Forecasting Economic Growth with V4 Countries' Composite Stock Market Indexes – a Granger Causality Test

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Abstract: In this paper, the findings from the previous work: "Forecasting economic growth with the BUX composite stock market index – a Granger causality test" are validated for the remaining countries in the Visegrád 4 Group. The role of the stock market, as a composite leading indicator of an economic cycle, has been subject to scrutiny, since the late 60s. This research builds on previous work involving stock market recession forecasting capabilities, with reasoning as to the choice of the specific composite stock indexes. As a means of revisiting the concepts, the methodologies, and the findings of previous works in this research field, the algorithm introduced in the first part of the research is further applied to the composite stock market log-returns indicators and the GDP growth rates of the Visegrád 4 group countries. The quarterly data from the stock indexes (PX, SAX, and WIG) are from the second quarter of 1995 through the second quarter of 2021 - comprising 86 observations over 26 years. We apply the ADF and the KPSS tests to test stationarity. An OLS regression test is performed, whereby, the lagged coefficients and their significance in the model are determined. Finally, a Granger causality test is run, to determine whether the stock indexes of the V4 group are helpful in predicting GDP declines within the economies in question. The research finds that changes in the Polish, Slovakian and Czech GDP, directly affect the immediate changes in the WIG, SAX, and PX composite stock indexes, correspondingly, in a expected way.

Keywords: economic growth; stock market; leading indicators; composite stock market index; efficient market hypothesis; johansen cointegration test; stationarity testing; autoregressive distributed lag model; granger causality

1 Introduction

It has been established in the first part of this work [1] that leading indicators are often used in predicting future economic conditions. The efficient market hypothesis is the underlying theoretical basis for this research, which states that security markets are efficient in reflecting all available information in equity and debt instrument prices. It introduces the idea that essentially beating the stock market is impossible in the long run since at best, the returns will be in line with the market or with a composite stock index.

Evidence from the previous research indicates that Moore and Shiskyn's [2] criteria for determining whether an indicator can be used in forecasting recessions efficiently do hold. The selection criteria support the transparency, wide availability, and precision of stock prices as an economic indicator of a country's financial condition. The 2nd and 3rd criteria for determining if an indicator can be considered worthy of consideration in an early warning system show that both statistical frequency and conformity to business cycles are present in a composite stock market indicator, and therefore provide strong support to the argument that the stock market is a leading economic indicator [3].

Economic indicators are classified into leading and lagging indicators. Future economic condition forecasting is conducted through the analysis of leading indicators. Per Comincioli, stocks reflect the future earnings potential of companies and therefore are showing which direction the economy is headed in terms of company profitability and therefore tax revenue [4].

It is essential to understand that because of the strong interconnectedness of the stock market and the economy – practically a direct relationship – this means that the market value of a company (conventionally calculated by the sum of all of its outstanding shares) signifies both the credit of the investors and the confidence of the consumers in the business and hence the economy. It's difficult to imagine a rational consumer spending hard-earned dollars on shares of a company during tightening monetary policy as a means of countering the effects of an impending recession.

The objective of the research is to evaluate the composite stock indexes of V4 group countries the Prague Stock exchange (PX), the Warsaw stock exchange (WIG), and the Slovakian stock index SAX for their capabilities as recession forecasting leasing indicators through an algorithm developed by the authors. Firstly, the research proposes building a regression model of the individual countries' GDP on past values of its stock indexes, whereby through determining the lagged coefficients the forecasting power of the index is evaluated in a given timeframe. The Granger Causality Test will show if past values of the PX, WIG, and the SAX are useful in predicting values of the Czech, Polish, and Slovakian GDP growth rates.

The rest of the research is organized the following way. The literature review presents the influence of variability on the stochastic dynamics of the stock market and highlights three pillars based on which stock markets predict a recession. The third chapter presents the methodology akin to the one presented in the first part of the paper. The fourth section presents how the data was procured, cleaned, and operated on. The fifth section presents the results of the Czech, Polish and Slovak stock indexes' relationship with their respective GDP growth percentage through the application of the Granger causality test. Lastly, the sixth presents a discussion and the seventh and final section, presents a summary.

2 Literature Review

Testing the relationship between the stock market and the economy has been the subject of thorough investigation, beginning in the late 80s, of the 20^{th} Century. These seminal works included those of Campbell [5], Madhavi and Sohrabian [6] and Peek and Rosengreen [7]. It has been widely known that recessions are generally preceded by significant declines in stock prices that result in bear markets sometimes the stock market generated false recession signals, while sometimes the recession came without a signal from the stock market whatsoever. Evidence of this can be found in Peek and Rosengreen's assessment. While Shapiro [8] points out that there was no reduction in variance between pre-World War I stock prices and post-World War II period prices, essentially indicating that the nature of the stock markets dynamics hasn't changed, rather the opposite, the variances in fundamentals have increased, rendering the stock market forecasting ineffective, Barro [9] ascertains that when stock index changes predict economic slowdowns instead of recessions, suddenly, three out of five signals are examined. From 1926 to 1987, eight out of nine recessions have been successfully predicted through the stock market indicator.

Three major conclusions can therefore be made, the first is: (i) Shapiro empirically proved that the nature of stochastic dynamics hasn't changed in the stock market, rather the opposite, the number of shocks and their magnitude increased, while their length decreased, indicating that the possibility of more false signals statistically increases. The variance between fundamentals and the performance of stocks has also been raising questions on how correctly are assets priced in the market.

Second, (ii) Pearce [10] finds overwhelming evidence on stocks successfully forecasting recessions and also provides theoretical support – the price of a stock being the discounted present value of all of the dividends earned by the investor whilst holding the security, factoring in corporate earnings of an inherently forward-looking asset class, it becomes trivial to regard the stock market as a leading economic indicator. Further evidence presented by Pearce includes Keynesian psychological elements, consumption decisions, and their causal connection with stock prices and the wealth effect. In support, Bosworth [11] presented an additional behavioral hypothesis comingled with wealth variables that assume causality between the stock market and the economy.

Third (iii) and finally, concrete and quite recent empirical evidence by Levine and Zervos [12] and Mauro [13] using the data from over 47 countries show an overwhelming amount of evidence of a positive correlation between stock market development and long-term economic growth. In the paper of [14], Lastly, by abstracting from previous empirical studies, and approaching the topic from a statistical standpoint – the research, as stated in its first part, proposes the full algorithm with an autoregressive distributed lag model, additional tests for cointegration, and autocorrelation, concluding in the Granger causality test.

The reason the Granger test is adopted concerns the fact that it can define causality bi-directionally. There is little to no empirical evidence of the stock markets and the economic relationship in the V4 group. Therefore, this study aims to test the relationship between the V4 economies and their respective stock markets.

3 Material and Method

This study evaluates the composite stock market index of Visegrad group countries by empirically testing for causality and cointegration, similarly to Sayed [15], Ikoku [16], and Comincioli and the previous research authors. The introduction and the literature review present the concept of the efficient market hypothesis – an idea that states that all past present and future information on earnings is already priced in the value of a share, as well as that all market participants have the same access to the information [17]. This is the theoretical background for deeming the stock market as an efficient leading economic indicator. The quarterly alert mechanism report issued by the IMF for individual countries has a number of disadvantages ranging from a mechanistic approach to economic indicator selection and the early warning system being too general in identifying potential areas of weakness in the economy.

The previous part of the research highlighted evidence on the ability and inability of stock movements to predict recessions. In this research, a more conclusive and assertive definition of a recession is introduced and evaluated for the rest of the V4 group countries. A Granger causality test in a nondeterministic continuously stochastic system is therefore implemented to determine if the V4 countries' individual stock markets are able to predict GDP growth downturns.

The algorithm, schematically defined in the previous research consists of seven logical steps, integral to the Granger causality test:

- (i) Gathering the data
- (ii) A visual inspection of the data for the presence of a trend, cyclicality and seasonality
- (iii) Testing for stationarity – determining if the time series contains a unit root
- (iv) Performing a normalization or a log transformation, of the time series, making it stationary around the mean, by Hassler [18]
- (v) Running the OLS regression test within the autoregressive distributed lag model to determine the coefficients of the lags
- (vi) Johansen cointegration test – to determine if a long-run relationship exists between the individual time series
- (vii) Performing the Granger Causality test

As in the previous work, we consider a stationary stochastic process. Both the ADF and the KPSS tests, described in detail in the latter part of the research are to determine whether the time series is stationary, we compute the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test as a means of getting two independent answers. A more detailed explanation of stationarity and its testing methodologies is provided in the subsequent chapters of this research.

To make inferences based on statistical computations, the Czech, Polish, and Slovakian GDP percentage change, the time series is regressed on the composite stock indexes of the respective countries back up to 4 quarters. Similarly, to the previous research, the number of lags was chosen to avoid variable bias.

The model for the autoregressive distributed lag test is specified below:

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

The OLS regression will show which β is statistically significant and will enable to determine a reasonable approximation of a lagged stock variable's ability to predict the value of the GDP. The application of the Johansen cointegration test from the perspective of determining autocorrelation between two nonstationary timeseries is superfluous. The assessment is in scope of proving or disproving the existence of a long-term relationship equilibrium between the stock market indicator and the corresponding GDP indicator, as well as finding if a stochastic trend exists between the variables.

In 1956 Wiener [19] introduces causality and Granger [20] introduces a feedback loop that shows causal relationships between two time series. Following Granger, if the past values of Y_t can predict X_t, then Y_t causes X_t. The novelty of Granger's work lies in the perception of causality as precedent of information. Granger defines U as all of the information accumulated since time $t-1$, and therefore states, that causality is $\sigma^2(X|U) < \sigma^2(X|\overline{U-Y})$, where Y is causing X. The test also checks if adding the lagged values of X_t improves the predictive power Y_t.

The research ascertains if the V4 stock indexes actually cause changes in the V4 group countries individual GDP growth rates (Stock market → GDP).

The models for the Granger causality test are specified below:

$$GDP = \sum_{i=1}^{n} \alpha_i StockMarket_{t-i} + \sum_{i=1}^{n} \beta_j GDP_{t-i} + u_{1t} \quad (2)$$

$$StockMarket = \sum_{i=1}^{n} \lambda_i GDP_{t-i} + \sum_{i=1}^{n} \delta_j StockMarket_{t-i} + u_{2t} \quad (3)$$

The regressions in equations 2 and 3 show that the variables are related to the past values of themselves, as well as the OAST values of the time series they are tested against.

As defined in the previous part of the research, in order to perform the Granger Causality Test the time series must be stationary, the lags must be justified by the Aikaike information criterion and the error terms must be tested for independence.

The methodology follows Gujarati's [21] definitions. The algorithm runs in four steps. First, a regression is run on the individual GDP time series, where the current GDP data are regressed on their own lagged values, thereby obtaining the restricted residual sum of squares. Next, the same procedure is performed on the stock market variable, whereby the unrestricted residual sum of squares is obtained. *Then, the null hypothesis is declared,* $H_0: \sum \alpha_i = 0$ *, which states that since lagged stock market variables cannot predict the economy and therefore don't belong in the regression.*

The hypothesis is tested in the next step through the following F test (Equation 4), where m is the number of lagged stock market terms, and $n - k$ is the degrees of freedom

$$F = \frac{\frac{(RSS_R - RSS_{UR})}{m}}{\frac{RSS_{UR}}{n-k}} \tag{4}$$

Lastly, the F statistic is compared to critical values of 95%, and inferences are made.

4 Preparing the Data

The PX, WIG, and SAX index time series going back until Q3 1995 have been obtained from marketwatch.com. The GDP data on the aforementioned countries were obtained from the IMF data warehouse. Both seasonal and trend adjustments were performed on the GDP data, however, it was unsuccessful in removing the unit root from the time series.

The skewness of the data is removed by the application of the following transformation: $S_t = \frac{P_t - P_{t-1}}{P_t}$ and $S_t = \ln(P_t) - \ln(P_{t-1})$. This allows to normalize the values, so that they move between 1 and -1 [22]. Patterns can therefore be investigated through inferential statistics. The data from PX represents the fifty biggest companies in the Czech Republic. The WIG index consists of a portfolio of 23 companies that operate in most Eastern and Western European countries, and therefore have big exposure to the economies of other European nations. The SAX Slovakian stock exchange listed on the Bratislava stock exchange has the smallest basked of domestic companies – only 4. Real economic activity is reflected in the

GDP growth rate, and therefore, the research utilizes the concept of going forward as the independent variable.

The data are of the same frequency and the number of observations is 86 – spanning 26 years from 1995 quarter 3 to 2021 quarter 2.

5 Results

5.1 Testing for Stationarity

The previous part of this research introduced the concept of stationarity and showed why non-stationary data could yield spurious results in research. When a time series is stationary, its statistical properties do not change over time. It would be mathematically incorrect to continue this research with the raw data presented by the IMF website. Therefore, the research proposes the utilization of both the ADF and the KPSS tests to determine whether the time series is stationary. Homoskedasticity can't capture or model the errors present in univariate systems according to Phillips [23] and therefore, they aren't considered random walks.

Within the scope of this research, the Augmented Dickey-Fuller (ADF) [24] and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are considered. Once both of the tests show supporting results in favor of the time series being stationary, it will be safe enough to assume that neither of the time series contain a unit root. Both the ADF and the KPSS test have the null hypothesis H_o = the series has a unit root.

The outputs of the ADF test are presented in the tables below.

Table 1

ADF tests of PX and Czech GDP time series

ADF Statistic: -8.572425 p-value: 0.000000 Critical Values: 1%: -4.067 Reject Ho - Time Series is Stationary	ADF Statistic: -9.461101 p-value: 0.000000 Critical Values: 1%: -4.068 Reject Ho - Time Series is Stationary

Source: Authors research and own compilation,

Table 2

ADF tests of SAX and Slovakian GDP time series

ADF Statistic: -7.917281 p-value: 0.000000 Critical Values: 1%: -4.049	ADF Statistic: -7.825711 p-value: 0.000000 Critical Values: 1%: -4.049

Reject Ho - Time Series is Stationary	Reject Ho - Time Series is Stationary

Source: Authors research and own compilation,

Table 3

ADF tests of WIG and Poland GDP time series

ADF Statistic: -9.783205 p-value: 0.000000 Critical Values: 1%: -4.049 Reject Ho - Time Series is Stationary	ADF Statistic: -8.892660 p-value: 0.000000 Critical Values: 1%: -4.067 Reject Ho - Time Series is Stationary

Source: Authors research and own compilation

Tables 1-3 display the results of the ADF test on the log returns of the Prague, Warsaw, and Slovakian stock indexes as well as the respective GDPs of the countries. Both the log-transformation of stock returns and the normalization of the GDP growth rate have proven to be successful in eliminating the unit root. Since the ADF test statistic doesn't reach the predetermined thresholds, it can therefore be concluded that in all of the cases the time series are stationary.

The reason why there are two stationarity tests involved in this research is that, according to Perron [25], ADF tests may not be fully powerful enough on their own to reject the null hypothesis and are required to be supplemented with a test that takes into the consideration a broken linear trend. The KPSS test accounts for structural breaks that may happen cyclically over specific dates. The left side of the table represents the stock indexes test statistic, while the right-hand shows the GDP time series.

Table 4

KPSS test of PX and Czech GDP time series

KPSS Statistic: 0.10222623455544386 p-value: 0.1 num lags: 3 Critial Values: 10% : 0.347 5% : 0.463 2.5% : 0.574 1% : 0.739 Result: The series is stationary	KPSS Statistic: 0.2787832590461547 p-value: 0.1 num lags: 1 Critial Values: 10% : 0.347 5% : 0.463 2.5% : 0.574 1% : 0.739 Result: The series is stationary

Source: Authors research and own compilation

The log transformation of the data has evidently improved the degree of stationarity of the data. While the unadjusted data had a linear trend, a seasonality, and a random walk. The elimination of these variances through the application of a log transformation has been successful.

Table 5
KPSS test of SAX and Slovakia GDP time series

KPSS Statistic: 0.2787832590461547 p-value: 0.1 num lags: 1 Critial Values: 10% : 0.347 5% : 0.463 Result: The series is stationary	KPSS Statistic: 0.3155400898580037 p-value: 0.03816 num lags: 3 Critial Values: 10% : 0.347 5% : 0.463 Result: The series is stationary

Source: Authors research and own compilation

Table 6
KPSS test of WIG and Poland GDP time series

KPSS Statistic: 0.10281641482077652 p-value: 0.1 num lags: 1 Critial Values: 10% : 0.347 5% : 0.463 Result: The series is stationary	KPSS Statistic: 0.3921942922366165 p-value: 0.08051970162214805 num lags: 3 Critial Values: 10% : 0.347 5% : 0.463 Result: The series is stationary

Source: Authors research and own compilation

Kwiatkowski et. al. [26] use parametrization and propose the Lagrange multiplier as a means of testing the null hypothesis for stationarity. The data generating process is taken as the basis for the test. The KPSS is most commonly used to verify the results of the ADF test and is both easy in understanding and essential in a full stationarity test.

To ensure that the data are stationary, the authors of the research performed the normalization of the GDP data, as well as a log-transformation of the stock returns.

The KPSS test affirms the results of the ADF test. All of the time series is stationary. A time series that doesn't have any long or short-term correlations with its values and that doesn't show any trends is close to a random set of observations. It is important to have tested the time series for cointegration, as it might also yield spurious results in the further steps of the Granger Causality test.

5.2 Testing the Relationship between Stock Prices and the Economy with an Autoregressive Distributed Lag Model

The PX, SAX, and WIG stock indexes are regressed to the individual countries' GDP growth rates to determine whether there exists a relationship between the variables. The null hypothesis states that the individual stock indexes' effect on the

GDP growth rate is zero. The variables are lagged back to four quarters to see how accurate is the model's movements compared to actual observations. The reason why the model looks back four quarters is also that it is within the scope of this study to determine whether a pattern of moves in the stock market could signal a move in the GDP one year in advance.

The results of the OLS regression are detailed in the tables below. The stationarity of the variables was a natural prerequisite of this test. A large F-statistic corresponds to a more significant degree of correlation. The null hypothesis states that the regression coefficients are zero. The test attempts to determine if the alternative hypothesis holds. The closer the regression coefficients are to zero, the better the model is. The table represents the model introduced in the methodology of the previous work. The coefficients along with the standard error, the t-statistic, and the p-value are displayed corresponding to the lag they represent. This is to determine the degree of accuracy of the stock markets' reaction to GDP changes. The program also outputs some additional information on the accuracy of the model. The homoscedasticity and the distribution of the residuals can both be interpreted from the results.

Table 7

OLS regression analysis for PX and CZGDP

OLS Regression Results

Dep. Variable:	CZGDP	R-squared:	0.231
Adj. R-squared:	0.181		
F-statistic:	4.622		
Prob (F-statistic):	0.000967		
Log-Likelihood:	232.61		
No. Observations:	83	AIC:	-453.2
Df Residuals:	77	BIC:	-438.7

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0102	0.002	6.045	0.000	0.007	0.014
lag(PX, 0)	-0.0028	0.015	-0.181	0.857	-0.034	0.028
lag(PX, 1)	0.0588	0.015	3.871	0.000	0.029	0.089
lag(PX, 2)	-0.0114	0.015	-0.775	0.441	-0.041	0.018
lag(PX, 3)	0.0253	0.015	1.714	0.091	-0.004	0.055
lag(PX, 4)	0.0262	0.015	1.775	0.080	-0.003	0.056

Omnibus:	35.482	Durbin-Watson:	2.047
Skew:	-1.094	Prob(JB):	2.26e-41
Kurtosis:	10.024	Cond. No.	9.98

Source: Authors research and own compilation

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

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

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

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

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

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

Table 8

OLS regression analysis for SAX and SGDP

OLS Regression Results

Dep. Variable:	SGDP	R-squared:	0.084
Adj. R-squared:	0.035		
F-statistic:	1.717		
Prob (F-statistic):	0.138		
Log-Likelihood:	223.32		
No. Observations:	99	AIC:	-434.6
Df Residuals:	93	BIC:	-419.1

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0166	0.003	6.267	0.000	0.011	0.022
lag(SAX, 0)	0.0321	0.028	1.165	0.247	-0.023	0.087
lag(SAX, 1)	0.0459	0.028	1.641	0.104	-0.010	0.101
lag(SAX, 2)	0.0111	0.027	0.406	0.686	-0.043	0.065
lag(SAX, 3)	0.0240	0.027	0.879	0.382	-0.030	0.078
lag(SAX, 4)	0.0045	0.027	0.168	0.867	-0.048	0.057

Omnibus:	12.374	Durbin-Watson:	1.545
Skew:	-0.265	Prob(JB):	9.19e-08
Kurtosis:	5.752	Cond. No.	12.5

Source: Authors research and own compilation

The SAX Slovak stock market index was found to have one of the weakest correlations with the economy, with the SAX only being able to explain less than 8.4% of the change in Slovak GDP. The probability that the coefficients determined in the table below have a zero effect on the model is 13.8%, which is higher compared to Czech Republic and Hungary. The coefficient corresponding to the 1-quarter lag was barely statistically significant at the 0.1 percent level, with $P > |t|_{PX,1}$ = 0.104 the rest of the coefficients have little to no statistical significance in the model. The Durbin Watson statistic shows 1.545, indicating little to no autocorrelation.

The Slovak GDP model is expressed as follows:

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

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

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

Table 9

OLS regression analysis for WIG and PGDP

OLS Regression Results

Dep. Variable:	PGDP	R-squared:	0.081	
Adj. R-squared:	0.032			
F-statistic:	1.646			
Prob (F-statistic):	0.155			
Log-Likelihood:	263.82			
No. Observations:	99	AIC:	-515.6	
Df Residuals:	93	BIC:	-500.1	

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0088	0.002	5.009	0.000	0.005	0.012
lag(SAX, 0)	0.0013	0.014	0.090	0.928	-0.027	0.030
lag(SAX, 1)	0.0366	0.014	2.555	0.012	0.008	0.065
lag(SAX, 2)	-0.0016	0.014	-0.111	0.912	-0.030	0.027
lag(SAX, 3)	0.0075	0.014	0.555	0.580	-0.019	0.034
lag(SAX, 4)	0.0162	0.014	1.197	0.234	-0.011	0.043

Omnibus:	49.272	Durbin-Watson:	2.692

Skew:	-1.170	Prob(JB):	7.65e-115
Kurtosis:	14.042	Cond. No.	8.45

Source: Authors research and own compilation

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

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

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

We interpret the findings as follows:

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

5.3 Johansen Cointegration Test

To find whether V4 stock indexes have a long-run relationship with the economies, the Johansen cointegration test is performed. To understand the output from the Python IDE, two key components must be taken into consideration: the maximum eigenvalue statistic and the trace statistic. The former shows the extent of the cointegration of the time series and the likelihood of their mean reversion. The null hypothesis is rejected if the matrix rank is greater than the confidence value at 95%.

The test is run on PX, SAX, and the WIG stock market indexes and the corresponding GDPs.

Table 10

Johansen cointegration test of PX log returns and CZGDP

```
max_eig_stat  trace_stat
r<0    25.305611   33.369268
r<1     8.063657    8.063657
CV(90%, 95%, 99%) of max_eig_stat
 [[ 9.4748 11.2246 15.0923]
 [ 2.9762  4.1296  6.9406]]
CV(90%, 95%, 99%) of trace_stat
 [[10.4741 12.3212 16.364 ]
 [ 2.9762  4.1296  6.9406]]
```

Source: Author's research. Own compilation

Table 11

Johansen cointegration test of SAX log returns and SGDP

```
max_eig_stat  trace_stat
r<0     18.543911   28.282130
r<1      9.738219    9.738219
CV(90%, 95%, 99%) of max_eig_stat
 [[ 9.4748 11.2246 15.0923]
 [ 2.9762  4.1296  6.9406]]
CV(90%, 95%, 99%) of trace_stat
 [[10.4741 12.3212 16.364 ]
 [ 2.9762  4.1296  6.9406]]
```

Source: Author's research. Own compilation

Table 12

Johansen cointegration test of WIG log returns and PGDP

```
max_eig_stat  trace_stat
r<0     33.273549   48.053206
r<1     14.779656   14.779656
CV(90%, 95%, 99%) of max_eig_stat
 [[ 9.4748 11.2246 15.0923]
 [ 2.9762  4.1296  6.9406]]
CV(90%, 95%, 99%) of trace_stat
 [[10.4741 12.3212 16.364 ]
 [ 2.9762  4.1296  6.9406]]
```

Source: Author's research. Own compilation

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

5.4 Granger Causality Test

Similarly, to the previous research, the Granger causality test is performed by lagging the stock market variable by 1 quarter. The null hypothesis is rejected in case the results show that the individual V4 stock indexes Granger Cause the GDP.

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

Table 13

PX log returns and Czech Republic GDP time series Granger Causality test results

```
Granger Causality 1 -lag
ssr based F test:         F=0.0312  , p=0.8602  , df_denom=82, df_num=1
ssr based chi2 test:   chi2=0.0324  , p=0.8572  , df=1
likelihood ratio test: chi2=0.0324  , p=0.8572  , df=1
parameter F test:         F=0.0312  , p=0.8602  , df_denom=82, df_num=1
Granger Causality – 2 lags
ssr based F test:         F=7.3769  , p=0.0012  , df_denom=79, df_num=2
ssr based chi2 test:   chi2=15.6877 , p=0.0004  , df=2
likelihood ratio test: chi2=14.3829 , p=0.0008  , df=2
parameter F test:         F=7.3769  , p=0.0012  , df_denom=79, df_num=2
Granger Causality – 3 lags
ssr based F test:         F=5.7609  , p=0.0013  , df_denom=76, df_num=3
ssr based chi2 test:   chi2=18.8746 , p=0.0003  , df=3
likelihood ratio test: chi2=17.0069 , p=0.0007  , df=3
parameter F test:         F=5.7609  , p=0.0013  , df_denom=76, df_num=3
Granger Causality – 4 lags
ssr based F test:         F=5.3591  , p=0.0008  , df_denom=73, df_num=4
ssr based chi2 test:   chi2=24.0793 , p=0.0001  , df=4
likelihood ratio test: chi2=21.1123 , p=0.0003  , df=4
parameter F test:         F=5.3591  , p=0.0008  , df_denom=73, df_num=4
```

Source: Author's research. Own compilation

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

Table 14

WIG log returns and Poland GDP time series Granger Causality test results

```
Granger Causality -1 lag
ssr based F test:         F=1.1463  , p=0.2869  , df_denom=99, df_num=1
ssr based chi2 test:   chi2=1.1811  , p=0.2771  , df=1
likelihood ratio test: chi2=1.1743  , p=0.2785  , df=1
parameter F test:         F=1.1463  , p=0.2869  , df_denom=99, df_num=1
Granger Causality -2 lags
ssr based F test:         F=0.2789  , p=0.7572  , df_denom=96, df_num=2
ssr based chi2 test:   chi2=0.5869  , p=0.7457  , df=2
likelihood ratio test: chi2=0.5852  , p=0.7463  , df=2
parameter F test:         F=0.2789  , p=0.7572  , df_denom=96, df_num=2
Granger Causality-3 lags
ssr based F test:         F=1.7401  , p=0.1642  , df_denom=93, df_num=3
ssr based chi2 test:   chi2=5.6132  , p=0.1320  , df=3
likelihood ratio test: chi2=5.4613  , p=0.1410  , df=3
parameter F test:         F=1.7401  , p=0.1642  , df_denom=93, df_num=3
```

```
Granger Causality -4 lags
ssr based F test:         F=2.0134  , p=0.0993  , df_denom=90, df_num=4
ssr based chi2 test:   chi2=8.8592  , p=0.0647  , df=4
likelihood ratio test: chi2=8.4849  , p=0.0753  , df=4
parameter F test:         F=2.0134  , p=0.0993  , df_denom=90, df_num=4
```

Source: Author's research. Own compilation

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

Table 15

WIG log returns and Poland GDP time series Granger Causality test results

```
Granger Causality -1 lag
ssr based F test:         F=3.7945  , p=0.0543  , df_denom=99, df_num=1
ssr based chi2 test:   chi2=3.9095  , p=0.0480  , df=1
likelihood ratio test: chi2=3.8364  , p=0.0502  , df=1
parameter F test:         F=3.7945  , p=0.0543  , df_denom=99, df_num=1
Granger Causality -2 lags
ssr based F test:         F=2.8040  , p=0.0655  , df_denom=96, df_num=2
ssr based chi2 test:   chi2=5.9002  , p=0.0523  , df=2
likelihood ratio test: chi2=5.7343  , p=0.0569  , df=2
parameter F test:         F=2.8040  , p=0.0655  , df_denom=96, df_num=2
Granger Causality -3 lags
ssr based F test:         F=1.6900  , p=0.1745  , df_denom=93, df_num=3
ssr based chi2 test:   chi2=5.4517  , p=0.1416  , df=3
likelihood ratio test: chi2=5.3083  , p=0.1506  , df=3
parameter F test:         F=1.6900  , p=0.1745  , df_denom=93, df_num=3
Granger Causality -4 lags
ssr based F test:         F=1.3185  , p=0.2692  , df_denom=90, df_num=4
ssr based chi2 test:   chi2=5.8015  , p=0.2145  , df=4
likelihood ratio test: chi2=5.6379  , p=0.2279  , df=4
parameter F test:         F=1.3185  , p=0.2692  , df_denom=90, df_num=4
```

Source: Author's research. Own compilation

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

6 Discussion

The goal of this research was to examine if a composite stock market index can predict the economy through an intrinsic assertive algorithm involving a stationarity test, a distributed lag analysis, a cointegration test, and finally, a granger causality test. Similar to the previous research, the lags were chosen based on the Akaike Information Criterion, and the results were computed in the Python IDE.

The data was retrieved from the IMF data warehouse and the member countries' official stock exchange websites. Following a log transformation of the data, it was tested for stationarity, which it passed. The coefficients obtained from the OLS regression have been fitted to a model that predicts GDP changes from lagged stock market returns. It has been found that the lagged coefficients of WIG were the least reliable in explaining the changes in the PGDP, nonetheless, based on the t-statistic, it was concluded that a relationship does exist. The Johansen cointegration test proved that there exists a long-run relationship between the composite stock indexes and the GDPs of V4 economies. Stock prices lead to economic growth do not Granger cause the economy. The Granger causality tests showed that there exists a causality between the composite stock indexes and the GDPs of the V4 countries. Some of the issues raised in the former work have been answered with the availability of more observations and more samples. The seasonal adjustment has been identified in the previous work to be a source of potential inconsistencies the extent of which has not been determined. In this work, however, it is pointed out in the 'data' section that within the data cleaning procedure seasonal adjustment have been omitted and the calculations were performed on unadjusted raw data. The nondeterministic nature of the data should be attributed to the logical conclusion that was the data non-stationary – no computations resulting in inferences could have been performed and there wouldn't have been any way to obtain the needed results. The reason stock index baskets were chosen instead of individual stocks, and the very reason why the equity market has been subject to this research is that, as it has been previously assessed, the stock market provides a forward-looking aspect of company earnings. Since a stock index, sometimes referred to as a basket of stocks, consists of many companies, the assumption that it provides a single reasonable estimate of forwarding earnings is of all of the companies in the basket is considered valid within the scope of this research.

Summary

The juxtaposition of economic indicators and forecasting has been the subject of many publications and research papers ever since the "Keynesian Revolution". Predicting the exact moment, a cycle shifts in a market environment and the length of the cycle itself is notoriously hard, and so far, very few, if any, economic indicators have stood the test of time. Economic recessions and crises are preceded by weak fundamental economic indicators such as unemployment, inflation, treasury, corporate bond yield curves, industrial production indexes, and the stock market, just to name a few. This research focuses on one specific fundamental indicator – the stock market. While other macroeconomic indicators may be more effective in predicting recessions and may show fewer errors, such as the yield curve inversion, the stock market is a more transparent, easily accessible, and regulated indicator that, through the reasoning established in the first part of the research, enables all market participants to obtain the same information at the same time without delay, provided that the efficient market hypothesis holds.

The question of the accuracy of the GDP's measure of an economy's success is debatable, however, as it has been mentioned in the first part of this work – this measure is the best and most reliable one yet. The GDP is therefore, used as the independent variable in the model of this research.

Emerging markets such as the countries of the V4 group are particularly interesting subjects for research of this kind, since the investigation of these countries' stock markets as recession forecasting tools hasn't been thorough before this research.

Within the autoregressive distributed lag model framework, it has been established that the stock index, which is most reactive to sudden GDP growth or decline is the Czech stock market index – the PX, which reacts by instantaneous 5.8% price movements. The least reactive – 3.6% change was the Polish stock market index - WIG. The reason for such discrepancy in a reaction is the fact that while the WIG incorporates all companies listed on the main market, the PX only includes the biggest and most influential companies. This research supports the studies of Sayed, Comincioli and Ikoku, who have all found that the stock market is justifiably, a leading indicator for the economies.

References

[1] Molnár, A., & Csiszárik, Á.: Forecasting economic growth with the Hungarian composite stock market index-a Granger causallity test. Acta Polytechnica, 19(8), 2022, pp. 205-227

[2] Moore, G. H., & Shiskin, J.: Indicators of business expansions and contractions. NBER Occasional Paper No. 103, 1967

[3] Chauvet, M.: Stock Market fluctuations and the business cycle. SSRN, 2001

[4] Comincioli, B.: The Stock Market as a Leading Economic Indicator: An Application of Granger Causality. University Avenue Undergraduate Journal of Economics, 1(1), Article 1

[5] Campbell, R. H.: Forecast of Economic Growth from the Bond and Stock Markets, Financial Analysis Journal, 45(5), 1989, pp. 38-45

[6] Peek, J. & Rosengreen, E.: The Stock Market and Economic And Economic Activity. New England Economic Review, May/June 1988, pp. 39-50

[7] Mahdavi, S., & Sohrabian, A.: The Link between the Rate of Growth of Stock Prices and the Rate of Growth of GNP in the United States: A Granger Causality Test. The American Economist, 35(2), 1991, pp. 41-48

[8] Shapiro, M. D.: The Stabilization of the U.S. Economy: Evidence from the Stock Market. The American Economic Review, 78(5), 1988, pp. 1067-1079

[9] Barro, R. J.: The Stock Market and the Macroeconomy: Implications of October 1987 Crash. In: Kamphuis, R. et al (Eds.).: Black Monday and Future of Financial Market, Homewood, IL, Jones/Irwin, New York, 1989

[10] Pearce, D. K.: Stock prices and the Economy. Federal Reserve Bank of Kasas City, Economic Review. November, 1983. pp. 7-22

[11] Bosworth, B.: The stock market and the economy. Brookings Papers on Economic Activity, 1975 (2), pp. 257-300

[12] Levine, R., & Zervos, S.: Stock markets, banks and economic growth. The American Economic Review, 88(3), 1998, pp. 537-558

[13] Mauro, P.: Stock returns and output growth in emerging and advanced economies. Journal of Development Economics, 71(1), pp. 129-153

[14] Tolner, F., Barta, B., Takács, M., Eigner, Gy.: Enhancing Cross-Border Co-operatation of business organizations based on the investigation of textual- and categorical information. Acta Polytechnica Hungarica, 19(5), 2022, pp. 235-255

[15] Sayed, A.: The stock market as a leading indicator of economic activity – Time-series evidence from South Africa. University of the Witwaterstand, 2016

[16] Ikoku, A.E.: Is the stock market a leading indicator of economic activity in Nigeria. CBN Journal of Applied Statistics, 1(1), 2010, pp. 17-38

[17] Adam, K., & Merkel, S.: Stock price cycles and business cycles. ECB Working Paper Series, No. 2316, 2019

[18] Hassler, U., & Wolters, J.: Autoregressive distributed lag and cointegration. Diskussionsbeitrage. No 2005/22 Freie Universität Berlin, Fachbereich Wirtschaftswissenschaft, Berlin

[19] Wiener, N.: The theory of prediction. In. Beckenbach, E, Modern Mathematics for Engineers. McGraw-Hill, New York. 1956

[20] Granger, C. W. J.: Investigating Causal Relationships by Econometric Models and Cross-spectral Methods. Econometrica 37(3), 1969, pp. 424-438

[21] Gujarati, D. N.: Econometrics. 3rd Edition, McGraw-Hill, New York. 1995

[22] Changying, F., Hongyue, W., Tian, C., Hua, H., & Ying, L. U.: Log transofrmation and its implications for data analysis. Shanghai archives of psychiatry, 26(2), 2014, pp. 105-109

[23] Philips, P. C. B.: Time Series Regression with a Unit Root. Econometrica, 55(2), 1987, pp. 277-301

[24] Dickey, D., & Fuller, W.: Distribution of the estimators of autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 1979, pp. 427-431

[25] Hawkins, J.: Economic forecasting: history and procedures. Economic Round-Up: Journal of the Department of the Treasury, 2005, pp. 1-10

[26] Kwiatkowski, D., Phillips, P., Schmidt, P., & Shin, Y.: Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of Econometrics. 54(1-3), 1992, pp. 159-178