. Another approach used in the same study was the evaluation process in terms of different models and defining the ratio of correct predictions with respect to the preset threshold value. By applying the total percentage of crisis observation to the total number of observations in the sample, the mentioned threshold value was determined. The logit and probit approaches were only second best compared to such threshold performance valuation, for

[2] *Source: ILO report, Oct 2021, Figure 3.- Change in global working hours (adjusted for population ages 15-64) relative to 2019 Q4 (percentage)*

both in- and out-of-sample estimations. The combination of individual methods of probit, logit, extreme values, and switching regression models were outperformed by the dynamic model averaging (DMA), yielding a higher successful prediction rate, while equal weighting (EW) (type of weighting method, giving equal importance of weights of the included elements) outperformed slightly all three in case of out-of-sample estimation.

DMA is a version of the Bayesian Model Averaging (BMA), where the chosen parameters for all considered candidate models are learned according to posterior probabilities of the associated models, and are then combined (Hinne et al., 2020). BMA and DMA are often used to account for the uncertainty of the structural form of a model generating the data set. DMA is explicitly used in the case of sequentially arriving data and changes occurring over time (Onorante and Raftery, 2016).

Furthermore, the results of Abdelsalam et al. (2020) also show the improvement in accuracy of the combination of pure individual methods. However, the chosen set of data, viewed time periods, and specific countries included in the sample influence the prediction power and accuracy of the chosen EWS method, being equally true for individual and combined models. The accuracy improvement of Bayesian-based models depends on the additional connections between the data, the size of the data, the number of countries included in the dataset, and the characteristic similarities of included countries. Therefore, a custom tailoring of the model is also necessary when building such frameworks.

Comelli (2013) concluded that binary models (discrete outcome models, with value of 1 if a crisis took place in the upcoming 24 months, and 0 otherwise) for emerging market economies outperform all other models. Comelli specifically compared parametric models of EWS relying on macroeconomic indicators and non-parametric EWS models, by defining optimal threshold indicators, levels similarly to the alternative approach of Abdelsalam et al. (2020). Comelli found that in case of a currency crisis estimation and evaluation of this type of crisis events traditional macroeconomic indicators have a meaningful impact, such as the real GDP growth rate, the current account balance as a percentage of nominal GDP, the monthly growth rate in foreign exchange reserves and short-term external debt. He concluded that parametric macroeconomic indicator-based EWS models perform better in predicting crisis episodes for in- and out-of-sample estimations.

Boonman et al. (2019) also investigated the two mainstream approaches of EWS models likewise to Comelli (2013), the signal approach and the logit model for 15 emerging countries, consisting of an estimation period of 1991Q1 to 2010Q4, and a prediction period from 2011Q1-2017Q4, employing quarterly frequency for data, because of the rapid development of currency crises episodes. They found that in terms of in- and out-of-sample predictions, the logit model performed consistently better than the signal approach.

There are some earlier models of EWS designed to detect currency crises, as different researchers and institutions made their own EWS framework. Each differs in the time horizon, the definition of a crisis, the method used, and the chosen variables. One of these models is the so-called Developing Country Studies Division (DCSD) model, initially published by the corresponding division of the IMF and specified by Berg, Borensztein, Milesi-Feretti, and Pattillo (1999) (with the abbreviated name "DCSD" referring to the division of fund, where the model was originally created). The DCSD model views crisis periods for 24 months ahead of the signal in order to determine the most meaningful variables influencing crisis scenarios.

Another well-known model is the so-called KLR model introduced by Kaminsky, Lizondo, and Reinhart (1998). Ades, Masih, and Tenengauzer (1998) made their version of EWS at Goldman Sachs, which is often referred to under the name GS-WATCH. The model of Garber, Lumsdaine, and van der Leij (2000), called DB Alarm Clock is also a well-known short-term model. Out of these models, DCSD and KLR view a more extended time period, usually two years, DCSD applies probit regression and KLR uses the weighted average of indicators. GS-WATCH (3-months), and DB Alarm Clock (1-month) are short-horizon models. In each of the four models presented and designed for currency crises, overvaluation is one of the main variables. Other variables considered are current account, reserve losses, export growth, GDP indicators, reserve levels and financing indicators, contagions, and stock market-specific indexes (Berg et al., 2004).

The predictive power and goodness of fit were evaluated later in an IMF working paper in 2004 for several models. The DCSD model predicted 73% of the crises correctly (from 1985 to 1995), while the KLR model for the same period called 57% of the crises correctly. The success rate of the GS model was also relatively high, correctly calling 66% of the crisis events in the dataset from 1996 to 1998 (Berg et al., 2004).

3. Data and methodology

3.1. Scope of study and relevance

Kaminsky et al. (1999) studied the occurrence and relationship of different types of crises. They find that often different kinds of crises followed one another, in some instances banking crises were followed by currency crises. They identified both, external and internal shocks as crisis factors that play a decisive role in realizing a crisis event. In case of balance of payment shocks, the general deterioration of the performance of economies is common, with recessions perceived through several indicators. Therefore, monitoring such signals to anticipate and prepare for possible crisis scenarios may deem important.

Foroni et al. (2020) built a model to forecast and estimate the economic effects and severity of COVID-19. They based this model on and adjusted it accordingly to the Great Recession in 2007-08, as both periods have some factors and underlying relationships in common, although the causative reasons and type of suffered shock are non-identical. They also identified growing uncertainty along with several shocks to the supply and demand of goods and services (e.g. house prices, mortgages) caused by the suffered economic recessions as common points, providing the basis for comparison and testing the two, otherwise different economically distressed periods. Babecky et al. (2012) explored the role of indicators in EWS. They observed that the domestic private credit to GDP ratio is the most meaningful one in forecasting and alarming banking crises, also showing the increase of inflation rates and money market rates. For currency crises, the main indicators were the deterioration of government balances and bank reserves.

The below-elaborated methodology and models are based on the framework of Bussiere and Fratzscher (2006). They showed that their multinomial model has enhanced efficiency and prediction power, which outperformed most similar models. They also noticed that by switching from a binomial logit regression to a multinomial logit model, the correct prediction of crises increased from 66.7% to 73.7% and reduced the false alarms from 50% to 44.1% successfully. As a result, the prediction of a crisis has also improved. Given an alarm, the probability of experiencing a crisis rose from 50% to 55.9%. Therefore, the efficiency of different EWS models is relatively high, especially compared to the unconditional probability of experiencing a crisis in similar models.

Only data of countries who are members of the European Union (EU) with an emerging market were selected. Each year a reassessment is carried out to evaluate emerging markets, countries in Europe and across the globe. Based on last year's classification and evaluation of emerging markets published by the International Monetary Fund (IMF) (Duttagupta and Pazarbasioglu, 2021), countries belonging to this group are Argentina, Brazil, Chile, China, Colombia, Egypt, Hungary, India, Indonesia, Iran, Malaysia, Mexico, the Philippines, Poland, Russia, Saudi Arabia, South Africa, Thailand, Turkey, and the United Arab Emirates.

According to the country selection criteria (EU member state with an emerging market), Hungary and Poland were included in the sample from the list of countries identified by Duttagupta and Pazarbasioglu (2021). The classification of the IMF was based on several factors:

- The **income level** of a country *(GDP/capita)*, measured by GDP per capita and expressed in nominal US dollars.
- **Systemic presence** *(nom.GDP, population, share in global trade)*: the measured size of a country according to nominal GDP levels, the share of the given country from the global, total exports and population size.
- **Market access** *(share in the global external debt level)***:** the total share of a country in the world's global, external debt levels, international bonds issued from the country (both in terms of issuing frequency and the amounts that had been issued), lastly, whether the country appears for international investors in global indices.

Variables of the five elements were weighted to define emerging market score (EMS):

$$\text{EMS} = \frac{2}{5}(nom.GDP) + \frac{3}{20}(population) + \frac{3}{20}\left(\frac{GDP}{capita}\right) + \frac{3}{20}(share\ in\ global\ trade) + \frac{3}{20}(share\ in\ the\ global\ external\ debt\ level) \quad (1)$$

The listed variables are dummy variables having the value of one or zero, depending on whether the given country was in the top 20 list of countries for the given kind of variable or not (Duttagupta and Pazarbasioglu, 2021).

3.2. Data and variables

EWS models for the analysis of crises require mostly publicly available indexes, data and macroeconomic indicators. The database of the Bank of International Settlements (BIS), Eurostat, the IMF, the Organisation for Economic Co-operation and Development (OECD), Oxford Economics and Reuters (Datastream) were used to compile raw data.

For the input, data with quarterly frequency were used over the period of 2000Q1 to 2021Q4. The last quarter data of 2021 of some indicators and included variables were not available for querying and public access. The scarcity of these data inputs can be led back to the date of data collection, not all the most recent statistical data were made public at the time of data querying and database aggregation. The sample of countries includes Hungary and Poland, as already stated in the previous section.

As mentioned above, some similar characteristics of the chosen countries and indicators are required and advantageous when building an EWS model for currency crises, especially in terms of economical openness to capital flows (Bussiere and Fratzscher, 2006). The selection of independent variables is also based on the thorough analysis of indicators of Kaminsky et al. (1998) and the model choice of Bussiere and Fratzscher (2006). The following independent variables were applied in the models:

- Real GDP growth rate (GDP_GR)
- Gas price (GASP)
- Rate of inflation (INFL)
- Credit to private sector from domestic banks (CRTPS)
- Short-term debt over total reserves (SHTD_RES)
- Visible Trade Balance in %GDP (VT_GDP)
- Pandemic Misery Index (PMI)
- Overvaluation of real effective exchange rate (R_OVERV)
- Government surplus and deficit (GOV_BALANCE)

In the following section, the usage and details of the data inputs and variables included in the model are briefly explained. Variable names are captured in brackets. The indicators and included variables are defined and explained in (more) detail in Appendix 1.

One of the main components in the presented framework is the Exchange Market Pressure (EMP) indicator, which is defined for each of the included countries individually. The EMP variable, which will be presented in section 3.3, consists of the **real effective exchange rate, short-term interest rate** and **foreign exchange reserve excluding gold.**

Real effective exchange rate:

The real effective exchange rate (REER) is based on the change of the relative price levels, using the consumer price indexes (CPI) along with the market exchange rates. REER provides an index for the trade competitiveness of the countries, while also identifying any possible short-term disruptions and capacity changes in the economic well-being of a country (OECD, 2016, 2022).

Short-term interest rate:

The central bank policy rate is the index of short-term interest rates for both countries included in the sample. This variable integrates the signal of the monetary policy of the central bank and to some extent the interventions of the government (IMF, 2022a, 2022b). The variable is therefore deemed sufficient to signal short-term policy changes and incorporate this factor in the component of EMP.

Foreign exchange reserve excluding gold:

Foreign currency reserves are often deemed important as an element of the macroeconomic policy of the central bank and the government. It is possible to use it for interventions of foreign exchange, as a buffer to smooth and absorb liquidity shocks of the balance of payment, as well as to lower the volatility in foreign exchange markets (Chitu et. al, 2019). Gold was not taken into consideration as it is not liquid enough to be processed, transformed, or otherwise used in the balance of payments[3] (Kenton, 2022).

Overvaluation of the exchange rate (R_OVERV):

The overvaluation of the real effective exchange rate (REER) was added as a competitiveness indicator. Following Bussiere and Fratzscher (2006), the REER overvaluation may be simply defined as a percentage change over a given period, leading however to possible large overvaluations at a later time in the future. The devalued rates may become overvalued in the future, distorting (exaggerating) the level of change (e.g. growth) of REER levels, depending also on the time horizon of the comparison of values. As the authors suggested, this can be avoided by comparing current REER levels to a trend, instead of previous REER levels.

The simple percentage change of REER over a given period ($REERCH_t^i$) supposing four months lag (t-4), which is ideal to smooth short-term volatility is described by equation (2). The preferred method of generating REER overvaluation is the deviation from the trend ($REERDEV_t^i$) described by equation (3) (Bussiere and Fratzscher, 2006).

$$REERCH_t^i = \frac{REER_t^i - REER_{t-4}^i}{REER_{t-4}^i} * 100 \tag{2}$$

$$REERDEV_t^i = \frac{REER_t^i - TREND_t^i}{TREND_t^i} * 100 \tag{3}$$

In order to generate the given independent variable, a trend estimation of the real effective exchange rate was implemented and then used as a baseline to define deviation at a given point in time, according to equation (3). The trend estimation of the real effective exchange rate was done in a country-wise manner, to treat the change over time as a country-specific feature. The nonlinearity of REER values was expected at the start of the trend estimation process.

After analyzing the skewness of the data, in case of Hungary negative skewness has been found, as shown in Tables 1 and 2. To treat the negative skewness of the variable and elongate the right-hand tail in case of Hungary, the values were squared and stored in variable REER2. In Table 1 the skewness of variable REER2 changed and is closer to 0. The skewness of REER in case of Poland was positive and remained below 1 (moderately skewed).

Variables	N	SD	Mean	Min	Max	**Skewness**
REER	88	7.9757806	103.0581	83.556663	123.16	**-.2120317**
REER2	88	1633.2096	10683.8556	6981.7158	15168.387	**.0403087**

Table 1: Real effective exchange rate values for Hungary before and after transformation

[3] After the Great Depression countries exchanged the gold standard.

Variables	N	SD	Mean	Min	Max	**Skewness**
REER	88	5.9875693	101.7951893	87.639999	123.09	**.958906**

Table 2: Real effective exchange rate values for Poland

Following the fitting of linear models in case of both countries (before any alterations), the linear models were proven to be less successful at following a trend in the REER values. To resolve this and avoid large, constant differences in the numerator in equation (3), the values stored in REER2 were inverted (multiplied by -1) and adjusted by the original values of REER variable to arrive to the trend depicted on Figure 3. For Poland, from 2000Q1 until 2008Q3 the trend values were created in the same way (original values were squared and inverted, then adjusted by the original REER values). In the quarter of 2008Q3, a sudden large fallback of values was captured. Surprisingly, from this time point the same method of estimation (as in case of Hungary) had to be reconsidered for Poland, as the adjusted, estimated values were further away from their true values than in the presented solution (Figure 3). From 2008Q3 until the end of the sample period a linear trend was assumed. The trend estimation was

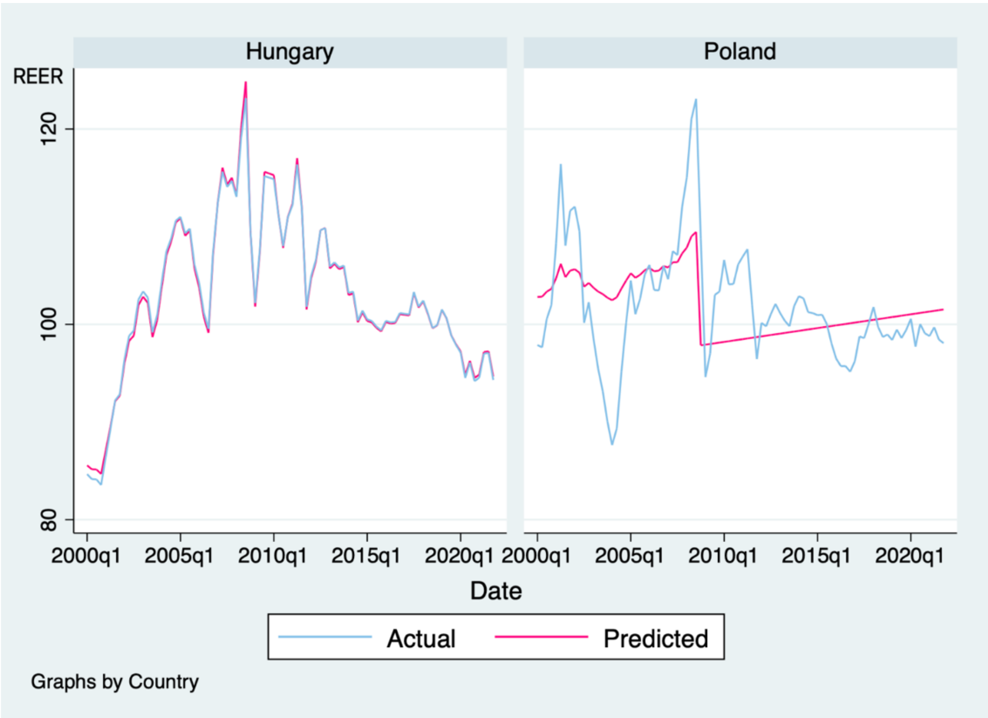

Figure 3: Fitted REER trend lines and actual values

therefore treated as a country-specific feature. The fitted trends for both countries described the changes in REER values significantly different from randomly fitted models. The fitted trends are presented in Figure 3.

Current account balance in %GDP (CURGDP_02):

Milesi-Ferretti and Razin (1996) analyzed the sustainability of the current account deficit, taking into consideration the motivations of lending, borrowing and repaying the taken debt amounts during imbalances. They identified the current account balance expressed in GDP as a vulnerability indicator.

The lower the amount of current account balance, the less likely is that a given country would be able to raise external funds and resources to mitigate a balance of payment shock. They also stated that current account imbalances are ought to be observed together with other vulnerability factors, such as in connection with exchange rate policies applied.

Current account balance data were extracted in millions of US dollars and were also converted into EUR during the processing of the data. It captures the international trade transactions of a country and is a proxy for vulnerabilities, as already mentioned. The converted EUR values were divided by the nominal GDP values to arrive at the current account balance expressed in percentage of the GDP, in order to be able to compare the index between countries and to appropriately apply it within the model.

It is rather common to smooth variables and data by considering moving averages. It allows to remove seasonality and smooth volatility (Bussiere and Fratzscher, 2006). For this purpose, a moving average (ma_w) of two quarters (six months) lag, two quarters forward with equal weight was computed:

$$ma_w = \frac{1}{4}[x(t-2) + x(t-1) + 0 * x(t) + x(t+1) + x(t+2)], where\ x(t) = CURGDP \qquad (4)$$

It provided a similar standard deviation value as the four-quarter lagged, backward-looking weighting with equal weights. However, the moving average smoothing described by equation (4) changed the value of the mean by approximately 1-1.8%, instead of ~3.5-4.9% change in the case of the alternative moving average method (four-quarter lagged, backward-looking weighting with equal weights). Volatility was successfully reduced as presented in Figures 4 and 5.

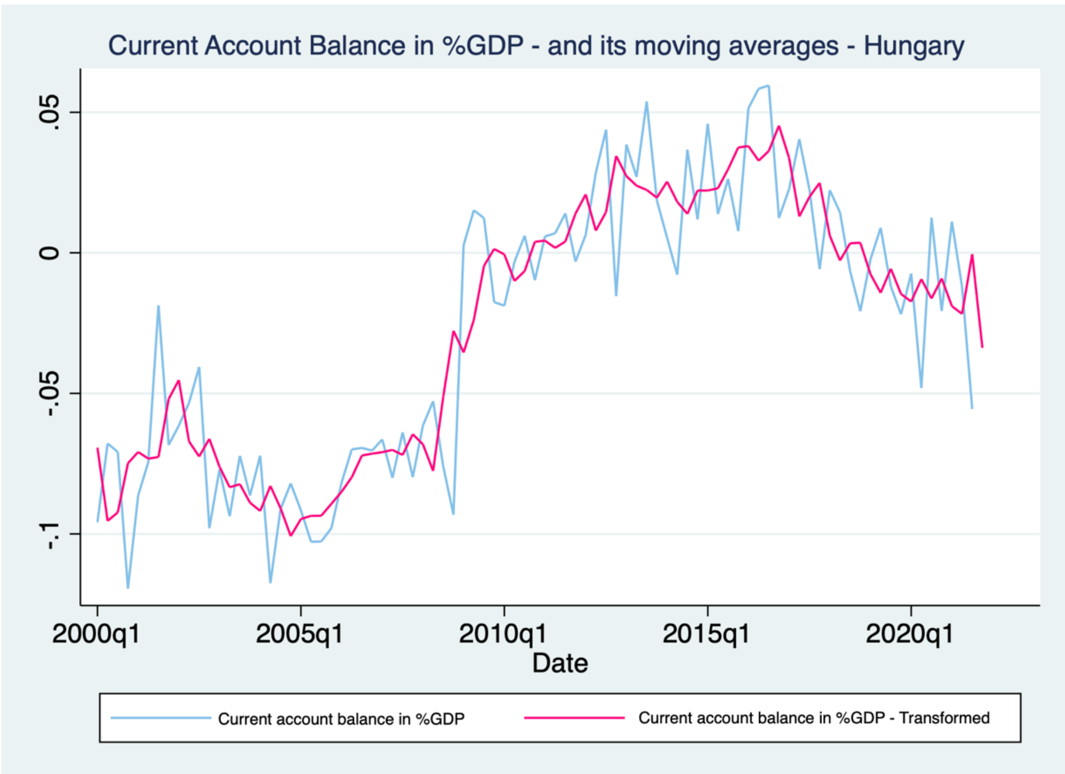

Figure 4: Current account balance in %GDP – and its moving averages - Hungary

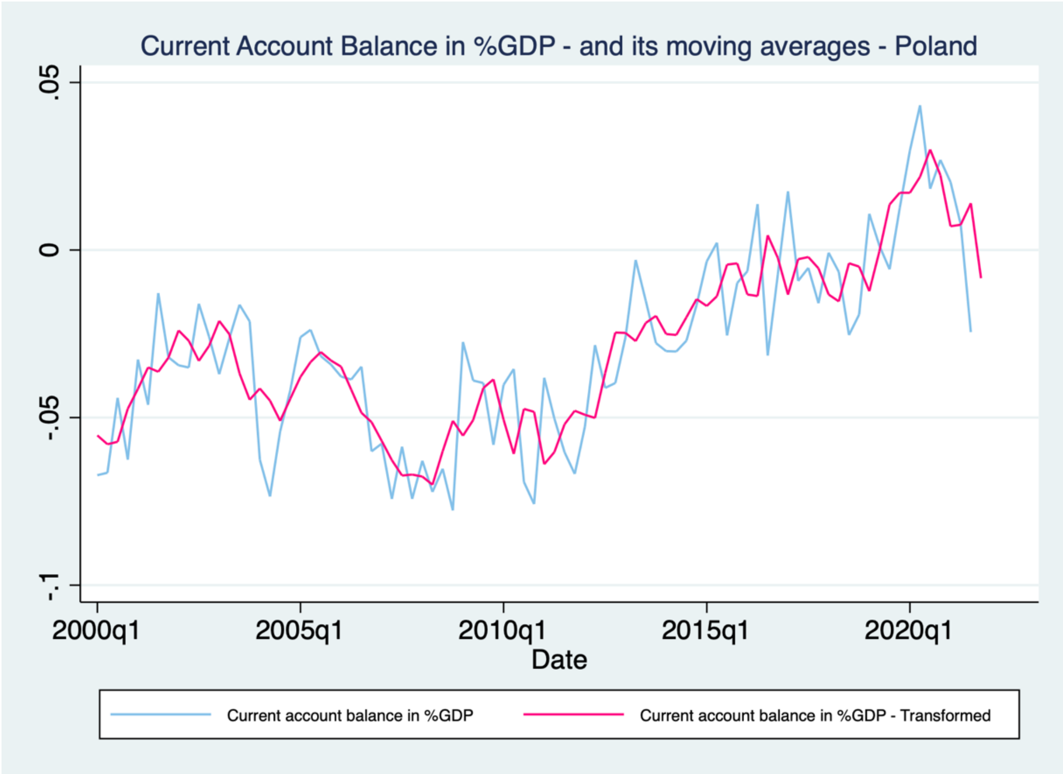

Figure 5: Current account balance in %GDP – and its moving averages – Poland

Visible trade balance in %GDP (VT_GDP_02):

It is an alternative variable for the current account balance, which incorporates the balance of export and import levels and is expressed in %GDP (Bussiere and Fratzscher, 2006). The raw data of trade balance were in USD currency and exchanged to EUR. After currency conversion it was divided by the real GDP values, because as explained in Appendix 1, the original values were given on market exchange rates. The data of visible trade balance were also smoothed in the same, above given structure as current account balance over GDP with less alteration in the mean (Figure 6 -7).

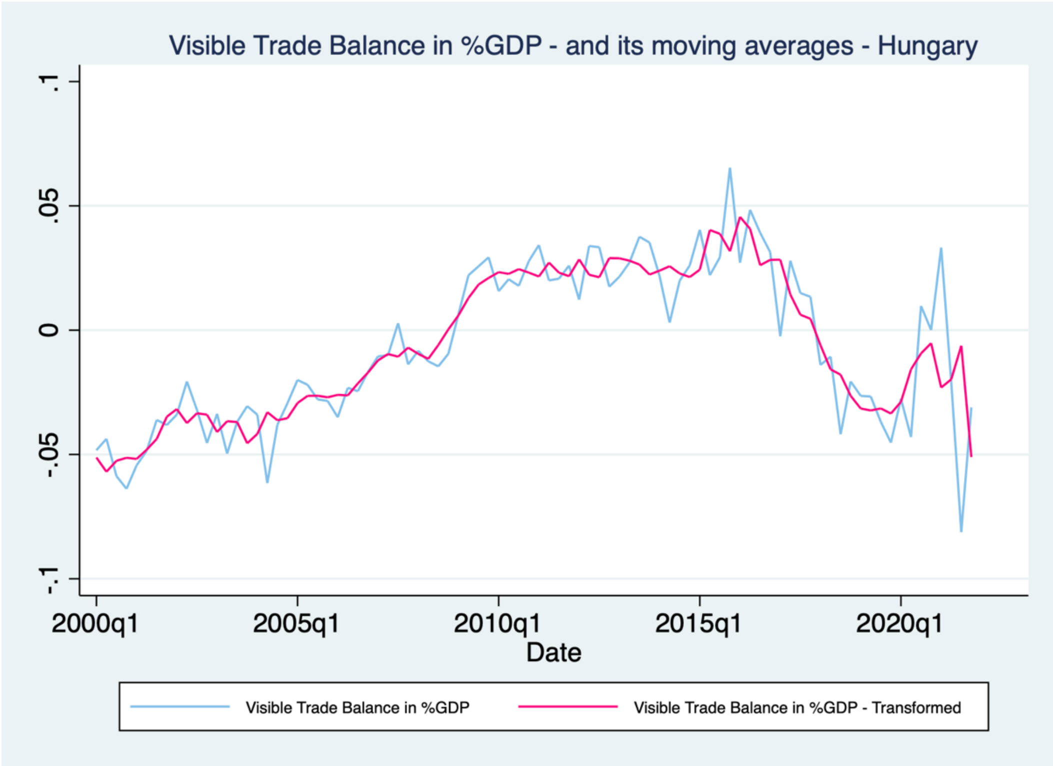

Figure 6: Visible Trade Balance in %GDP – and its moving averages - Hungary

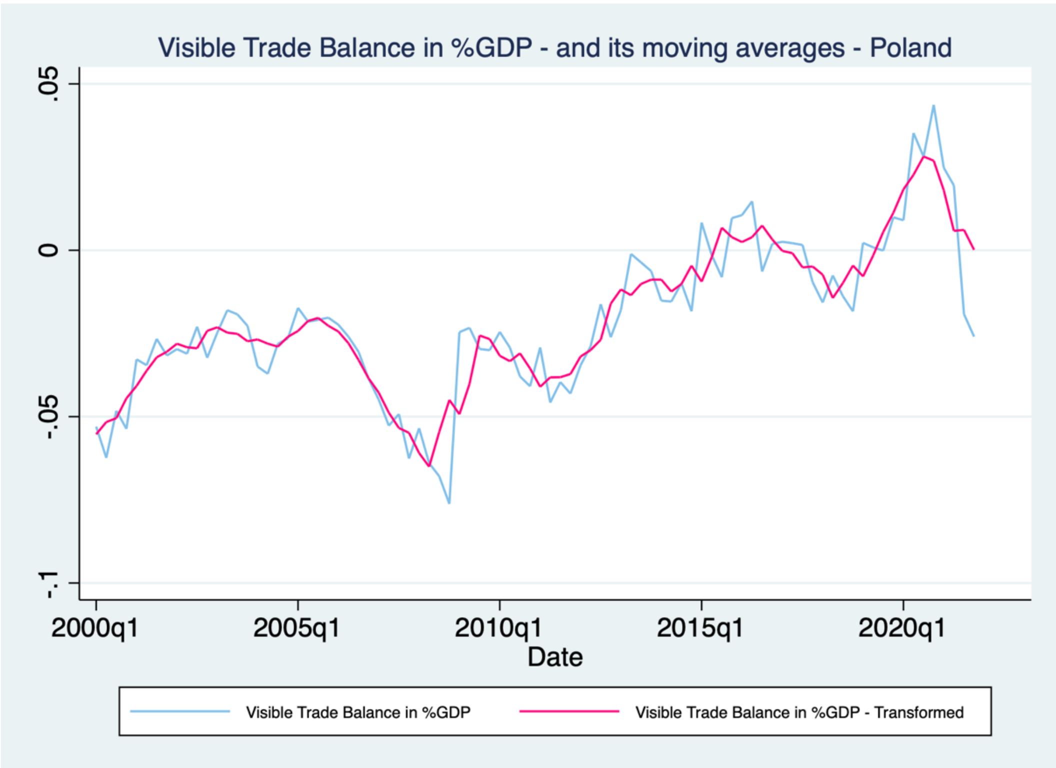

Figure 7: Visible Trade Balance in %GDP – and its moving averages - Poland

Real GDP growth rate (GDP_GR):

The growth rate of real GDP was an obvious choice to include in the model, as it may incorporate fiscal policy decisions, economic growth and may signal economic disruptions (Bussiere and Fratzscher, 2006).

Short-term debts over total reserves (SHTD_RES):

Rodrik and Velasco (1999) found that short-term debt plays a decisive role in the development of illiquidity. Their main goal was to recognize and describe the link between short-term debt, the vulnerability it possibly conveys and the link with crisis events. On the one hand, they applied the changing nature and expectations of lenders and the tendency, motivation of large institutions such as banks, governments and also firms, to borrow short-term. They found that the short-term debt ratio is a significant factor in determining a higher probability of a crisis event.

Short-term debt data were not scaled with GDP, but rather the total reserves including gold holdings. This ratio provides an insight into whether there is a growing level of short-term debt which is unbacked by reserves of some kind and whether there is an increased probability of illiquidity problems (Bussiere and Fratzscher, 2006).

Credit to private sector from domestic banks in units of GDP (%GDP) (CRTPS):

The credit to private sector from domestic banks variable looks for signals of overheating in the economy of a country. The rapid and significant progression of credits flowing into the private sector is meant to depict a so-called "lending boom". This variable includes and brings the effect of financial sector fragility into the models (Bussiere and Fratzscher, 2006).

General Government deficit and surplus (GOV_BALANCE):

The data lines were rescaled by a division of 10 000 for model stability. The positive and negative indication of surplus or deficit includes significant information about the government's financial situation. Therefore, no percentage change or growth rate calculation was applied on the variable.

Pandemic Misery Index (PMI_0):

As it has been introduced and will be further elaborated on in section 3.4, one of the main questions of my thesis is whether it is possible to signal economic distress in the recent years (especially starting from the time of the pandemic) and possibly extract a forecasting signal for the upcoming years. For this purpose, several variables were considered and added to the models, combining elements which bear the information inherently on the effectiveness of government interventions and the direct or indirect effects of the pandemic, also supported by other variables incorporating the most recent observations with regards to changes in the economies.

To incorporate the effects of the global virus events, the so-called Pandemic Misery Index (PMI) introduced by Jansen, Navarro and Rettenmaier (2020), was integrated as an independent variable. Jansen et. al. (2020) introduced a way to better reflect the effectiveness of the intervention of local institutions and governments during the COVID-19 pandemic across the United States. They built on a method introduced by Arthur M. Okun[4] where the Misery Index (MI) is the sum of the average unemployment rate and the annual rate of inflation (Lovell, 2022). The goal is to measure the effectiveness of interventions. Generalized as protecting the population and minimizing fatal cases of the virus, while also minimizing the fallback of economic activity and keeping the unemployment rates stable.

PMI includes two main components: one is serving as an indicator of the effectiveness on public health, the other is the indicator of economic health, from the perspective of workforce. The indicator of public health is the number of Covid-19 fatal cases over the total population, the indicator of economic health is the average unemployment rate in the given period. The PMI adds the two indicators for public and economic health. The Pandemic Misery Index is calculated as (Jansen et al., 2020):

$$PMI = (UNEMPLY) + (\frac{CD19}{(POPU*1\,000)} * 100) \tag{5}$$

where UNEMPLY is the quarterly rate of unemployment, CD19 is the number of fatal cases of Covid-19 on a quarterly basis and POPU is the total population of the countries, with quarterly frequency as well (Jansen et. al., 2020).

Population data were multiplied by 1000 due to the scaling of the original data and afterward scaled by 100 to keep the original measures of the index. The multiplication with only 100 is different from the original suggestion of Jansen et al. (2020), however, for the uniform scaling of the dataset it was the preferred procedure. Contrary to the original model of Misery Index, the rate of inflation is not explicitly included in equation (5) but is included as an individual independent variable. Before the first quarter of 2020, the officially registered COVID-19 related deaths are not included in the data. Therefore, before this date, the PMI variable solely reflects the rate of unemployment.

Gas price after carbon tax (GASP):

Data were collected from the original source quarterly. Growth rates were interpolated to quarters by the data provider. The growth rate of the price of gas is included in the model to capture the prominent, observed worldwide events in the economies. At the time of writing this thesis a sharp increase in gas prices is observed, which has a reflexive effect on the indicators and overall on the economies.

[4] The essays of Arthur Okun were collected and edited by Pechman (2004). Okun applied and explained his theory of misery index in several of his books, such as Curing chronic inflation (1978) and Prices and Quantities: A macroeconomic analysis (1981) (Brookings Institution, 2008).

Rate of inflation (INFL):

During the last few quarters included in the dataset, a strong rise of inflation in Europe and America is observed, being a problem both, for emerging and wealthy economies (Reinhart and Graf von Luckner, 2022). This fact also influences other macroeconomic indicators and should therefore be included in the regressions and models to capture the effect and aftermath of COVID-19 pandemics, as well as the recent global changes and policies enacted. Inflation data are based on the consumer price index (CPI).

Unemployment rate:

The level of unemployment is a significant factor in economies, especially during the pandemic and the upcoming recovery periods, as described in section 2. This variable also interacts with and influences other elements of the model, such as GDP levels. The increase in the rate of unemployment was a great risk during the pandemic, especially if paired with higher inflation rates. The unemployment rate was used for computing the independent variable of PMI.

3.3. Methodology

The presented EWS model focuses on currency crises and is built on the framework of Bussiere and Fratzscher (2006), also taking speculative currency attacks into account and some variables which were identified as a proxy for determining banking crises, e.g. domestic credit to private sector index (Babecky, 2012).

One of the main components of the model is the exchange market rate pressure (EMP) variable. EMP is the weighted average of three elements: real effective exchange rate, foreign exchange reserve and short-term interest rate. $EMP_{i,t}$ is defined as (Bussiere and Fratzscher, 2006):

$$EMP_{i,t} = \omega_{RER}\left(\frac{RER_{i,t}-RER_{i,t-1}}{RER_{i,t-1}}\right) + \omega_r\left(r_{i,t} - r_{i,t-1}\right) - \omega_{res}\left(\frac{res_{i,t}-res_{i,t-1}}{res_{i,t-1}}\right) \tag{6}$$

for country i and time period t, where *RER* is the real effective exchange rate, *r* is the short-term interest rate and *res* is the foreign exchange reserve. Equation (6) describes the changes in the three factors over time, which are weighted by the so-called relative precision (ω), which is the inverse of the variance of the variables over the sample period.

The setup of the EWS model is as follows: I=2 countries are included in the dataset which are observed during T=88 periods. The probability of a crisis (*Y*) is given by a non-linear, log function and is evaluated by a binary and a multinomial logit model.

As shown by Bussiere and Fratzscher (2006), the non-linearity feature of logit models often pictures reality better than a linear distribution model. For instance, a one percent change of a certain variable could be less or more significant depending on whether it reaches a pre-constructed threshold. If that one percent change contributes to reaching the given threshold, the same amount of change is more

significant from the point of economic interpretation as if it were to occur below the given threshold limit value. A linear relationship would assign the same weight to a one percent change, regardless of it exceeding any threshold.
The constructed EMP variable is used to determine a threshold for the alarming of crises. Currency crisis ($CC_{i,t}$) events are defined as the exchange market pressure variable ($EMP_{i,t}$) being above its respective country average ($\overline{EMP_i}$) plus its standard deviation, implying that EMP levels are unique for each of the countries, as given by equation (7).

$$CC_{i,t} = \begin{cases} 1 & if\ EMP_{i,t} > \overline{EMP_i} + SD(EMP_i) \\ 0 & otherwise \end{cases} \tag{7}$$

In the model of Bussiere and Fratzscher (2006), the variable $CC_{i,t}$ is defined as 1 if the EMP levels ($EMP_{i,t}$) of a country i at a given time period t is at least two standard deviations away from the country average ($\overline{EMP_i}$). Setting the multiplicator of standard deviation in equation (7) is based on the data and countries involved and is arbitrary. For example, Comelli (2013) set this multiplicator to three to fit the used dataset. For the presented dataset and model, the multiplicator of one achieved great results in terms of having a balanced amount of alarms signaled.

The value of the dependent variable is given by the realization of variable $CC_{i,t}$ at a certain time period t. The possible values of the dependent variable for the binary model are described by equation (8), and for the multinomial model by equation (9) with three possible values (Bussiere and Fratzscher, 2006), where k denotes the number of quarters.

$$Y_{i,t} = \begin{cases} 1 & if\ \exists k \in \{1, \dots, 4\}\ s.t.\ \ CC_{i,t+k} = 1, \\ 0 & otherwise \end{cases} \tag{8}$$

$$Y_{i,t} = \begin{cases} 1 & if\ \exists k \in \{1, \dots, 4\}\ s.t.\ \ CC_{i,t+k} = 1, \\ 2 & if\ \exists k \in \{1, \dots, 4\}\ s.t.\ \ CC_{i,t-k} = 1, \\ 0 & otherwise \end{cases} \tag{9}$$

This framework transforms a variable extracted from present data into a future, predictive variable, by taking the values of variable $CC_{i,t}$ and turning them into a signal to predict the values of $Y_{i,t}$. Moreover, it is constructed in such a way as to predict whether a crisis will occur at any time in the upcoming four quarters. Compared to previously presented models (Comelli (2013), Ades, Masih and Tenengauzer (1998)), which take time horizons of two years and one quarter of a year, this model applies to a time horizon of one year.

In equation (8), the dependent variable $Y_{i,t}$ of the binary model can take two values based on the realized value of the $CC_{i,t}$ variable. $Y_{i,t}$ will take the value of 1 for four quarters, given that $CC_{i,t}$ takes the value of 1. In every other case the dependent variable will take the value of 0.

In the multinomial model $Y_{i,t}$ has three possible values and is different from the binary model in state 2, which is the value of crisis itself and a post-crisis, recovery period ($Y_{i,t} = 2$), which applies for four quarters after the last signal of a crisis (last quarter of $CC_{i,t} = 1$). The dependent variable takes the value of 1 for four quarters, which are the pre-crisis states ($Y_{i,t} = 1$) preceding the signal of crisis ($CC_{i,t} = 1$).

This also implies that such periods are not limited to four quarters only, but also depend on how many signals ($CC_{i,t} = 1$) the model sends following one another. As will be discussed in section 4.5, the chosen time horizon depends on the policy maker's choice (Bussiere and Fratzscher, 2006).

The binary and multinomial models are each implemented with logistic regressions. The general logit function is given by (Grace-Martin, 2016):

$$log(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k, \tag{10}$$

where the log of $Y$is the dependent variable and $X_1,\ldots, X_k$ are the independent variables.

The probability of a crisis in the binary logit model is defined by equation (11) and in the multinomial model by equation (12) (Bussiere and Fratzscher, 2006).

$$Pr(Y = 1) = \frac{e^{X\beta}}{1+ e^{X\beta}} \tag{11}$$

$$\begin{cases} Pr(Y = 1) = \dfrac{e^{(X_{i,t-1}\beta_1)}}{1+ e^{(X_{i,t-1}\beta_1)}+e^{(X_{i,t-1}\beta_2)}} \\ Pr(Y = 2) = \dfrac{e^{(X_{i,t-1}\beta_2)}}{1+ e^{(X_{i,t-1}\beta_1)}+e^{(X_{i,t-1}\beta_2)}} \end{cases} \tag{12}$$

3.4. Research questions

One of the main research questions of this thesis is, whether the application of an EWS logit model with previously proven goodness-of-fit (e.g. Bussiere and Fratzscher (2006), Comelli (2013), Kaminsky, Lizondo and Reinhart (1998), Ades, Masih and Tenengauzer (1998), Berg et al. (2004), Berg, Borensztein, Milesi-Ferretti and Pattillo (1999)) could be helpful for the prediction of crisis events throughout the novel situation of a global pandemic, or whether different models should be established.

Furthermore, I will address whether a statistically significant prediction of a crisis event or signal is perceived after the great financial crisis in 2007-2008 and for the pandemic struck global time horizon, starting from 2020, with predictions regarding the future signals for 2022.

The following H_0 hypothesis is tested:

- There is no statistically significant (with a 95% confidence or 5% =α) relationship between chosen macroeconomic indicators (independent variables) and the occurrence of currency crisis periods in the applied EWS models. The sample estimates (beta coefficients) are not significantly different from zero. Therefore, the model cannot capture or explain the effects and impacts during and after currency crisis scenarios.

The alternative hypothesis:

- The discrete-dependent-variable logit EWS model can appropriately describe the underlying relationships in tranquil and crisis-struck periods as well (capturing the underlying economic relationships), the beta coefficients are significantly different from zero.

Given that the outcome of the binary and multinomial models are significant and the H_0 hypothesis has to be rejected, expectations are the following:

- There is at least one crisis signal detected in the data after 2019.
- The conducted out-of-sample estimations will signal the 2007-2008 crisis appropriately.
- The estimated beta coefficient of the Pandemic Misery Index is significantly different from zero, the variable corresponds to and influences the dependent variable (probability of a crisis event) at least in one of the models (either binomial, multinomial, or both).

In the first section, it has been suggested that due to the global pandemic and enacted policies, some macroeconomic indicators, such as volatility of exchange rate, unemployment rates, and stock market indicators may foreshadow a possible currency crisis. Since necessary, early data are already available, these data can be used in an EWS model to compare the performance of in- and out-of-sample estimations. The flexibility of an EWS is unprecedented and carries great potential. More precisely, the most recent data suggest higher volatility of exchange rates, adverse stock market effects, and higher unemployment rates in close connection to the global situation. Thus, it creates the necessity to forecast and illuminate the future with the prediction of economic models.

4. Models and results

According to the methodology presented in chapter 3, a binomial and a multinomial logistic regression was conducted on the dataset to measure the effectiveness and impact of the macroeconomic indicators influencing the dependent variable. The depend variable signals the states of the economies in ways described in section 3.3, either by signaling the upcoming of a crisis or “undisturbed” periods. In order to conduct the described logit models and regressions, the program Stata is used.

4.1. Binary logit model

In this section the results of the binary logit model are discussed and interpreted. The model signals either tranquil period or the forming of a crisis. The output of the binary logistic model is shown in Table 3.

Binary Logistic Regression Model for Currency Crisis - 12 months					
	Odds Ratio	Std. error	z	P>|z|	95% CI
Real GDP Growth Rate	1.0498	0.0712	0.72	0.4732	[0.9192,1.1990]
Gas Price	1.0420	0.0099	4.33	0.0000***	[1.0228,1.0615]
Inflation rate %	1.3399	0.1587	2.47	0.0135*	[1.0624,1.6899]
Credit t.Private sector/GDP	1.2533	0.0997	2.84	0.0045**	[1.0724,1.4648]
Sht. debt / total reserves	17.6319	26.2649	1.93	0.0540	[0.9513,326.7917]
Vis.Trade.B./GDP	6.52e-32	1.99e-30	-2.36	0.0185*	[7.46e-58, 5.70e-06]
Pandemic Misery Index	3.074e+17	4.143e+18	2.99	0.0028**	[1.0e+06, 9.1e+28]
REER Overvaluation	350.3846	2694.9040	0.76	0.4462	[0.0001, 1.2e+09]
Gov. Surpl. Deficit	151.0617	387.8050	1.95	0.0506	[0.9862, 2.3e+04]
Intercept (_cons)	0.0000	0.0000	-3.36	0.0008	[0.0000,0.0006]
Prob > chi2					**0.0000**
N					172
Pseudo R^2					0.4002
AIC					131.9084
BIC					163.3833
Wald chi2(9)					38.9866
Log-Likelihood					-55.9542

Note: 1 failure and 0 successes completely determined. ** p<0.05; ** p<0.01; *** p<0.001*

Table 3: Output of the binary logistic model

It is evident that the model itself is significant, the p-value of the model (Prob>chi2) is statistically significant at the 1% level and most of the beta coefficients of the regression equation differ from zero. Therefore, in the presented binary model the independent variables significantly predict the outcome of the dependent variable and thus, are a good predictor of crisis events. The individual significance test is at least significant at the 5% level for the variables capturing changes in the gas price, rate of inflation, domestic credit to the private sector, the visible trade balance, and the pandemic misery index as well. In the output table, according to the individual p-values of the independent variables, the significant predictors are marked with a * symbol. The confidence intervals of real GDP growth rate, short-term debt over total reserves, REER overvaluation and government balance each contain one, which indicates that the accuracy of these independent variables correctly predicting the dependent variable is unreliable, their individual p-values are not statistically significant.

In the note section of the output, there is one mentioned failure of the model during the process of converging. In the framework of Stata, this information means that one of the independent variables forecasts the results with great efficiency. From alternative tests and the low value of standard error and coefficient interval spread, it is evident that the visible trade balance expressed in percentage of the GDP is responsible for this. However, this does not influence the overall efficacy and success of the model (Sribney, 2022).

The odds ratio is reported in the output table (Table 3), describing the unit increase (or decrease) in the odds of the outcome given the increase of an independent variable. The odds ratio of one describes that the independent variable (or exposure) does not affect the odds of the outcome (the odds of a crisis). An odds ratio higher than one indicates higher odds of the outcome and vice-versa (Szumilas, 2010).

Although the odds ratio is reported for each variable in the table above, the individual effect is difficult to compare for logistic outputs. To explain the relationships within the model, marginal effects were measured and are presented in Table 4.

	dy/dx	std. err.	z	P>z	[95% conf. interval]	
Real GDP Growth Rate	0.00290	0.00398	0.73	0.466	-0.00489	0.01069
Gas Price	0.00245	0.00101	2.42	0.016*	0.00047	0.00444
Inflation rate %	0.01744	0.01030	1.69	0.090	-0.00274	0.03762
Credit t.Private sector/GDP	0.01346	0.00339	3.97	0.000***	0.00682	0.02010
Sht. debt / total reserves	0.17105	0.07886	2.17	0.030*	0.01650	0.32561
Vis.Trade.B./GDP	-4.28023	1.12637	-3.80	0.000***	-6.48787	-2.07258
Pandemic Misery Index	2.40018	0.61733	3.89	0.000***	1.19023	3.61013
REER Overvaluation	0.34924	0.51975	0.67	0.502	-0.66945	1.36792
Gov. Surpl. Deficit	0.29909	0.13455	2.22	0.026*	0.03537	0.56281

** p<0.05; ** p<0.01; *** p<0.001*

Table 4: Marginal effects of the binary logistic model

The significance of the marginal effects and the individual significance of the variables according to the p-values differ mainly for three variables. Firstly, the marginal effect of short-term debt over reserves ratio shows a significant marginal effect on the change of the dependent variable. This marginal effect is unreliable, as in the output (Table 3) the individual significance (p-value test) is not statistically significant. The same applies to the variable of government balance (government surplus and deficit independent variable from here on interchangeably referred to as government balance). Furthermore, the marginal effect of inflation is only significant at the 10% level, while the individual significance test is at the 5% level. Therefore, the changes occurring in the inflation rate have less impact on the dependent variable despite their individual significance in the model overall.

Marginal effects should be compared to some pre-set levels of the variables to be able to compare the change. The reported marginal effects are measured at the means, i.e. reported values in column dy/dx are the marginal effects of the variables while keeping all the other variables at their mean values, to capture the partial effects (Bussiere and Fratzscher, 2006).

According to the marginal effects, the probability of crisis in the framework of the model becomes 1.346% more likely, if the credit to private sector from domestic banks (expressed in percentage of GDP) grows by one unit. If the gas price grows by one percent, the probability of crisis increases by 0.245%. This change causes a less drastic growth in the probability of crisis, however still provides valuable information about underlying relationships. The PMI index, which, as mentioned previously, before 2020 contains only the unemployment rate, can have the greatest impact (doubling the probability for every unit change) and exacerbates the probability of a crisis. The other variable, which carries the potential to mitigate and minimize the probability of crisis, is the index of visible trade balance. If the trade balance over GDP ratio is raised by 1%, the crisis probability decreases by approximately four times.

To summarize, policy makers have the ability to stabilize the economy by increasing the ratio of visible trade balance, or so to say, economies with a more stable trade balance (measured against GDP levels) have a better chance to keep the occurrence of a crisis at bay. Keeping economies going by providing work opportunities, even in economically challenging, pressuring times (which was created by the global pandemic), further increases the success probability of preventing and alleviating crisis events. Work opportunities can be created by the government and local governments, authorities, instead of or in addition to providing short-term government aid for the unemployed population. Even more so, as short-term, unorthodox aids for households, although in many situations necessary, may draw the aggravation of the government balance as a consequence, which could further deteriorate the probability of a crisis, and may lengthen the recovery periods.

4.2. Multinomial logit model

As mentioned previously, the multinomial model differentiates between the pre-crisis and the crisis/recovery periods. The advantage and purpose of this is, on the one hand, to model the real-world practices more accurately. On the other hand, the prediction ability of the model is enhanced, since it captures the difference in the behavior of independent variables and their values across three states of the modeled economies (Bussiere and Fratzscher, 2006).

The results of the multinomial logistic model are presented in Table 5. The base outcome is set to Y=0, meaning that tranquil times are the standard, to which the other two states are compared to (Bussiere and Fratzscher, 2006). The base outcome, therefore, is not included in the regression table.

Multinomial Logistic Regression Model Currency Crisis – 12 months					
	Coefficient	Std. error	z	p-value	95% CI
Y=1					
Real GDP Growth Rate	0.1285	0.0732	1.76	0.0790	[-0.0149,0.2719]
Gas Price	0.0773	0.0157	4.92	0.0000***	[0.0465,0.1080]
Inflation rate %	0.3029	0.1108	2.73	0.0062**	[0.0858,0.5200]
Credit t.Private sector/GDP	0.1731	0.0477	3.63	0.0003***	[0.0796,0.2666]
Sht. debt / total reserves	2.9720	1.7452	1.70	0.0886	[-0.4485,6.3925]
Vis.Trade.B./GDP	-28.3114	14.6662	-1.93	0.0536	[-57.0567,0.4339]
Pandemic Misery Index	23.5060	6.5186	3.61	0.0003***	[10.7297,36.2823]
REER Overvaluation	-27.4760	8.3570	-3.29	0.0010**	[-43.8555,-11.0966]
Gov. Surpl. Deficit	-2.6326	0.9010	-2.92	0.0035**	[-4.3985,-0.8668]
Intercept (_cons)	-13.9528	3.1100	-4.49	0.0000	[-20.0484,-7.8573]
Y=2					
Real GDP Growth Rate	0.1053	0.0971	1.08	0.2781	[-0.0850,0.2956]
Gas Price	0.0908	0.0163	5.58	0.0000***	[0.0589,0.1227]
Inflation rate %	0.4671	0.1405	3.32	0.0009***	[0.1916,0.7425]
Credit t.Private sector/GDP	0.3062	0.0828	3.70	0.0002***	[0.1440,0.4685]
Sht. debt / total reserves	4.5027	2.1552	2.09	0.0367*	[0.2786,8.7268]
Vis.Trade.B./GDP	-76.1321	31.3277	-2.43	0.0151*	[-1.4e+02,-14.7309]
Pandemic Misery Index	48.6675	14.0915	3.45	0.0006***	[21.0488,76.2863]
REER Overvaluation	-8.8848	11.7862	-0.75	0.4510	[-31.9854,14.2158]
Gov. Surpl. Deficit	2.8221	2.7282	1.03	0.3010	[-2.5252,8.1693]
Intercept (_cons)	-23.4069	5.4906	-4.26	0.0000	[-34.1682,-12.6455]

Prob > chi2	**0.0000**
N	173
Pseudo R^2	0.3929
AIC	249.0560
BIC	312.1218
Wald chi2(18)	71.3243
Log-Likelihood	-104.5280

** p<0.05; ** p<0.01; *** p<0.001*

Table 5: The output results of the multinomial logistic model

Similarly to the binary model, the multinomial model is highly significant. The beta coefficients of the regression equation differ from zero for the majority of the independent variables, the p-value (Prob>chi2) of the model is statistically significant at the 1% level. The number of observations is one greater than in the binary model, as the first quarter of 2000 can be inferred for Poland (Country=2) from the following quarter signals.

According to Table 5, the following variables have an impact on determining the dependent variable for the pre-crisis state (Y=1), at least within the 5% significance band: change in gas price, inflation rate, the credit supplied to the private sector from domestic banks, PMI, overvaluation of the exchange rate and the government balance. Compared to the crisis state of the dependent variable (Y=2), the significance of the variables changes in the case of short-term debt over reserves index, trade balance index, which become significant at the 5% significance level, while the overvaluation of the exchange rate and the balance of government variables no longer fall into the specified significance band. The difference in terms of the change in the significance of the independent variables across the states of the dependent variable stems from the fact that different indexes and macroeconomic factors contribute to the signaling of a crisis and during the actual event of crisis and recovery periods. While, for example, the overvaluation of the real exchange rate along with imbalances in the net lending and borrowing of the government may be an important factor in forecasting a possible crisis, they become less relevant during the actual crisis and recovery quarters. The output results in Table 5 also suggest that given a governmental leadership can stabilize the ratio of trade balance and the index of short-term debts over reserves, recovery is more likely. However, to truly understand the punctual impact of the independent variables, their marginal effects are shown in Tables 6 and 7.

Y=1 ME	dy/dx	std. err.	z	P>z	[95% conf. interval]		X
Real GDP Growth Rate	0.02048	0.01242	1.65	0.099	-0.00387	0.04484	0.60301
Gas Price	0.01187	0.00263	4.52	0.000***	0.00672	0.01702	7.46168
Inflation rate %	0.04474	0.01803	2.48	0.013*	0.00941	0.08007	3.42141
Credit t.Private sector/GDP	0.02493	0.00772	3.23	0.001***	0.00980	0.04005	41.61680
Sht. debt / total reserves	0.44029	0.29919	1.47	0.141	-0.14611	1.02669	0.28145
Vis.Trade.B./GDP	-3.65705	2.38495	-1.53	0.125	-8.33147	1.01738	-0.01322
Pandemic Misery Index	3.27133	1.07314	3.05	0.002**	1.16801	5.37466	0.09041
REER Overvaluation	-4.59961	1.29296	-3.56	0.000***	-7.13377	-2.06546	0.00028
Gov. Surpl. Deficit	-0.50008	0.17028	-2.94	0.003**	-0.83382	-0.16634	-0.21869

** p<0.05; ** p<0.01; *** p<0.001*

Table 6: Marginal effects of the multinomial model in pre-crisis periods (Y=1)

Y=2 ME	dy/dx	std. err.	z	P>z	[95% conf. interval]		X
Real GDP Growth Rate	0.00503	0.00586	0.86	0.39	-0.00646	0.01653	0.60301
Gas Price	0.00488	0.00224	2.18	0.029*	0.00050	0.00927	7.46168
Inflation rate %	0.02665	0.01608	1.66	0.098	-0.00487	0.05817	3.42141
Credit t.Private sector/GDP	0.01789	0.00502	3.56	0.000***	0.00805	0.02772	41.61680

Sht. debt / total reserves	0.25608	0.11429	2.24	0.025*	0.03209	0.48008	0.28145
Vis.Trade.B./GDP	-4.68446	1.40839	-3.33	0.001***	-7.44486	-1.92407	-0.01322
Pandemic Misery Index	2.90715	0.78981	3.68	0.000***	1.35915	4.45516	0.09041
REER Overvaluation	-0.15604	0.73314	-0.21	0.831	-1.59298	1.28089	0.00028
Gov. Surpl. Deficit	0.23315	0.15994	1.46	0.145	-0.08033	0.54663	-0.21869

** p<0.05; ** p<0.01; *** p<0.001*

Table 7: Marginal effects of the multinomial model in crisis and post-crisis/recovery periods (Y=2)

The marginal effects for the multinomial model in the pre-crisis state (Y=1) in Table 6 show the same significant variables as the model output itself. There is a difference however in the level of significance. The marginal effects of inflation rate and PMI are only relevant at the 5% and 1% levels respectively, overvaluation is significant at the 0.1% level, however. The change in significance levels across marginal effects and the output of the variables for state 2 (crisis and post-crisis periods) concerns the gas price change variable (marginal effects significant at 5% level), and trade balance index variable (marginal effects significant at the 0.1% level). The multinomial model's marginal effects are in parallel with the binomial model's marginal effects with regard to the effects of the inflation rate. While this variable is significant from the perspective of the overall models and is a good predictor, its marginal effect has less of a magnitude on the crisis probability.

The pre-crisis (Y=1) state is most determined by the change of PMI (one unit change of PMI increases the crisis probability about three times), government balance changes (one unit positive change or surplus decreases the probability by 50%) and the overvaluation of the exchange rate. The overvaluation of REER has a negative relationship with the crisis probability in both states of the multinomial model.

The overvaluation of the exchange rate causes the national products to have a relatively higher value, making the exports of the given country less attractive and less competitive, while also making the imports less costly. Further effects of overvaluation are that the purchasing power and general demand are reduced and the market participants such as households and companies show less demand for products because the same products are now more expensive (Pettinger, 2017). The variable for REER overvaluation will have a growing value given that the actual overvaluation during the period grows in an unexpected way compared to the estimated trend values. The economic intuition would dictate a positive relationship between the probability of a crisis signal (pre-crisis, Y=1) and the growth of the REER overvaluation index. The REER overvaluation variable is evaluated at its mean which is 0.00028, as can be seen in the X column (Tables 6 and 7). The X column contains the means of each variable, which are fixed, to evaluate the partial effects of the individual independent variables. The negative relationship may be due to the fact that such means provide a constellation where any minimal unit increase of REER overvaluation (from its zero-converging mean) mitigates the adverse effect of the other mean-fixed variables, such as the government deficits with an inflation rate exceeding 2% and moderate GDP growth rate, which translates to a steady economic increase of performance or the slowing down of economic production. In crisis and post-crisis states (Y=2), overvaluation is not significant anymore, neither are its marginal effects, which corresponds to the findings of Bussiere and Fratzscher (2006). This could confirm that there is a temporary balancing economic force based on the growing value of overvaluation occurring before a crisis. This effect was not captured by the binomial model, as it cannot differentiate between pre- and post-crisis scenarios (and the effect of overvaluation was not significant anymore outside pre-crisis).

The different states of the multinomial model provide policy makers with additional information about which variables to pay attention to and which ones to control in order to mitigate the adverse effects of an economic downfall. In pre-crisis states (Y=1), PMI, credit to private sector from domestic banks, government balance, gas price index, inflation rate and overvaluation will signal the upcoming of crisis and its following recovery states later (Y=2). During the pre-crisis states (Y=1), decision makers may stabilize the index of PMI by methods which reduce the rate of unemployment (e.g. creating government-provided or aided work opportunities) and aid the health of the population (e.g. government-provided vitamin packages or organized health campaigns), while also increasing the trade balance ratio (provided that the economic output and exports can be increased), meanwhile lowering the credit received by the private sector by controlling interest rates. Inferring from the marginal effects shown in Table 7, the outbalancing of the trade balance index and the short-term debt over reserves ratio may be rather meaningful during crisis and recovery periods. To conclude, the multinomial model does a better job at differentiating between the underlying economic forces with its three possible states and helps to better understand and dissect the results of the binary model.

4.3. Alternative variables and robustness tests

In section 3 two alternative ratios, current account balance (%GDP) and visible trade balance (%GDP) were included in the model as independent variables, as suggested by Bussiere and Fratzscher (2006).

With the binary model, testing the two variables together yielded the significance of both indicators. Running the model with only the current account balance (%GDP) index along the other independent variables excluding visible trade balance, however, did not prove the individual significance of the current account balance indicator (CURGDP_02). However, the alternative indicator of trade balance (VT_GDP_02) alongside the other predictors did. The multinomial model tests yielded similar results. To justify the alternative choice and to ensure that there are no collinearities, pre-testing was elaborated on the independent variables. The results of the test are recorded in the correlation matrix in Table 8.

	GDP_GR	GASP	INFL	CRTPS	SHTD_RES	VT_GDP_02	CURGDP_02	PMI_0	R_OVERV	GOV_BALANCE
GDP_GR	1.0000									
GASP	0.1613	1.000								
INFL	0.1440	0.2694	1.000							
CRTPS	-0.1695	-0.1826	-0.2115	1.000						
SHTD_RES	0.0291	0.2138	0.3632	-0.4861	1.000					
VT_GDP_02	-0.0971	-0.3711	-0.4304	0.4923	-0.1731	1.000				
CURGDP_02	-0.0854	-0.4116	-0.5184	0.2663	-0.3546	0.8336	1.000			
PMI_0	0.0414	0.0787	-0.0088	-0.3261	-0.1584	-0.1987	-0.1399	1.000		
R_OVERV	0.1000	0.2206	0.0523	0.1723	-0.0544	-0.1682	-0.1303	-0.1959	1.000	
GOV_BALANCE	0.1852	0.1370	0.1547	-0.1831	0.3542	0.0961	0.0434	-0.1291	-0.1589	1.000

Table 8: Collinearity test on independent variables

As a general rule, any variables which had a greater correlation than 0.5 were removed from the list of independent variables. The values in Table 8 for the current account balance index (CURGDP_02) exceeded this limit. Unsurprisingly, it correlates with the trade balance index, but also with the rate of inflation. As a result, the current account balance index was removed and was substituted by its close correlating alternative, the trade balance ratio (%GDP).

4.4. Panel Data

Although after the completion of the filtering process of country selection only two countries, Hungary and Poland remained in the sample, the approach for treating the data sample as panel data was taken. The sample was declared along the time dimension and also the country dimension and was run as panel data with the same setup of binary and multinomial models. The likelihood ratio test of rho=0, chibar2(01) concluded with the probability Prob>=chibar2 =1.000, that treating the data as a panel is inferior compared to the implementation of pooled models. In other words, according to the interpretation of Stata built-in manuals, it is not meaningful to treat the data as a panel and there is no additional information to conclude by using panel data analytical tools on the sample. In line with the above results, no panel data models were included. This result is similar to the conclusion of Bussiere and Fratzscher (2006). They found that panel data approaches were not adding relevant information to the analysis and pooled models performed better.

4.5. The success of the models and trade-off problem

In order to measure the success rates of the presented models, it is necessary to define distressed and undisturbed periods in the economies. The evaluation of performance of the two models differs in some way to let flexibility for the distinction of pre-crisis and post-crisis.

To measure the performance of the multinomial model, from 2006Q1 to 2006Q4 the signal of the great financial crisis in 2007-08 should start with the signal of Y=1. The crisis itself and recovery periods should have the value of Y=2. The values of Y=1 and Y=2 are expected after one another (without a signal of Y=0) in 2007-2008. During 2009Q1-2009Q4, depending on the signals captured in the quarters of 2008, the observed values should be either 0 or 2. The second wave of stressful times is during the suspected global pandemic years, starting from 2020. A positive signal of pre-crisis is expected after 2020Q2. From 2021 either the value Y=1 or Y=2 is expected. There may be individual country-specific effects present, which determine the exact signal in certain periods, which happened in 2009. There is possibility that the last quarter of 2008 was economically stressful for either of the countries in the sample and a crisis signal was sent in the last quarter. This would cause the upcoming four quarters in 2009 to be recovery periods (Y=2). The multinomial model takes such country-wise minor differences into account. As discussed in the literature overview of section 2, the effect of the global pandemic was prominent and could be observed on several macroeconomic indicators. However, due to the lack of further studies and country-specific features regarding the handling of pandemic situations and adverse effects, the signal of Y=1 from 2020Q3 onwards in both models is expected, as the World Health Organization (WHO) declared COVID-19 to be a pandemic on 19 March 2020 (WHO, 2020). Therefore, any sign of disruption is expected from 2020Q3 onward, letting enough time of three months in 2020Q2 for the market and governments to adjust and signs to be visible.

For the binary model, state Y=1 should be signaled at the quarters of 2007-2008. A value Y=1 is expected from the quarter of 2020Q3, similarly to the multinomial model benchmark. Tables 9 and 10 show the observations across possible states and the performance statistics of the binary model, while Tables 11 and 12 contain these for the multinomial model, following the method of determining success rates and performance evaluations of Bussiere and Fratzscher (2006) and of Kaminsky et al. (1998). The state-wise observation tables (Tables 9 and 11) include letters A-D, which correspond to the formulas of the performance statistics described below in equation (13).

	No crisis (Y=0)	Crisis (Y=1)

Signaled crisis (S=1)	27 [B]	15 [A]
No signal of crisis (S=0)	119 [D]	13 [C]
Total	146	28

Table 9: Observations of the binary model across states (S=1, S=0)

Observations called correctly (=overall efficiency):	77.01%
Crises called correctly:	53.57%
Proportion of false alarms out of total alarms:	64.29%
The probability of crisis given **no** alarm:	9.85%
The probability of **crisis** given an alarm:	35.71%

Table 10: Performance statistics in the binary model

The performance statistics (included in Table 10 and Table 12) were computed in the following way (Bussiere and Fratzscher, 2006 and Kaminsky et al. 1998):

$$\begin{gathered}\text{Observations called correctly: } \frac{A+D}{A+B+C+D}\\ \text{Crises called correctly: } \frac{A}{A+C}\\ \text{False alarms of total alarms: } \frac{B}{A+B}\\ \text{Prob. crisis given no alarm: } \frac{C}{C+D}\\ \text{Prob. crisis given an alarm: } \frac{A}{A+B}\end{gathered} \tag{13}$$

	No crisis (Y=0)	Crisis (Y=1)	Post-crisis (Y=2)
Signaled crisis (S=1)	19 [B]	17 [A]	18
No signal of crisis (S=0)	95 [D]	1 [C]	24
Total	114	18	42

Table 11: Observations of the multinomial model across states (S=1, S=0)

Observations called correctly (=overall efficiency):	84.85%
Crises called correctly:	94.44%
Proportion of false alarms out of total alarms:	52.78%
The probability of crisis given **no** alarm:	1.04%
The probability of **crisis** given an alarm:	47.22%

Table 12: Performance statistics in the multinomial model

As can be seen in Table 10 and Table 12, the multinomial model performs better than the binomial model. Firstly, the overall efficiency improved from 77.01% to 84.85%. The crisis periods called correctly increased by 40.87% and there was only one missed crisis period in the multinomial model. Secondly, the probability of a crisis given an alarm grew by almost 12%, while also reducing the percentage of false alarms in the multinomial model.

By comparing the models, it becomes apparent that there is an underlying trade-off between false signals and missed signals. The intuitive trade-off while choosing the appropriate model is how sensitive should the model be with regard to sending a signal. The crisis event threshold ($CC_{i,t}$) described in equation (7), infers when the model should ring the alarm for an upcoming crisis. The more sensitive this threshold is, the more signals will be perceived, while the opposite is also valid. Therefore, while setting up an EWS model, the choice between false alarms (a crisis was signaled but did not happen) and missed signals should be made. Inferring from the data of Tables 9-12, the applied models favour false alarms over missed signals. From a policy maker's point of view, it can be inferred that the cost of false alarms is less than the cost of missed signals.

To tackle the trade-off problem from the perspective of the policy maker, Bussiere and Fratzscher (2006) identified a loss function depending on a threshold and cost of the alternative choice, which depend on the risk aversion of the policy maker, based on the fact that a sent signal and a missed signal are both costly. This original loss function was reconsidered and modified as:

$$L(T) = \theta \Pr(crisis\ given\ no\ signal)\,(T) + (1-\theta) \Pr(no\ crisis\ given\ a\ signal)\,(T) \qquad (14)$$

where $\theta \in [0,1]$. The threshold (T) is the factor on which the terms depend on, being the feature of every EWS model. The equation conveys the risk type θ of the policy maker who has to choose between false alarms and missed signals. The decision maker seeks to minimize the weighted, aggregated value of the two types of errors according to the loss function.

The function $L(T)$ can be calculated for the two models above, while keeping the time-horizon constant at four quarters (one year) and the threshold (T) at the value defined by equation (7)-(9), based on the values of $EMP_{i,t}$ and $CC_{i,t}$. The threshold value is $T_{HU} = 0.04705$ for Hungary and $T_{PO} = 0.02535$ for Poland.

If the policy maker is indifferent between false signals and missed signals, $\theta = 0.5$ and the value of $L(T)$ is $L_B(T) = 0.3707$ for the binomial model and $L_M(T) = 0.2691$ for the multinomial model, therefore $L_M(T) < L_B(T)$.

Now consider different values for θ, keeping other factors the same. If $\theta = 0.1$, the policy maker gives less (little) preference weight to missing a signal. This indicates that the cost of false alarms outweighs the cost of missed alarms in line with their preference. The values of the loss functions are: $L_B(T)$ =0.58846 and $L_M(T)$= 0.47606. Still $L_M(T) < L_B(T)$, but each value is larger than for $\theta = 0.5$.

If $\theta = 0.9$ the policy maker is highly risk-averse to missing signals of crises. From the values of the loss function, it may be inferred that if the current policy maker's objective is to minimize the value of $L(T)$, the policy maker would prefer the multinomial model above the binomial one. A policy maker characterized by $\theta = 0.9$ prefers to minimize the number of missed signals in the chosen model, as the cost of missed signals is larger: $L_B(T)$ =0.15294 > $L_M(T)$= 0.06214. Differentiating between the three groups of preferences and their loss function values, the loss function takes the lowest value for $\theta = 0.9$. This confirms that both, binary and multinomial models, focus on minimizing missed signals and thus are more successful in minimizing the loss function for larger θ values.

Furthermore, the loss function suggests that there is a difference between model approaches (e.g. binomial or multinomial with regards to the states of *Y*) in terms of loss function values, even if the same threshold (T) for crisis and the same time horizon is set. Naturally, this also demonstrates that enlarging the time horizon of the model is less costly for decision makers who are risk-averse towards missed crises (when θ is relatively larger). The opposite is true for shorter time horizon models.

Varying the threshold has similar effects, decision makers with larger θ values will aim to have a lower threshold to avoid missing more signals of crises. They prefer false signals, which are less costly for them, over the more costly unexpected recessions, and vice-versa.

4.6. Out-of-sample performance

4.6.1. Estimation parameters on restricted sample

In order to better measure the performance of the models, out-of-sample predictions and tests are often advised. Berg and Pattillo (1999) analyzed the performance of EWS models out-of-sample, to shed light on how useful these models could have been if they were used before the actual crisis events. Their results are mixed and confirmed the necessity of such tests.

In the sample period the great depression of 2007-2008 was identified as a crisis period. To conclude out-of-sample estimations, the same models were applied to a subsample of the data from 2000Q1 until 2006Q4. In the binary model the visible trade balance variable was removed from the independent variables, as the restricted sample became only a fraction of the full sample (54 observations instead of the 174). The proportion of the independent variables was too large compared to the subsample size and as presented in section 4.1, the trade balance variable caused one observation to be completely determined. For this reason and to keep the results balanced, only the remaining eight independent variables were included in the model, as shown by Table 13.

Binary Logistic Regression Model – Out-of-Sample estimation until 2007Q1					
	Odds Ratio	Std. error	z	P>|z|	95% CI
Real GDP Growth Rate	1.223	0.174	1.41	0.158	[0.925,1.618]
Gas Price	1.178	0.048	3.99	0.000***	[1.087,1.276]
Inflation rate %	2.846	0.917	3.24	0.001***	[1.513,5.352]
Credit t.Private sector/GDP	1.415	0.177	2.78	0.006**	[1.107,1.808]
Sht. debt / total reserves	3833330.4	15721885	3.70	0.000***	[1237.339, 1.188e+10]
Pandemic Misery Index	6.623e+42	1.736e+44	3.76	0.000***	[3.205e+20, 1.369e+65]
REER Overvaluation	9.48e-10	1.21e-08	-1.63	0.103	[1.34e-20, 66.79]
Gov. Surpl. Deficit	0.002	0.026	-0.51	0.612	[1.10e-13, 4.30e+07]
Intercept (_cons)	6.85e-19	7.03e-18	-4.08	0.000	[1.27e-27, 3.71e-10]
	Prob > chi2				**0.0000**
	N				54
	Pseudo R^2				0.656
	AIC				40.602
	BIC				58.503
	Wald chi2(9)				29.621
	Log-Likelihood				-11.301194

** p<0.05; ** p<0.01; *** p<0.001*

Table 13: Out-of-sample output of the binary model

The model remained highly significant with regard to the p-test (Prob>chi2). The independent variables remained significant compared to the original benchmark model (in-sample model applied to the entire sample), but the short-term debt over reserves ratio in terms of significance exceeded the 5% significance level. The rate of inflation, PMI and gas price changes remained statistically significant.

Multinomial Logistic Regression Model – Out-of-sample estimation until 2007Q1					
	Coefficient	Std. error	z	p-value	95% CI
Y=1					
Real GDP Growth Rate	0.219	0.164	1.34	0.181	[-0.102127, 0.5403272]
Gas Price	0.09	0.039	2.29	0.022*	[0.0131434, 0.1672852]
Inflation rate %	-0.846	0.416	-2.03	0.042*	[-1.661364, -0.0308274]
Credit t.Private sector/GDP	0.24	0.121	1.99	0.046*	[0.0038492, 0.4767282]
Sht. debt / total reserves	3.064	4.618	0.66	0.507	[-5.987294, 12.11622]
Vis.Trade.B./GDP	-367.646	102.27	-3.59	0.000***	[-568.091, -167.2002]
Pandemic Misery Index	-10.976	22.791	-0.48	0.63	[-55.64556, 33.69381]
REER Overvaluation	-72.288	16.963	-4.26	0.000***	[-105.5337, -39.04178]
Gov. Surpl. Deficit	-6.133	10.388	-0.59	0.555	[-26.49424, 14.22793]
Intercept (_cons)	-20.403	7.039	-2.90	0.004	[-34.19858, -6.608069]
Y=2					
Real GDP Growth Rate	0.149	0.217	0.69	0.492	[-0.2762556, 0.5747206]
Gas Price	0.356	0.215	1.66	0.098	[-0.0651835, 0.7765881]
Inflation rate %	3.06	3.128	0.98	0.328	[-3.070402, 9.190878]

Credit t.Private sector/GDP	0.209	0.15	1.39	0.164	[-0.0851114, 0.5024332]
Sht. debt / total reserves	28.1	18.226	1.54	0.123	[-7.621905, 63.82161]
Vis.Trade.B./GDP	444.032	707.274	0.63	0.53	[-942.2003, 1830.264]
Pandemic Misery Index	122.161	60.685	2.01	0.044*	[3.220912, 241.1007]
REER Overvaluation	-66.681	47.579	-1.40	0.161	[-159.9338, 26.57232]
Gov. Surpl. Deficit	-19.416	18.206	-1.07	0.286	[-55.0996, 16.26688]
Intercept (_cons)	-48.203	17.89	-2.69	0.007	[-83.26574, -13.13931]
Prob > chi2					**0.0000**
N					55
Pseudo R^2					0.651
AIC					81.755
BIC					121.901
Wald chi2(18)					57.162
Log-Likelihood					-20.877407

Note: 1 observation completely determined. ** p<0.05; ** p<0.01; *** p<0.001*

Table 14: Out-of-sample output of the multinomial model

The multinomial out-of-sample estimated model presented by Table 14, is also statistically significant and the p-value is smaller than the 0.05 threshold. Regarding the individual significance of the predictors, there are three main changes perceived in the restricted sample output in contrast to the output of the benchmark model.

The independent significance of the visible trade balance variable exceeded the 5% significance threshold in the restricted sample model in the pre-crisis state (Y=1). Similarly, during pre-crisis states (Y=1) the PMI ratio (which before 2020 only consists of the unemployment rate) is not deemed significant in the restricted model, although it was a highly significant predictor in the unrestricted model. This could imply that this predictor did not have a significant influence in inciting the upcoming crisis event in 2007-2008. In contrast, it became more impactful in the periods after the great financial depression and especially in the last two years of the benchmark model (presented in section 4.2), when it also provides information about the general health of society and economy. Lastly, the government balance ratio is not a significant predictor anymore in the restricted out-of-sample model. During the crisis and recovery states (Y=2) the statistical significance of the predictors was reduced, leaving only PMI as a statistically significant independent variable.

In conclusion, the cause and effect and the individual importance of certain variables may vary across crisis scenarios and time. While the 2007-2008 crisis was signaled by and more dependent on short-term debt ratio according to the restricted out-of-sample binary model, which relates to illiquidity problems, and also the visible trade balance ratio (according to the restricted out-of-sample multinomial model), which refers to the competitiveness of the economies. The results of the full sample benchmark model suggest the importance of the government balance ratio and the PMI, however, the importance of the constantly significant variables should not be overlooked. The three variables which are non-changing in terms of not exceeding the 5% significance threshold are the change in gas price, inflation rate and the variable forecasting the overheating of and excessive lending in economies, the credit to private sector index.

Most importantly, the out-of-sample estimations signal the upcoming crisis in 2007 and 2008. The binary model has partial success, as for Poland (Country 2) the signal came too early at the end of 2004 and the beginning of 2005. The multinomial model however signals the great depression for both countries.

4.6.2. Full sample out-of-sample estimations

Out-of-sample estimations were executed on the full sample as well. Both, the binary and multinomial models were set up as in sections 3, 4.1 and 4.2. Based on the benchmark models, the entire sample was forecasted and estimated for the same sample period, in a "pseudo out-of-sample" model. The actual forecasting for the four quarters of 2022 is presented in section 4.6.3.

The benchmark for interpreting the performances of the pseudo out-of-sample estimated models are the original models, i.e. the country-specific features are included in the benchmark models, for example how long the recovery period lasts for one country.

Tables 15-18 summarize the results, which are inferior to the original in-sample measured performances. However, the overall efficiency of the models come very close to the original ones. The binary model performs better than the multinomial in this case. The rather high proportion of false alarms confirms the decision maker's risk aversion described in section 4.5, assuming the inherent cost of false signals and that preventive measures are more affordable than an unsignaled, unexpected deepening recession. As a consequence, 50% of the crisis periods were predicted by both models, which remain sufficiently high. Each of the pseudo out-of-sample models signalled the crisis correctly in 2007-2008 and also had a positive signal for the last few quarters of 2021.

	No crisis (Y=0)	Crisis (Y=1)
Signaled crisis (S=1)	17 [B]	12 [A]
No signal of crisis (S=0)	129 [D]	14 [C]
Total	146	26

Table 15: Out-of-sample performance of the binomial estimated model

Observations called correctly (=overall efficiency):	81.98%
Crises called correctly:	46.15%

Proportion of false alarms out of total alarms:	58.62%
The probability of crisis given **no** alarm:	9.79%
The probability of **crisis** given an alarm:	41.38%

Table 16: Out-of-sample binary model performance rates

	No crisis (Y=0)	Crisis (Y=1)	Post-crisis (Y=2)
Signaled crisis (S=1)	31 [B]	13 [A]	13
No signal of crisis (S=0)	107 [D]	8 [C]	1
Total	138	21	14

Table 17: Out-of-sample performance of the multinomial estimated model

Observations called correctly (=overall efficiency):	75.47%
Crises called correctly:	61.9%
Proportion of false alarms out of total alarms:	70.45%
The probability of crisis given **no** alarm:	4.28%
The probability of **crisis** given an alarm:	29.54%

Table 18: Out-of-sample multinomial model performance rates

4.6.3. Forecasting with ARIMA

Finally, the quarters of 2022 were forecasted by using Auto regressive integrated moving average (ARIMA) models on the entire sample. Sahai et al. (2020) used ARIMA modeling to forecast the severity and spread of COVID-19 in the top five most affected countries in that time period. Their approach was successful in terms of significant predictions and guiding governments to improve health care.

The Box-Jenkins (1994) analysis determines a valid model considering the autocorrelation of the sample. In the model selection process it is necessary to identify whether the sample is stationary by default in order to apply the further steps of the analysis. A stationary series is advantageous because the series will be described in future periods (as well as current and past periods) by its variance and mean, the statistical characteristics of the series will not change significantly (NCSS LLC., 2022).

An ARIMA model consists of the autoregressive function and the partial autocorrelation function (moving average terms), which Stata requires to determine the parameters of, in order to fit the model (Stata Inc., 2022, NCSS LLC., 2022).

The three consecutive steps to fit the models are (NCSS LLC.,2022):

- The identification and characterization of the data, determination of stationary characteristics. Estimate the values for the p, d, q terms included in the ARIMA model, where p is the partial autocorrelation term (order of autoregressive components), d is the parameter for the differentiation of independent variables and q is the autocorrelation term (order of moving average components).
- Run the identified models, collect features.
- Run diagnostics.

The ARIMA models were estimated for country 1 and 2, as Stata commands do not support the pooling of the same time periods with multiple values. This also allows to capture country-wise specific information and tailor the chosen ARIMA model accordingly.

Figures 8-9 and Figures 10-11 in Appendix 2 summarize the partial autocorrelation plots (PACF) and the (moving average) autocorrelation function (ACF) for the two countries, respectively. From the autocorrelation graphs, the parameter q=2 (which is the estimation for the autocorrelation function) for Hungary and Poland was inferred. The partial autocorrelation parameters were more difficult to interpret, as there is an increased number of outliers exceeding the 95% confidence band. The p parameters are presented in Table 19 for Hungary and Table 20 for Poland (with the structure of ARIMA(p, d, q)).

The stationary characteristic of the data was evaluated with the augmented Dickey-Fuller test and Phillips-Perron test. The H_0 hypothesis of these tests is that the dependent variable has a unit root. The presence of a unit root or a so-called stochastic or deterministic trend suggests that a time-series data is non-stationary (Rajbhandari, 2016). Since for both countries both tests produced the same outcome, the null hypotheses were rejected, i.e. the dataset is stationary.

Criteria	Model 1 ARIMA(4,0,2)	Model 2 ARIMA(6,0,2)	Model 3 ARIMA(7,0,2)	Which is better?
Significant components	2/7	3/9	2/10	2
SigmaSQ	0.2706949	0.2690212	0.2688622	3
Log likelihood	-11.20769	-10.72349	-10.68062	3
Akaike	38.41538	41.44698	43.36125	1
Bayesian	58.14264	66.10607	70.48624	1
Df	8	10	11	-
Chosen model:				**1**

Table 19: Choosing the appropriate ARIMA model for forecasting (Hungary)

Criteria	Model 1 ARIMA(5,0,2)	Model 2 ARIMA(6,0,2)	Model 3 ARIMA(7,0,2)	Model 4 ARIMA(8,0,1)	Which is better?
Significant components	4/8	2/9	1/10	3/10	1
SigmaSQ	0.2585519	0.2670625	0.2674933	0.263693	1

Log likelihood	-8.996338	-9.682812	-9.728322	-8.623894	4
Akaike	33.99268	39.36562	41.45664	39.24779	1
Bayesian	53.71994	64.0247	68.58163	66.37278	1
Df	8	10	11	11	-
Chosen model:					**1**

Table 20: Choosing the appropriate ARIMA model for forecasting (Poland)

In Tables 19-20 three models were evaluated for Hungary and four potential models for Poland. The choice from the alternative models was more obvious for Poland. For Hungary model 1 was chosen, because of the higher ratio of significant components in the model.

Diagnostic tests were carried out on the chosen models. The Portmanteau test for white noise was used to scan the residuals and determine whether these values are only white noise, which is the preferred outcome. If the residuals are white noise, the fitting of the model is sufficient and it implies that no important signals were missed by the fitted model (MathWorks Inc., 2022). The H_0 of the Portmanteau test is that the residuals are white noise. With p-values of 0.939 for Hungary and 0.5613 for Poland, the H_0 could not be rejected.

The second diagnostic test was the root test of the model components for AR (autoregressive) and MA (moving average) roots. Figures 12-13 in Appendix 2 show that no components are out of the boundary, the test concludes that all eigenvalues lie inside the unit circle (model stability condition) and that the models satisfy the invertibility condition, which are both necessary for a successful ARIMA model to be used for forecasting. The model stability condition addresses the autoregressive components (AR) of the time series model, while the invertibility condition addresses the moving average (MA) components. The condition of stability provides that the time series data is weakly stationary (stable) and that it has infinitely many representations of moving average components. The condition of invertibility provides that the time series data has infinitely many autoregressive representations. The invertibility condition ensures that the current values of the model are dependent on their past values (Pelgrin, 2012).

ARIMA models constructed this way were used for forecasting the next four quarters in the sample. The model sends signals of crises for Hungary in the periods 2021Q4, 2022Q1 and 2022Q2. For Poland the results are similar, the signal starts in 2022Q1 and continues in the following two quarters, 2022Q2 and 2022Q3.

4.7. Discussion of results

Section 3.4 contains the defined research questions, the null hypothesis and expectations. The H_0 hypothesis is:

- There is no statistically significant (with a 95% confidence or 5% $=\underline{\alpha}$) relationship between chosen macroeconomic indicators (independent variables) and the occurrence of currency crisis periods in the applied EWS models. The sample estimates (beta coefficients) are not significantly different from zero. Therefore, the model cannot capture or explain the effects and impacts during and after currency crisis scenarios.

According to the presented model outputs in sections 4.1-4.6, the H_0 hypothesis must be rejected for each of the two models, binary and multinomial one. This reflects that the independent variables described in section 3 are appropriate tools for understanding crises and the connection of crisis probability with the macroeconomic variables and indexes of:

- real GDP growth rate,
- change of gas price,
- rate of inflation,
- credit to private sector from domestic banks,
- short-term debt over total reserves,
- visible trade balance (in %GDP),
- Pandemic Misery Index,
- overvaluation of the real effective exchange rate,
- government surplus and deficit.

This implies the validity of the models based on macroeconomic input and in some aspects the similarities between the recent recession periods and that in 2007-08. The alternative hypothesis (H_1) can be accepted:

- The discrete-dependent-variable logit EWS model can appropriately describe the underlying relationships in tranquil and crisis-struck periods as well (capturing the underlying economic forces), the beta coefficients are significantly different from zero.

The models can capture the effects and impacts during and after currency crisis events, especially with regards to the global pandemic induced recession.

Expectations were formulated in section 3.4, which are evaluated according to the findings:

- There was at least one crisis signal detected in the data after 2019 and crisis was predicted for the quarters of 2022 for both countries.
- The out-of-sample estimations signaled crises appropriately. However, in the binary model, the great financial crisis signal was called too early for Poland at the end of 2004 and beginning of 2005.
- The estimated beta coefficient of the Pandemic Misery Index is significantly different from zero for both benchmark models. The variable corresponds to and influences the dependent variable, the probability of a crisis event in both benchmark models, but not in the out-of-sample restricted models.

  This supports the PMI variable as an independent variable for the recent virus-induced economic shocks starting from 2020. PMI is an adequate independent variable for capturing the changes of the dependent variable in the applied framework and recent time periods.

5. Conclusions

This master thesis considered an Early Warning System (EWS) for the new market circumstances and the observed shortfalls of some macroeconomic indicators. The model was built on the framework of Bussiere and Fratzscher (2006) and further tailored for the perceptible, contemporary changes in economic factors, concluded on the sample of emerging markets that are a member state of the EU, Hungary and Poland. The presented models incorporated for example PMI as an independent variable, introduced by Jansen et al. (2020) to include the advancement and direct repercussions of the global COVID-19 pandemic. The list of independent variables also included real GDP growth rate, inflation rate, overvaluation of REER, change of gas price, and further economic indexes describing the economic well-being of the countries, such as credit to private sector from the domestic banks (describing lending booms), short-term debt over total reserves, visible trade balance and the government balance variable. The outcome of both applied models, binary and multinomial suggests that the H_0 hypothesis, which states that there is no statistical relationship between the probability of currency crisis periods and the stated independent variables, must be rejected.

The performance of the fitted models was measured against the Great Recession similarly to Foroni et al. (2020) when concluding the out-of-sample performances. The discrete dependent variable approach presented is successful in capturing the determined out-of-sample periods and also warns of crisis signals in the years 2020-2022, with the beginning in terms of quarter signals being country-specific. The presented methodology assumes a preference for false signals over missed signals, from the perspective of policy makers and their level of risk aversion.

One of the main findings of the models is that previously proposed EWS models may work effectively, given they are further expanded with relevant variables which capture the underlying economic effects describing a crisis (e.g. gas price changes and PMI).

The most important independent variables, remaining stable during the analysis of the entire sample, are the domestic credit to private sector index, inflation rate, gas price changes, and PMI. The multinomial model was able to differentiate between the effects and influence of the independent variables in the pre-crisis and post-crisis/recovery states, which the binary model failed to do due to its design. Comparing the two types of models in the post-crisis recovery period short-term debt over total reserves ratio and the visible trade balance ratio were significant, unlike the government balance and overvaluation variables in the pre-crisis state.

Another finding of the concluded analysis is that in the out-of-sample periods the PMI variable, which was specifically designed for the current recession after/during the global pandemic, could not explain the dependent variable during the Great Recession. This indicates that the formulation of the variable uniquely explains some of the underlying macroeconomic effects in the observed recent recession periods.

To summarize, the presented models are promising in forecasting and explaining the current and upcoming economic downturns. By providing the marginal effects of the indicators (along with the output describing relationships of the dependent and independent variables), such analyses may help leaders and governments to recognize underlying economic relationships and minimize the aftereffect of similar kind of shocks in the future, and possibly accelerate the recovery after such downturns. For future analysis, the pool of countries may be further developed to depict regional connections, effects, and also further observable indicators may be added to the list of independent variables, providing information about the upcoming changes and states in the economies.

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APPENDIX 1

In this appendix the origin of the variables and dataset components are described in detail, indicating the sources of certain data inputs. To find the economic reasoning and the general setup of the model framework applied, see Chapter 3.

The concepts and definitions stated below are used for both countries to represent the same statistical and economical intuitions and facts. To further ensure this, the source of all of the stated economical concepts and variables were the same for Hungary and Poland, thereby making sure that no misinterpretations were made. The dataset contains data for the two mentioned countries from 2000Q1 until 2021Q4.

Data used for calculating the EMP country-wise indicators consist of the real effective exchange rate, short-term interest rates (central bank rates), and foreign exchange reserve (no gold included). For the calculation of Pandemic Misery Index (PMI) measurements, the total population and confirmed COVID-19 deaths data were used.

Real effective exchange rate

The effective exchange rates are a measure of the changes in the exchange rates of a specific country and its trading partners. The series takes into consideration also the relative price levels (in this case using consumer prices, CPI), along with the market exchange rates. As a result, the competitiveness of countries is also indirectly included. A rise in the real effective exchange rate value refers to the deterioration in the competitiveness of the country. Therefore, as was referred to previously, the real effective exchange rate is also used to determine and identify the short-run capacity, economic „well-being" of a country (OECD, 2016, 2022). Data were available for both countries on monthly basis and were transformed into quarterly data using averaging.

According to the definitions of the OECD (Main Economic Indicators), the source of the data, the real effective exchange rates is: „the change in a country's index of relative consumer prices between two years is obtained by comparing the change in the country's consumer price index (converted into US dollars at market exchange rates) to a weighted average of changes in its competitor's consumer price indices (also expressed in US dollars), using the weighting matrix for the current years (based on the importance of bilateral trade)" (OECD, 2022).

Central bank policy rate

The central bank policy rate is used as a weighted component to define EMP. It is a proxy for a short-term interest rate, through this rate the central bank signals its monetary policy. The source for both countries included in the dataset is the International Financial Statistics (IFS) database provided by the International Monetary Fund (IMF). According to the IMF from December 2001, the raw data are backed and sourced by the Bank of International Settlements (BIS).

In case of Hungary, the data reflect the official base rate (IMF, 2022a). In case of Poland, the data reflect the official reference rate to set the minimum yield which is obtainable by basic 7-day market transactions, influencing the short-term deposit rates in the interbank deposit market (IMF, 2022a, 2022b).

Foreign exchange reserve excluding gold

The source of the data for reserves of foreign exchange (excluding gold holdings) was extracted from the database of the International Financial Statistics (IFS) database of the IMF. The total reserves line excluding gold is defined as the sum of the respective items held by monetary authorities: foreign exchange, reserve positions in the fund, US dollar value of SDR (special drawing rights) holdings. The claims of monetary authorities on non-residents in the form of various securities and assets are also included, therefore according to the IMF (2022a, 2022b) the following items are also considered: foreign banknotes, bank deposits, treasury bills, short- and long-term government securities, also any other claim which could be used in the need of balance of payments. As mentioned previously, the data of foreign exchange reserves were used as the third component in determining and creating the EMP country-wise levels. Data were extracted in USD currency for both countries.

Total reserves including gold

The international liquidity data, more precisely, the total reserves including gold were queried from the IFS, the database of the IMF. The total reserves line excluding gold is defined as the sum of the respective items held by monetary authorities (such as central banks, currency boards, exchange stabilization funds, and treasuries, all to their respective extent of performing functions of monetary authorities): foreign exchange, reserve positions in the fund, US dollar value of SDR (special drawing rights) holdings. The official gold holdings (national valuation, in US dollars) were added to the total reserves excluding gold database line. Data were extracted in USD currency for both countries (IMF, 2022a, 2022b).

Real GDP and nominal GDP

The GDP quarterly levels for the countries were extracted from the IFS database. According to the source, GDP is defined as: "(…) the sum of the consumption expenditure (of households, NPISHs and general government), gross fixed capital formation, changes in inventories, and exports of goods and services, less the value of imports of goods and services. If available, the statistical discrepancy must be added to the components to equal GDP." In the case of Hungary, the data were compiled in line with the 2010 ESA methodology, as reported by the IMF. The data for Poland were compiled in accordance with 2010 ESA and 2008 SNA methodologies (IMF, 2022a, 2022b).

Inflation rate

The data for inflation rates have been obtained from the database of the OECD for Hungary and Poland. The database contains quarterly percentage rates, measured from the perspective of consumer price index, in order to include the general deterioration or improvement of the living standards in a given country. OECD (2022) defines its database element and index in the following way:

„Inflation measured by consumer price index (CPI) is defined as the change in the prices of a basket of goods and services that are typically purchased by specific groups of households. Inflation is measured in terms of the annual growth rate and in index, 2015 base year with a breakdown for food, energy and total excluding food and energy. Inflation measures the erosion of living standards. A consumer price index is estimated as a series of summary measures of the period-to-period proportional change in the prices of a fixed set of consumer goods and services of constant quantity and characteristics, acquired, used or paid for by the reference population."

Credit to the non-financial sector

The data have been collected directly from the Bank for International Settlements (BIS). The dataset includes credit that was provided by domestic banks to the private, non-financial sector. The private, non-financial sector comprises of non-financial corporations, households and non-profit organizations, institutes serving households (following the definition and methodology of 2008 SNA). The chosen data line for both countries includes the credit levels in percentage units of GDP (BIS, 2022). As mentioned previously, the credit to the non-financial sector index level indicates the credit levels delivered to non-financial members of the economies. It is an indicator of any lending booms or sudden fallbacks in credit lending.

Visible trade balance

The trade balance information has been extracted from Oxford Economics (2022) through the Refinitiv Eikon Datastream services. The last period of historical data is 2021Q3, the last quarter (2021Q4) values in the dataset are forecasted values. The metadata of the included, country-wise trade balance in USD currency, is defined as:

"the monetary value of country's exports less imports of goods, expressed in US dollars, at market exchange rate" (Oxford Economics, 2022).

General Government deficit and surplus (non-financial accounts for general government)

The information about the general governments' non-financial account, specifically the deficit and surplus quarterly data were extracted from the database of Eurostat. The final values of the net lending (+) / net borrowing (-) indicator have been used in the aggregated dataset. The deficit/surplus of the government (the final row of the indicator) is defined according to the ESA 2010 methodology, by the general government's net borrowing/net lending activity (therefore it indicates the difference between the revenue and the expenditure of the general government sector). The data were extracted in millions of EUR. The data are further explained by the metadata of the source:

"Public deficit/surplus is defined in the Maastricht Treaty as general government net borrowing/lending according to the European System of Accounts. The general government sector comprises central government, state government, local government, and social security funds." (EUROSTAT, 2022a, 2022b).

Current account balance

Data regarding each country's current account balance were compiled from the IFS database in millions of USD. The current account balance of payments captures the international trade transactions of a country. The line 'Current Account' in the source database is the sum of several elements: the balance on goods, balance on services, credit from the secondary income line, primary income lines, less the debit line from secondary income (IMF, 2022a).

Unemployment rates

The unemployment rate was extracted from the database of the OECD. The official definition and data characteristics are given by OECD (2022) as follows:

„The unemployed are people of working age who are without work, are available for work, and have taken specific steps to find work. The uniform application of this definition results in estimates of unemployment rates that are more internationally comparable than estimates based on national definitions of unemployment. This indicator is measured in numbers of unemployed people as a percentage of the labour force and it is seasonally adjusted. The labour force is defined as the total number of unemployed people plus those in employment. Data are based on labour force surveys (LFS)."

Gas price after carbon tax

The data for gas prices after carbon tax is expressed as a growth rate. Quarterly frequent data were extracted from the data table of 'International Sources' of Oxford Economics, through the service of Refinitiv Eikon Datastream. The last period of historical data is for 2021Q2, the upcoming, but also included two quarters are forecasted data (Oxford Economics, 2022).

Covid-19 deaths

The source of the data is Reuters, the dataset includes COVID-19 related weekly deaths in the two countries (Reuters, 2022). To transform it to quarterly data, the weekly deaths of a quarter's months have been summed up.

Total population

Total population (in thousands) data were extracted from the OECD 'Quarterly National Accounts' database, Population and Employment data rows. Data are seasonally adjusted (OECD, 2022).

Short-term debt of government

Data on short-term debt of the general government were obtained from Eurostat (2022) databases. Data are obtained quarterly, in millions of EUR. Short-term debt securities statistics are part of the quarterly government debt statistical data. The quarterly government debt statistical data pool follows the definitions of ESA 2010, also in defining the general government (consisting of central government, state government, local government and social security funds) (Eurostat, 2022c).

Historical exchange rates (spot rates)

The above-mentioned data rows were not obtainable in a single, uniform currency, therefore all data rows were exchanged to and expressed in EUR. For comparison and further transformations and analytic purposes performed on the dataset, these data lines were exchanged according to historical spot exchange rates. The exchange rate data were collected from FxTop company (fxtop.com). The database accessible via the website and the software uses official historical data published by the European Central Bank (ECB) since May 2000. Before that, rates were retrieved from the Dutch Central Bank, Deutsche Bundesbank, Bank of England, US federal reserve, World Bank, and Bank of Japan (FxTop, 2022).

APPENDIX 2

In this appendix Figures 8-13 are shown. The figures show the graphical representation of autocorrelation, partial autocorrelation and the test of stability and invertibility conditions, according to the ARIMA models described in section 4.6.3.

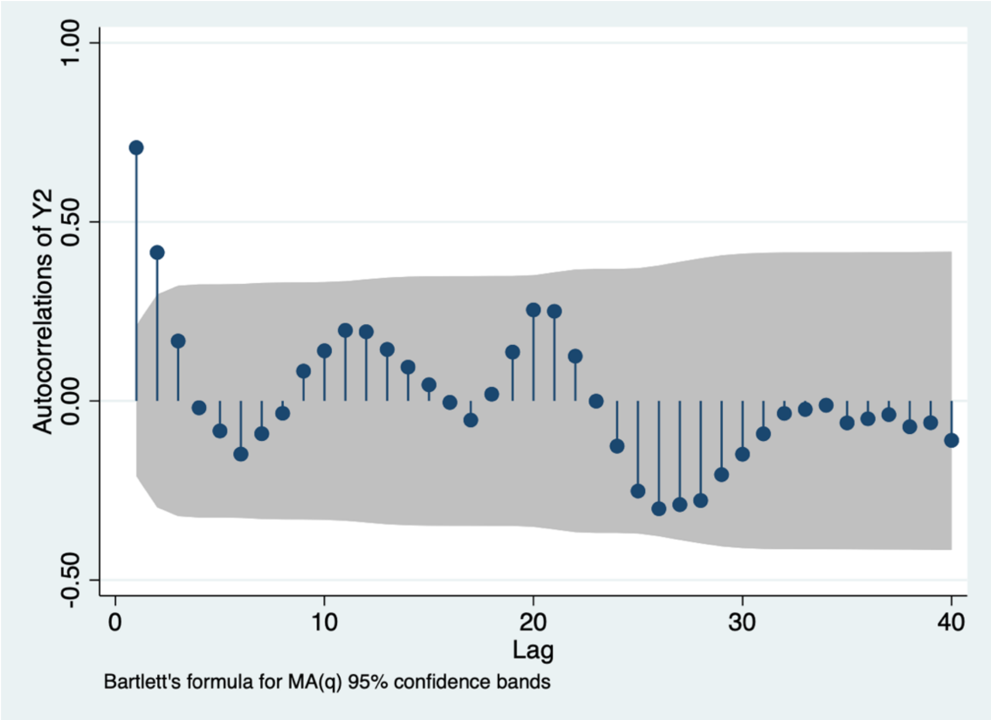

Figure 8: Autocorrelations of Y2 – Hungary

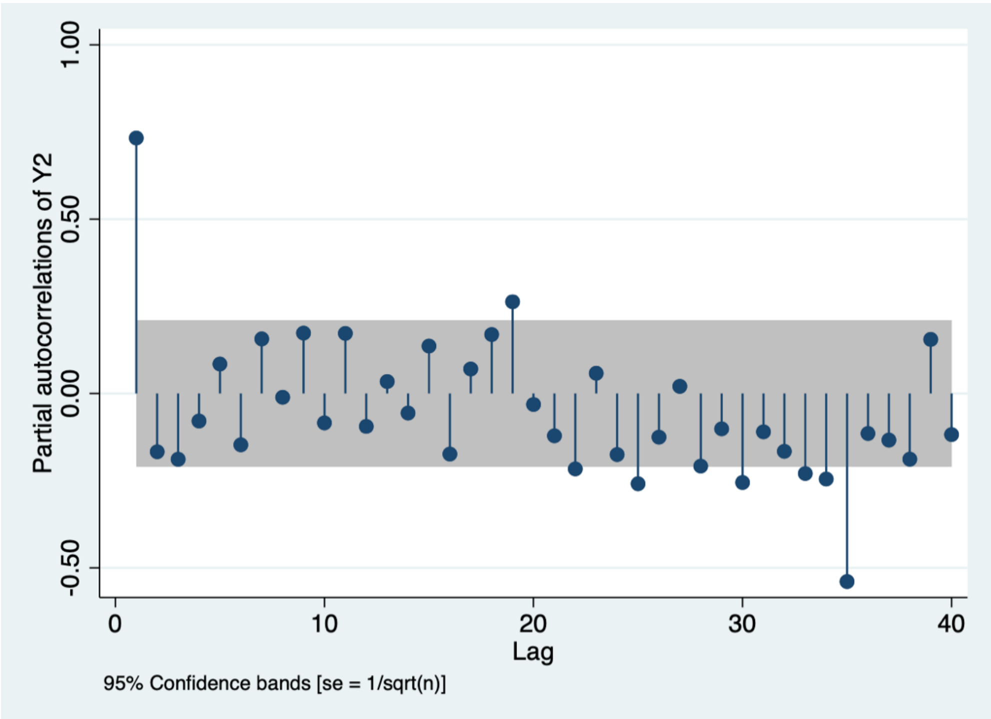

Figure 9: Partial autocorrelation of Y2 – Hungary

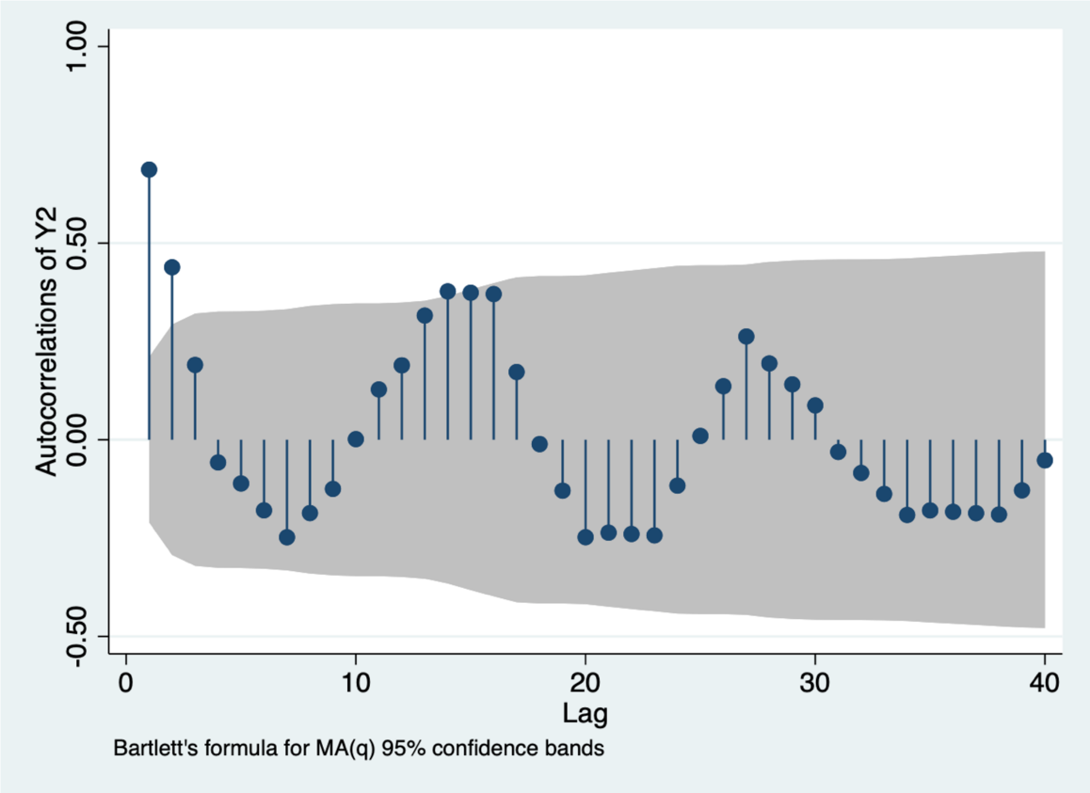

Figure 10: Autocorrelations of Y2 – Poland

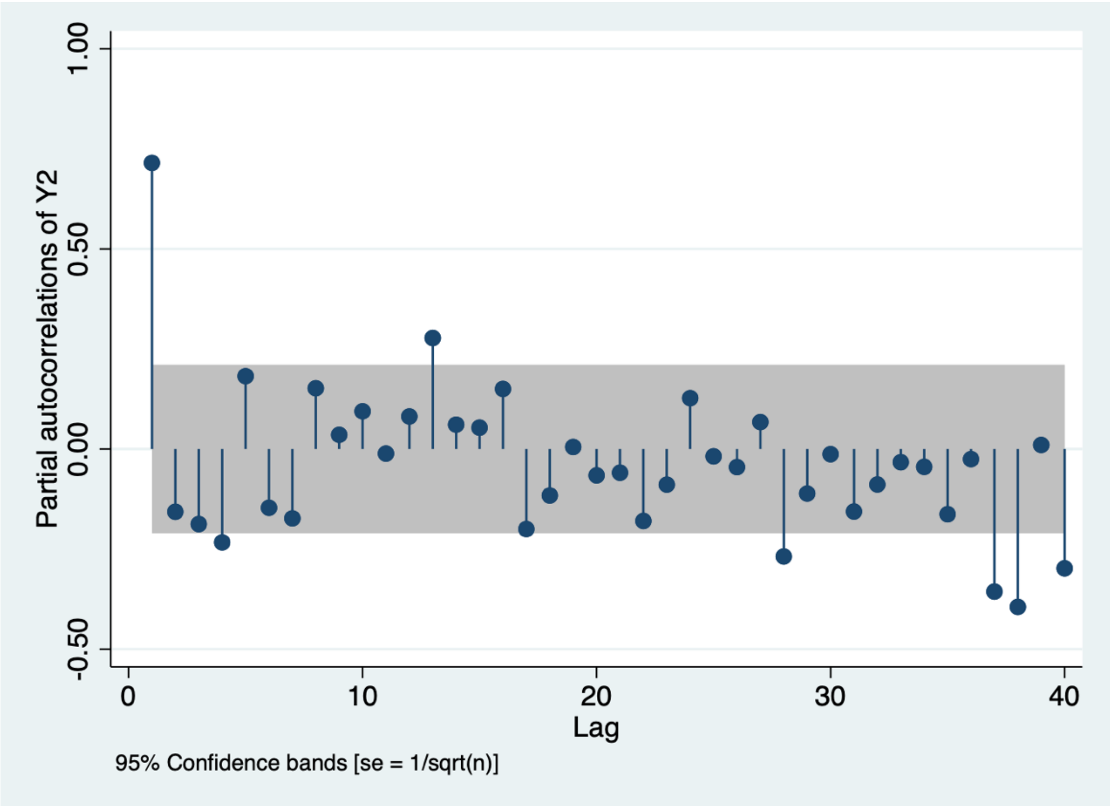

Figure 11: Partial autocorrelation of Y2 – Poland

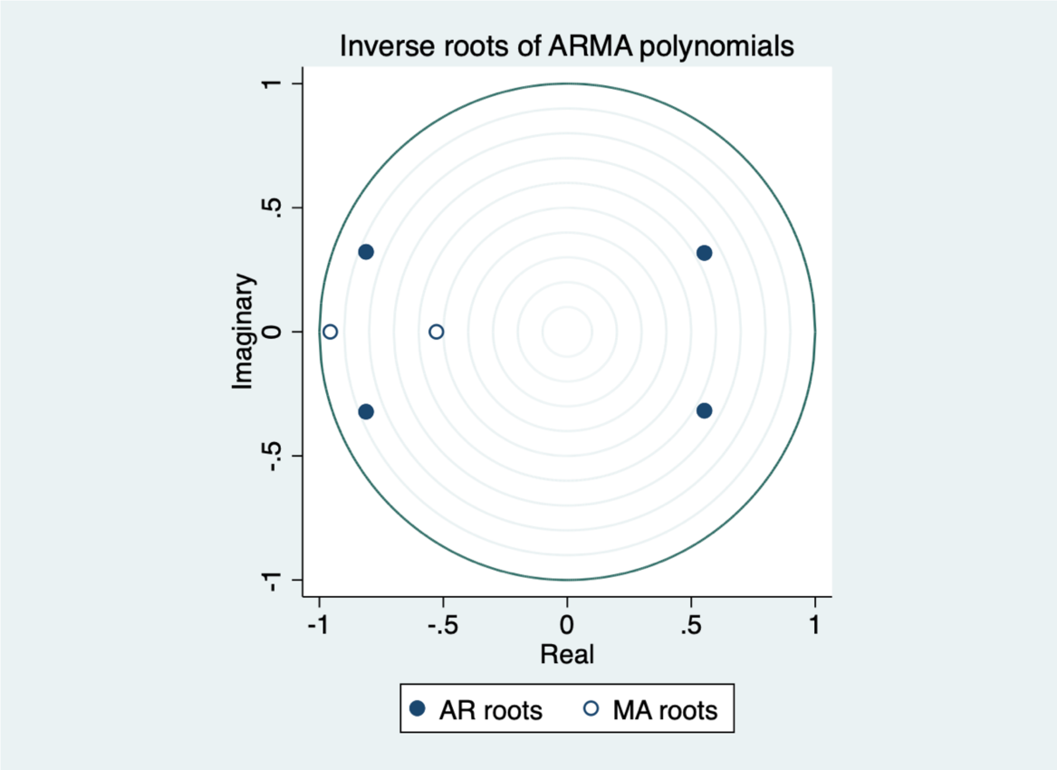

Figure 12: Test of stability and invertibility conditions – Hungary

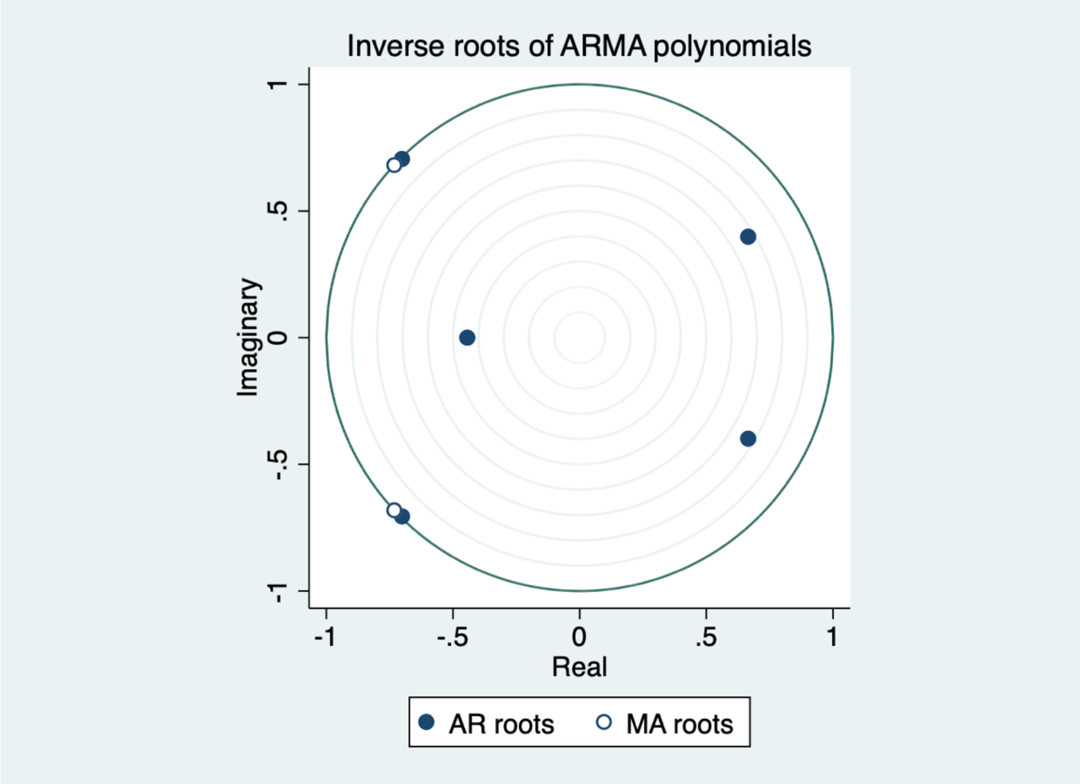

Figure 13: Test of stability and invertibility conditions – Poland

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Zusammenfassung

Die wirtschaftliche Situation und ökonomische Schocks aufgrund der globalen COVID-19-Pandemie seit Ende des Jahres 2019 stellen politische Entscheidungsträger und Marktteilnehmer vor viele neue Herausforderungen. Die aktuelle Masterarbeit betrachtet ein Frühwarnsystem (Early Warning System, EWS) für den kürzlich beobachteten Konjunkturabschwung. Ziel der Arbeit ist es festzustellen, ob EWS-Modelle, welche um Variablen erweitert werden, die die neuen Veränderungen im Marktumfeld und in der Weltwirtschaft beschreiben, Rezessionen und Krisen zuverlässig vorhersagen können. Mittels eines solchen statistischen Modells sollen die wesentlichen zugrunde liegenden Zusammenhänge erfasst werden. Das vorgestellte Modell versucht Variablen und Indikatoren, die eine entscheidende Rolle beim Signalisieren möglicher wirtschaftlicher Rezessionsperioden spielen, zu bestimmen. Die Ergebnisse der Masterarbeit legen nahe, dass die neuen Herausforderungen mit Hilfe der vorgestellten Modelle geprüft werden. Währungskrisen können mit bestehenden Frühwarnsystemen prognostiziert werden, indem das Modell um zusätzliche unabhängige Variablen wie dem Pandemic Misery Index (PMI) erweitert wird, die die gegenwärtigen markanten Veränderungen der makroökonomischen Indikatoren erfassen. Für die Quartale des Jahres 2022 generiert das Modell Signale für das Auftreten von Krisen.