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The Yield Curve as a Predictor of Business Cycle

Navn: Iryna Dadashova, Ivanna Demchuk

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Iryna Dadashova
Ivanna Demchuk

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Sven Klingler

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ABSTRACT

In the Master Thesis, we study the yield curve's predictability power for the business cycle in developing countries. For this research, we want to answer the question if the inverted yield curve can predict the recessions for emerging markets. We consider four countries: Greece, India, South Africa, and Ukraine. Based on the analysis of previous researches, we identify the advantages of different modelling and forecasting tools. We find that the interest rate spread is statistically significant for recession prediction based on OLS and probit modelling for mentioned above countries. The out-of-sample forecasting works better than in-sample for Greece and India, for Ukraine and Greece such performance is weaker. We conclude that the yield curve has partial power in predicting a recession in developing countries.

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List of Abbreviations

AUC	The area under the curve
COVID-19	Coronavirus disease of 2019
CPI	Consumer Price Index
EU	European Union
FDI	Foreign Direct Investment
FRED	Federal Reserve Economic Data
GDP	Gross Domestic Product
HAC	Heteroscedasticity and autocorrelation consistent
HCI	Huber-White-Hinkley heteroscedasticity consistent
LIBOR	London Inter-Bank Offered Rate
LR	Likelihood-ratio
MAD	Mean absolute deviation
MAPE	Mean absolute per cent error
MSE	Mean squared error
NBER	National Bureau of Economic Research
NBU	National Bank of Ukraine
NFIB	The National Federation of Independent Business
OECD	The Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
RMSE	Root Mean Square Error
ROC	Receiver Operating Characteristic
SVM	Support Vector Machine
US	United States

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List of Symbols

Δ	Change in economic indicators relative to the previous period
Φ	Cumulative distribution function of the standard normal distribution
α_0	Parameter for intercept
α_1	Parameter for slope
β_0	Parameter for intercept
$\beta_{1,2\ldots n}$	Parameter for slope
ε	Error term

1 Introduction and motivation

1.1 The academic and practical motivation

The yield curve power makes investors consider the probability of rapid changes in business cycles of the world economies. The most debated topic within business cycles arises from a yield curve inversion. This phenomenon is not investigated yet to make forecasts on how it influences other economic factors and movements in business. March 2019 marked the period when, for the first time since the Great Recession in 2007-2008, the yield curve began to have a negative slope in the United States of America (Moore, 2019). The next shift occurred in August 2019 signalising alarms for investors; after inverting investors expect that the economy would be worst in the future, therefore they put money on the line to bet that the expectations will be met (Drum, 2019; Leatherby & Greifeld, 2019). On February 2020, the 10-year US Treasury minus the 1-year US Treasury yield curve inverted. The question asked in recent articles is whether the inversion is caused by the risk perceived by the market regarding coronavirus (COVID-19) or the inherent risk of pending recession (LaBrecque, 2020).

Mostly, discussions arise from the controversial thoughts whether the inverted yield curve can predict the recession for the US. Moreover, the confidence to trust the US monetary policy is not evaluated as "appropriate," considering the yield curve behaviour (Davies, 2019).

In literature, we can find proof for the hypothesis of the yield curve prediction power for the recession par excellence in the US. In contrast, the existence of the yield curve inversion did not lead to a recession in France, Italy, and the UK (Estrella & Mishkin, 1996). The lack or low amount of studies on the yield curve as an indicator of economic development or recession in developing countries like Ukraine, Greece, South Africa, and India makes our research forward-looking. Besides, the next important part that we discover in the paper is whether all shifting of the yield curve downwards signals the harmful consequences for the economy.

The Asian signals of adverse economic conditions also took place in 2019, flattening the yield curve, and the yield curve inversion happened in China and

Singapore accordingly (Guy, 2019). Being the essential partners for the US and Australia, these countries provide worries for investors on how to manage this issue and for governments how to stimulate economic growth and solve the slowdown in international trade (Guy, 2019; Bloomberg, 2019a). The Japanese and Malaysian curves also experienced an inversion that put the price pressure (Bloomberg, 2019a). That is why the yield curve inversion can be considered as an essential factor for measuring the stage of business cycles.

The presence of opposing points of view indicates that the question of the yield curve is relevant and requires a detailed study. Moreover, such a phenomenon is not discussed broadly on other countries' examples that make research of yield curve actual and considerable nowadays. That is why, in this paper, we pay attention to noteworthy articles that discover the examined topic from the 20th to the 21st centuries.

1.2 Research problem and purpose

The research question leans on what the predictive power of the yield curve in developing countries is. Based on it, the zero hypotheses are that a yield curve has some power to predict changes in the business curve, while the alternative hypothesis is that we do not have evidence of yield curve prediction.

1.3 Contribution

In our research, to prove the power of the yield curve in predicting recessions in developing countries, we use two model techniques – binary and multiple regression modelling in order to check if one of them is more efficient and can be used for further researches. Moreover, here, we investigate the model by in-sample and out-of-sample forecasting.

Our research is valuable given the countries studied, as there are not enough scientific papers that show the impact of the interest rates spread on the economy in developing countries such as Greece, India, South Africa, and Ukraine. Another novelty here is that we include in the analysis the most recent period, that is 2000-2019, which include several recessions for each of the selected countries.

Due to the current COVID-19 crisis and analytics predictions of an upcoming recession, it is even more important to know what signals precede the crisis in emerging markets, which hardly suffer recessions and have long-period of the economy recovering.

1.4 Limitations of the study

We consider three limitations of the data access that can influence on the depth of our analysis. First, the data is obtained from various statistical resources as no one database could provide the necessary datasets altogether. Another limitation here is that different data portals use matchless methodologies. Moreover, they gather and present the data differently. Lastly, the available data for the desired variables mostly does not outline the period before 2000. That is why the simulation is limited by the period that can be analysed.

1.5 Structure of the study

The research paper has the following structure. In Section 2, we present an empirical investigation of the theory about yield curve prediction power based on the US and Non-US economies. In Section 3, we examine the main theoretical concepts about recession, its prediction, and yield curve together with the appropriate model techniques. Also, in this section, we develop the model hypothesis that we would check in the next sections and prove the evidence of recession in four developing countries that will be tested. In Section 4, we outline the data used, provide statistical sources of data mining, and represent the relationship between the data variables. Besides, we describe the forecasting method that we use for binary models. In Section 5, we go into the analysis of probit and OLS modelling and discuss the principal findings. In Section 6, we summarise the key results of this study and consider its value for further researches.

1.6 Summary and implications of the findings

In our research, we prove the partial predictive power of the yield curve for developing countries. We identify that the combination of OLS regression, probit modelling and the out-of-sample forecasting is the most effective modelling tools for the specific analysis. By using them, we check the significance of the yield curve predictability separately for each country. For OLS modelling, only India and South Africa passed all adequacy tests, and by probit modelling, Greece and India got the best results in model sufficiency and forecasting.

All our findings may be used by potential investors of those developing economies to make an effective investment decision, by governments, and National Banks of those countries to develop new models for business cycle forecasting and by next researches, who can use this analysis as an example for the cases of other countries.

2 Prior Literature

2.1 Empirical research on the yield curve as a predictor of the recession

The question of the ability of the yield curve to predict recessions and forecast economic changes is raised in scientific researches for many years. Before starting new research, it is necessary to review previous studies and analyse the main obtained results. We perform a literature review in chronological order to determine historical changes in scientist opinions under the influence of various events, including the time before and after financial crises.

One of the first work about the yield curve as a predictor of real economic activity is written by Estrella and Hardouvels (1991). Their analysis presents evidence that the slope of the yield curve can predict for up to 4 years for cumulative and up to a one year and a half for marginal changes in real output. Then so, the positive slope of the yield curve predicts the future increase in real economic activity.

Later on, Estrella and Mishkin (1996) focus on the ability of the yield curve to forecast recessions rather than on their success in quantitative measures of future economic activity. Also, the authors discuss the out-of-sample performance. The paper shows a probit model with the data set of the yield spread between ten-year Treasury note and the three-month Treasury note from the first quarter of 1960 to the first quarter of 1995. According to the results, the yield curve spread can forecast recessions six quarters. Then so, authors perform the same model for France, Germany, Italy, and the United Kingdom. For the United Kingdom and Germany, results are excellent, and forecasts are accurate. The results for Italy and France much weaker, which can be explained by the fewer differences between probabilities in recession and non-recession period for those countries.

In their review, Haubrich and Dombrosky (1996) analyse the ability of a yield curve to predict a recession and future economic activity. An eclectic approach, which they use, differs from other studies in how economists judge the forecast results. Authors use out-of-sample forecasts with extended data set to the mid-1990s. Also, they consider not only how the curve can predict the probability of recession, but also its severity. The model shows GDP growth (dependent variable) prediction four-quarter into the future based on the current yield spread (independent variable). The initial study result is that the 10-year and the three-month Spread has substantial predictive power. In the review, the authors mention that for further studies, it would be interesting to check if a rolling regression model or more lags could improve the performance of the yield curve.

The next considered paper is written by Chauvet and Potter (2005). This study examines the predictability of the yield curve for the US recessions with the use of the four different specifications of the probit model: time-invariant conditionally independent version, a business cycle-specific conditionally independent model, a time-invariant probit with autocorrelated errors, and business cycle-specific probit with autocorrelated errors. Authors propose the analysis of out-of-sample forecasting performance using standard and hitting probabilities of the recession, which consider the length of the business cycle stages. The main finding is that the standard specification probit model can predict slowdowns and recessions. Nevertheless, it is unknown if the slowdown will turn into a recession and, thus, what the model is precisely signalling in real-time. Then so, more sophisticated models of the yield curve are processing information and uncertainty more efficiently because they consider the business cycle information, such as duration, phases, and changes concerning the yield curve.

The next study is answering the question of why the yield curve tends to invert before the recession. In this paper, Cwik (2005) uses the capital-based macroeconomic approach to analyse the correlation that exists between the yield curve's spread and economic outputs and to trace out the effect of injection of short-term working capital into the model. Paper also discusses the Wicksell and Fisher effects, which entails downward and upward pressure on interest rates, respectively. The main finding is that credit crunch, which is one of the forms of liquidation of the malinvestments in the social structure of production, culminates in an inverted yield curve one year before the recession.

In their paper, Estrella and Trubin (2006) offer practical guidelines on how to construct the yield curve indicator and how to interpret the measure. They build the probability model with the term spread as input and probability of a recession occurring in the future as output. Among the main findings are that the treasury rates most likely to produce precise forecasts. Also, what is necessary for the methodology part, the best maturity combination is three months and ten years, while the three-months rate is best represented by the secondary market rate, and a ten-year constant maturity rate produces excellent results.

Papadimitriou, Gogas, Matthaiou, and Chresanthidou (2011), in their paper, use Machine Learning Framework to investigate the forecasting ability of the yield curve in terms of the US real GDP cycle. The purpose of the study is to create a forecast for future economic activity using yield curve data and Support Vector Machine (SVM) classifier. The result shows the overall forecasting accuracy of 66.7% and a 100% accuracy in forecasting recessions. The importance of results is in the implementation of fiscal and monetary policies that can prevent identified negative trends, and government institutions can react adequately to reduce or avoid them. There are some disadvantages of the model. For instance, the model shows some false alarms in the case of below-trend output.

The next their study in 2015 shows two forecasting methodologies: the probit model, which is commonly used in literature and the SVM, from their prior research. Based on the empirical results, both methodologies can show 100% out-of-sample forecasting accuracy for recessions and overall accuracy of 80% in the case of the best SVM model. This performance again shows the evidence that the yield curve can be used as a factor for forecasting future economic activity.

C.R. Proano and T. Theopald (2014) use alternative dynamic probit models for US and German economies. The authors' composite model seems to outperform existing approaches among the class of econometrics models, such as Estrella and Mishkin (1996). The advantage of this approach is in the use of both the real economy and financial market repressors and in the flexible lag structure, which results from the automated general-to-specific and specific-to-general lag selection procedure and the combination of various forecasting models.

Gebka and Wohar (2018) introduce a new approach which is aim to utilise yield curve's predictive ability for the whole distribution of the future GDP's growth, rather than predicting the centre of this distribution. Among the main findings is that the yield spread has higher predictability for lower quantiles of future growth.

2.2 Yield curve predictability for Non-US economies

After an in-depth look into the ability of the yield curve to predict the recessions in the US, the scientist starts to test the predictability of the yield curve not only on US data but for other countries. Mehl (2006) investigates how the slope of the yield curve predicts the growth in emerging economies. The study uses a sample of 14 emerging economies, such as India, Brazil, Mexico, and Poland. The author suggests that differences across emerging economies are linked to market liquidity. The analysis shows the following: for half of the countries in the sample for inflation US and Euro area slope of the yield curve could better predict than these economies' domestic slope. The same is true for two-third of the countries in the sample for growth.

A more in-depth look at predictability power of yield curve for emerging markets can be seen in Anand and Singh's (2011) paper on Indian market example. However, for this case, the yield curve demonstrates itself as a weak indicator of recession. The domestic yield curve there inverted after the spillover effect of the US downturn had reached India.

One more example among developing countries is the South African yield curve predictability describing in Clay and Keeton (2011) paper. The authors describe two methods to predict future turning points in the business cycle. The first one is the estimation of future GDP's levels using multi-variable regression using historical GDP's and leading economic indices growth rates and the yield spread 3-months' treasury bills and 10-year and over government bonds. The second method is estimating a non-linear probit model, which is already used by Estrella and Mishkin (1996). The main findings of the paper are that the yield curve success in predicting downswing in South Africa, and it can forecast up to 18 months ahead.

In their paper, Gooptu, Chettopadhyay, Varghese, and Lai (2015) explain the relationship between the yield curve and its ability to predict recessions in the US and other countries. For non-US economies, authors do not observe inversion in the yield curve, which was noticeв in the US before the recession. Thus, they conclude that the predictive power is weaker for those countries. Since the bond market is under-developed further empirical analysis is needed to assess the benefits of the yield curve for those countries.

One more study of the yield curve predictability power across counties and time is written by Chinn and Kucko (2015). They use a large time sample from 1970 to 2013 for Canada, France, Italy, Japan, the Netherlands, Sweden, the United Kingdom, and the United States. In contrast to previous studies, their measure of economic activity is industrial production, which has advantages of timeliness and reliability. Also, the data set for industrial production are reported monthly. Yield spread data is constructed as in previous research from ten-year and three-month government bond rates. The results for in-sample forecasting is that the yield spread has significant predictive power for the one-year horizon, while for the our-of-sample prediction shows good result only for the US, Germany, and Canada.

Hvozdenska (2015) analyses predictability for the Nordic countries: Denmark, Finland, Iceland, Norway, and Sweden. The results show that 10-year and 3-month yield spread has predictive power to real GDP growth after the financial crisis. These findings can be used by investors and provide further evidence of the potential usefulness of the yield curve spreads. Also, the study shows that the best predictive lags of spreads are lags of four and five quarters to get the best results for predictive models. Moreover, the behaviour of the models changed during and after the financial crisis.

Summary of part 2

A review of the literature helps to outline which methods are most likely to be used for future research and which models are most relevant to apply, such as probit model. Also, the articles show opposing views on the availability of the yield curve to predict a recession, which is exceedingly doubtful for developing countries. Therefore, the topic remains relevant for further research.

In the covered above articles, there is no research on Greece and Ukraine as examples of emerging markets in Europe, both with recession and crisis in 2009 and 2014, respectively. Then so, the current research will show there is evidence of yield curve's prediction power for these countries.

3 Theory and hypotheses

3.1 Concept of Recession

Recession concepts can be explained through the phenomenon of the economic business cycle. In general, the business cycle consists of expansions, followed by recessions, contraction, and revivals, which lead to the expansion of the next cycle (NBER, 2001). Expansion and recession have a boundary, which manifests in the form of a peak; that is, this peak is a conditional end of the expansion and the beginning of a recession in the business cycle (NBER, 2001). The recession does not have an official definition. Still, it is commonly describing as a period of decline in economic activity (Claessens & Kose, 2009). Alternatively, it is a downward swing of the business cycle. However, the falls which do not exceed two consecutive quarters are not defined as a recession.

The National Bureau of Economic Research provides one more common definition, and a recession occurs if there is a considerable decline in activity spread across the economy, lasting more than a few months, visible in industrial production, GDP growth, employment, real income, and wholesale-retail trade (NBER, 2001). This definition is explicit since NBER identifies variable which can show the change in economy and business cycle. The only obstacle here is that definition does not explain if all parameters decline should be observable at the same time or if the presence of one signifies a recession (Mazurek, 2012). Therefore, Mazurek (2012) proposes NBER definition in a way that occurrence of decline in real GDP growth or/and in industrial production or/and in personal income or/and in unemployment or/and in wholesale-retail trademark signify a recession.

Even though the NBER definition is criticised because of the usage of two quarters for downturn interpretation, it is still considered as an accurate one (Gaski, 2012). In further research, to describe recession in more quantitative measures, we consider a recession as an economic activity decline for two and more quarters and use adapted definition of a recession.

3.2 Recession indicators

Most analysts focus on GDP decline as a recession predictor. For instance, Mazurek (2012) defines a downturn in the economy as GDP per capita decline. This downturn can be explained in more detail by the example of the quarterly change in real GDP (ΔGDP) and quarterly change of population (ΔPop) in the same period. If the difference between quarterly ΔGDP and ΔPop is negative for at least two quarters, it may signal a recession (Mazurek, 2012).

Instead of real GDP growth, Lebanon (2011) focuses attention on the unemployment rate to define economic slowdown as this indicator declines when unemployment declines or when employing rate growths slower than the labour force.

Researching the Great Recession Ng and Wright (2013) find that usage of term spreads can help predict further economic activity while credit spreads may fare way better. Estimating the recession probability Levanon (2011) uses another methodology by grouping different criteria into the labour market, economic activity, and sentiment indicators and supposes that the labour market group produces the most reliable results for recession forecasts. Such group includes total non-farm employment, claims for unemployment, part-time working people number, the difference between personal income and transfer payment indicator, and an unemployment rate that often found in other studies (Levanon, 2011).

Among other indicators that are used for modelling are personal consumption expenditure, change in building permits, NFIB optimism index, 3month LIBOR – Treasure Spread, and change in the S&P 500 index that are rarely used for recession studies (Levanon, 2011). Another economic indicator – inflation that mostly used in the form of a consumer price index, was not investigated as a predictor of recession. The tricky point in using it is that low inflation may signal about low demand for products and services that consequently lead to unemployment and, in turn, to a recession. At the same time, too high inflation can cause the same results (Ferrell, 2019).

3.3 Yield Curve

By the formal definition, a yield curve is a line that shows interest rates of bonds that have the same credit quality but different maturity (Chen, 2020). Also, it can be defined as a term structure of interest rates (Mishkin, 1990). The slope of a yield curve is determined by the difference between long-term and short-term interest rates. In normal conditions, when the above difference is positive, there is upward sloping, otherwise flat or downward sloping. If the upward sloping is usually linked to economic expansion because of the investor's belief that longer-maturity bonds would produce a higher yield than the opposite situation happens for downward sloping (Chen, 2020). In the last case, investors suppose that in the future, longer-maturity bonds would give a lower yield than now, so it is better to buy such bonds until they decrease more (Chen, 2020). A yield curve that has downward sloping, also called an inverted yield curve, because of an abnormal situation when yields for shorter-maturity bonds are higher than bonds with higher duration (Amadeo and Boyle, 2020). Moreover, there is evidence of the inverted yield curve as a recession predictor that was discussed earlier in the literature overview. Flat yield curve called a transition period when the economy starts to fall after expansion or recover after the recession.

Generally, the yield curve is regulated by expectations hypothesis theory that assigns the equality between the interest rates of a long-term bond and the average of interest rates of the short-term bonds that expected to be over the long-term bond lifetime (Mishkin, 1990). In practice, this relationship can be shown by this formula (Mishkin, 1990):

$$R_t^n = (\frac{1}{n})E_t(r_t + r_{t+1} + \ldots + r_{t+n-1}), \quad (3.1)$$

where R_t^n is an interest rate of an n-period bond at time t, E_t is a mathematical expectation at time t, r_t is a one-period interest rate at time t.

Explanation on why the yield curve varies from time to time can be discussed in terms of market segmentation theory, preferred habitat theory, and liquidity preference theory.

Market segmentation theory states that yields for short-term and long-term instruments are established independently (Anand & Singh's, 2011). Preferred habitat theory certifies that longer-term rates tend to be higher than short-term rates because short-term investors are prevailing in the fixed income market (Anand & Singh's, 2011). Liquidity preference theory manifests that long-term bond yields are inclined to be higher than short-term yields because of the availability of the term premium (Anand & Singh's, 2011).

3.4 Out-of-sample forecasting

Forecasting of recessions is somewhere essential not only for investors, governments, and professionals but for all involved in the economy. In our study, we use econometric forecasting that is presented by using dependent variables and independent – the yield spread between ten-year and three-month treasury bills. The goal of it is to measure how a spread, yield inversion, in particular, can influence the leading economic indicators presented as GDP growth, industrial production index, and inflation. Reviewing the researches, we find that the out-of-sample period is presented as a more trustworthy technique rather than in-sample. In-sample forecasting is used to predict the value of observations that are part of the data sample. At the same time, out-of-sample make forecasts for observations that are not included in a dataset (Brooks, 2014). The last one works better for forecasting evaluation and is more sensitive when in-sample mostly appropriate for parameter estimation and model fit. Haubrich & Dombrosky (1996) show that in-sample results can be deceptive. Moreover, plotting forecasted GDP growth with actual data on one graph, authors observe that the out-of-sample technique is more accurately follow the GDP oscillations.

To obtain the out-of-sample results, we estimate the available data in quarterly measures. This evaluation is the base for the projected four quarters. Adding one more quarter to the estimated sample, we add again forecast for the next four quarters. This procedure is repeated and would imitate results based on the available data in the past (Estrella and Mishkin, 1996).

3.5 Probit model

The next crucial part of our research part is to decide on a type of model that we are going to use. The linear regression is the most common type of model that can be used to show the causal relationship between the yield spread and GDP growth. Nevertheless, to measure the probability of a recession, we instead use a non-linear model that is the so-called probit model. In this model, a yield spread becomes an explanatory variable that gives the probability of a recession as an output (Estrella and Mishkin, 1996). As the model specifications, we take the model features that are designed by Chauvet and Potter (2005), where $\mathrm{Y_t}$ is an indicator of a recession or expansion. If this indicator takes the value of 0, it will signal about the expansion, and 1 is the cue of a recession. The next variable that we consider is $\mathrm{Y_t^*}$ that appears for the state of the economy. Aggregating those variables together we have:

$$Y_t = \begin{cases} 0 \ \ if \ Y_t^* < 0 \\ 1 \ if \ Y_t^* > 0 \end{cases} \quad (3.2)$$

The next critical equation occurs because $\mathrm{Y_t^*}$ is unnoticeable and directly relates to a yield curve in the regression form:

$$\mathrm{Y_{t+K}^*} = \beta_0 + \beta_1 \mathrm{S_t} + \varepsilon_t, \quad (3.3)$$

where S_t is a yield spread between long-term ad short-term Treasury bill rates, β_0 and β_1 are the coefficients in a regression, ε_t is an error term ~ N (0,1), K is a forecasted horizon. By using this type of regression, we believe in removing the correlation between the error term and the yield spread (Clay and Keeton, 2011). To prove the significance of the estimated variables, we use p-values and z-statistics. To get the model that fit the best to our research, we run a regression with different amount of lags and make a decision which model is the most appropriate taking into account the R^2 and RSME criteria (Clay and Keeton, 2011).

Combining both equations above we get the conditional probability of the recession for a predicted horizon K:

$$\mathrm{P}(Y_{t+K}^* \geq 0 \mid S_t, \beta) = \Phi[\beta_0 + \beta_1 S_t], \quad (3.4)$$

where Φ is a CDF of the standard normal distribution.

We expect to combine the model findings with actual recessions data that happened in the past. If the high probability of the recession follows the upcoming crises, we conclude that the zero hypotheses of the yield curve predictive power are coming true. Our study stands in line with researches that prove that, if not, the alternative hypothesis would compromise the absence of the predictive power of the yield curve.

3.6 Hypothesis

Measuring the predictive power of a yield curve for prognosis a future state in the economy, we use the most effective empirically methods – probit modelling and out-of-sample forecasting. The zero hypotheses in both cases are linked to that a yield curve has the power to predict changes in the business curve, while the alternative hypothesis is that we cannot prove such evidence of a yield curve power. By theory that is discussed above, the hypotheses for a probit model can be examined first. Including to a model, only a yield spread as an independent variable and $\mathrm{Y}_{\mathrm{t}}^{*}$ as a dependent variable that stands for the state of the economy (1 – recession, 0 – expansion) in equation three, we have:

$$H0: \beta_1 = 0 \; vs. H1: \beta_1 \neq 0. \quad (3.5)$$

Zero hypotheses testify that β_1 the coefficient is statistically significant, and the yield curve has an impact on a state of the economy, otherwise, if $\beta_1 \neq 0$ we cannot prove that a yield spread can influence on a business cycle. However, to investigate the recession issue more sophisticated, we propose to include other economic indicators such as real GDP growth, CPI, and the unemployment rate as all of them were used in researches before and have shown significant influence on the state of the economy. Altogether, the new equation is represented here:

$$\mathrm{P}(Y_{t+K}^{*} \geq 0 \mid S_t, \beta) = \Phi[\beta_0 + \beta_1 S_t + \beta_2 GDPg_t + \beta_3 CPI_t + \beta_4 UR_t] \quad (3.6)$$

where S_t is a yield spread, $GDPg_t$ is real GDP growth, CPI_t is a consumer price index, UR_t is an unemployment rate, β_0, β_1, β_2, β_3, β_4 are the regression coefficients. For equation 3.6 to check the simultaneous impact of all indicators, the joint hypotheses are the following: the null hypothesis is that all coefficients except the intercept are zero. That is, we have:

$$H0: \beta_1 = 0 \; and \; \beta_2 = 0 \; and \; \beta_3 = 0 \; and \; \beta_4 = 0 \; vs.$$

$$H1: \beta_1 \neq 0 \; or \; \beta_2 \neq 0 \; or \; \beta_3 \neq 0 \; or \; \beta_4 \neq 0.$$

Confirmation of the null hypothesis shows that the coefficients of economic indicators are statistically significant at the same time. Therefore, in the complex, they affect the state of the economy.

The next hypotheses are centred across OLS modelling. In contrast to the probit model, the dependent variable here is GDP growth change to determine whether there is, in fact, an effect of the yield spread on the economy, which is often expressed in GDP measures. First and foremost, the essential element of modelling is an equation that has the following form:

$$\frac{RGDP_{t+k}-RGDP_t}{RGDP_t} = \alpha_0 + \alpha_1 S_t, \quad (3.7)$$

where $RGDP_t$ is a real GDP at a period t, S_t is a yield spread between short-term and long-term Treasure interest rates, k is a period that stands for how many time units ahead we make a forecast, $\beta_0,\ \beta_1$ are coefficients in the regression. Based on the equation, the hypotheses are:

$$H0: \alpha_1 = 0\ vs. H1: \alpha_1 \neq 0. \quad (3.8)$$

By zero hypotheses we test the statistical significance of α_1 coefficient. If the coefficient is 0, then we can state that the yield spread has an impact on GDP growth, in turn, to the economy, otherwise, if $\alpha_1 \neq 0$ we cannot suggest the significance of a yield spread influence on GDP growth.

However, like in a probit modelling, for OLS regression we include other economic indicators such as the CPI, the unemployment rate, and the recession indicator as independent variables and test the significance of their impact on real GDP change.

3.7 The evidence of the Recession in Ukraine

In order to analyse the yield curve predictability power, we look at the pieces of evidence of the recession in each country separately.

Ukraine was the part of the Soviet Union until 1991, following its declaration of independence, Ukraine has undertaken reforms aimed at creating an efficient market economy (USAID, 2020). During the short time of its independent development, Ukraine suffered several large-scale crises that threatened economic stability in the country and even were at risk of default. Among the central crises of the modern history of Ukraine are the global crisis of 2008-2009 and the Ukrainian crisis of 2014-2015. The declines of the GDP growth for these periods are shown in the graph below.

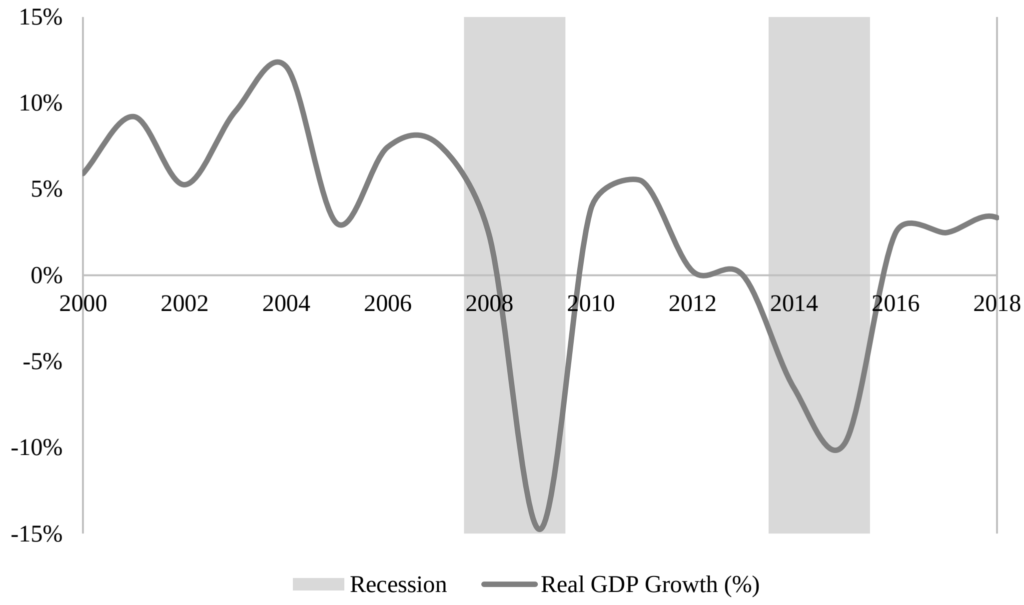

Figure 3.1: Gross Domestic Product Growth in Ukraine. This figure illustrates the dynamic of real GDP growth in Ukraine collected from the World Bank database and identifies the recession periods between the dataset from 2000 to 2018 based on authors estimations.

In the second part of 2008, the global financial crisis spread across Ukraine (Boreiko & Mitchuk, 2018). It provoked a decrease in the growth of the gross domestic product (GDP) from 7.59% in 2007 to 2.3% in 2008 (The World Bank, 2020). In 2009, the crisis enlarged that caused the decline of GDP by 14.8%. In 2010, Ukraine's GDP grew in comparison with the previous year by 103.83% and 2011 – by 105.47% (The World Bank, 2020). That showed stabilisation of the national economy and its gradual recovery from the crisis (Boreiko & Mitchuk, 2018). Nevertheless, in 2012 this index increased only by 0.23%, in 2013 decreased by 0.03%. In 2014, the dropping of Ukraine's GDP by 6.55% in comparison with the same period of last year was recorded (The World Bank, 2020). This was the indicator of the next financial crisis.

The recession began as an internal Ukrainian crisis in November 2013, when former President Viktor Yanukovych rejected a deal for greater integration with the

European Union, sparking mass protests (known as Maidan or 2014 Ukrainian revolution), which Yanukovych attempted to put down violently (Fisher, 2014). Inverted the yield curve in Ukraine occurred for about two months before that, suggesting investors were seriously concerned before demonstrations began on the streets of Kyiv (Wheatley, 2013). In February 2014, anti-government protests toppled the government and ran Yanukovych out of the country. After this, in March 2014, Russia invaded and annexed Crimea. Then, in April 2014, pro-Russia separatist rebels started seizing territory in eastern Ukraine (Fisher, 2014).

In 2015 the GDP dropped by 9.77% in comparison to the previous year. In 2016, after two years of deep crisis, Ukraine's economy resumed growth. Real GDP increased by 2.44% in 2016, 2.37% in 2017, and 3.34% in 2018 (The World Bank, 2020). By the end of 2018, three years of economic growth had allowed Ukraine to reclaim around half of these 2014-15 losses in dollar terms (Inozemtsev, 2020). The Ukrainian government is currently implementing reforms and new regulations to get financial support from the IMF to deal with the result of the crisis.

The Ukraine credit rating from September 2019 is B, according to Standard & Poor's agency, which is much better compare to rating CCC- in 2014 (Trading Economics, 2020). However, the yield curve is inverted in Short-Term Maturities (World Government Bonds, 2020a).

3.8 The evidence of the Recession in Greece

Greece joined the European Union in 1981 and adopted the euro in January 2002 in the first wave of countries to launch euro banknotes and coins (European Commission, 2018). Despite the rapid development before the Eurozone entry and good indicators of economic growth in Greece, the global crisis hit it the hardest among the countries of the European Union. The massive decline in GDP growth is shown in the figure below.

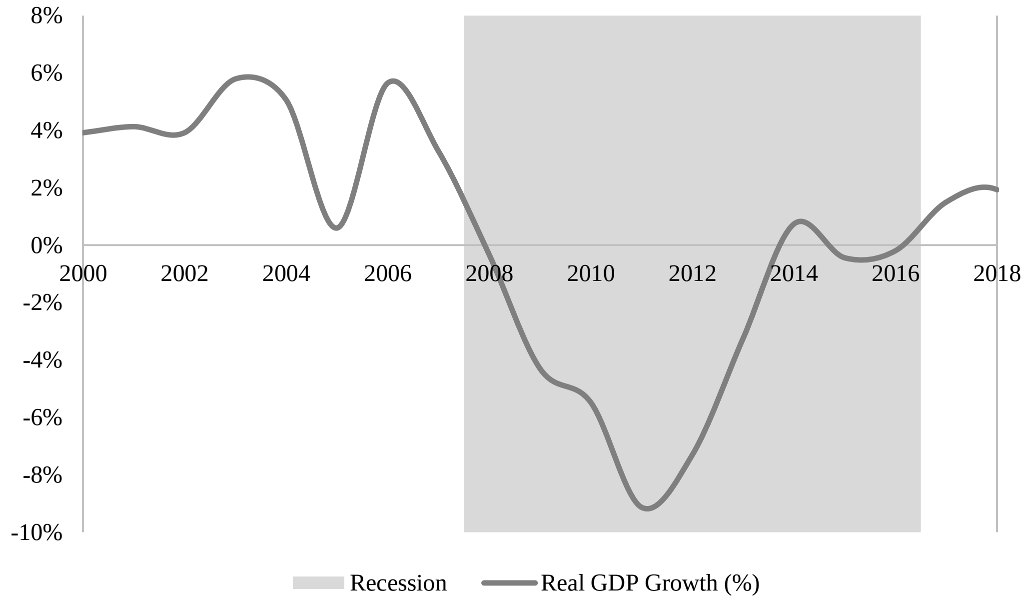

Figure 3.2: Growth Domestic Product Growth in Greece. This figure illustrates the dynamic of real GDP growth in Greece collected from the World Bank database and identifies the recession periods between the dataset from 2000 to 2018 based on OECD estimations.

Eurozone Debt Crisis started in 2008 with the global financial crisis but was triggered mainly due to the Greece Crisis in 2009, and by 2011 it was the world's most massive threat. The GDP declined by 4.3% in 2009, then by 5.84% in 2010 and more than 9% in 2011 (The World Bank, 2020). The Greece Crisis was so massive that its debts exceeded the size of its country and thus affected all EU countries. To avoid default, the EU bailout Greece by loaning the country money to continue paying its debts. However, this was not a quick fix; Greece is scheduled to make debt payments back to the EU until 2060, prolonging the EU's debt crisis into the long-term (Amadeo, 2019a). After a minor stabilisation in 2014, when the outlook for the Greek economy was optimistic, Greece's GDP again declined by 0.44% in 2015 and by 0.19% in 2016. Only from 2017 GDP started to increase again by 1.51% in 2017 and 1.93% in 2018 (The World Bank, 2020).

According to Standard & Poor's agency, the Greece credit rating from 2019 is BB- (World Government Bonds, 2020b). Moreover, in March 2019, Greece sold 10-year bonds for the first time after the bailout (Bloomberg, 2019b).

3.9 The evidence of the Recession in South Africa

Based on all downturns in the South African economy during 1960-2012, we find ten periods with negative growth followed more than two quarters. Taking only the 1980-2012 period, we discover five recessions: 1981: Q4 – 1983: Q1, 1984: Q3 – 1986: Q1, 1989: Q2 – 1993: Q2, 1996: Q4-1999: Q3, 2008: Q1 – 2009: Q3 according to SARB (2012) estimation.

Mohapi, Tjhaka Alphons and Botha (2013) shows that negative GDP was supported by the negative yield from 1989 through 1991: Q3, which has been identified as a recession in the South Africa economy. The stagnant economy remembered 1990-1993. The reason for this was in the apartheid system that did not allow to mobilise resources and effectively use it together with sanctions to participate in the international economy. Moreover, business and economic climate were expected to make some improvements (Dinar, n.d). As the evidence of a recession can be a negative GDP growth dynamic during 1990-1993 (Figure 3.3).

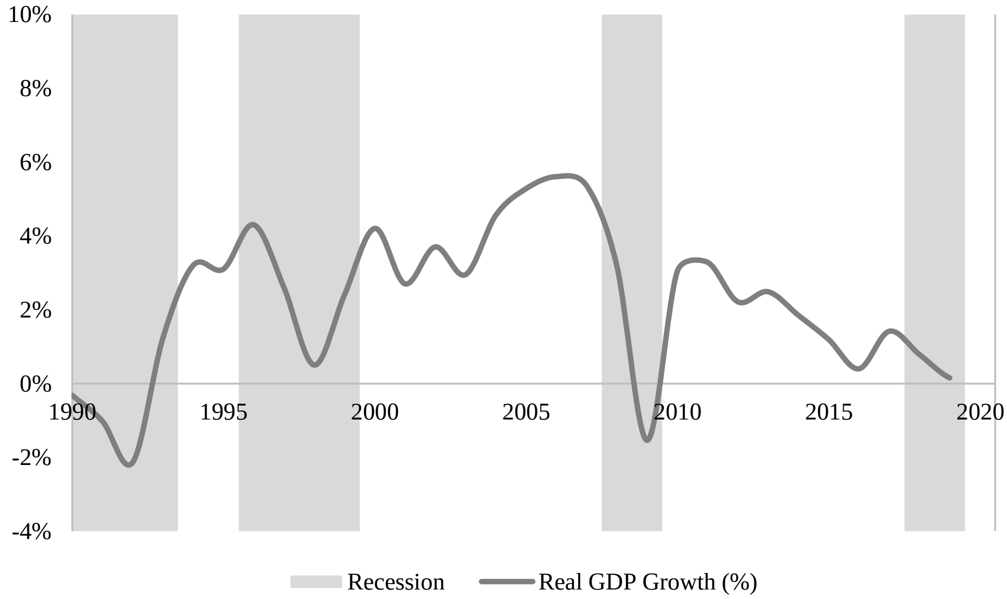

Figure 3.3: Growth Domestic Product Growth in South Africa. This figure illustrates the dynamic of real GDP growth in South Africa collected from the World Bank database and South Africa Reserve Bank and identifies the recession periods between the dataset from 1990 to 2019 based on OECD estimations.

The next recession of 2008-2009 that occupied the whole world has touched the SA economy as well (Figure 3.3). While being dependent on international trade and foreign inflows, the SA economy was affected by the world's slowdown. Technically the recession in SA started in 2009, which was accompanied by a decline in GDP, dropping manufacture, mining production, and retail and wholesale trade output (Baxter, n.d; Padayachee, 2019). However, in 2008, inflation has reached 9.9 % that already exceeded the range of 3-6 % (Padayachee, 2019). Meanwhile, the ratio of national deficit to GDP has alarmed a problem in financing due to a reduction in FDI that, in turn, depended on the global crisis in financial markets (Padayachee, 2019). Unsecured lending was growing from 2006 when banks charged high-interest rates (approximately 30 %) and made loans risky that lead to a credit bubble in 2009 (News24, 2014; Kantor, 2018). Moreover, around 50 % of bank credit was concentrated in private sector hands (Kantor, 2018).

According to the newest data, 2019 was not productive for the South African economy that can be noticed by downing GDP growth in the last two quarters (Figure 3.3). The declining in the economy was mostly caused by shrink in freight and passenger transportation, trade industry (specifically, in the motor trade, wholesale), manufacture (lowering production rate of paper, publishing and wood production), agriculture and military services and non-residential construction (Statistics South Africa, 2020). The problems in the SA economy in 2019 were caused by power issues, specifically by electricity crises, and it went together with a significant drop in revenue collection (Cotterill, 2020). Other sources state that the newest recession caused by power cuts combined with the pressure of the central bank on cutting interest rates (Naidoo & Mbatha, 2020). Annual GDP growth for the entire 2019 was 0.2 % that is the lowest number since the Global Financial Crisis in 2008-2009 (SARB, 2020). Moreover, the low dynamics of GDP growth over the last five years, together with low rates of revenue collection, make it challenging to curb existing debt, budget deficits, and high unemployment of about 30% (Naidoo & Mbatha, 2020).

Given the recent recession in South Africa, it can be said that recession forecasting is essential to avoid negative consequences that SA faces now. However, in literature, false prediction of a recession in 2002-2003 casts doubt on the ability to predict recession using a yield curve that was examined in Khomo and Aziakpono (2007), Clay and Keeton (2011) studies. Moreover, other recessions were successfully forecasted that make the study of South Africa more promising.

3.10 The evidence of the Recession in India

Studying Indian history from 1970 becomes clear that economic development was initially directly dependent on the agricultural sector (40 % of GDP), which was later displaced by the IT sector. In turn, until the 1990s Indian economy due to its dependence on agriculture (that shorten to 25 %) often suffered from weather-related shocks that influenced the recessions (Dua & Banerji, 2001). The short recession in March 1991 – September 1991 in the economy was caused by another exogenous factor that is the Gulf crisis and was reinforced by the macroeconomic crisis (balance of payment crisis). The downturn in the economy can be followed by a decline in GDP growth (Figure 3.4). Indian economy experienced a high decline in imports to 38 % that was mostly due to the spike in price for petroleum (Kumar & Alex, 2009).

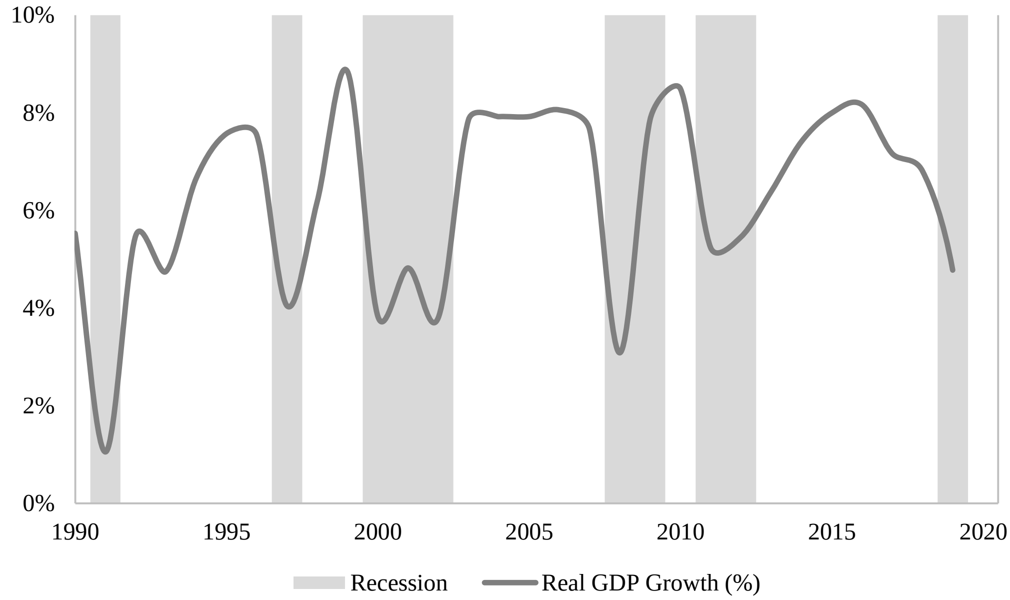

Figure 3.4: Growth Domestic Product Growth in India. This figure illustrates the dynamic of real GDP growth in India collected from the World Bank database and Ministry of Statistics and Programme Implementation and identifies the recession periods between the dataset from 1990 to 2019 based on OECD estimations.

The next crisis of May 1996 – November 1996 was caused by endogenous factors (Dua & Banerji, 2001). Namely, high-interest rates, default in companies because of loans led to a crisis in the bank sector (Aiyar, 2009). However, before the prior recessions, the Indian economy experienced long-term expansion from 1980 until 1991 (Dua & Banerji, 2006).

2000-2002 period faced another decline in the economy when GDP growth fell from 8.85 % in 1999 to 3.84 % in 2000, shifted to 3.80 % in 2002 (Figure 3.4). Such a downturn can be explained by the Dot Com Bubble that brought falling stock prices in IT companies that had a significant part in the creation of GDP value.

The next shock of 2008-2009 in the world economy influenced the Indian economy by the decline in automobile, construction, petrochemicals, retail, real estate, and finance output (Acharya, 2008; Kumar & Alex, 2009). Moreover, a decline in international trade, exchange rate fluctuations adversely had an impact on the Indian economy. The trade collapse in India was characterised by shrinking in export and import for around 20 % in October 2008 – December 2009 (Kumar & Alex, 2009). The exchange rate of Indian currency experienced a considerable shock that was in depreciation of rupee for 12.5 % against the US dollar, 12.2 % against euro, and 23.5 % against yen (Sinha, Randev, & Gupta, 2010). Because of high capital outflows in 2008-2009, Indian rupee experienced the highest weakening since the 1991 crisis (Sinha, Randev, & Gupta, 2010).

At the same time comparing Indian growth in this challenging period with other countries, we see that GDP growth fluctuated around 6 % that exceeded Word Bank expectations of 4 % yearly growth in 2009 (Aiyar, 2009). Accumulation of foreign reserves as of 2008 helped India to avoid such a shock of withdrawing money by foreign investors in the stock market and kept the economic growth (Aiyar, 2009).

2011-2012 period was also damaging for India, as the economy lost 5.5 percentage points off cumulative growth during five quarters (Rajadhyaksha, 2019). The contraction in export, falling in the investment industry, problems in corporate sectors that influenced business loans harmed the economy (Smith, 2020). Besides, the Indian economy faced with a lack of effective mechanisms on controlling the fiscal deficit that reached a point of 8 %, slowdown in the export of service sector, other depreciation of rupee (Rao, 2012).

The warning signals for the Indian economy appeared in 2019 by the fact of slowing down the GDP growth, job creation rate, industrial production (The Economic Times, 2019). It makes the investigation of the possible incoming recession more valuable and needed.

Summary of part 3

In the theoretical part, we look at the concept of recession and identify recession indicators, such as real GDP growth, inflation, unemployment, and Spread, which will be used in our further analysis. Also, we provide an overview of inverted yield curve phenomena. Based on the literature overview, we show that the out-of-sample forecasting and probit model is the best methodologies to use for our analysis, so we provide an overview for them. We state our central hypothesis about the linkage between the interest rate spread and a state of the economy. We provide evidence of the recession in each of the selected countries to identify which period we need to consider in our analysis for each country.

4 Methods and data

4.1 Data sources

In our research, we use the data series for Greece, India, Ukraine, and South Africa obtained in the global databases and country-specific ones for six variables. Critical results of used variables, sources, and periods for all countries are summarised in Tables 4.1 – 4.4. The difficulties in the process of collecting data arise from the reliability of databases and, accordingly, data presented there. Therefore, we decide on OECD, FRED, Bloomberg, Statistic Services of South Africa, and Ukraine, National Bank of Ukraine as the most trustworthy databases.

Our goal is to find seasonally adjusted data not to have cyclicality and have all datasets consistent. Observations periods are different for countries, as databases have missing observations for some quarters or government, and statistical websites do not publish information openly. The data is quarterly and concentrated mostly on a period of 2000Q1-2019Q4; the number of observations variates from 67 to 88. All variables are numerical except for the categorical recession indicator, which is a dummy variable of the value 0 if it was an expansion and 1 for a recession.

Table 4.1: Summary of the collected data for Greece. This table explains the variable indicators, sources of datasets for Greece used its period, frequency, and number of observations.

Variable	Explanation	Source
Real GDP	Gross Domestic Product in constant prices of 2010, millions of euros, seasonally adjusted	Federal Reserve Economic Data: St. Louis Fed (FRED)
Recession indicator	OECD based recession indicator, 1-recession, 0-expansion	FRED
Inflation rate	Measured by CPI that is the change in prices for a basket of goods in services in terms of 2015 base year, percentage estimation	OECD Database
Unemployment rate	The ratio of unemployed people to the labour force in percentage	OECD Database
Long-term rate	Rates for government bonds that have the maturity of 10 years, in %	OECD Database
Short-term rate	Treasury bill rate estimated in three-month money market measures, percentage estimation	OECD Database
Spread	Difference between long-term and short-term rates, in per cent	Author's estimation
Period:	**Frequency:**	**Observations:**
1998Q1:2019Q4	Quarterly	88

Table 4.2: Summary of the collected data for India. This table explains the variable indicators, sources of datasets for India used its period, frequency, and number of observations.

Variable	Explanation	Source
Real GDP	Gross Domestic Product in constant prices of 2010, millions of Indian rupees, seasonally adjusted	Federal Reserve Economic Data: St. Louis Fed
Recession indicator	OECD based recession indicator, 1-recession, 0-expansion	FRED
Inflation rate	Measured by CPI (the change in prices for a basket of goods and services in 2015 base year), in %	OECD Database
Long-term rate	Ten-years zero-coupon rate of Indian Sovereign bonds, in %	Bloomberg Market Data
Short-term rate	Three-month zero-coupon rate, in percentage	Bloomberg Market Data
Spread	Difference between long-term and short-term rates, in per cent	Author's estimation
Period: 2000Q1:2019Q4	**Frequency:** Quarterly	**Observations:** 80

Table 4.3: Summary of the collected data for South Africa. This table explains the variable indicators, sources of datasets for South Africa used its period, frequency, and number of observations.

Variable	Explanation	Source
Real GDP	Gross Domestic Product at market prices, in constant prices of 2010, millions of local currencies, seasonally adjusted	Statistics South Africa
Real GDP growth	Leading Indicators OECD: Growth Rate Same Period Previous Year at 2010 prices, Seasonally Adjusted, in percentage	FRED
Recession indicator	OECD based recession indicator, 1-recession, 0-expansion	FRED
Inflation rate	Measured by CPI (the change in prices for a basket of goods and services in 2015 base year), in %	OECD Database
Unemployment rate	The ratio of unemployed people to the labour force in percentage	OECD Database
Long-term rate	Ten-years zero-coupon rate of Indian Sovereign bonds, in %	Bloomberg Market Data
Short-term rate	Three-month zero-coupon rate, in percentage	Bloomberg Market Data
Spread	Difference between long-term and short-term rates, in per cent	Author's estimation
Period: 2000Q1:2019Q4	**Frequency:** Quarterly	**Observations:** 80

The most critical variable in this study is a term spread between long-term and short-term rates for treasury bills. In the OECD database, they are described as ten-years and three-month rates. To match the OECD dataset for Greece with other data, we use the access to Bloomberg terminal and find data for the same rates periods – 3-month and 10-years for India and South Africa. The situation with Ukraine is different as the access to data is limited, and government bonds have another structure. To get data, we requested the information from the Statistic Department of the National Bank of Ukraine and received data for the bonds in local currency that are presented in the primary market. Because the short-term bonds mature less than one year, medium-term bonds – between one and five years, and long-term in 5 and more years, in this research for Ukrainian case, we also consider such periods for short and long-term rates.

Table 4.4: Summary of the collected data for Ukraine. This table explains the variable indicators, sources of datasets for Ukraine used its period, frequency, and number of observations.

Variable	Explanation	Source
Real GDP growth	Growth of Gross Domestic Product in constant prices of 2010 for data from 2011Q1, data prior that date is at 2007 prices for Ukrainian hryvnia, estimated in percentage	CEIC Data's Global Database based on the data of the State Statistics Service of Ukraine
Recession indicator	OECD based recession indicator, 1-recession, 0-expansion	Author's estimation
Inflation rate	Consumer price indices change to December of the previous year, %	National Bank of Ukraine Database (NBU Database)
*Unemployment rate**	ILO unemployment rate of population, per cent of the total population in working age	NBU Database (data starts from 2003Q2)
Long-term rate	The average of five-years and more zero-coupon rates of domestic sovereign bonds of Ukraine, in %	Combination of NBU Database and Bloomberg Market Data
Short-term rate	The average of less than 1-year zero-coupon rates and three-month rates, in percentage	NBU Database and Bloomberg Market Data
Spread	Difference between long-term and short-term rates, in per cent	Author's estimation
Period: 2002Q1:2019Q4	**Frequency:** Quarterly	**Observations:** 72/67*

4.2 Data statistics

For each data set, we conducted descriptive statistics. All results are summarised in Appendix A. The means of GDP Growth over the selected period are 0.68, 7.05, 2.64 and 2.14 for Greece, India, South Africa, and Ukraine accordingly. While Spread means are 4.35, 1.06 and 1.18 for Greece, India, and South Africa. For Ukraine, the average Spread is negative and equal to -0.16.

Also, we check the correlations matrix for the variable in each data set as it helps us to identify which factors can be used as independent variables in the further regression analysis for each country.

Based on the results for Greece Spread and the Inflation rate has high degree correlation. Since the correlation is negative, we can assume that the rises in Inflation rate and Spread will negatively influence on GDP growth. We also check the data for the Granger Causality test, which is presented below.

Table 4.5: Correlation Matrix for Greece. This table represents the correlation between GDP growth, inflation rate, unemployment rate and interest rate spread for the collected data for Greece.

Variable	*GDP Growth*	*Inflation rate*	*Unempl. rate*	*Spread*
Real GDP Growth	1.00			
Inflation rate	**-0.65**	1.00		
Unemployment rate	-0.42	**0.68**	1.00	
Spread	**-0.76**	0.76	0.69	1.00

*High degree correlation $|\rho| > 0.5$ in a **bold** font

Table 4.6: Granger Causality Test Results for Greece. This table represents the results of the Granger test on the detection of the causal relationship between GDP growth and inflation rate, unemployment rate, and interest rate spread for the collected data for Greece.

Null Hypothesis	***F-Statistic***	***Prob.***	***Result***
INFLATION_RATE does not Granger Cause GDP_GROWTH	0.50	0.60	Do not reject
SPREAD does not Granger Cause GDP_GROWTH	1.57	0.21	Do not reject
UNEMPLOYMENT does not Granger Cause GDP_GROWTH	1.76	0.18	Do not reject

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

For India, the GDP Growth has a high degree correlation. Granger Causality Test shows that Spread Granger causes GDP growth change.

Table 4.7: Correlation Matrix for India. This table represents the correlation between GDP growth, inflation rate, and interest rate spread for the collected data for India.

Variable	*GDP Growth*	*Inflation rate*	*Spread*
Real GDP Growth	1.00		
Inflation rate	-0.02	1.00	
Spread	0.12	-0.38	1.00

*High degree correlation $|\rho| > 0.5$ in a **bold** font

Table 4.8: Granger Causality Test Results for India. This table represents the results of the Granger test on the detection of the causal relationship between GDP growth and inflation rate, and the interest rate spread for the collected data for India.

Null Hypothesis	***F-Statistic***	***Prob.***	***Result***
INFLATION_RATE does not Granger Cause GDP_GROWTH	0.19	0.83	Do not reject
SPREAD does not Granger Cause GDP_GROWTH	3.18	0.05 **	Reject

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

For South Africa, the only Inflation rate has a high degree correlation, meaning that while inflation increases, GDP Growth decreases. The unemployment rate shows a lower degree of correlation, but there is a possibility that they still will be significant in regression analysis. Moreover, the Granger Causality Test shows that the Inflation rate causes GDP growth change.

Table 4.9: Correlation Matrix for South Africa. This table represents the correlation between GDP growth, inflation rate, unemployment rate, and interest rate spread for the collected data for South Africa.

Variable	*GDP Growth*	*Inflation rate*	*Unempl. Rate*	*Spread*
Real GDP Growth	1.00			
Inflation rate	**-0.67**	1.00		
Unemployment rate	-0.47	**0.52**	1.00	
Spread	-0.29	0.27	0.23	1.00

*High degree correlation $|\rho| > 0.5$ in a **bold** font

Table 4.10: Granger Causality Test Results for South Africa. This table represents the results of the Granger test on the detection of the causal relationship between GDP growth and inflation rate, unemployment rate, and interest rate spread for the collected data for South Africa.

Null Hypothesis	***F-Statistic***	***Prob.***	***Result***
INFLATION_RATE does not Granger Cause GDP_GROWTH	5.22	0.007 *	Reject
SPREAD does not Granger Cause GDP_GROWTH	1.68	0.19	Do not reject
UNEMPLOYMENT does not Granger Cause GDP_GROWTH	0.05	0.95	Do not reject

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Based on the correlation analysis for Ukraine, GDP growth does not have a high degree of negative correlation with considered variables. Based on Granger Causality, none of the considered factors Granger cause GDP growth.

Table 4.11: Correlation Matrix for Ukraine. This table represents the correlation between GDP growth, inflation rate, unemployment rate, and interest rate spread for the collected data for Ukraine.

Variable	*GDP Growth*	*Inflation rate*	*Unempl. rate*	*Spread*
Real GDP Growth	1.00			
Inflation rate	-0.43	1.00		
Unemployment rate	-0.30	0.07	1.00	
Spread	0.36	-0.29	-0.36	1.00

*High degree correlation $|\rho| > 0.5$ in a **bold** font

Table 4.12: Granger Causality Test Results for Ukraine. This table represents the results of the Granger test on the detection of the causal relationship between GDP growth and inflation rate, unemployment rate, and interest rate spread for the collected data for South Ukraine.

Null Hypothesis	***F-Statistic***	***Prob.***	***Result***
INFLATION_RATE does not Granger Cause GDP_GROWTH	0.60	0.55	Do not reject
SPREAD does not Granger Cause GDP_GROWTH	0.89	0.41	Do not reject
UNEMPLOYMENT does not Granger Cause GDP_GROWTH	1.54	0.22	Do not reject

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

4.3 Forecasting methodology technique

Obtaining the forecasting results in this research is based on the estimated models. That is, the first step to get predictions is to evaluate models based on the controlled dataset. We use the period from 1998: Q1 to 2016: Q4 for Greece, 2000: Q1 to 2016: Q4 for India and South Africa, and 2002: Q1 to 2016: Q4 for Ukraine. The second step is checking the model's efficiency and, if needed, changing the model's equations. All models have quarterly measures so that forecasting is done for each quarter by adding one quarter to the estimated sample and evaluating the forecast for the next quarter.

For binary recession, we add data for independent variables of the next quarter (for instance, 2017: Q1) and find the value for the probability of a recession in that quarter (in 2017: Q1). We repeat the procedure, but in addition to adding values of independent variables, we add the value of the real dependent variable in the previous quarter (for prediction the value of recession indicator in 2017: Q2 we add the values of independent variables in 2017: Q2 and the real value of recession indicator in 2017: Q1). We perfume this procedure for 12 quarters (for the period from 2017: Q1 to 2019: Q4), which is consistent with the theory proposed by Estrella and Mishkin (1996) for out-of-sample forecasting. After forecasting is done, we can compare the prediction values with real values by conducting the ROC and AUC analysis. Such model forecasting procedure we apply for all estimated countries – Greece, India, South Africa, and Ukraine.

Summary of part 4

To ensure the adequacy of the data used for the model, we conduct an overview and data descriptive statistics. Also, we make a correlation analysis to show that the data used has not only theoretical but also meaningful statistical connection. In the end, we conduct a Granger Causality test to see which variables influence GDP Growth and find that the inflation rate, interest rate spread, and the unemployment rate have an impact on GDP differently. That finding helps us to build regression models with statistically and economically meaningful variables. Additionally, we describe the procedure of model forecasting for binary regressions.

5 Results and analysis

5.1 OLS regression

5.1.1 Application of the OLS regression

We use linear regression to test the influence of the selected factor on GDP change. The primary purpose is to analyse if the Spread causes the change in GDP growth and, if yes, what is the influence. Based on the obtained correlation analysis results, we try the Inflation rate, the Unemployment rate, and the Recession indicator as independent variables for the models. Moreover, we check if the previous period GDP Growth has influence as well. We conduct regression for each country using the available data until 2016: Q4 (Appendixes B to E). Each model is tested for main linear regression assumptions and independent variables significance. Then so, we removed insignificant variables from the models to improve them. Thus, for instance, for India and South Africa, the unemployment rate and inflation rate are not included in the final regression. In case when the model does not meet criteria, the issue is resolved by using appropriate instruments, such as Newey-West's heteroscedasticity and autocorrelation consistent (HAC) standard errors to deal with autocorrelation by using a dummy variable to deal with non-normality or by deleting independent variables from the models due to insignificant in order to improve the model.

All results are summarised in the table below (Table 5.1.1), and adequacy results are presented in Appendix E4. For all models mean of the disturbances is zero due to significant intercept coefficients presented in the models. For all four models, only the autocorrelation of the 4th order is significant. This can be explained by the presence of seasonal fluctuations in GDP. For all uncertain Durbin-Watson criteria and heteroscedasticity issues HCI or HAC accordingly is used. Normality is violated for the South Africa model and is resolved by adding a dummy variable. Also, checking only independent variables except for intercept shows that the coefficients are simultaneously significant for all models.

The change in GDP for Greece, India, South Africa, and Ukraine is explained by the selected factors accordingly by 84.6%, 74.8%, 88.7%, and 79.0%.

Based on the adjusted coefficient of determination, the South Africa model has shown the highest result.

Table 5.1.1: Comparison of the efficacy of OLS regressions. This table presents the results of SPREAD coefficients and its significance, Adjusted R-squared estimated for the models built on quarterly frequency between 1998 and 2016 for Greece, from 2000 to 2016 for India and South Africa, between 2002 through 2016 for Ukraine models.

	Greece (1)	*India (2)*	*South Africa (3)*	*Ukraine (4)*
SPREAD	-0.139 (0.044)**	0.498 (0.005)*	0.202 (0.000)*	-0.322 (0.011)**
Constant	8.609 (0.002)*	3.768 (0.000)*	-0.682 (0.009)*	-10.81 (0.017)**
Observations	73	67	64	53
Adjusted $\overline{R^2}$	0.846	0.748	0.887	0.790

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.
(1) $GDP\_Growth_t = \beta_1 + \beta_2 \times SPREAD_t + \beta_3 \times RECESSION_t + \beta_4 \times INFLATION\_RATE_{t-3} + \beta_5 \times UNEMPLOYMENT_{t-2} + \beta_6 \times GDP\ GROWTH_{t-2}$
(2) $GDP\_Growth_t = \beta_1 + \beta_2 \times SPREAD_{t-1} + \beta_3 \times GDP\_Growth_{t-1} + \beta_4 \times Recession_{t-1}$
(3) $GDP\_Growth_t = \beta_1 + \beta_2 \times SPREAD_{t-1} + \beta_3 \times RECESSION_{t-4} + \beta_4 \times GDP\ GROWTH_{t-1}$
(4) $GDP\_Growth_t = \beta_1 + \beta_2 \times SPREAD_{t-1} + \beta_3 \times GDP\_Grothw_{t-1} + \beta_4 \times UNEMPLOYMENT_{t-2}$

5.1.2 Significance of the interest spread on recession prediction

Based on the obtained results, we find that for all models, independent variable SPREAD is statistically significant. For the Greece model, change in Spread by 1% would lead to a change in GDP growth by 0.139% in the opposite direction. For the India model, change in Spread by 1% would lead to a change in GDP growth by 0.498%. For South Africa, model change in Spread by 1% would lead to a change in GDP growth by 0.202%. Furthermore, for Ukraine, the change in Spread by 1% would lead to a change in GDP growth by 0.322% in the opposite direction.

5.1.3 Forecast results

Based on the estimated regressions, we did a forecast for each country to see if the model can produce consistent data compare to actual numbers. The forecasts were done for the period from 2017: Q1 to 2019: Q4. On the graphs below, there are results and visual differences between forecast and actual numbers. For Greece, the forecast was accurate till 2018: Q4, and after that trend was opposite to actual GDP changes.

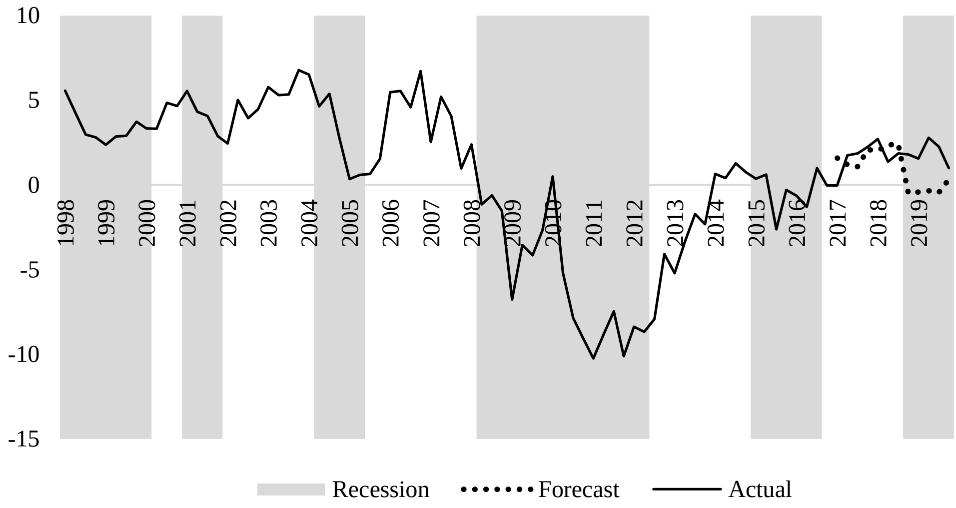

Figure 5.1.1: Forecasted GDP growth for Greece. This figure illustrates the comparison between the actual GDP growth, recession states for the period from 1998 to 2019 and forecasted GDP growth during 2017 – 2019 based on Greece datasets.

From Figure 5.1.2 for India, we can see the trend was captured better, and forecast results match the actuals better.

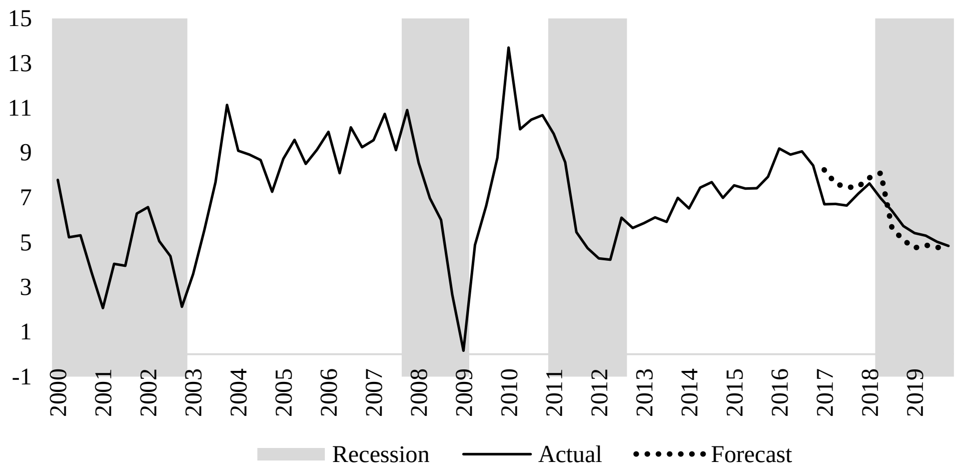

Figure 5.1.2: Forecasted GDP growth for India. This figure illustrates the comparison between the actual GDP growth, recession states for the period from 2000 to 2019 and forecasted GDP growth during 2017 – 2019 based on India datasets.

For South Africa, forecast visually looks very similar and not only well replicate the trend but also almost the same in values.

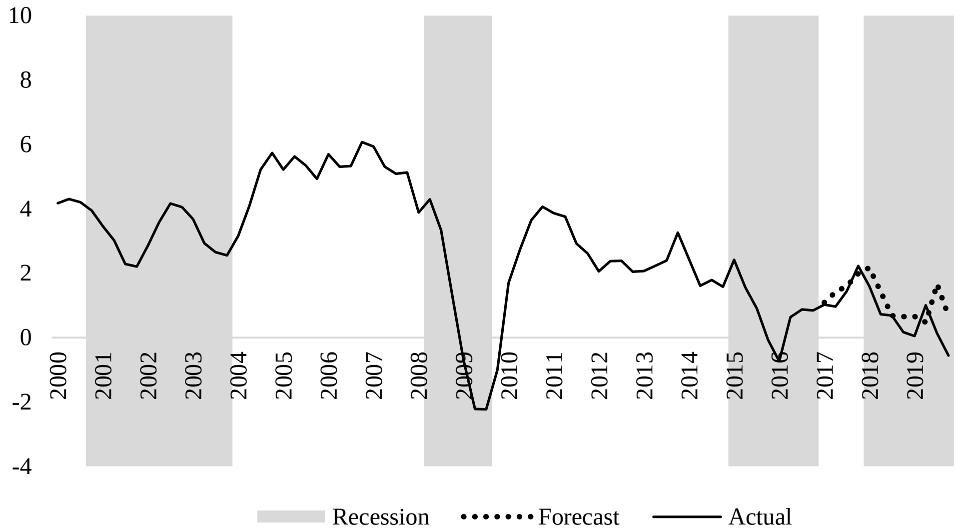

Figure 5.1.3: Forecasted GDP growth for South Africa. This figure illustrates the comparison between the actual GDP growth, recession states for the period from 2000 to 2019 and forecasted GDP growth during 2017 – 2019 based on South Africa datasets.

For Ukraine, the forecasted results are very closed to actuals, and trends are similar during the whole forecasted period.

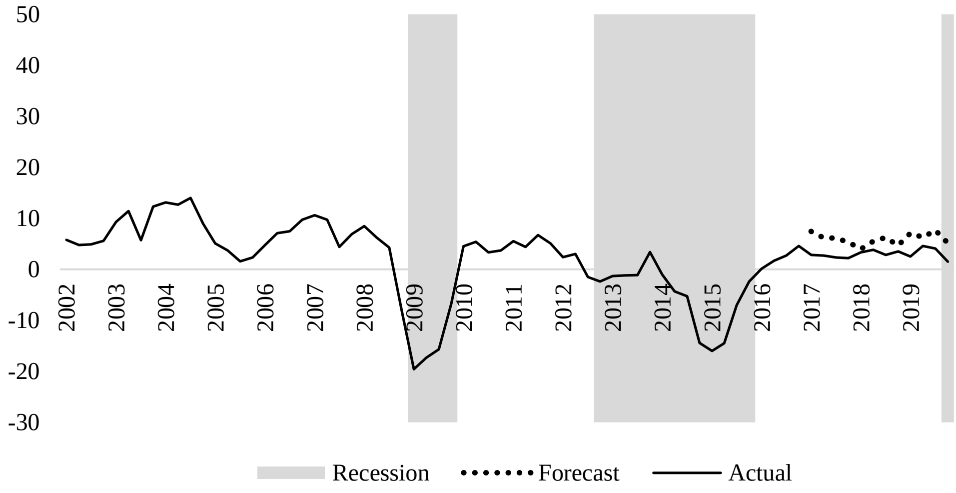

Figure 5.1.4: Forecasted GDP growth for Ukraine. This figure illustrates the comparison between the actual GDP growth, recession states for the period from 2002 to 2019 and forecasted GDP growth during 2017 – 2019 based on Ukraine datasets.

We use Mean Absolute Deviation, Mean Square Error, and Root Mean Square Error criteria to evaluate the quality of the forecasts and compare them to each other.

Based on the obtained results forecast for South Africa has better outcomes for MAD, MSE, and RMSE. Based on MAD, MSE and RMSE South Africa show the best results. India shows that second-best results. For Ukraine and Greece, the results are less accurate and cannot be defined as an accurate forecast.

Table 5.1.2: Evaluation of forecasting results using the error measures criteria. This table demonstrates the MAD, MSE, and RMSE values based on real and forecasted GDP growth for regression models of Greece, India, South Africa, and Ukraine between 2017: Q1 through 2019: Q4.

	Greece	*India*	*South Africa*	*Ukraine*
MAD	1.341	0.643	0.548	2.963
MSE	2.674	0.577	0.487	10.393
RMSE	1.635	0.759	0.698	3.224

5.2 Probit model

5.2.1 Application of the binary regression

In our research, we use a probit regression model technique to analyse the impact of key economic indicators – GDP growth, inflation rate, unemployment rate, and interest rate spread on a recession probability. Regarding the investigated research topic here, we want to find specific evidence of the yield curve power to predict a change in business cycles – that is, from expansion to recession in the economies of developing countries. As with the OLS regression described above, we also consider the correlation matrix between the variables to estimate which one, other than the yield spread, could affect the probability of recession. So, for binary regression, we use the inflation rate, unemployment rate, and GDP growth as additional independent variables. In the process of modelling, we find that the unemployment rate does not have a significant influence on the recession indicator for all countries except South Africa and cannot help in explaining the change in the dependent variable, that is why it is removed from three regressions. The same issue occurs in the model for Ukraine with an inflation rate indicator, that is why we remove such a variable from the regression equation.

Using the probit modelling theory, we conduct four regressions for the available data at the beginning of the series, and until 2016: Q4 for all countries (Appendix F-I). To compare the adequacy of all regressions, we use pseudo R^2 (McFadden R^2) that shows what part of the variants of the practical demonstration found with the variants of the factorial results. According to that criteria, the change in recession status Greece, India, South Africa, and Ukraine is explained accordingly by 28.9%, 37.5%, 53.6% and 70.5% of the selected factors (Table 5.2.1). The Greece model is explained on 71.1 % by the random variables that are not included in the model, whereas the Ukrainian model has shown the highest results.

Table 5.2.1: Comparison of the efficacy of Probit models. This table presents the results of SPREAD coefficients and its significance, LR statistics, and pseudo-R-squared for a model built on quarterly frequency between 1998 and 2016 for Greece, from 2000 to 2016 for India and South Africa, between 2002 through 2016 for Ukraine models.

	Greece (1)	*India (2)*	*South Africa (3)*	*Ukraine (4)*
SPREAD	-0.109 (0.030) **	-0.577 (0.059) ***	-0.590 (0.001) *	0.204 (0.030) **
Constant	4.652 (0.032) **	4.595 (0.000) *	-8.387 (0.108)	-0.833 (0.029) **
LR statistic	29.83 (0.000) *	33.56 (0.000) *	49.00 (0.000) *	50.45 (0.000) *
Observations	76	68	68	60
McFadden R^2	0.289	0.375	0.536	0.705

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.
(1) $Recession_t = \beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_{t-1} + \beta_4 \times CPI_t$
(2) $Recession_t = \beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_t + \beta_4 \times CPI_t$
(3) $Recession_t = \beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_t + \beta_4 \times CPI_t + \beta_5 \times UNEP\_RATE_t$
(4) $Recession_t = \beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_t$

To check how adequately these models coped with the division of states into recession and expansion, we use the relevant statistics, namely Expectation-Prediction Evaluation. As a cut-off value, we use 0.5: values under this value are considered as expansion and above as recession. The percentage of total correct prediction is higher by 80% for all countries except for Greece, where this value is 67 %, that is all models are adequate by this test. Another criterion that we use to estimate if the model works effectively is L.R. statistics and Wald test that measure the significance of all coefficients simultaneously. By Likelihood Ratio, all models passed the verification of the significance of all coefficients. Moreover, checking only independent variables except for intercept shows that the coefficients are simultaneously significant for all countries (Appendix F-I).

5.2.2 Significance of the interest spread on recession prediction

After checking the adequacy of the built models, we can evaluate the interest spread power on changing the state of the economy. In Table 5.2.1, we have p-values and coefficients values for the spread variable. At the significance level of 5 % interest spread appears statistically significantly different from zero for Greece, South Africa, and Ukraine, but switching to the 10 % level, the spread parameter for India also passed this verification. The results show the increase in interest spread by 1 % decrease the probability of recession of 10.9 % for Greece, for India of 57.7 % for South Africa – of 59%. Such an outcome is reasonable because widening the Spread that is the difference between long-term and short-term rates is not a cause of recession in the upcoming four quarters. The model for Ukraine does not show the same results; the impact is reversed: for each 1 % increase in the Spread, the probability of recession increases by 20.4 %. Such unfavourable output we can explain by the data used for the yield spread, as in some periods, only short-term or long-term government bonds were presented on the market. Another explanation for this could be a shorter, modelled period.

5.2.3 Out-of-sample and in-sample forecasting approaches

As we discussed earlier in the theory section, the out-of-sample forecasting usually forecasts better. That is why, in this section, we compare the in-sample and out-of-sample prediction. All forecasted probabilities for all countries we contrast to the actual recession data, finding are in Figures 5.2.5-5.2.8 As an out-of-sample forecasting period, we have quarter one of 2017 to quarter four of 2019.

Comparing in-sample probabilities and real recession indicators for the period until 2016, we see that models for India, South Africa, and Ukraine show reliable results as probabilities higher than 0.5 points. The Greece model forecasts work well until 2012 after we notice 2013 where the probability of recession was high (more than 50 %), but the economy did not struggle with the slump, whereas the real recession of 2015-2016 is not forecasted.

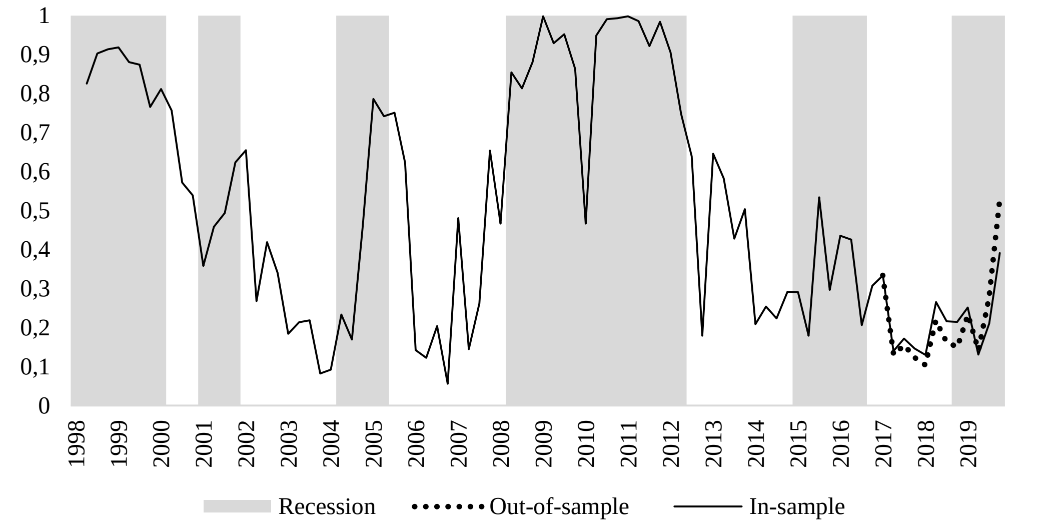

Figure 5.2.1: Forecasted probabilities of recessions in Greece. This figure illustrates the quarterly dynamics of in-sample and out-of-sample forecasting of recession probability for Greece for a period from 1998 to 2019 together with real recession states (1 denotes the recession state, 0 – the expansion state).

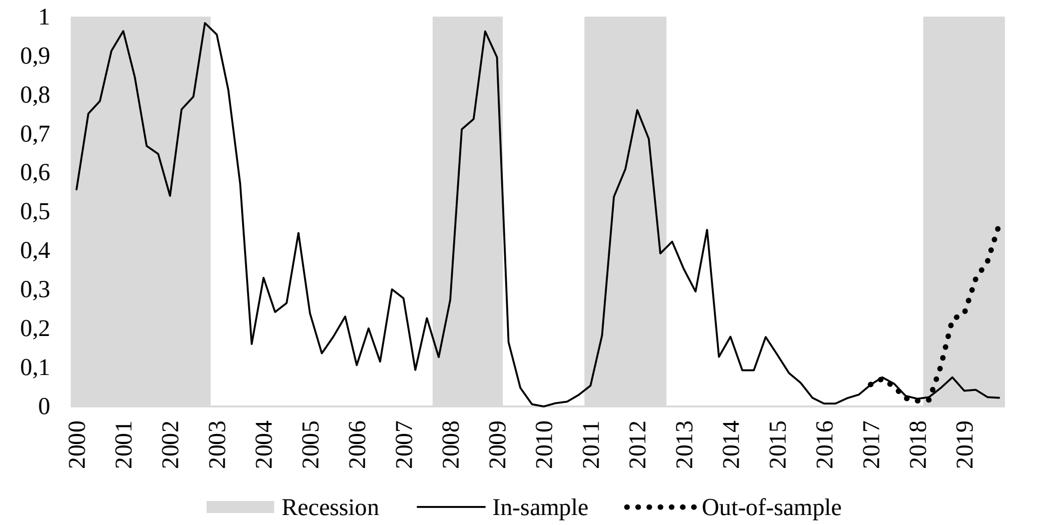

Figure 5.2.2: Forecasted probabilities of recessions in India. This figure illustrates the quarterly dynamics of in-sample and out-of-sample forecasting of recession probability for India for a period from 2000 to 2019 together with real recession states (1 denotes the recession state, 0 – the expansion state).

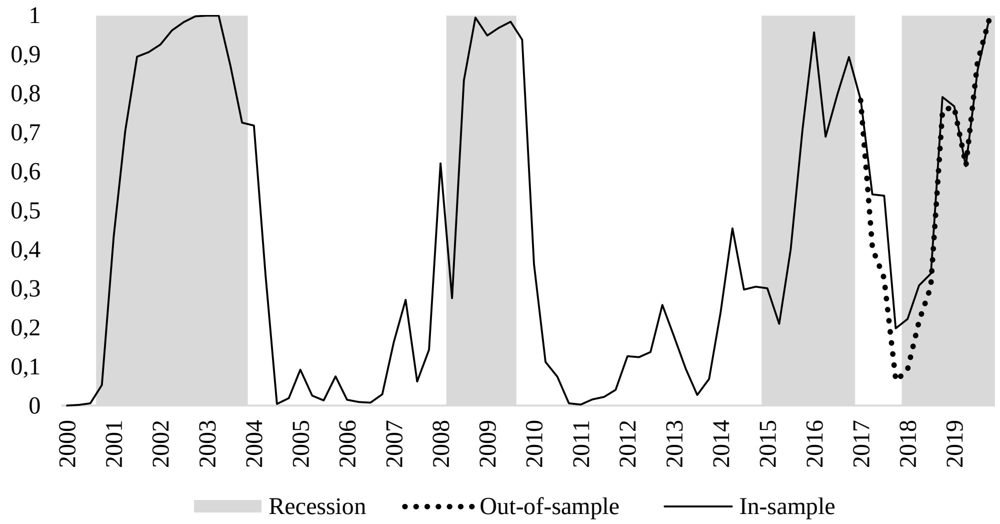

Figure 5.2.3: Forecasted probabilities of recessions in South Africa. This figure illustrates the quarterly dynamics of in-sample and out-of-sample forecasting of recession probability for South Africa for a period from 2000 to 2019 together with real recession states (1 denotes the recession state, 0 – the expansion state).

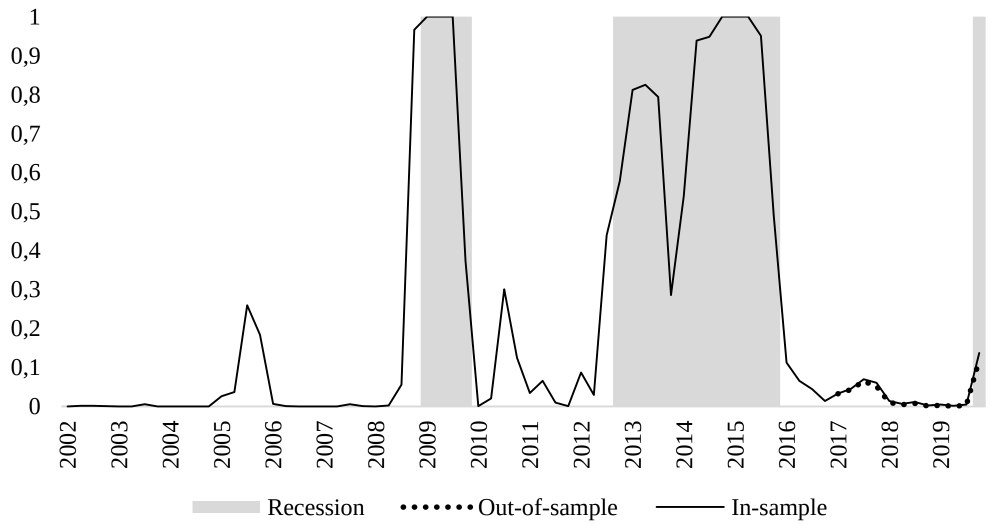

Figure 5.2.4: Forecasted probabilities of recessions in Ukraine. This figure illustrates the quarterly dynamics of in-sample and out-of-sample forecasting of recession probability for Ukraine for a period from 2002 to 2019 together with real recession states (1 denotes the recession state, 0 – the expansion state).

For the forecasted period of 2017-2019 by visual analysis of Figure 5.2.1-5.2.4, we observe that probabilities match with the real situation only for the non-recession period for all countries. The last recession in Greece is well forecasted only with out-of-sample forecasting; the same applies to South Africa. In the case of India, out-of-sample forecasting works better, but still, the probabilities lower than 50 %. For Ukraine, both in-sample and out-of-sample techniques show the probabilities that lower 15 %, but in fact, the recession started. This discrepancy can be explained by the fact that the recession only began in the last quarter of 2019, so the model could not catch it.

To liken the two forecasting techniques, we use the ROC curve and values of the area under the curve (AUC) estimated for all available data of all countries. The ROC curve can be found in Appendix J - M. Here, we focus more on the AUC values that determine the performance of the actual favourable rates against false. The value of 1 stand for the perfect classifier of the state. In Table 5.2.2, we have AUC value for in-sample and out-of-sample forecasting with the significance level.

Table 5.2.2: Evaluation of the in-sample and out-of-sample forecasting. This table shows the comparison of the AUC criteria for the Probit model of Greece, India, South Africa, and Ukraine.

	Greece	*India*	*South Africa*	*Ukraine*
AUC (in-sample)	0.794 (0.000) *	0.751 (0.000) *	0.915 (0.000) *	0.980 (0.000) *
AUC (out-of-sample)	0.802 (0.000) *	0.842 (0.000) *	0.906 (0.000) *	0.979 (0.000) *
Observations	88	80	80	72

*Denotes the 1 % significance level, ** – the 5 %significance level, *** – the 10 % significance level.

The out-of-sample forecasting evaluation is made by a combination of in-sample probabilities of recession until 2016: Q4 and out-of-sample probabilities of recession from 2017: Q1 to 2019: Q4 and then analysed by a program software (IBM SPSS Statistics). We compare the forecasted values of recession state with real values of recessions during the period from 1998: Q1 to 2019: Q4 for Greece, from 2000: Q1 to 2019: Q4 for India and South Africa, from 2002: Q1 to 2019: Q4 for Ukraine.

For all models, the AUC value is significant at the 5 % level and higher than 0.7. As expected, the out-of-sample works better than in-sample forecasting for Greece and India. For Ukraine, both techniques perform on a high level and have almost the same value. Only in the South Africa case, we see that in-sample forecasting works better.

Summary for part 5

We provide OLS regressions and probit model results for each country. Based on OLS regression results for each country, Spread as an independent variable has a significant influence on GDP growth. All models meet the main adequacy criteria and can be used for forecasting. Thus, based on developed models, we conduct a forecast for each country. Only for India model gives high accuracy of the estimates. Hence, the quality of the model for India is better compares to others.

As an outcome of probit modelling, we show that all models estimated a high percentage (the point of 70%) of correct predictions for the estimation period. Comparing the pseudo-R^2, we find that models differ in the adequacy of the independent variable to predict the recession state from 28.9 % for Greece to 70.5% for Ukraine. We provide the significance of interest spread at a 10 % level and show that all models passed this test. Besides, we reveal the widening the interest spread has a positive influence on lowering the probability of a recession in all countries except for Ukraine. To prove the theory behind out-of-sample forecasting abilities, we use a ROC analysis that proves such reasoning for Greece and India.

6 Summary and conclusion

The main goal of this thesis is to provide an answer to the research question on what the predictive power of the yield curve in developing countries is. If we find that the yield curve does not have a significant impact on the economic growth of the emerging markets, we will conclude that theoretical assumptions and previous studies are not consistent with our findings. Moreover, it is inefficient to use the T-bills interest rate data to predict a recession in the emerging markets. If the result is the opposite, we will conclude that there is evidence of the yield curve predicting power. Furthermore, the yield curve helps to determine the upcoming recession, and we can show how strong is the impact of the yield curve on the state of the developing economies.

The main insights of our research are the following:

- The yield spread is statistically significant at a 5 % level in regard to the GDP change level for Greece, India, South Africa, and Ukraine in OLS regression. Moreover, it has a positive impact on the GDP of India and South Africa, that is, increasing the spread value by one unit cause the GDP grows. Whereas, for Greece and Ukraine cases, the spread has an adverse impact. Such results are controversial because widening the yield spread value should have a positive influence on GDP. However, at the same time, all models are adequate by R-squared criteria.
- Conducting the forecast, we found that India, South Africa, and Greece have shown relatively adequate results comparing to Ukraine; the actual and forecasted values have the same dynamics and trend. The error measure criteria confirm such results: by RMSE standards, only India and South Africa have fair values.
- By using bivariate regression (probit models in our case), we found that all models except for Greece are efficient by McFadden R^2 (exceed 35 % level) and have the value of Expectation-Prediction Evaluation higher than 80 %. We compared the significance of the yield spread concerning the recession indicator. We discovered that at the 5 % significance, the yield spread is statically significant for Greece, South Africa, and Ukraine and at the 10 % level for India. Besides, results have shown that increasing the spread value

on one unit could lower the probability of the recessions for all countries, excluding Ukraine.

- We determined that out-of-sample forecasting works better than the in-sample prediction for Greece and India, which was confirmed by ROC and AUC analysis. For Ukraine, both forecasting work at the same level. Such finding is consistent with the newest researches that use out-of-same forecasting as the most precise and effective technique.
- Taking all together, we conclude that the yield curve has a partial predictive power for developing countries. As by OLS modelling, only India and South Africa show good results, and by probit modelling Greece and India got the best results in model sufficiency and forecasting.
- Such findings can be valuable for potential investors of Greece, India, South Africa, and Ukraine and countries with similar economies. Based on the anxious signals of the yield curve as an indicator of the peak of expansion or decline of business cycles of the economy of such countries, investors would be able to decide on how to invest in such counties or move funds elsewhere. Moreover, the governments and the National banks of the investigated countries can use the results of this study for building forecasts for economy business cycles. That is, by incorporating the yield curve data to the model techniques. Our findings can be valuable for future researches as our paper shows a historical base analysis and a combination of model tools.

To have the study consistent with the recent literature, we checked prior research to compare and identify what was missing. We used methods that were identified as the most effective for this type of analysis and incorporated them by combing OLS regression and probit modelling, using out-of-sample forecasting. We analysed countries that were rare in prior literature but had many pieces of evidence of the recessions to make the research not trivial, as mostly all papers on the yield curve power study the US, European, Chinese, and Japanese economies.

The main limitation of this study is the data analysed. As we were not able to obtain information from one source for all countries for a one-time period, this made it difficult to search for data and further analyse it. However, at the same time, such limitation can be a reason for further investigations. As such, it would be practical to extend the analysis for the longer timeline, add more countries, and do it case by case. Moreover, as the additional model tool, panel data model with fixed and random effects can be used to analyse the yield curve predictive power in a more sophisticated way.

The unfavourable circumstances in which the world economy found itself during the Coronavirus pandemic make the study of recessions even more relevant. That is why the study of the impact of yield curves is essential given when a new recession will occur and whether it will be decisive only for developing economies or for the whole world.

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APPENDICES

Appendix A: Descriptive Statistics

Table A.1: Descriptive Statistics of Variables for Greece

Variable	Mean	Standard Error	Standard Deviation	Minimum	Maximum
GDP Growth	0.68	0.46	4.32	-10.25	6.78
Inflation rate	90.16	1.30	12.21	66.05	105.08
Unemployment rate	15.29	0.70	6.58	7.61	27.83
Spread	4.35	0.66	6.17	-6.36	24.70

Table A.2: Descriptive Statistics of Variables for India

Variable	Mean	Standard Error	Standard Deviation	Minimum	Maximum
GDP Growth	7.05	0.27	2.38	0.16	13.69
Inflation rate	70.21	3.16	28.22	35.79	125.34
Spread	1.06	0.10	0.87	-0.48	3.92

Table A.3: Descriptive Statistics of Variables for South Africa

Variable	Mean	Standard Error	Standard Deviation	Minimum	Maximum
GDP Growth	2.64	0.22	1.95	-2.23	6.07
Inflation rate	78.36	2.65	23.71	44.63	123.46
Unemployment rate	25.11	0.22	1.94	21.03	29.82
Spread	1.18	0.21	1.89	-4.29	4.36

Table A.4: Descriptive Statistics of Variables for Ukraine

Variable	Mean	Standard Error	Standard Deviation	Minimum	Maximum
Real GDP Growth	2.14	0.85	7.18	-19.60	14.00
Inflation rate	7.79	1.07	9.12	-3.30	43.30
Unemployment rate	8.81	0.12	1.02	6.50	10.50
Spread	-0.16	0.58	4.92	-14.26	15.49

Appendix B.1: OLS Regression result for Greece

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Estimation Equation:

$$GDP\_Growth_t = \beta_1 + \beta_2 \times SPREAD_t + \beta_3 \times RECESSION_t + \beta_4 \times INFLATION\_RATE_{t-3} + \beta_5 \times UNEMPLOYMENT_{t-2} + \beta_6 \times GDP\ GROWTH_{t-2}$$

Table B.1: OLS Regression output for Greece

Dependent Variable: GDP_GROWTH				
Method: Least Squares				
Sample (adjusted): 1998Q4 2016Q4		*Total obs.:* 73		
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	8.609	2.603	3.308	0.002 *
SPREAD	-0.139	0.068	-2.053	0.044 **
RECESSION	-2.120	0.446	-4.752	0.000 *
INFLATION_RATE(-3)	-0.101	0.032	-3.126	0.003 *
UNEMPLOYMENT(-2)	0.152	0.044	3.429	0.001 *
GDP_GROWTH(-2)	0.579	0.082	7.019	0.000 *
R-squared	0.856	Mean dependent var		0.358
Adjusted R-squared	0.846	Log-likelihood		-144.3
S.E. of regression	1.824	F-statistic		79.87
Sum squared resid	222.9	Prob(F-statistic)		0.000*
Durbin-Watson stat	1.596			

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Autocorrelation test

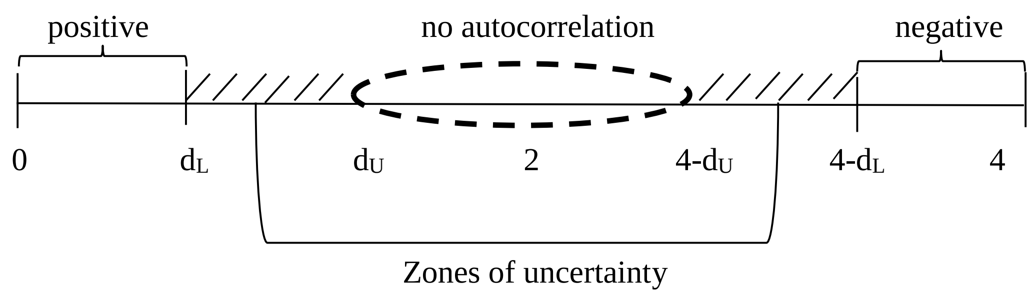

Figure B.1: Durbin-Watson test decision-making area.

For this figure we have k = 4, n = 72, d_L= 1.313, d_u = 1.611. Thus, Durbin–Watson estimation, which is equal to 1.6, lays in the uncertainty zone, but very close to the no autocorrelation border.

Appendix B.2: OLS Regression result for Greece

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Autocorrelation test

Table B.2: Breusch-Godfrey Serial Correlation LM Test for Greece. From the test results, it is possible to determine the serial correlation in the residuals up to the specified order. Since according to the p-value, the coefficient at RESID (-4) is statistically significant at the level of 5%, the autocorrelation of the 4th order is significant. This is logical given the presence of seasonal fluctuations in GDP.

Null hypothesis: No serial correlation at up to 4 lags				
F-statistic	6.607	Prob. F(4,63)		0.000 *
Obs*R-squared	21.57	Prob. Chi-Square(4)		0.000 *
Method: Least Squares				
Pre sample missing value lagged residuals set to zero.				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.927	2.448	-1.195	0.236
SPREAD	0.055	0.066	0.841	0.403
RECESSION	-0.133	0.389	-0.342	0.733
INFLATION_RATE(-3)	0.035	0.030	1.170	0.246
UNEMPLOYMENT(-2)	-0.033	0.040	-0.829	0.410
GDP_GROWTH(-2)	0.180	0.102	1.765	0.083
RESID(-1)	0.152	0.111	1.366	0.177
RESID(-2)	-0.294	0.147	-1.998	0.050
RESID(-3)	0.049	0.114	0.433	0.667
RESID(-4)	-0.581	0.123	-4.729	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Homoscedasticity test

Table B.3: White test result for Greece. This table shows that there is homoscedasticity.

Null hypothesis: Homoskedasticity			
F-statistic	1.598	Prob. F(19,53)	0.092 ***
Obs*R-squared	26.58	Prob. Chi-Square(19)	0.115
Scaled explained SS	33.37	Prob. Chi-Square(19)	0.022

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level

Appendix B.3: OLS Regression result for Greece

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Normality test

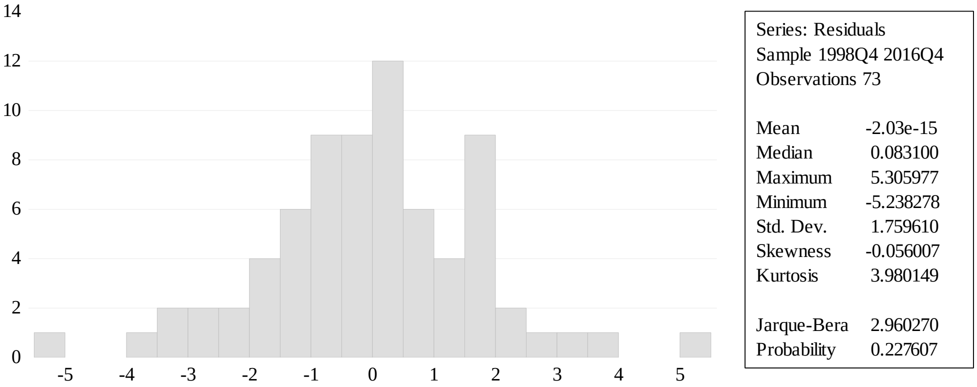

Figure B.2: Jarque-Bera Normality Test Result for Greece. This figure shows that the skewness and the excess kurtosis are jointly zero

Coefficient diagnostics

Table B.4: Wald Test Results for Greece. This table shows results for the Wald Test on the joint significance of independent variables except for intercept. The coefficients are jointly significant.

Null Hypothesis: β_2=0, β_3=0, β_4=0, β_5=0			
Test Statistic	*Value*	*df*	*Probability*
F-statistic	11.91	(4, 67)	0.000 *
Chi-square	47.63	4	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Actual, Fitted, Residual

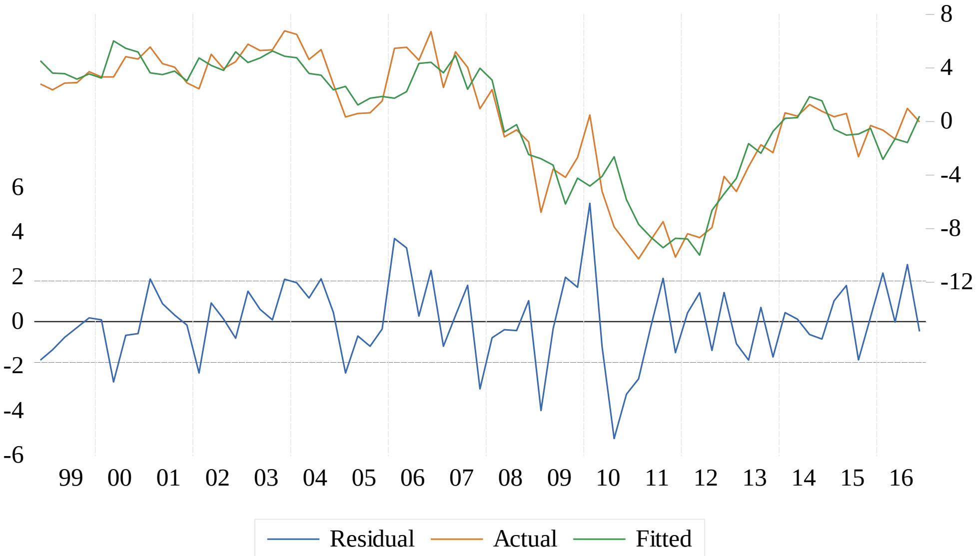

Figure B.3: Actual, Fitted, Residual Graph for Greece. This figure displays the actual and fitted values of the dependent variable and the residuals from the regression in graphical form.

Appendix C.1: OLS regression results for India

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Estimation Equation:

$$GDP\_Growth_t = \beta_1 + \beta_2 \times SPREAD_{t-1} + \beta_3 \times GDP\_Growth_{t-1} + \beta_4 \times Recession_{t-1}$$

Table C.1: OLS regression output for India

Dependent Variable: GDP_GROWTH				
Method: Least Squares				
Sample (adjusted): 2000Q2 2016Q4			*Total obs.:* 67	
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	3.768	0.655	5.754	0.000 *
SPREAD(-1)	0.498	0.170	2.927	0.005 *
GDP_GROWTH(-1)	0.516	0.074	6.957	0.000 *
RECESSION(-1)	-2.231	0.386	-5.786	0.000 *
R-squared	0.760	Mean dependent var		7.192
Adjusted R-squared	0.748	S.D. dependent var		2.548
S.E. of regression	1.279	Log-likelihood		-109.5
Sum squared resid	103.0	F-statistic		66.38
Durbin-Watson stat	2.316	Prob(F-statistic)		0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Autocorrelation test

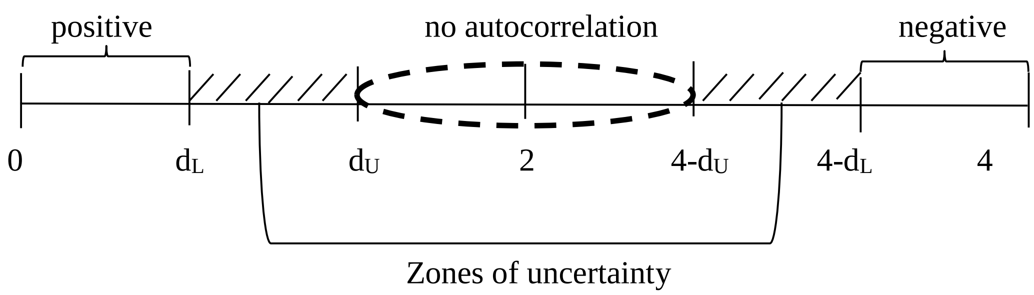

Figure C.1: Durbin-Watson test decision-making area. For this figure we have k = 3, n = 67, d_L= 1.346 and d_u = 1.534. Thus, Durbin–Watson estimation, which is equal to 2.31, lays in no autocorrelation area.

Appendix C.2: OLS regression results for India

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Autocorrelation test

Table C.2: Breusch-Godfrey Serial Correlation LM Test for India. From the test results, it is possible to determine the serial correlation in the residuals up to the specified order. Since according to the p-value, the coefficient at RESID (-4) is statistically significant at the level of 1%, the autocorrelation of the 4th order is significant. This is logical given the presence of seasonal fluctuations in GDP.

Null hypothesis: No serial correlation at up to 4 lags				
F-statistic	7.512	Prob. F(4,59)		0.000 *
Obs*R-squared	22.61	Prob. Chi-Square(4)		0.000 *
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	-0.799	0.737	-1.083	0.283
SPREAD(-1)	-0.149	0.154	-0.963	0.340
GDP_GROWTH(-1)	0.112	0.090	1.248	0.217
RECESSION(-1)	0.401	0.382	1.050	0.298
RESID(-1)	-0.183	0.146	-1.251	0.216
RESID(-2)	-0.145	0.128	-1.134	0.261
RESID(-3)	0.026	0.121	0.214	0.831
RESID(-4)	-0.548	0.113	-4.841	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Homoscedasticity test

Table C.3: OLS regression output with Huber-White-Hinkley heteroskedasticity consistent standard errors and covariance for India. After checking for heteroscedasticity, the model was estimated to solve the issue manually by adding HCI.

Dependent Variable: GDP_GROWTH *Method:* Least Squares Sample (adjusted): 2000Q2 2016Q4 Total obs.: 67 Huber-White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance				
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	3.768	0.732	5.147	0.000 *
SPREAD(-1)	0.498	0.244	2.040	0.046 **
GDP_GROWTH(-1)	0.516	0.084	6.156	0.000 *
RECESSION(-1)	-2.231	0.339	-6.579	0.000 *
R-squared	0.760			
Adjusted R-squared	0.748			

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Appendix C.3: OLS regression results for India

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Normality Tests

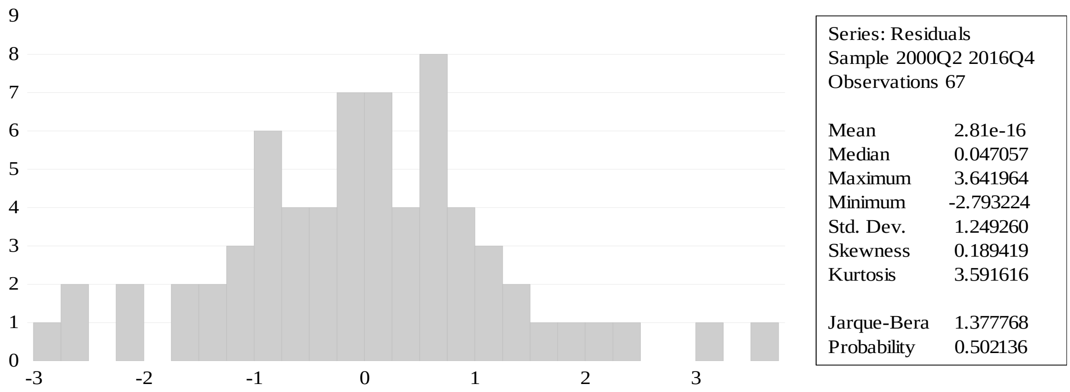

Figure C.2: Jarque-Bera Normality Test Result for India. This figure shows that the skewness and the excess kurtosis are jointly zero

Coefficient Diagnostics

Tablet C.5: Wald Test Results for India. This table shows results for the Wald Test on the joint significance of independent variables except for intercept. The coefficients are jointly significant.

Null Hypothesis: β_2=0, β_3=0, β_4=0			
Test Statistic	*Value*	*df*	*Probability*
F-statistic	45.34	(3, 63)	0.000 *
Chi-square	136.0	3	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Actual, Fitter, Residual

Figure B.3: Actual, Fitted, Residual Graph for India. This figure displays the actual and fitted values of the dependent variable and the residuals from the regression in graphical form.

Appendix D.1: OLS regression for South Africa

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Estimation Equation:

$$GDP\_Growth_t = \beta_1 + \beta_2 \times SPREAD_{t-1} + \beta_3 \times RECESSION_{t-4} + \beta_4 \times GDP\_GROWTH_{t-1}$$

Table D.1: OLS regression output for South Africa

Dependent Variable: GDP_GROWTH
Method: Least Squares
Sample (adjusted): 2001Q1 2016Q4 *Total obs.:* 64
Huber-White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	-0.682	0.253	-2.696	0.009 *
SPREAD(-1)	0.202	0.042	4.796	0.000 *
RECESSION(-4)	0.760	0.142	5.334	0.000 *
GDP_GROWTH(-1)	1.063	0.060	17.830	0.000 *

R-squared	0.892	Mean dependent var	2.894
Adjusted R-squared	0.887	S.D. dependent var	1.947
S.E. of regression	0.656	Log-likelihood	-61.72
Sum squared resid	25.79	F-statistic	165.3
Durbin-Watson stat	1.605	Prob(F-statistic)	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Autocorrelation tests

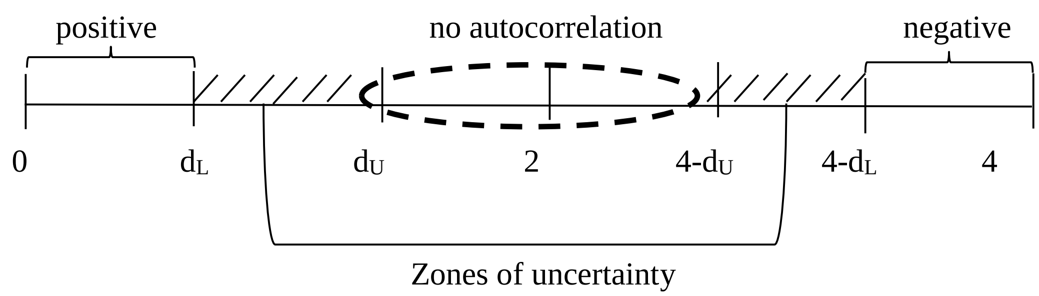

Figure D.1: Durbin-Watson test decision-making area.

For this Figure k = 3, n = 64, d_L= 1.346 and d_u = 1.534. Thus, Durbin–Watson estimation, which is equal to 1.6, lays in no autocorrelation area.

Appendix D.2: OLS regression for South Africa

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Autocorrelation tests

Table D.2: Breusch-Godfrey Serial Correlation LM Test for South Africa. From the test results, it is possible to determine the serial correlation in the residuals up to the specified order. Since according to the p-value, the coefficient at RESID (-4) is statistically significant at the level of 5%, the autocorrelation of the 4th order is significant. This is logical given the presence of seasonal fluctuations in GDP.

Breusch-Godfrey Serial Correlation LM Test:				
Null hypothesis: No serial correlation at up to 4 lags				
F-statistic	2.307	Prob. F(4,56)		0.069 **
Obs*R-squared	9.056	Prob. Chi-Square(4)		0.060 **
Method: Least Squares				
Pre sample missing value lagged residuals set to zero.				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.110	0.220	0.499	0.619
SPREAD(-1)	-0.018	0.045	-0.409	0.684
RECESSION(-4)	-0.147	0.200	-0.733	0.467
GDP_GROWTH(-1)	-0.013	0.053	-0.251	0.803
RESID(-1)	0.179	0.133	1.344	0.184
RESID(-2)	-0.019	0.135	-0.138	0.891
RESID(-3)	0.010	0.149	0.069	0.946
RESID(-4)	-0.361	0.141	-2.560	0.013 **

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Heteroscedasticity Tests

Table D.3: White test result for South Africa. After checking for heteroscedasticity, the model was estimated to solve the issue manually.

Null hypothesis: Homoskedasticity			
F-statistic	2.212	Prob. F(8,55)	0.040 **
Obs*R-squared	15.58	Prob. Chi-Square(8)	0.049 **
Scaled explained SS	23.40	Prob. Chi-Square(8)	0.003 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Appendix D.3: OLS regression for South Africa

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Normality test

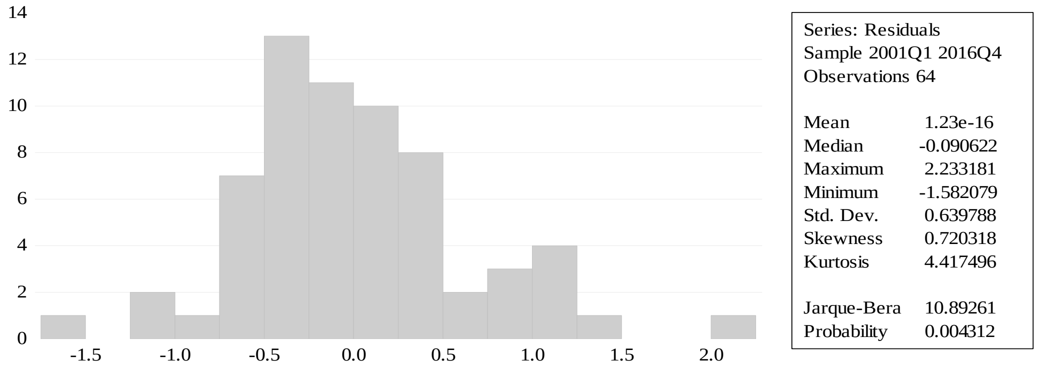

Figure D.2: Jarque-Bera Normality Test Result for South Africa. This figure shows that the skewness and the excess kurtosis are jointly zero

Coefficient diagnostics

Tablet D.5: Wald Test Results for South Africa. This table shows results for the test on the joint significance of independent variables except for intercept. The coefficients are jointly significant.

Null Hypothesis: β_2=0, β_3=0, β_4=0			
Test Statistic	*Value*	*df*	*Probability*
F-statistic	124.1	(3, 60)	0.000 *
Chi-square	372.4	3	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Actual, Fitted, Residual

Figure D.3: Actual, Fitted, Residual graph for South Africa. This figure displays the actual and fitted values of the dependent variable and the residuals from the regression in graphical form.

Appendix E.1: OLS regression for Ukraine

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Estimation Equation:

$$GDP\_Growth_t = \beta_1 + \beta_2 \times SPREAD_{t-1} + \beta_3 \times GDP\_Growth_{t-1} + \beta_4 \times UNEMPLOYMENT_{t-2}$$

Table E.1: OLS regression output for Ukraine

Dependent Variable: GDP_GROWTH
Method: Least Squares
Sample (adjusted): 2003Q4 2016Q4 *Total obs.:* 53

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	-10.81	4.376	-2.470	0.017 **
SPREAD(-1)	-0.322	0.122	-2.629	0.011 **
GDP_GROWTH(-1)	0.999	0.076	13.199	0.000 *
UNEMPLOYMENT(-2)	1.289	0.500	2.576	0.013 **

R-squared	0.803	Mean dependent var	1.330
Adjusted R-squared	0.790	S.D. dependent var	8.107
S.E. of regression	3.711	Log-likelihood	-142.6
Sum squared resid	674.7	F-statistic	66.40
Durbin-Watson stat	1.421	Prob(F-statistic)	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Autocorrelation tests

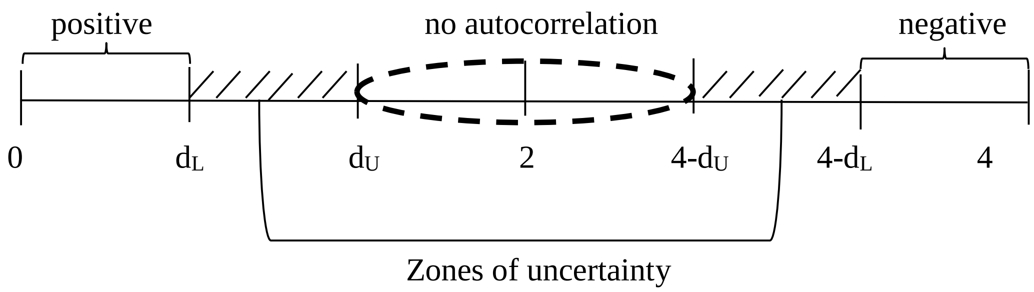

Figure E.1: Durbin-Watson test decision-making area. For this figure k = 3, n= 53, d_L= 1.245 and d_u = 1.491. Thus, Durbin–Watson estimation, which is equal to 1.42, lays in a zone of uncertainty.

Appendix E.2: OLS regression for Ukraine

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Autocorrelation tests

Table E.2: Breusch-Godfrey Serial Correlation LM Test for Ukraine. From the test results, it is possible to determine the serial correlation in the residuals up to the specified order. According to the p-value, only the coefficient at RESID (-4) is statistically significant at the level of 1%.

Null hypothesis: No serial correlation at up to 4 lags				
F-statistic	3.393	Prob. F(4,45)		0.017 **
Obs*R-squared	12.28	Prob. Chi-Square(4)		0.015 **
Method: Least Squares				
Pre sample missing value lagged residuals set to zero.				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.659	4.151	0.881	0.383
SPREAD(-1)	0.137	0.120	1.136	0.262
GDP_GROWTH(-1)	0.016	0.107	0.148	0.883
UNEMPLOYMENT(-2)	-0.438	0.477	-0.918	0.364
RESID(-1)	0.219	0.162	1.351	0.183
RESID(-2)	-0.111	0.164	-0.678	0.501
RESID(-3)	-0.056	0.161	-0.347	0.731
RESID(-4)	-0.461	0.164	-2.804	0.007 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Homoscedasticity test

Table E.3: White test result for Ukraine. After checking for heteroscedasticity, the model was estimated to solve the issue manually.

Null hypothesis: Homoscedasticity			
F-statistic	1.776	Prob. F(9,43)	0.101
Obs*R-squared	14.36	Prob. Chi-Square(9)	0.110
Scaled explained SS	15.79	Prob. Chi-Square(9)	0.071 ***

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Coefficient diagnostics

Tablet E.5: Wald Test Results for Ukraine. This table shows results for the test on the joint significance of independent variables except for intercept. The coefficients are jointly significant.

Null Hypothesis: $\beta_2=0$, $\beta_3=0$, $\beta_4=0$			
Test Statistic	*Value*	*df*	*Probability*
F-statistic	66.40	(3, 49)	0.000 *
Chi-square	199.2	3	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Appendix E.3: OLS regression for Ukraine

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

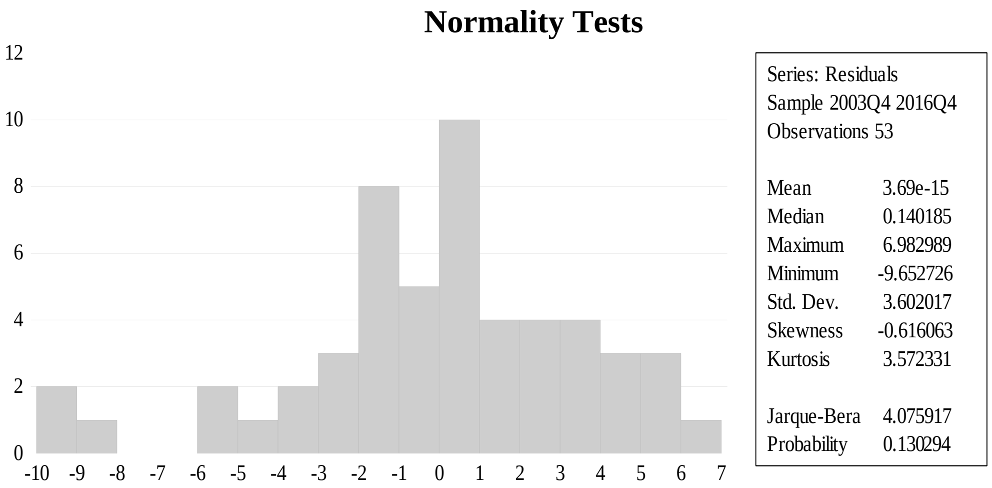

Figure E.2: Jarque-Bera Normality Test Result for Ukraine. This figure shows that the skewness and the excess kurtosis are jointly zero

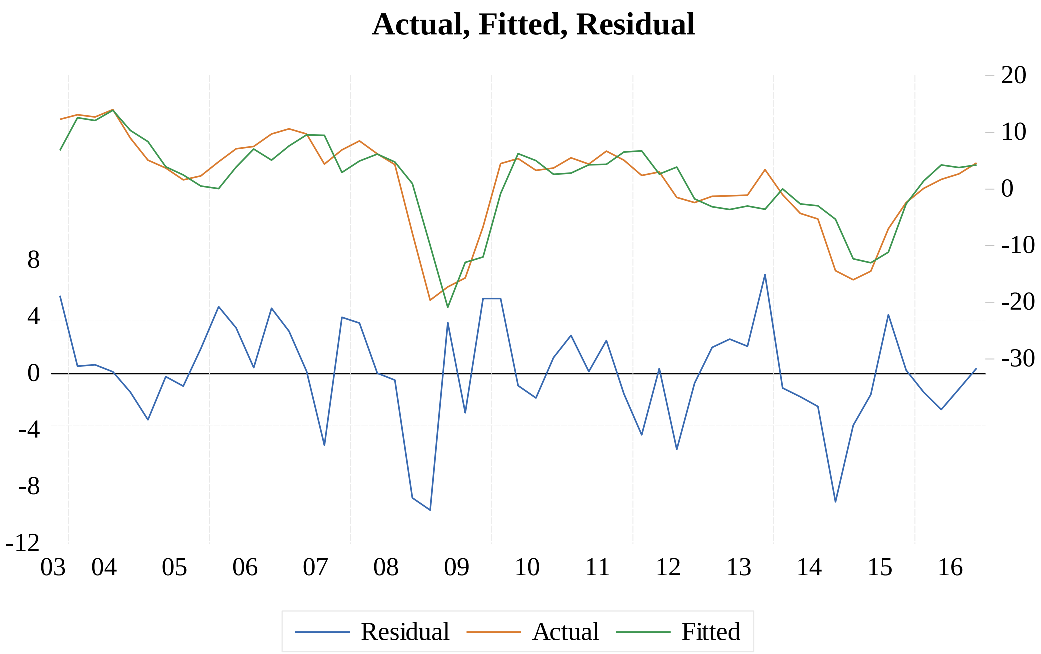

Figure D.3: Actual, Fitted, Residual graph for Ukraine. This figure displays the actual and fitted values of the dependent variable and the residuals from the regression in graphical form.

Appendix E.4: Comparison of the efficacy of OLS regression models for Greece, India, South Africa, and Ukraine

Table E.4: Comparison of the efficacy of OLS regressions (Source: Prepared by authors based on modelling results obtained in EViews software). The following table shows the four models results, and if the regression model satisfies the OLS assumptions.

		Country name			
		Greece	*India*	*South Africa*	*Ukraine*
Criteria	Assumption 1: Mean of the disturbances is zero *The test used: Constant term significance*	β_1 = 8.60 $\rho - \text{value}$ =0.015 ** Significant	β_1 = 3.76 $\rho - \text{value}$ =0.0000 * Significant	β_1 = -0.68 $\rho - \text{value}$ =0.0091 * Significant	β_1 = -10.8 $\rho - \text{value}$ =0.01114 ** Significant
	Assumption 2: Homoscedasticity *The test used: White test*	Homoscedastic	HCI used	HCI used	Homoscedastic
	Assumption 3: Autocorrelation *The test used: Durbin-Watson*	Uncertain area HAC used	No autocorrelation	No autocorrelation	Uncertain area HAC used
	Assumption 4: Stochastic repressors *The test used: Breusch-Godfrey Serial Correlation LM*	No autocorrelation up to 3 lags	No autocorrelation up to 3 lags	No autocorrelation up to 3 lags	No autocorrelation up to 3 lags
	Assumption 5: Normality *The test used: Jarque Bera*	Normality	Normality	Non-normality (solved by adding dummy variables)	Normality
	Joint significance of independent variables except for the intercept *The test used: Wald*	Significant	Significant	Significant	Significant
	Value of the coefficient near SPREAD variable	-0.1386	0.4976	0.2018	-0.3217
	Significance of the SPREAD variable *Test used: Student's t-distribution p-value*	$\rho - \text{value} =$ 0.0440 ** Significant	$\rho - \text{value} =$ 0.0048 * Significant	$\rho - \text{value} =$ 0.0000 * Significant	$\rho - \text{value} =$ 0.0114 ** Significant
	Adjusted $\overline{R^2}$	0.8456	0.7482	0.8866	0.7905

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Appendix F.1: Regression results of the probit modelling for Greece

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Estimation Equation:

$$Recession_t = \beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_{t-1} + \beta_4 \times CPI_t$$

Forecasting Equation:

$$Recession_t = 1 - CNORM(-(\beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_{t-1} + \beta_4 \times CPI_t))$$

Table F.1: Binary regression model of the recession's prediction. This table reports the coefficients, significance, standard errors and z-Statistics values of the independent variables (*constant*, GDP_Change_t,$SPREAD_{t-1}$, CPI_t) impact on $Recession_t$ variable. It also presents the main statistical measures for the regression model, such as R-squared, LR statistics, Log-likelihood, Sum squared residuals, S.E. of regression estimated, number of observations for a period from 1998: Q1 to 2016: Q4.

Dependent Variable: $Recession_t$				
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)				
Sample: 1998Q1 2016Q4			*Total obs*: 75	
Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
β_1	4.652	2.166	2.146	0.032 **
GDP_Change_t	-0.353	0.080	-4.391	0.000 *
$SPREAD_{t-1}$	-0.109	0.050	-2.168	0.030 **
CPI_t	-0.043	0.025	-1.686	0.092 ***
McFadden R^2	0.289	*Mean dependent var*		0.547
S.D. dependent var	0.501	*S.E. of regression*		0.423
LR statistic	29.83	*Sum squared resid*		12.68
Prob (LR statistic)	0.000 *	*Log likelihood*		-36.74
Obs with Dep=0	34	*Obs with Dep=1*		41

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Table F.2: Wald Test on joint significance of independent variables except for the intercept. This table shows results for the test on the joint significance of independent variables except for intercept. The coefficients are jointly significant.

Null Hypothesis: β_2*=0,* β_3*=0,* β_4*=0*			
Test Statistic	*Value*	*df*	*Probability*
F-statistic	6.552	(3, 71)	0.001 *
Chi-square	19.66	3	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Appendix F.2: Regression results of the probit modelling for Greece

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Table F.3: Expectation-Prediction Evaluation for Binary Specification. This table reports the number of correct and incorrect categorizing based on a specified cut-off value of 0.5 (top two tables represent such calculations) and expected value calculations (bottom two tables).

Success cut-off: C = 0.5						
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	23	13	36	0	0	0
P(Dep=1)>C	11	28	39	34	41	75
Total	34	41	75	34	41	75
Correct	23	28	51	0	41	41
% Correct	67.65	68.29	68.00	0.00	100.00	54.67
% Incorrect	32.35	31.71	32.00	100.00	0.00	45.33
*Total Gain**	67.65	-31.71	13.33			
*Per cent Gain***	67.65	NA	29.41			
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	21.49	12.17	33.66	15.41	18.59	34.00
E(# of Dep=1)	12.51	28.83	41.34	18.59	22.41	41.00
Total	34.00	41.00	75.00	34.00	41.00	75.00
Correct	21.49	28.83	50.32	15.41	22.41	37.83
% Correct	63.20	70.31	67.09	45.33	54.67	50.44
% Incorrect	36.80	29.69	32.91	54.67	45.33	49.56
*Total Gain**	17.87	15.64	16.65			
*Percent Gain***	32.69	34.50	33.60			

**Change in "% Correct" from default (constant probability) specification*
***Percent of incorrect (default) prediction corrected by equation*

Appendix G.1: Regression results of the probit modelling for India

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Estimation Equation:

$$Recession_t = \beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_t + \beta_4 \times CPI_t$$

Forecasting Equation:

$$Recession_t = 1 - CNORM(-(\beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_t + \beta_4 \times CPI_t))$$

Table G.1: Binary regression model of the recession's prediction. This table reports the coefficients, significance, standard errors and z-Statistics values of the independent variables (*constant*, GDP_Change_t,$SPREAD_t$, CPI_t) impact on $Recession_t$ variable. It also presents the main statistical measures for the regression model, such as R-squared, LR statistics, Log-likelihood, Sum squared residuals, S.E. of regression estimated, number of observations for a period from 2000: Q1 to 2016: Q4.

Dependent Variable: $Recession_t$				
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)				
Sample: 2000Q1 2016Q4			*Total obs*: 68	
Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
β_1	4.595	1.108	4.146	0.000 *
GDP_Change_t	-0.339	0.086	-3.942	0.000 *
$SPREAD_t$	-0.577	0.306	-1.882	0.059 **
CPI_t	-0.033	0.013	-2.879	0.004 *
McFadden R^2	0.375	*Mean dependent var*		0.368
S.D. dependent var	0.486	*S.E. of regression*		0.361
LR statistic	33.56	*Sum squared resid*		8.360
Prob (LR statistic)	0.000 *	*Log likelihood*		-27.94
Obs with Dep=0	43	*Obs with Dep=1*		25

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Table G.2: Wald Test on joint significance of independent variables except for the intercept. This table shows results for the test on the joint significance of independent variables except for intercept. The coefficients are jointly significant.

Null Hypothesis: β_2=0, β_3=0, β_4=0			
Test Statistic	*Value*	*df*	*Probability*
F-statistic	7.548	(3, 64)	0.000 *
Chi-square	22.64	3	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Appendix G.2: Regression results of the probit modelling for India

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Table G.3: Expectation-Prediction Evaluation for Binary Specification. This table reports the number of correct and incorrect categorizing based on a specified cut-off value of 0.5 (top two tables represent such calculations) and expected value calculations (bottom two tables).

Success cut-off: C = 0.5						
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	40	5	45	43	25	68
P(Dep=1)>C	3	20	23	0	0	0
Total	43	25	68	43	25	68
Correct	40	20	60	43	0	43
% Correct	93.02	80.00	88.24	100.00	0.00	63.24
% Incorrect	6.98	20.00	11.76	0.00	100.00	36.76
*Total Gain**	-6.98	80.00	25.00			
*Per cent Gain***	NA	80.00	68.00			
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	34.29	8.86	43.16	27.19	15.81	43.00
E(# of Dep=1)	8.71	16.14	24.84	15.81	9.19	25.00
Total	43.00	25.00	68.00	43.00	25.00	68.00
Correct	34.29	16.14	50.43	27.19	9.19	36.38
% Correct	79.75	64.54	74.16	63.24	36.76	53.50
% Incorrect	20.25	35.46	25.84	36.76	63.24	46.50
*Total Gain**	16.51	27.78	20.66			
*Percent Gain***	44.92	43.93	44.42			

**Change in "% Correct" from default (constant probability) specification*
***Percent of incorrect (default) prediction corrected by equation*

Appendix H.1: Regression results of the probit modelling for South Africa

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Estimation Equation:

$$Recession_t = \beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_t + \beta_4 \times CPI_t + \beta_5 \times UNEP\_RATE_t$$

Forecasting Equation:

$$Recession_t = 1 - CNORM(-(\beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_t + \beta_4 \times CPI_t + \beta_5 \times UNEP\_RATE_t))$$

Table H.1: Binary regression model of the recession's prediction. This table reports the coefficients, significance, standard errors and z-Statistics values of the independent variables (*constant*, GDP_Change_t,$SPREAD_t$, $UNEP\_RATE_t, CPI_t$) impact on $Recession_t$ variable. It also presents the main statistical measures for the regression model, such as R-squared, LR statistics, Log-likelihood, Sum squared residuals, S.E. of regression estimated, number of observations for a period from 2000: Q1 to 2016: Q4.

Dependent Variable: $Recession_t$				
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)				
Sample: 2000Q1 2016Q4			*Total obs*: 68	
Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
β_1	-8.387	5.220	-1.607	0.108 ***
GDP_Change_t	-0.685	0.176	-3.900	0.000 *
$SPREAD_t$	-0.590	0.181	-3.267	0.001 *
$UNEP\_RATE_t$	0.550	0.215	2.565	0.010 *
CPI_t	-0.041	0.014	-2.861	0.004 *
McFadden R^2	0.536	*Mean dependent var*		0.397
S.D. dependent var	0.493	*S.E. of regression*		0.321
LR statistic	49.00	*Sum squared resid*		6.486
Prob (LR statistic)	0.000 *	*Log likelihood*		-21.18
Obs with Dep=0	41	*Obs with Dep=1*		27

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Table H.2: Wald Test on joint significance of independent variables except for the intercept. This table shows results for the test on the joint significance of independent variables except for intercept. The coefficients are jointly significant.

Null Hypothesis: $\beta_2=0, \beta_3=0, \beta_4=0, \beta_5=0,$			
Test Statistic	*Value*	*df*	*Probability*
F-statistic	5.960	(4, 63)	0.000 *
Chi-square	23.84	4	0.000 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Appendix H.2: Regression results of the probit modelling for South Africa

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Table H.3: Expectation-Prediction Evaluation for Binary Specification. This table reports the number of correct and incorrect categorizing based on a specified cut-off value of 0.5 (top two tables represent such calculations) and expected value calculations (bottom two tables).

Success cut-off: C = 0.5						
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	38	6	44	41	27	68
P(Dep=1)>C	3	21	24	0	0	0
Total	41	27	68	41	27	68
Correct	38	21	59	41	0	41
% Correct	92.68	77.78	86.76	100.00	0.00	60.29
% Incorrect	7.32	22.22	13.24	0.00	100.00	39.71
*Total Gain**	-7.32	77.78	26.47			
*Per cent Gain***	NA	77.78	66.67			
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	34.50	6.58	41.08	24.72	16.28	41.00
E(# of Dep=1)	6.50	20.42	26.92	16.28	10.72	27.00
Total	41.00	27.00	68.00	41.00	27.00	68.00
Correct	34.50	20.42	54.92	24.72	10.72	35.44
% Correct	84.14	75.64	80.77	60.29	39.71	52.12
% Incorrect	15.86	24.36	19.23	39.71	60.29	47.88
*Total Gain**	23.85	35.93	28.65			
*Percent Gain***	60.06	59.59	59.83			
**Change in "% Correct" from default (constant probability) specification*						
***Percent of incorrect (default) prediction corrected by equation*						

Appendix I.1: Regression results of the probit modelling for Ukraine

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Estimation Equation:

$$Recession_t = \beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_t$$

Forecasting Equation:

$$Recession_t = 1 - CNORM(-(\beta_1 + \beta_2 \times GDP\_Change_t + \beta_3 \times SPREAD_t))$$

Table I.1: Binary regression model of the recession's prediction. This table reports the coefficients, significance, standard errors and z-Statistics values of the independent variables (*constant*, $GDP\_Change_t, SPREAD_t$) impact on $Recession_t$ variable. It also presents the main statistical measures for the regression model, such as R-squared, LR statistics, Log-likelihood, Sum squared residuals, S.E. of regression estimated, number of observations for a period from 2000: Q1 to 2016: Q4.

Dependent Variable: $Recession_t$				
Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)				
Sample: 2002Q1 2016Q4			*Total obs*: 60	
Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
β_1	-0.833	0.381	-2.184	0.029 **
GDP_Change_t	-0.365	0.097	-3.743	0.000 *
$SPREAD_t$	0.204	0.094	2.176	0.030 **
McFadden R^2	0.705	*Mean dependent var*		0.283
S.D. dependent var	0.454	*S.E. of regression*		0.231
LR statistic	50.45	*Sum squared resid*		3.044
Prob (LR statistic)	0.000 *	*Log likelihood*		-10.54
Obs with Dep=0	43	*Obs with Dep=1*		17

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Table I.2: Wald Test on joint significance of independent variables except for the intercept. This table shows results for the test on the joint significance of independent variables except for intercept. The coefficients are jointly significant.

Null Hypothesis: β_2*=0,* β_3*=0*			
Test Statistic	*Value*	*df*	*Probability*
F-statistic	7.020	(2, 57)	0.002 *
Chi-square	14.04	2	0.001 *

*Denotes the 1 % significance level, ** – the 5 % significance level, *** – the 10 % significance level.

Appendix I.2: Regression results of the probit modelling for Ukraine

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed.

Table I.3: Expectation-Prediction Evaluation for Binary Specification. This table reports the number of correct and incorrect categorizing based on a specified cut-off value of 0.5 (top two tables represent such calculations) and expected value calculations (bottom two tables).

Success cut-off: C = 0.5						
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	42	3	45	43	17	60
P(Dep=1)>C	1	14	15	0	0	0
Total	43	17	60	43	17	60
Correct	42	14	56	43	0	43
% Correct	97.67	82.35	93.33	100.00	0.00	71.67
% Incorrect	2.33	17.65	6.67	0.00	100.00	28.33
*Total Gain**	-2.33	82.35	21.67			
*Per cent Gain***	NA	82.35	76.47			
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	40.10	3.46	43.57	30.82	12.18	43.00
E(# of Dep=1)	2.90	13.54	16.43	12.18	4.82	17.00
Total	43.00	17.00	60.00	43.00	17.00	60.00
Correct	40.10	13.54	53.64	30.82	4.82	35.63
% Correct	93.26	79.62	89.39	71.67	28.33	59.39
% Incorrect	6.74	20.38	10.61	28.33	71.67	40.61
*Total Gain**	21.59	51.28	30.00			
*Percent Gain***	76.20	71.56	73.88			

*Change in "% Correct" from default (constant probability) specification
**Percent of incorrect (default) prediction corrected by equation

Appendix J.1: ROC analysis: Greece

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed. The out-of-sample forecasting evaluation is made by combination of in-sample probabilities of recession from 1998: Q1 until 2016: Q4 and out-of-sample probabilities of recession from 2017: Q1 to 2019: Q4 and then analysed by a program software (IBM SPSS Statistics). We compare the forecasted values of recession state with real values of recessions during the period from 1998: Q1 to 2019: Q4 for Greece.

Table J.1: Case Processing Summary. This table represents the number of positive and negative cases for recession occurrence (the positive state is a recession, the negative state – the absence of recession).

RECESSION	*Valid N*
Positive	46
Negative	41
a. The actual positive state is 1.	

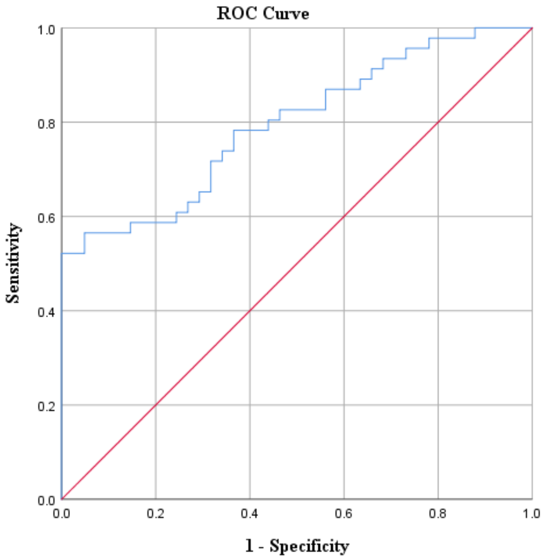

Figure J.1: ROC curve for in-sample forecasting

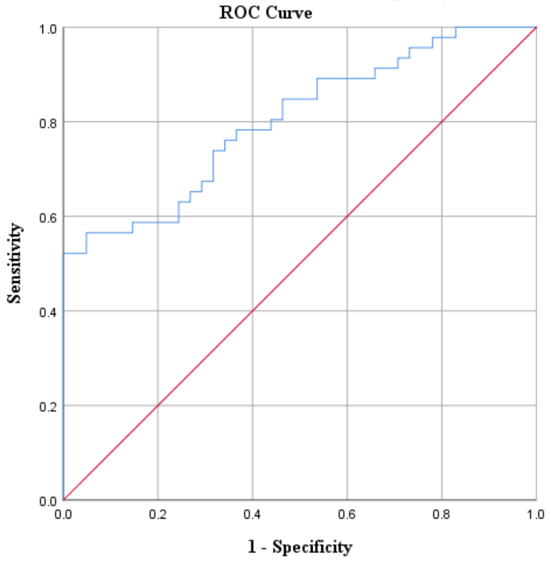

Figure J.2: ROC curve for out-of-sample forecasting

Appendix J.2: ROC analysis: Greece

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed. The out-of-sample forecasting evaluation is made by combination of in-sample probabilities of recession from 1998: Q1 until 2016: Q4 and out-of-sample probabilities of recession from 2017: Q1 to 2019: Q4 and then analysed by a program software (IBM SPSS Statistics). We compare the forecasted values of recession state with real values of recessions during the period from 1998: Q1 to 2019: Q4 for Greece.

Table J.2: Area Under the Curve for in-sample forecasting. This table represents the accuracy measure AUC of how the model predicts the recession state, the standard error of this value, and the significance of this AUC value for the in-sample forecasting dataset.

Area	*Std. Error*	*Asymptotic Sig.*[b]	*Asymptotic 95% Confidence Interval*	
			Lower Bound	*Upper Bound*
0.794	0.047	0.000	0.702	0.887

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

Table J.3: Area Under the Curve for out-of-sample forecasting. This table represents the accuracy measure AUC of how the model predicts the recession state, the standard error of this value, and the significance of this AUC value for the out-of-sample forecasting dataset.

Area	*Std. Error*	*Asymptotic Sig.*[b]	*Asymptotic 95% Confidence Interval*	
			Lower Bound	*Upper Bound*
0.802	0.046	0.000	0.712	0.893

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

Appendix K.1: ROC analysis: India

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed. The out-of-sample forecasting evaluation is made by combination of in-sample probabilities of recession from 2000: Q1 until 2016: Q4 and out-of-sample probabilities of recession from 2017: Q1 to 2019: Q4 and then analysed by a program software (IBM SPSS Statistics). We compare the forecasted values of recession state with real values of recessions during the period from 2000: Q1 to 2019: Q4 for India.

Table K.1: Case Processing Summary. This table represents the number of positive and negative cases for recession occurrence (the positive state is a recession, the negative state – the absence of recession).

RECESSION	*Valid N*
Positive	32
Negative	48
a. The actual positive state is 1.	

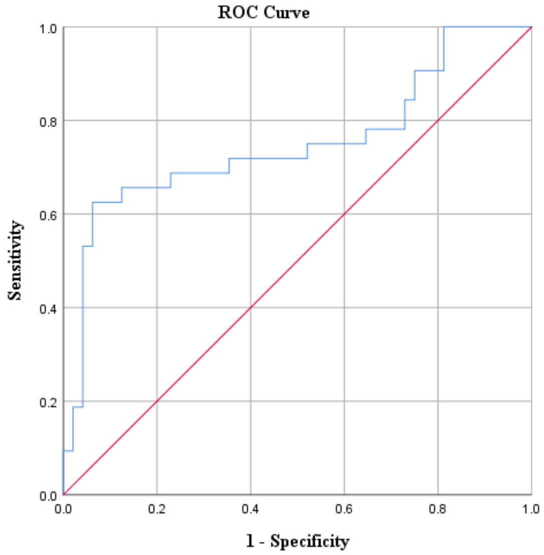

Figure K.1: ROC curve for in-sample forecasting

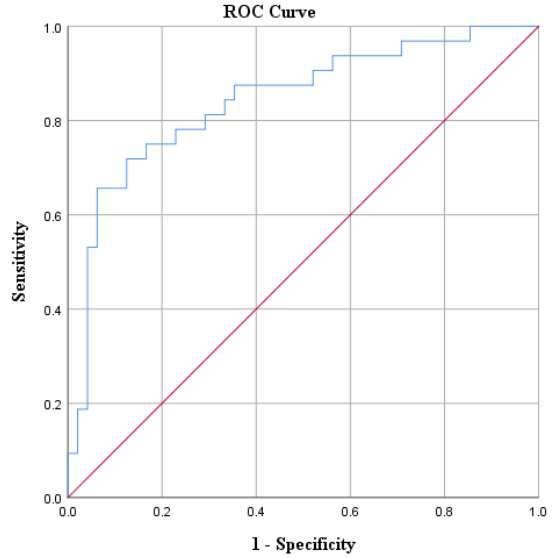

Figure K.2: ROC curve for out-of-sample forecasting

Appendix K.2: ROC analysis: India

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed. The out-of-sample forecasting evaluation is made by combination of in-sample probabilities of recession from 2000: Q1 until 2016: Q4 and out-of-sample probabilities of recession from 2017: Q1 to 2019: Q4 and then analysed by a program software (IBM SPSS Statistics). We compare the forecasted values of recession state with real values of recessions during the period from 2000: Q1 to 2019: Q4 for India.

Table K.2: Area Under the Curve for in-sample forecasting. This table represents the accuracy measure AUC of how the model predicts the recession state, the standard error of this value, and the significance of this AUC value for the in-sample forecasting dataset.

Area	*Std. Error*	*Asymptotic Sig.*[b]	*Asymptotic 95% Confidence Interval*	
			Lower Bound	*Upper Bound*
0.751	0.061	0.000	0.631	0.870

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

Table K.3: Area Under the Curve for out-of-sample forecasting. This table represents the accuracy measure AUC of how the model predicts the recession state, the standard error of this value, and the significance of this AUC value for the out-of-sample forecasting dataset.

Area	*Std. Error*	*Asymptotic Sig.*[b]	*Asymptotic 95% Confidence Interval*	
			Lower Bound	*Upper Bound*
0.842	0.047	0.000	0.751	0.934

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

Appendix L.1: ROC analysis: South Africa

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed. The out-of-sample forecasting evaluation is made by combination of in-sample probabilities of recession from 2000: Q1 until 2016: Q4 and out-of-sample probabilities of recession from 2017: Q1 to 2019: Q4 and then analysed by a program software (IBM SPSS Statistics). We compare the forecasted values of recession state with real values of recessions during the period from 2000: Q1 to 2019: Q4 for South Africa.

Table L.1: Case Processing Summary. This table represents the number of positive and negative cases for recession occurrence (the positive state is a recession, the negative state – the absence of recession).

RECESSION	*Valid N*
Positive	35
Negative	45
a. The actual positive state is 1.	

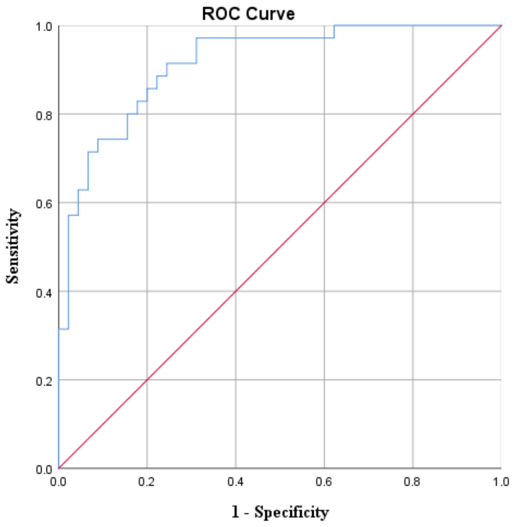

Figure L.1: ROC curve for in-sample forecasting

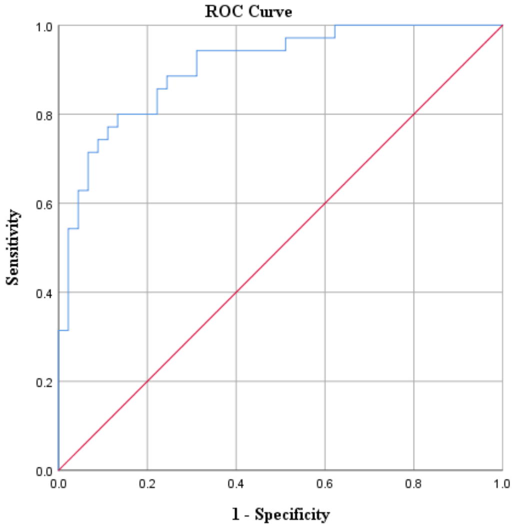

Figure L.2: ROC curve for out-of-sample forecasting

Appendix L.2: ROC analysis: South Africa

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed. The out-of-sample forecasting evaluation is made by combination of in-sample probabilities of recession from 2000: Q1 until 2016: Q4 and out-of-sample probabilities of recession from 2017: Q1 to 2019: Q4 and then analysed by a program software (IBM SPSS Statistics). We compare the forecasted values of recession state with real values of recessions during the period from 2000: Q1 to 2019: Q4 for South Africa.

Table L.2: Area Under the Curve for n sample forecasting. This table represents the accuracy measure AUC of how the model predicts the recession state, the standard error of this value, and the significance of this AUC value for the in-sample forecasting dataset.

Area	*Std. Error*	*Asymptotic Sig.*[b]	*Asymptotic 95% Confidence Interval*	
			Lower Bound	*Upper Bound*
0.915	0.031	0.000	0.855	0.975

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

Table L.3: Area Under the Curve for out-of-sample forecasting. This table represents the accuracy measure AUC of how the model predicts the recession state, the standard error of this value, and the significance of this AUC value for the out-of-sample forecasting dataset.

Area	*Std. Error*	*Asymptotic Sig.*[b]	*Asymptotic 95% Confidence Interval*	
			Lower Bound	*Upper Bound*
0.906	0.033	0.000	0.842	0.970

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

Appendix M.1: ROC analysis: Ukraine

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed. The out-of-sample forecasting evaluation is made by combination of in-sample probabilities of recession from 2002: Q1 until 2016: Q4 and out-of-sample probabilities of recession from 2017: Q1 to 2019: Q4 and then analysed by a program software (IBM SPSS Statistics). We compare the forecasted values of recession state with real values of recessions during the period from 2002: Q1 to 2019: Q4 for Ukraine.

Table M.1: Case Processing Summary. This table represents the number of positive and negative cases for recession occurrence (the positive state is a recession, the negative state – the absence of recession).

RECESSION	*Valid N*
Positive	*18*
Negative	*54*
a. The actual positive state is 1.	

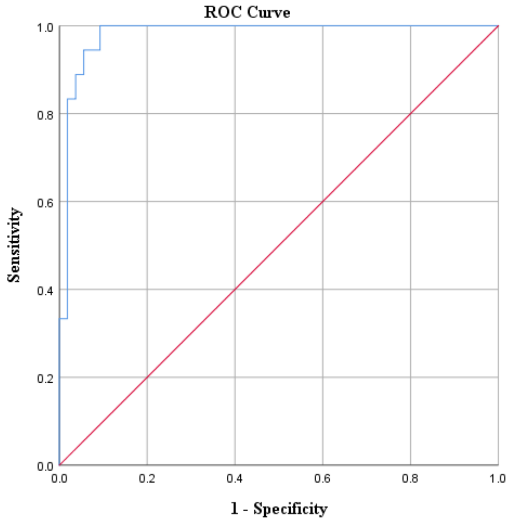

Figure M.1: ROC curve for in-sample forecasting

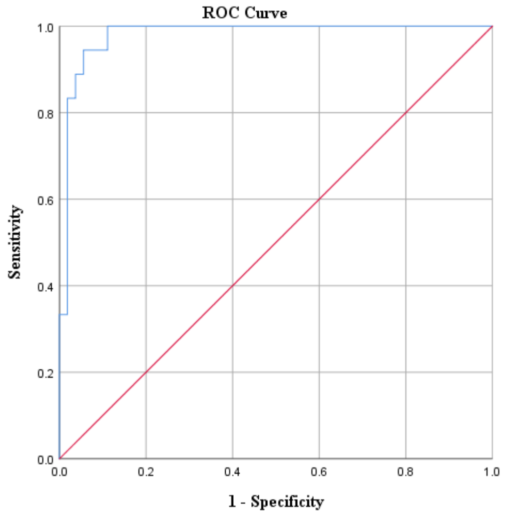

Figure M.2: ROC curve for out-of-sample forecasting

Appendix M.2: ROC analysis: Ukraine

The analysis was conducted in EViews 11 and SPSS software, where is no coding needed. The out-of-sample forecasting evaluation is made by combination of in-sample probabilities of recession from 2002: Q1 until 2016: Q4 and out-of-sample probabilities of recession from 2017: Q1 to 2019: Q4 and then analysed by a program software (IBM SPSS Statistics). We compare the forecasted values of recession state with real values of recessions during the period from 2002: Q1 to 2019: Q4 for Ukraine.

Table M.2: Area Under the Curve for in-sample forecasting. This table represents the accuracy measure AUC of how the model predicts the recession state, the standard error of this value, and the significance of this AUC value for the in-sample forecasting dataset.

Area	*Std. Error*	*Asymptotic Sig.*[b]	*Asymptotic 95% Confidence Interval*	
			Lower Bound	*Upper Bound*
0.980	0.014	0.000	0.953	1.000

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

Table M.3: Area Under the Curve for out-of-sample forecasting. This table represents the accuracy measure AUC of how the model predicts the recession state, the standard error of this value, and the significance of this AUC value for the out-of-sample forecasting dataset.

Area	*Std. Error*	*Asymptotic Sig.*[b]	*Asymptotic 95% Confidence Interval*	
			Lower Bound	*Upper Bound*
0.979	0.015	0.000	0.951	1.000

a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5