



# **STOCK MARKET INDICES AND ECONOMIC GROWTH**

**Empirical Evidence and Comparison between Germany  
and Greece**

Dissertation submitted

by

Pitta G. Anna

to

**Department of Economics,  
University of Cyprus**

in partial fulfilment of the requirements for the degree of  
Master in Monetary and Financial Economics

Supervised by: Prof. **Mamuneas Theofanis**

Nicosia, Cyprus

December 2023

**Sworn statement:**

“I hereby solemnly declare that I have personally and independently prepared this paper. All quotations in the text have been marked as such, and the paper or considerable parts of it have not previously been subject to any examination or assessment.”

**Author:** Pitta G. Anna

**Signature:**

Pitta G. Anna

## Contents

Abstract.....	4
1. Introduction.....	4
2.Literature Review.....	6
2.1 Historical Overview .....	7
2.2 What is the Stock Market index? .....	9
2.2.1 S&P 500 Index .....	10
2.2.2 Dow Jones Industrial Average .....	10
2.2.3 Nasdaq 100.....	11
2.2.4 Russell 2000.....	11
3. Empirical Analysis.....	13
3.1 Data description .....	13
3.1.1 Data description for both countries GDP .....	13
3.1.2 Data description for Indices .....	14
3.2 Testing Regression assumptions .....	18
3.3 Regression Analysis.....	21
3.3.1 Base Model Regression Analysis for Greece.....	21
3.3.2 Base model Regression Analysis for Germany .....	24
3.4 Prediction Process .....	28
3.4.1 Prediction for Greece .....	29
3.4.2 Prediction for Germany.....	32
4. Conclusion .....	37
5. References.....	39
Appendix.....	41
1. Base model regression for Geece.....	41
2. Base model regression for Germany .....	68
3.Assumption testing results .....	91

## Abstract

This thesis explores the dynamic relationships between the major stock market indices and Gross Domestic Product (GDP) growth. The study focuses on the examples of Germany and Greece. GDP represents the collective monetary or market worth of all finalized goods and services produced within an economy during a particular timeframe, typically a calendar year. GDP serves as a performance indicator of a country's overall domestic output, and is essentially an extensive assessment of the economic well-being of the economy. This study systematically analyzes the temporal dependencies within these relationships, employing univariate linear regression analysis using indices such as Dow Jones (^DJI), S&P 500 (^GSPC), Nasdaq 100 (^NDX), and Russell 2000 (^RUT) as main determinants. The study covers multiple lagged periods that range from one quarter to two years. The research methodology employs Ordinary Least Squares (OLS) regressions, followed by out-of-sample testing of the suggested models. The outcomes illuminate the nuanced interplay between index movements and economic performance of Germany and Greece, offering valuable insights into the temporal dynamics shaping these intricate relationships.

## 1. Introduction

With an emphasis on the situations of Greece and Germany, this master's thesis explores the complex relationship between stock market indices and economic growth. Understanding the relationship between stock market indices and the overall economic health of countries is

crucial since financial market dynamics have a significant impact on the global economic landscape. With an emphasis on the goals, context, and importance of the study, this introduction seeks to give a thorough synopsis of the research.

This study aims to clarify the intricate relationships between a few chosen stock market indexes and the GDP growth rates of Germany and Greece. The study aims to offer significant insights that are relevant to investors, policymakers, and economic analysts by investigating the relationship between economic indicators and financial markets. In order to capture both broad trends and subtle features of this relationship, the research focuses on well-known indexes, such as the Russell 2000 Index (^RUT), S&P 500 Index (\GSPC), and Dow Jones Industrial Average (\DJI).

It is imperative to comprehend the ways in which stock market volatility can impact or mirror wider economic patterns in order to make well-informed decisions. This research is important because it can provide insights that go beyond conventional analysis. The study overcomes the shortcomings of previous research by taking into account lag effects and out-of-sample forecasting accuracy, offering a more complex view of the relationship between stock market indexes and economic development. The investigation's methodology blends out-of-sample forecasting models with robust regression analysis. These techniques are chosen to guarantee a thorough analysis of the indices' ability to forecast future events. In addition to measuring the correlation between indices and economic growth, the study intends to investigate the shortcomings and difficulties associated with predicting models, particularly in dynamic economic environments.

Anticipated findings are anticipated to provide insightful information on the predicting ability of particular indices and provide a more comprehensive understanding of their influence on economic growth. Furthermore, the research will illuminate the constraints and difficulties related to forecasting models, offering a practical viewpoint on their effectiveness.

The thesis is developed in the following parts through an in-depth examination of the regression results and an investigation of the accuracy of out-of-sample forecasting. Every segment adds to a comprehensive comprehension of the connection between economic growth and stock market indices. The thesis seeks to provide economic stakeholders with a practical explanation of the complex landscape of global financial markets by means of this investigation.

After the first chapter, the literature review focuses on previous studies related on stock indices and economic growth. This chapter will provide our study with a solid theoretical understanding before proceeding into the empirical part. We define how Dow Jones Industrial Average, Nasdaq 100 and Russell 2000 and S&P 500 are constituted and what each of them

represents. Therefore, this chapter will present why these indices are highly important for the stock market in general along and future economic growth as a whole.

The empirical analysis resides in the third chapter of this thesis. We discuss the data collection procedure, respective data sources, appropriateness of the inputs, transformations, and descriptive statistics. After understanding the macroeconomic data and the indices we proceed to the analysis. The analysis involves several linear regressions for Greece and Germany at different lagged periods. All regression assumptions are extensively tested as well. The significant sub-models that will be created will be used to test the out-of-sample accuracy of model estimates. Finally, chapter four of the thesis presents the conclusions of the study

## 2.Literature Review

Financial markets are powerful predictors of future macroeconomic trends; they have a significant impact on gauging investor confidence and predicting the state of the economy shortly. This paper explores the rich field of forecasting potential of US stock indexes and reveals how well they may predict GDP growth in Germany and Greece. Although there has

been a lot of research done on the connection between financial markets and economic aggregates, a careful re-evaluation of this intricate link is required due to the varied and nuanced empirical evidence. This chapter will look at the research on stock market indices and economic growth that was done before this thesis.

## 2.1 Historical Overview

The historical panorama unfolds a longstanding concept wherein both bond and stock markets emerge as predictors of future output growth, with seminal works by Harvey (1989, 1991), Estrella and Hardouvelis (1991), and Estrella and Mishkin (1998) laying foundational groundwork. However, empirical substantiation of this notion showcases diversity, manifesting variations across countries and temporal epochs, as underscored by Stock and Watson (2003). Recent dynamics, marked by phenomena like quantitative easing, policy rate fluctuations, and pivotal events such as the dotcom bubble and the financial crisis, prompt pertinent questions about the enduring predictive power of financial markets on output growth.

Navigating economic volatility, a critical element in understanding predictive power, sees assertions by Chinn and Kucko (2015) that economic volatility enhances predictive prowess, while Kuosmanen and Vataja (2018) correlate forecast efficacy with turbulent economic conditions. This study strategically shifts the spotlight from the term structure of interest rates to focus on stock returns. Its aim is to discern the maintenance of predictive power and investigate potential sources contributing to the mixed empirical results associated with these dynamic stock indices. Stock returns, encapsulating investor expectations of future earnings, have been implicated in a causal link to output growth, as indicated by Fischer and Merton (1984), Fama (1990), and Schwert (1990). Nevertheless, the landscape is not without complexities, as evidenced by mixed results from studies by Stock and Watson (1990) and Binswanger (2000). Exploring differences in the intrinsic nature of bonds and stocks becomes pivotal, encapsulating responses to inflationary expectations, changes in interest rates, and investor anticipations of future economic performance. By examining time- and market-dependent changes, this research carefully examines whether stock returns have long-term predictive capacity for future output growth, revealing the contradictory nature of previous empirical findings. The study's careful examination of the individual and combined predictive capacities of stock returns positions it to add significantly to the body of knowledge, which will benefit policymakers. The research provides a detailed view of the complex relationship

between financial markets and future economic performance, taking into account factors such as time variation, economic regimes, and out-of-sample predictive content.

In the quest for variables with predictive power for aggregate output, a historical pursuit in macroeconomics, financial variables have emerged as intriguing candidates. While early endeavors focused on economic series associated with the early stages of the production process, there's a growing interest in the deployment of financial variables to anticipate changes in aggregate output. This study elevates the discourse by exploring the predictive power of American stock indices in forecasting the GDP growth of Greece and Germany. Building upon the foundational works of Harvey (1989, 1991), Estrella and Hardouvelis (1991), and Estrella and Mishkin (1998), the research navigates the diverse empirical landscape highlighted by Stock and Watson (2003), acknowledging variations across countries and temporal epochs. Contemporary dynamics, characterized by quantitative easing, policy rate fluctuations, and impactful events like the dotcom bubble and the financial crisis, prompt critical questions about the enduring predictive prowess of financial markets on output growth.

In the realm of economic volatility, Chinn and Kucko (2015) posit that economic volatility enhances predictive prowess, while Kuosmanen and Vataja (2018) correlate forecast efficacy with turbulent economic conditions. This research deliberately moves its attention away from the term structure of interest rates and toward stock returns in an effort to determine whether predictive capacity persists and to look into possible causes of the contradictory empirical findings related to these dynamic stock indices. Stock returns, encapsulating investor expectations of future earnings, have been implicated in a causal link to output growth, as indicated by Fischer and Merton (1984), Fama (1990), and Schwert (1990). However, complexities arise, evident in mixed results from studies by Stock and Watson (1990) and Binswanger (2000). Examining how bonds and stocks differ from one other inherently becomes crucial since it captures how investors will react to changes in interest rates, inflationary expectations, and future economic performance. By examining time- and market-dependent changes, this research carefully examines whether stock returns have long-term predictive capacity for future output growth, revealing the contradictory nature of previous empirical findings. The study presents a detailed view of the complex relationship between financial markets and future economic performance, which provides policymakers with important insights.

Macroeconomics has a long history of searching for variables with the ability to predict aggregate output, going all the way back to the NBER's groundbreaking work in the 1930s. While early endeavours focused on economic series linked to the early production stages,



there's a growing fascination with financial variables' potential to anticipate changes in aggregate output.

This study takes a leap into exploring the predictive power of American stock indices in forecasting the GDP growth of Greece and Germany. Pivoting from traditional variables, the research builds upon foundational works by Harvey (1989, 1991), Estrella and Hardouvelis (1991), and Estrella and Mishkin (1998), recognizing the diverse empirical landscape outlined by Stock and Watson (2003), reflecting variations across countries and temporal epochs.

Contemporary dynamics, shaped by quantitative easing, policy rate fluctuations, and impactful events like the dotcom bubble and the financial crisis, raise pivotal questions about the enduring predictive prowess of financial markets on output growth. In navigating economic volatility, Chinn and Kucko (2015) suggest that economic volatility enhances predictive prowess, while Kuosmanen and Vataja (2018) correlate forecast efficacy with turbulent economic conditions. This study strategically shifts focus from the term structure of interest rates to delve into stock returns, aiming to discern the maintenance of predictive power and investigate potential sources contributing to the mixed empirical results associated with these dynamic stock indices.

Stock returns, encapsulating investor expectations of future earnings, have been implicated in a causal link to output growth, as indicated by Fischer and Merton (1984), Fama (1990), and Schwert (1990). However, complexities arise, evident in mixed results from studies by Stock and Watson (1990) and Binswanger (2000).

## 2.2 What is the Stock Market index?

An essential tool in the finance industry, a stock market index provides a critical picture of the overall performance of a certain set of stocks in a financial market. It offers a benchmark for financial experts and investors to assess the state and direction of the market or a specific industry. An industry or the overall market are represented by a carefully chosen set of equities that make up the composition of a stock market index. The stock prices of the firms that make up an index are used in the construction of the index. These prices are weighted to ensure that larger companies have a greater influence on the index value, usually based on market capitalization. Most indices have a designated base value set at a specific point in the past, serving as a reference point for assessing changes. Movements in the index value are expressed as a percentage relative to this base value.

Stock market indices act as reliable barometers, offering insights into market trends and conditions. A rising index is generally interpreted as a positive indicator, signalling overall

market strength, while a declining index may suggest challenges or a weakening market. Investors and financial professionals frequently use indices such as the S&P 500, Dow Jones Industrial Average (DJIA), Nasdaq Composite, and FTSE 100 to track the performance of the U.S. market, technology sector, and UK market, respectively. Beyond serving as performance benchmarks, stock market indices play a crucial role in portfolio management. Investors often compare the performance of their portfolios or individual stocks to the movements of relevant indices to assess investment success and make informed decisions. In summary, stock market indices aid in trend analysis, give an overview of the state of the market, and contribute to a thorough comprehension of the state of the economy. They are essential instruments in the finance industry, directing investment plans and supporting the assessment of market trends.

### 2.2.1 S&P 500 Index

The Standard & Poor's 500, or S&P 500 (^GSPC) index, is a collection of 500 of the biggest firms that are traded on US stock markets. As a leading gauge of the performance of the US stock market and the nation's economy as a whole, it is a well-known equity index. Although the S&P 500 is the benchmark used by financial professionals, the general public and mainstream media are better familiar with the Dow Jones Industrial Average (DJIA). The S&P 500 comprises businesses from every industry in the United States, offering a wide-ranging depiction of the market. Based on variables including industry, liquidity, and market capitalization, companies are chosen. Market capitalization determines the S&P 500's weighting, in contrast to the Dow Jones Industrial Average. This indicates that the value of the index is more influenced by larger companies. A common benchmark for evaluating the performance of individual stocks, mutual funds, and the U.S. stock market as a whole is the S&P 500. Due to its lengthy history, which dates back to its founding in 1957, it is also a useful tool for investors to research past trends and choose wisely. Because of its diversity, the S&P 500 is regarded as a representative sampling of the whole U.S. stock market. Global investors keep a close eye on movements in the S&P 500.

### 2.2.2 Dow Jones Industrial Average

The performance of thirty major businesses listed on US stock exchanges is tracked by the Dow Jones Industrial Average (DJIA or \DJI), an index of the stock market. It is the second-oldest U.S. market index after the Dow Jones Transportation Average and is extensively watched. It is seen as a gauge of the state of the US economy overall as well as the performance

of the stock market. Known by its common name, the Dow, it is one of the most widely followed stock market benchmarks in the world. The index is made up of thirty notable stocks that reflect different economic sectors. Businesses can be added or withdrawn in response to changes in the economy and market trends. Price-weighted accounting is used to create the DJIA, meaning that higher-priced equities have a greater impact on the index's value. The DJIA is not market-cap weighted, in contrast to other major indices. Historically, the DJIA has featured a number of well-known corporations, including Microsoft, Apple, Coca-Cola, IBM, and Goldman Sachs. When evaluating the performance of a single stock or the stock market as a whole, the DJIA is used as a benchmark. It was founded in 1896 by Charles Dow and Edward Jones, marking the beginning of its existence.

### 2.2.3 Nasdaq 100

The biggest non-financial firms listed on the Nasdaq stock exchange are included in the Nasdaq-100 (^NDX) stock market index. It is a well-known performance benchmark for the technology industry because of its emphasis on internet-related and technology-related firms. The index comprises a wide variety of businesses from several sectors, with a focus on technology, biotechnology, and internet-related businesses. Like the S&P 500, the Nasdaq-100 index is weighted by market capitalization, which indicates that larger companies have a bigger influence on the index's value. It is strongly related to innovation and technology, and it usually consists of big tech businesses like Alphabet, the parent company of Google, Apple, Microsoft, and Amazon. Investors all throughout the world use the Nasdaq-100 as a gauge for how well the technology industry and other innovation-driven industries are performing. The Nasdaq-100 is sometimes more volatile than wider market indices because of its composition. Because of this, it's commonly used as a benchmark to compare the performance of funds and portfolios that are technology-focused. According to the Nasdaq 100's liquidity rules, each security needs to have a minimum of 200,000 shares traded on a daily average for the three months prior. Interestingly, there is no requirement for market size to be included in this index.

### 2.2.4 Russell 2000

An index of the stock market that follows the performance of about 2,000 small-cap stocks in the US is called the Russell 2000(^RUT) Index. It belongs to the family of Russell Indices, which includes popular benchmarks for large- and small-cap equities. The Russell 2000 is designed to represent the performance of the small-cap sector of the US equity market and is

smaller in composition than indices like the S&P 500 or Dow Jones Industrial Average. It offers a wide representation of minor US firms with a varied range of organizations from different sectors. Because the Russell 2000 is a market-capitalization-weighted index, the value of the index is more heavily influenced by companies with larger market capitalizations. In comparison to larger-cap equities, small-cap stocks are frequently linked to increased volatility and maybe higher returns. Because of this, the Russell 2000 is commonly used as a benchmark to assess how well small-cap investment strategies are performing. Investors, fund managers, and analysts frequently use the index as a standard for evaluating the performance of small-cap stocks. Every year, the Russell 2000 is reconstructed to make sure it accurately reflects the state of the small-cap market. The Frank Russell Company launched the Russell 2000 Index in 1984, and FTSE Russell, a division of the London Stock Exchange (LSE) Group, is in charge of it. This U.S.-based index, which comprises over 2,000 small-cap companies, represents a wide range of lower market size businesses.

### 3. Empirical Analysis

#### 3.1 Data description

##### 3.1.1 Data description for both countries GDP

We have access to GDP data from the Federal Reserve Economic Data for the German and Greek markets, as well as stock index return data from the Dow Jones, S&P 500, Russell 2000, and Nasdaq 100. The availability of data played a major role in the selection of markets. The sample period, albeit it varies for different markets, starts from the beginning of the second quarter of 1992 and ends at the end of the fourth quarter of 2022. To preserve the broadest accessible data set, we have permitted varying commencement dates.

Figure 1: Quarterly GDP Growth of Greece and Germany

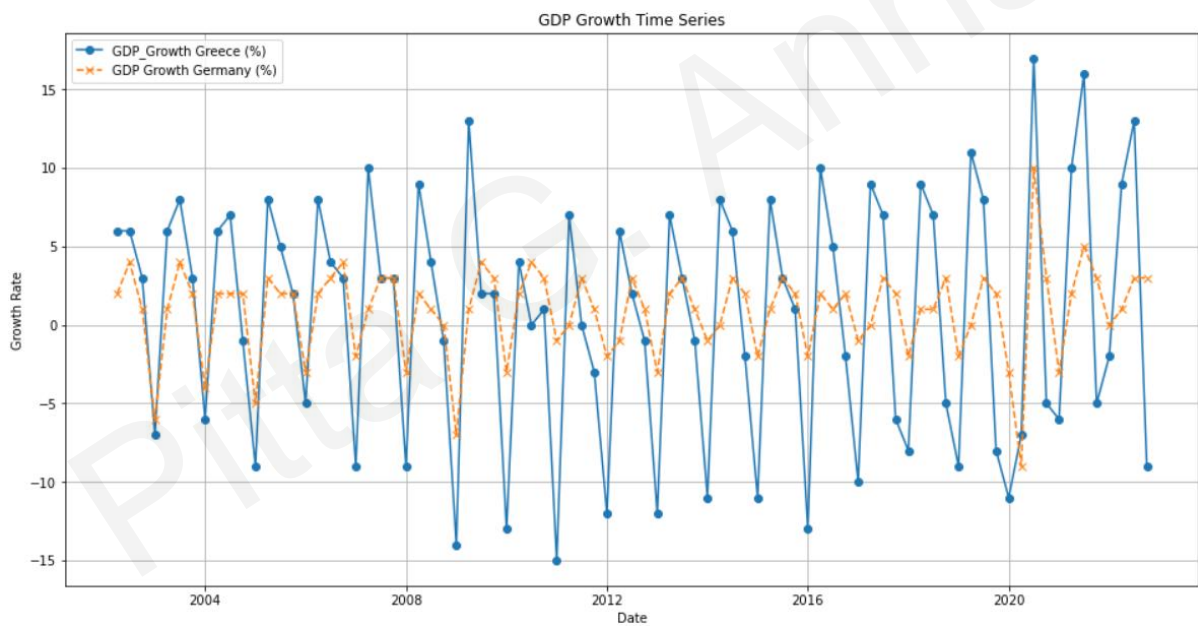


Table 1: Descriptive statistics of Greek and German GDP (Source: FRED)

	Greek GDP	German GDP
count	112.000000	112.000000
mean	44430.647321	6.645355E+05
std	9668.737584	1.439221E+05

<b>min</b>	22209.300000	4.620400E+05
<b>25%</b>	39785.275000	5.426325E+05
<b>50%</b>	45419.900000	6.328750E+05
<b>75%</b>	50594.025000	7.796400E+05
<b>max</b>	63078.400000	1.006610E+00

The phrase "Millions of Chained 2010 Euros" refers to the GDP numbers that have been expressed in constant euros after being adjusted for inflation using the chained (or chain-weighted) approach. 2010 serves as the base year in this modification. In economic analysis, this is frequently used to compare values over time while taking shifts in the general level of prices into consideration. It offers a method of seeing economic data in real terms by accounting for how inflation affects the value of the currency's purchasing power.

Both countries have the same number of observations (112), indicating that the datasets are of equal size. The mean GDP for "Germany" (approximately 664,535.5) is significantly higher than that of "Greece" (approximately 44,430.65). This suggests that, on average, the economic output of Germany ("DEU\_gdp") is much higher than that of Greece ("GR\_gdp"). The standard deviation for "DEU\_gdp" (approximately 143,922.1) is also considerably higher than that of "GR\_gdp" (approximately 9,668.74). This indicates that the economic performance of Germany has a larger degree of variability compared to Greece. Both countries have different minimum and maximum GDP values, with Germany consistently having higher values than Greece. The range of GDP values in Germany is wider. In every quartile (25%, 50%, and 75%), the GDP values for Germany are substantially higher than those for Greece. This implies that Germany has a better GDP distribution throughout a range of percentiles, in addition to having a higher GDP on average. All of the aforementioned points to a more robust and varied German economy.

### 3.1.2 Data description for Indices

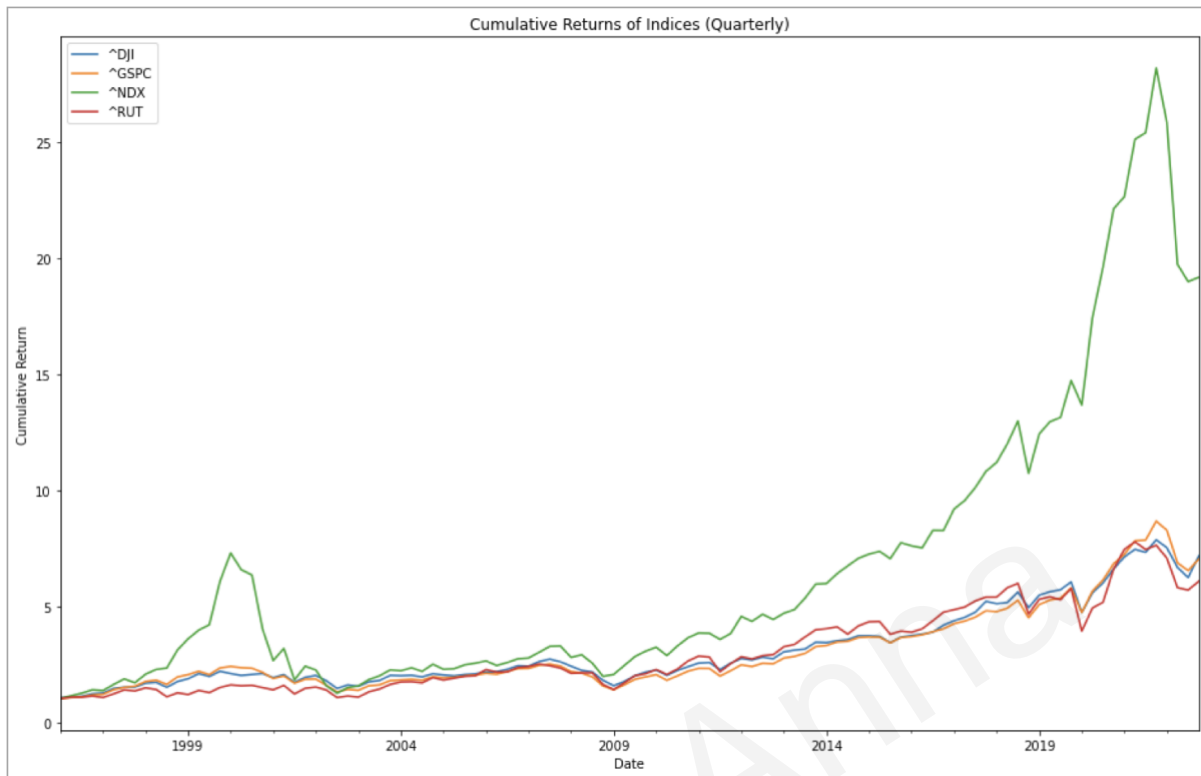
Table 2: Descriptive statistics of stock market indices (source: "Yahoo finance")

	^DJI	^GSPC	^NDX	^RUT
Count	123.000000	123.000000	123.000000	123.000000

Mean	0.022113	0.021741	0.037683	0.023283
Std	0.077177	0.080192	0.130921	0.104770
min	-0.232013	-0.225582	-0.361613	0.308888
25%	-0.016595	-0.008743	-0.017615	0.035452
50%	0.025653	0.029126	0.046137	0.029949
75%	0.073700	0.068661	0.108043	0.086061
max	0.177748	0.208670	0.539861	0.309858

The summary statistics table provides a detailed overview of the historical performance and variability of four prominent financial indices: ^DJI (Dow Jones Industrial Average), ^GSPC (S&P 500), ^NDX (Nasdaq-100), and ^RUT (Russell 2000). The "Count" row indicates that there are 123 observations for each index in the dataset, offering a reasonably robust sample size for analysis. The "Mean" row presents the average returns, highlighting that ^NDX has the highest average return among the indices at 0.037683. This indicates that, on average, ^NDX has shown stronger positive returns compared to the other indices. The "Std" row, representing the standard deviation, serves as a measure of the volatility or dispersion of returns. ^NDX has the highest standard deviation (0.130921), suggesting that it has experienced greater variability in returns, potentially indicating higher risk compared to the other indices. The "Min" and "Max" rows showcase the minimum and maximum returns observed for each index. Notably, ^NDX has the highest maximum return at 0.539861, indicating periods of strong positive performance. Quartiles (25%, 50%, 75%) offer insights into the distribution of returns. For instance, the 25th percentile (Q1) to 75th percentile (Q3) range for ^NDX is wider compared to the other indices, further emphasizing its potential for larger price swings.

Figure 2: Cumulative returns of stock market indices (source: "Own work")



Cumulative returns refer to the overall percentage change in an investment's value over a defined timeframe, taking into account not only the price appreciation but also any dividends or interest earned. This is calculated by multiplying each period's return, adding 1, and then expressing the resulting value as a percentage.

Over the observed period, the Nasdaq 100 index showed a distinctive pattern. It reached a peak of 7, followed by a subsequent decline, which was different from the trend other indices followed. However, from 2009 to 2021, the Nasdaq index exhibited a notable contrast. While other indices demonstrated a steady and consistent increase, the Nasdaq index had an intense climb. This intense growth set the Nasdaq apart and signifies its unique market dynamics, different from its counterparts during the same timeframe. It is worth noting that the Nasdaq is mostly composed of technology companies.



Figure 3: Matrix of correlation between Greek GDP and stock market indices (Source: "Own work")

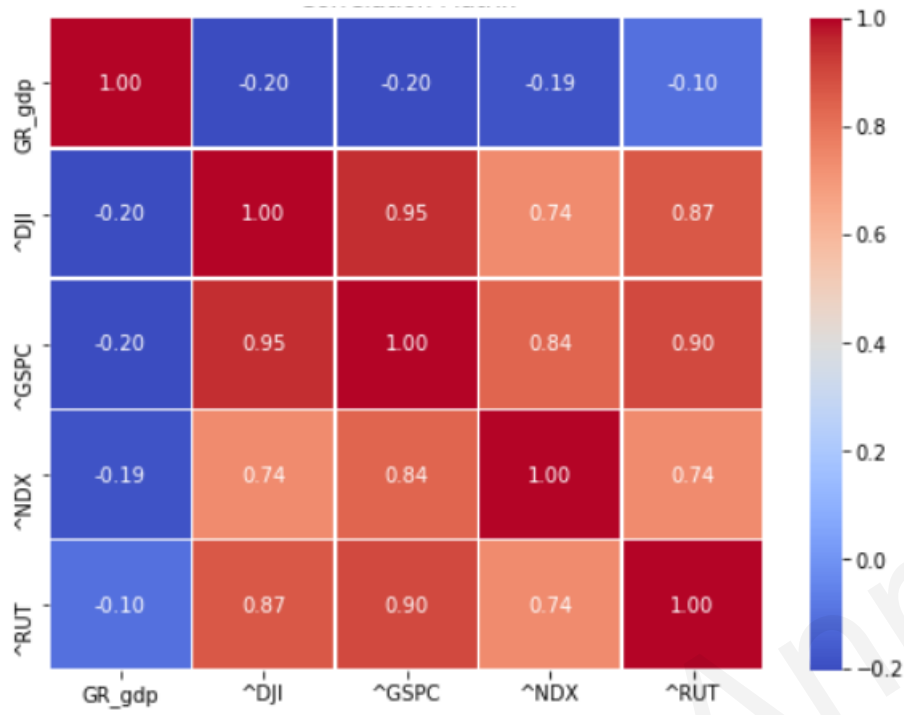
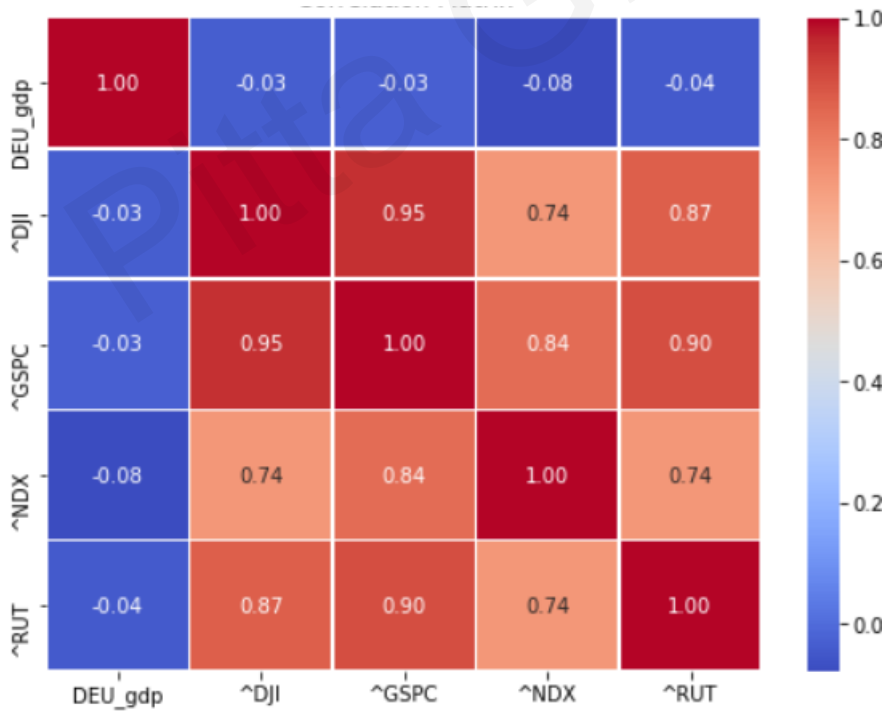


Figure 4: Matrix of correlation between German GDP and stock market indices (Source: "Own work")



There is a high positive correlation between American stock indices, such as the S&P 500, Dow Jones Industrial Average, and Nasdaq. This indicates that these indices tend to move in the same direction. If one index experiences gains, the others also tend to register increases, and vice versa. In the U.S., this high positive correlation suggests that overall market movements are closely aligned.

The correlation between GDP and stock indices in Greece is weaker (-0.03 to -0.08) when compared to Germany (-0.10 to -0.20). These negative correlation values indicate an inverse relationship between GDP and stock indices in both countries. This highlights the complex relationship between economic indicators and stock market dynamics in different national contexts.

### 3.2 Testing Regression assumptions

The assumptions of the Multiple Linear Regression are several and should be explained in more detail and in-depth, however, this is not the purpose of my thesis. The regression assumptions according to Gujarati and Porter (2009) are the following:

1. The model is linear in its parameters.
2. Zero covariance between the error term and each explanatory variable.
3. The expected value of the error terms is zero.
4. The variance of the error terms is constant (Assumption of Homoskedasticity).
5. Not serially correlated error terms.
6. The size of the sample must be greater than the number of explanatory variables.
7. Sufficient variance in the values of explanatory variables.
8. No Multicollinearity.
9. The model is correctly specified.
10. The error terms are normally distributed.

when these assumptions hold then the estimated coefficients, according to the theorem of Gauss & Markov, are “BLUE” and no other model produces better estimates than those produced from the OLS method. “BLUE” coefficients have three properties:

1. They have the minimum variance.
2. The coefficients are linear, and so the regression is linear in parameters.
3. The coefficients are unbiased, and their expected values are equal to their true values.

To begin with, I conducted a stationary test on all my variables to ensure that their statistical properties remain consistent over time. For this, I used the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test, which examines the null hypothesis that a time series is trend-stationary around a deterministic trend. The results are presented in the table below and indicate that the data is stationary.

Table 3 Stationarity ('own work')

	<b>Variable</b>	<b>p-value</b>	<b>Stationarity</b>
<b>0</b>	^DJI	0.1	Stationary
<b>1</b>	^GSPC	0.1	Stationary
<b>2</b>	^NDX	0.1	Stationary
<b>3</b>	^RUT	0.1	Stationary
<b>4</b>	GR_gdp_growth	0.1	Stationary
<b>5</b>	DEU_gdp_growth	0.1	Stationary

After that, I began testing the assumptions for my models. I want to point out that assumption 1 is met in all specifications, and all the specifications are linear, without any quadratic variables.

Assumption 2 states that there should be no correlation between the explanatory variables and the error term. However, I'm not sure if this assumption holds true in my case. The coefficients of the explanatory variables, such as Coef\_Index and Coef\_DEU\_growth, have low p-values. This means that the null hypothesis of zero covariance can be rejected, which indicates potential issues with omitted variable bias or model misspecification. It's likely that my model suffers from omitted variable bias, which happens when one or more variables that affect and are correlated with one of my explanatory variables exist but are not included in the model. This bias leads to a correlation between the error term and an explanatory variable, violating assumption 2. Unfortunately, it's challenging to control for this bias because there's no information available on which factors that affect my dependent variable are not included in the model.

Assumption 3 holds, as all the specifications include a constant, which ensures that the mean of the error terms is zero. Assumption 4 is known as the assumption of homoskedasticity. This means that the variance of errors should be constant. If this assumption is violated, that will lead to inaccurate results in the F and t-tests, making the coefficients produced by the regression not “best”. The White Test detects whether heteroskedasticity is present. The test has the following hypothesis:

$H_0$ : The errors have constant variance (assumption of homoskedasticity)

$H_1$ : The errors do not have equal variance (heteroskedasticity).

The p-values in all consequently are significant at the 1% significance level. The errors have constant variance and I accept that assumption 4 holds. Even if the tests had shown that heteroskedasticity is present, I use robust standard errors in all of my specifications, which is a way to eliminate the heteroskedasticity issue. The robust standard errors provide more accurate standard errors of the regression coefficients.

Assumption 5 refers to the problem of serial correlation. According to the Autocorrelation Test (Breusch-Godfrey Test)

$H_0$ : There is no autocorrelation in the residuals.

$H_1$ : There is autocorrelation in the residuals.

The Breusch-Godfrey Test results, with significant p-values, suggest the presence of autocorrelation in the residuals in some tests which violates this assumption. However, lagged variables can still capture the problem.

Assumption 6 holds. In all regressions, the number of parameters that I use is way less compared to the size of the sample.

Assumption 7 should hold if there is sufficient variance in the values of explanatory variables, meaning that extreme values or outliers should not be present. Not every outlier though has a considerable impact on the specification.

Assumption 8 is the most important of the OLS regression. It states that there should be no multicollinearity present in the model. If some of the explanatory variables are correlated, it

will impact the standard errors of the produced results. This means that the standard errors will be larger than they should be, which affects the F and t-tests. To assess multicollinearity, the Max VIF values are provided. If these values are below a certain threshold (commonly 5), it suggests that multicollinearity is not a severe issue. You mentioned that VIF values are lower than 5, indicating that multicollinearity is not a major concern. To ensure that the predictors are not correlated, I will use initial correlation matrices for each specification. The Variance Inflation Factor also provides a measure of correlations among the different variables. The higher the VIF of a variable, the higher the correlation of this variable to another independent variable. The general rule of thumb is that VIF coefficients higher than 5 should not be accepted, in the sense that above 5, there is more than acceptable correlation. I conducted the VIF for all specifications, and the results were way lower than 5. Therefore, assumption 8 holds.

Assumption 9 is also one that can be violated as it is linked to assumption 2 (omitted variables bias). In smaller datasets, the normal distribution of error terms significantly influences the validity of statistical inferences. We can examine the residuals in the dataset to determine if the normality assumption is met. The Shapiro Normality Test results with non-significant p-values suggest that the normality assumption is not strongly violated, at least for larger sample sizes.

In conclusion, the meticulous testing and verification of these assumptions ensure the reliability and validity of the Multiple Linear Regression model. The robustness of the estimated coefficients, guided by these assumptions, underscores the credibility of the Ordinary Least Squares (OLS) method in delivering optimal parameter estimates.

### 3.3 Regression Analysis

#### 3.3.1 Base Model Regression Analysis for Greece

Within this master thesis, an in-depth analysis is conducted, exploring the relationship between the returns of major stock market indices - the Dow Jones Industrial Average, S&P 500 Index, Nasdaq 100 Index, and Russell 2000 Index - at various lagged periods and the GDP growth in Greece. In this analytical framework,  $y_t$  signifies the period-over-period growth of GDP observed over time. The chosen independent variable for each model is an index return at the

particular lagged period of interest. The term  $\varepsilon_t$  represent the regression residuals. Additionally, in each specification an autoregressive term ( $y_{t-h}$ ) is added in order to take future output growth and output growth over the same time horizon into account. In other words, my model may have serial correlation, as found by the assumption testing of my specifications. Adding a lag version of the independent variable is a popular solution to the problem. The study encompasses a diverse range of horizons, spanning from  $h = 1$  (one quarter) to  $h = 8$  (eight quarters), attempting to explore the significance between dependent and explanatory variables. The model formulations are carefully constructed to clarify the complex linkages between GDP growth and index returns, offering a thorough comprehension of the processes at work in the Greek economic environment.

The following is how the models are created:

#### **Dow Jones Index Returns:**

$$(1) y_t = \alpha + \beta * DJI_{t-h} + \rho * y_{t-h} + \varepsilon_t$$

The regression analysis for Dow Jones Index Returns reveals a dynamic relationship with Greek GDP growth. Equation (1) highlights the significance of Lag 4, with a robust fit evidenced by a high R-squared value of 0.817. Lag 4 stands out as a crucial time lag, showing statistically significant coefficients for the Intercept, Dow Jones Index, and the lagged version of dependant variable. The coefficients for Index and GR\_growth at Lag 4 (0.901 and 0.381, respectively) emphasize their substantial impact on the dependent variable, underlining the importance of considering lagged effects.

#### **S&P 500 Index Returns:**

$$(2) y_t = \alpha + \beta * GSPC_{t-h} + \rho * y_{t-h} + \varepsilon_t$$

The regression analysis for S&P 500 Index Returns explores the intricate relationship with Greek GDP growth across lag periods 1 to 8. The equation . reveals nuanced dynamics. Lag 4 emerges with a high R-squared (0.807), indicating a strong connection. Lag 1 has little ability to explain, but Lag 5 raises the possibility of an inverse relationship. Strong explanatory power is shown by lag 8, suggesting a favourable correlation between Greek GDP growth and S&P 500 returns at lag 8.

### Nasdaq 100 Index Returns:

$$(3) y_t = \alpha + \beta * NDX_{t-h} + \rho * y_{t-h} + \varepsilon_t$$

The regression analyses for Nasdaq 100 Index Returns shed light on the temporal dynamics of its relationship with Greek GDP growth. Equation (3) highlights ^NDX Lag 4 as particularly significant, with a high R-squared of 0.803. The negative coefficient for ^NDX Lag 4 suggests a negative impact on current Greek GDP growth, while the positive coefficient for lagged Greek GDP growth indicates a self-reinforcing effect. Lag 1 and Lag 2 exhibit lower R-squared values, suggesting varying impacts over different time spans. These results highlight how crucial it is to take into account various lag times when analysing the connection between Greek economic development and returns on the Nasdaq 100 Index.

### Russell 2000 Index Returns:

$$(4) y_t = \alpha + \beta * RUT_{t-h} + \rho * gr\_y_{t-h} + \varepsilon_t$$

The regression analyses for Russell 2000 Index Returns provide insights into its relationship with Greek GDP growth across various lag periods. The equation

(4) highlights ^RUT Lag 4 as particularly significant, with a remarkably high R-squared value of 0.803. The negative coefficient for ^RUT Lag 4 suggests a negative impact on current Greek GDP growth, while the highly significant coefficient for lagged Greek GDP growth implies a robust positive association. These findings highlight the dynamic character of the relationship between the returns on the Russell 2000 Index and the growth of the Greek economy, highlighting the significance of Lag 4 in offering insightful information for economic forecasting and policymaking.

Table 4: Regressions' results - Greece (Source: "Own work")

Index	Lag	R-squared	Intercept	Coef_Index	Coef_GR_growth	P-value Intercept	P-value_Index	P-value_GR_growth
^DJI	1	0.030	0.010	0.059	-0.158	0.221	0.539	0.125
^DJI	2	0.229	0.013	0.016	-0.484	0.075	0.850	0.000
^DJI	3	0.022	0.011	0.007	-0.149	0.171	0.941	0.150

^DJI	4	0.817	0.003	-0.092	0.901	0.381	0.030	0.000
^DJI	5	0.048	0.008	0.142	-0.151	0.294	0.148	0.146
^DJI	6	0.257	0.016	-0.068	-0.527	0.030	0.456	0.000
^DJI	7	0.032	0.013	-0.037	-0.186	0.124	0.725	0.081
^DJI	8	0.825	-0.002	0.029	0.947	0.627	0.502	0.000
^GSPC	1	0.028	0.010	0.043	-0.161	0.206	0.642	0.117
^GSPC	2	0.228	0.013	0.001	-0.485	0.067	0.991	0.000
^GSPC	3	0.022	0.011	0.013	-0.149	0.175	0.888	0.148
^GSPC	4	0.815	0.003	-0.080	0.906	0.422	0.049	0.000
^GSPC	5	0.051	0.008	0.145	-0.157	0.292	0.125	0.128
^GSPC	6	0.260	0.016	-0.081	-0.525	0.026	0.349	0.000
^GSPC	7	0.031	0.012	-0.018	-0.182	0.134	0.853	0.085
^GSPC	8	0.825	-0.002	0.030	0.945	0.629	0.473	0.000
^NDX	1	0.026	0.011	0.001	-0.163	0.173	0.986	0.115
^NDX	2	0.229	0.013	0.013	-0.484	0.082	0.787	0.000
^NDX	3	0.024	0.010	0.021	-0.149	0.204	0.701	0.150
^NDX	4	0.812	0.003	-0.036	0.906	0.468	0.150	0.000
^NDX	5	0.034	0.009	0.045	-0.164	0.241	0.428	0.116
^NDX	6	0.254	0.015	-0.017	-0.519	0.040	0.728	0.000
^NDX	7	0.031	0.012	-0.004	-0.181	0.143	0.941	0.087
^NDX	8	0.824	-0.001	0.003	0.943	0.750	0.897	0.000
^RUT	1	0.031	0.010	0.049	-0.163	0.216	0.482	0.114
^RUT	2	0.229	0.013	-0.005	-0.485	0.063	0.937	0.000
^RUT	3	0.023	0.011	0.018	-0.150	0.175	0.802	0.146
^RUT	4	0.814	0.002	-0.057	0.909	0.491	0.072	0.000
^RUT	5	0.047	0.009	0.103	-0.164	0.246	0.160	0.112
^RUT	6	0.267	0.016	-0.092	-0.524	0.021	0.173	0.000
^RUT	7	0.032	0.013	-0.029	-0.182	0.121	0.705	0.084
^RUT	8	0.827	-0.002	0.038	0.945	0.575	0.253	0.000

### 3.3.2 Base model Regression Analysis for Germany

In the next phase of this analysis, focused on Germany, we investigate the relationship between the returns of the major stock market index in question (i.e. Dow Jones Index, S&P 500 Index,



Nasdaq 100 Index, and Russell 2000 Index) and the GDP growth in Germany. We use the symbol  $y_t$  to signify the period growth in GDP. For each model, we choose an index return as the independent variable, while  $\varepsilon_t$  represents the persistent white noise error term. Additionally, we include an autoregressive term to account for output growth over the same time horizon as future output growth. The study encompasses a diverse range of horizons, spanning from  $h = 1$  (one quarter) to  $h = 8$  (eight quarters), attempting to explore the significance between dependent and explanatory variables.

### **Dow Jones Index Returns:**

$$(5) y_t = \alpha + \beta * DJI_{t-h} + \rho * y_{t-h} + \varepsilon_t$$

In the regression analysis for ^DJI (Dow Jones Index) lags 1 to 8 targeting Germany's GDP growth, various models were examined to understand the temporal dynamics of their relationship. Notably, the statistical significance of the index's impact on GDP growth varied across different lag periods. In the case of ^DJI Lag 1 model, the model exhibited limited explanatory power (R-squared: 0.031), and neither the ^DJI Lag 1 coefficient nor the DEU\_gdp\_growth Lag 1 coefficient were statistically significant, suggesting a weak or no connection between Dow Jones Index returns and German GDP growth at this lag. However, as the lag periods progressed, the significance and explanatory power of the models evolved. For instance, ^DJI Lag 4 model, demonstrated a considerable R-squared value of 0.570, indicating reasonably strong explanatory power. The statistically significant coefficient for ^DJI Lag 4 (-0.0871, p-value: 0.001) and DEU\_gdp\_growth Lag 4 (0.7070, p-value: 0.000) suggested a brief negative impact of Dow Jones Index returns four periods prior to the quarter of study. This highlights the self-reinforcing effect of prior economic growth.

### **S&P 500 Index Returns:**

$$(6) y_t = \alpha + \beta * GSPC_{t-h} + \rho * y_{t-h} + \varepsilon_t$$

The regression analyses examined the relationship between ^GSPC (S&P 500 Index) returns at different time lags and Germany's GDP growth. The statistical significance of the index varied across lag periods. Notably, in ^GSPC Lag 4, the model exhibited a high R-squared value of 0.547, indicating robust explanatory power. Both ^GSPC Lag 4 and DEU\_gdp\_growth Lag 4 had statistically significant coefficients, suggesting a substantial negative impact of S&P

500 returns four periods ago on current German GDP growth. This significance could be attributed to the potential influence of economic events or market dynamics that unfold over a specific lag period, capturing a more meaningful connection between stock market performance and subsequent economic performance. The impact observed in Lag 4 might reflect a delayed response of the German economy to changes in the S&P 500, providing insight into the persistence of economic effects and the importance of considering an appropriate lag structure when assessing such relationships.

### **Nasdaq 100 Index Returns:**

$$(7) y_t = \alpha + \beta * NDX_{t-h} + \rho * y_{t-h} + \varepsilon_t$$

The regression analyses conducted for different lags of the ^NDX (Nasdaq-100 Index) in relation to Germany's GDP growth revealed varying levels of statistical significance. In the regression for ^NDX Lag 1, the R-squared value was 0.031, indicating a limited explanatory power of the model. The coefficients for both ^NDX Lag 1 and DEU\_gdp\_growth Lag 1 were not statistically significant, with p-values of 0.390 and 0.170, respectively. This lack of significance suggests that, in the first lag, the Nasdaq-100 Index did not have a substantial impact on Germany's GDP growth. However, as the lag increased, the significance patterns changed. In ^NDX Lag 2, the model exhibited a higher R-squared value of 0.283, and the coefficient for DEU\_gdp\_growth Lag 2 was statistically significant at a 1% level, indicating a more substantial impact of Nasdaq-100 returns two periods ago on current German GDP growth. Similar patterns emerged for Lag 4, where both the R-squared value (0.516) and the coefficients for ^NDX Lag 4 and DEU\_gdp\_growth Lag 4 were statistically significant. The negative coefficient for ^NDX Lag 4 suggests an inverse relationship, implying that a decrease in Nasdaq-100 returns four periods ago corresponds to an increase in German GDP growth in the current period. Therefore, the significance of the Nasdaq-100 Index in influencing Germany's GDP growth becomes more pronounced with longer lag periods, potentially reflecting the delayed impact of global market dynamics on the German economy.

### **Russell 2000 Index Returns:**

$$(8) y_t = \alpha + \beta * RUT_{t-h} + \rho * y_{t-h} + \varepsilon_t$$

In the examination of the relationship between the Russell 2000 Index (RUT) returns and Germany's GDP growth, specific emphasis falls on Lag 4, Lag 5, and Lag 6 as key timeframes

with notable insights. Lag 4 stands out with a substantial explanatory power of 56%, indicating a statistically significant negative impact of Russell 2000 Index returns four periods ago on current German GDP growth. This finding is accentuated by the highly significant positive coefficient for prior GDP growth, underscoring the lasting influence of past economic performance. Moving to Lag 5, the model explains 8% of the variance in Germany's GDP growth. While the coefficient for the Russell 2000 Index is positive (0.06), suggesting a potential positive impact, it is not statistically significant. However, the negative and marginally significant coefficient for prior GDP growth (P-value\_DEU\_growth: 0.08) suggests a nuanced relationship. The Russell 2000 Index's negative and statistically significant coefficient and the prior GDP growth's highly significant coefficient highlight the significance of Lag 6, which has an explanatory power of 29% and further elucidates the complex dynamics between stock market movements and Germany's economic growth. These findings highlight the significance of Lag 4, Lag 5, and Lag 6 in deciphering the intricate link, with statistical significance being crucial in comprehending how the Russell 2000 Index affected Germany's GDP development throughout these particular time periods.

Table 5: Regressions' results - Germany (Source: "Own work")

Index	Lag	R-squared	Intercept	Coef_Index	Coef_DEU_growth	P-value_Intercept	P-value_Index	P-value_DEU_growth
^DJI	1	5%	0.01	0.05	-0.18	0.02	0.18	0.07
^DJI	2	25%	0.01	0.01	-0.49	0.00	0.74	0.00
^DJI	3	2%	0.01	0.04	-0.09	0.02	0.25	0.34
^DJI	4	58%	0.00	-0.08	0.72	0.05	0.00	0.00
^DJI	5	6%	0.01	0.06	-0.17	0.02	0.11	0.10
^DJI	6	28%	0.01	-0.07	-0.56	0.00	0.06	0.00
^DJI	7	2%	0.01	0.02	-0.15	0.01	0.67	0.17
^DJI	8	56%	0.00	-0.02	0.78	0.27	0.43	0.00
^GSPC	1	5%	0.01	0.05	-0.18	0.02	0.16	0.07
^GSPC	2	25%	0.01	0.01	-0.49	0.00	0.75	0.00
^GSPC	3	2%	0.01	0.03	-0.09	0.02	0.34	0.34
^GSPC	4	56%	0.00	-0.06	0.72	0.08	0.01	0.00
^GSPC	5	7%	0.01	0.07	-0.17	0.02	0.05	0.09
^GSPC	6	28%	0.01	-0.06	-0.55	0.00	0.05	0.00
^GSPC	7	2%	0.01	0.01	-0.16	0.01	0.86	0.15

^GSPC	8	56%	0.00	-0.01	0.79	0.35	0.77	0.00
^NDX	1	5%	0.01	0.02	-0.17	0.02	0.25	0.09
^NDX	2	25%	0.01	0.00	-0.48	0.00	0.98	0.00
^NDX	3	2%	0.01	0.02	-0.09	0.03	0.38	0.39
^NDX	4	53%	0.00	-0.01	0.71	0.16	0.40	0.00
^NDX	5	4%	0.01	0.02	-0.16	0.02	0.41	0.11
^NDX	6	27%	0.01	-0.03	-0.55	0.00	0.14	0.00
^NDX	7	2%	0.01	0.01	-0.15	0.01	0.79	0.16
^NDX	8	56%	0.00	0.01	0.79	0.47	0.69	0.00
^RUT	1	5%	0.01	0.04	-0.18	0.02	0.17	0.07
^RUT	2	25%	0.01	0.00	-0.48	0.00	0.91	0.00
^RUT	3	1%	0.01	0.02	-0.10	0.02	0.48	0.34
^RUT	4	56%	0.00	-0.04	0.72	0.10	0.02	0.00
^RUT	5	8%	0.01	0.06	-0.17	0.02	0.03	0.08
^RUT	6	29%	0.01	-0.05	-0.55	0.00	0.04	0.00
^RUT	7	2%	0.01	-0.01	-0.16	0.01	0.68	0.13
^RUT	8	56%	0.00	0.01	0.79	0.43	0.78	0.00

### 3.4 Prediction Process

In this analysis, we began by selecting pertinent columns from the dataset, focusing on GDP growth and stock market indices, including ^DJI, ^GSPC, ^NDX, and ^RUT. Subsequently, we created lagged variables for these indices and GDP growth, spanning lags from 1 to 8. To ensure the dataset's cleanliness, rows containing NaN values resulting from the lagging process were removed. The dataset was then split into training (95%) and testing (5%) sets, facilitating the estimation and evaluation of the regression model's performance, respectively. It is understood that the in/out of sample periods was dictated by the limited data availability, which is also considered a limitation of this thesis.

For each selected combination of index and lagged period, a linear regression model was fitted using Ordinary Least Squares (OLS) estimator on the training data set. The Ordinary Least Squares (OLS) estimator is a statistical technique employed to compute parameters within a linear regression model by reducing the sum of squared variances between the observed and predicted values. When applied to a training dataset, OLS seeks to ascertain the coefficients

(slope and intercept) of a linear equation that most accurately represents the association between independent variables (predictors) and the dependent variable (target) contained in the dataset. The independent variables comprised lagged index values and lagged GDP growth, while the dependent variable was the current GDP growth. All of the important data from each regression, including the R-squared value, intercept, coefficients, and p-values, were methodically saved in a data frame. Out-of-sample forecasting was done for every index and lag combination once the model was estimated, yielding estimated GDP growth estimates. These predictions were subsequently compared against the actual values from the testing set, enabling the calculation of percentage differences. The forecasted results, inclusive of actual and predicted values along with percentage differences, were diligently saved to distinct CSV files for each index and lag pairing. Essentially, this systematic workflow allows for a comprehensive evaluation of the predictive capabilities of each stock market index and lag combination concerning GDP growth.

### 3.4.1 Prediction for Greece

In the analysis conducted at lag 4 for Greece, it becomes evident that Greece holds a statistically significant influence on the performance of the Dow Jones and S&P 500 indices. These indicators can be used for predicting the path of economic growth of Greece. This statistical significance highlights the substantial impact of Greek economic indicators on the predictive power of these indices. The observed statistical significance emphasizes the robustness of the relationship between Greek economic conditions and the selected stock market indices, reinforcing the reliability of these lag-dependent predictions in capturing the dynamics of financial markets. At these delays, investors and analysts should keep a careful eye on Greek economic statistics because they provide important clues for predicting the behavior of important stock market indices.

Table 6: Model used for prediction – Greece (Source: “Own work”)

Index	Lag	R-squared	Intercept	Coef_Index	Coef_GR_growth	P-value_Intercept	P-value_Index	P-value_GR_growth
^DJI	4	0.8167	0.0030	-0.0917	0.9013	0.3814	0.0302	2.5905
^GSPC	4	0.8152	0.0028	-0.0804	0.9059	0.4219	0.0486	2.1508

The *table 5* provides key statistics derived from the regression analysis for Greek GDP growth using two different stock market indices,  $\hat{DJI}$  and  $\hat{GSPC}$ , both at a lag of 4.

The "Index" column specifies the stock market index utilized in the regression, while "Lag" denotes the lag value, which is 4 in both cases. "R-squared" represents the coefficient of determination, indicating the proportion of variability in Greek GDP growth explained by the model. For  $\hat{DJI}$  and  $\hat{GSPC}$ , the R-squared values are approximately 81.67% and 81.52%, respectively, reflecting a high explanatory power of the model. The "Intercept" column provides the estimated GDP growth when all predictors are zero. For  $\hat{DJI}$ , the intercept is 0.0030, and for  $\hat{GSPC}$ , it is 0.0028. "Coef\_Index" and "Coef\_GR\_growth" represent the coefficients associated with the stock market index and lagged Greek GDP growth, respectively. These coefficients quantify the impact of each predictor on the dependent variable. The "P-value" columns assess the statistical significance of each coefficient. For instance, a low p-value (below the conventional threshold of 0.05) suggests that the corresponding coefficient is statistically significant. In this case, both indices ( $\hat{DJI}$  and  $\hat{GSPC}$ ) exhibit significant coefficients for lagged Greek GDP growth, indicating their influence on the forecasting model.

*Table 7: Predicted GDP Growth rates - Greece (Source: "Own work")*

Test_Period	Index_Used	Actual_GR_growth	Forecasted_GR_growth	Percentage_Difference
2021-09-30	$\hat{GSPC}$	-0.052	-0.0474	-8.6697
2021-12-31	$\hat{GSPC}$	-0.023	-0.0645	180.69
2022-03-31	$\hat{GSPC}$	0.09	0.0896	-0.3779
2022-06-30	$\hat{GSPC}$	0.129	0.1411	9.4407
2022-09-30	$\hat{GSPC}$	-0.088	-0.0444	-49.498
2022-12-31	$\hat{GSPC}$	-0.055	-0.0265	-51.758

The table presents out-of-sample forecasting results for Greek GDP growth using the stock market index  $\hat{GSPC}$  at a lag of 4. The "Test\_Period" column indicates specific dates, "Index\_Used" specifies the stock market index employed in the forecast ( $\hat{GSPC}$ ), "Actual\_GR\_growth" represents the actual Greek GDP growth, "Forecasted\_GR\_growth" is the model-predicted GDP growth, and "Percentage\_Difference" denotes the relative variance between actual and forecasted values.

For example, on September 30, 2021, using the  $\hat{GSPC}$  index at a lag of 4, the model forecasted a Greek GDP growth of approximately -4.74%, while the actual growth was around -5.2%. The

percentage difference, which measures the relative error, is -8.67%, suggesting a slight underestimation by the model. Similar patterns are observed for the subsequent dates, with varying degrees of accuracy in the model's predictions. The highest percentage difference occurs on December 31, 2021, where the model significantly overestimates GDP growth by 180.69%.

Table 8: Actual vs forecasted DJI lag 4- Greece (Source: "Own work")

Test_Period	Index_Used	Actual_GR_growth	Forecasted_GR_growth	Percentage_Difference
2021-09-30	^DJI	-0.052	-0.047	-9.30
2021-12-31	^DJI	-0.023	-0.063	178.11
2022-03-31	^DJI	0.09	0.086	-3.37
2022-06-30	^DJI	0.129	0.143	10.91
2022-09-30	^DJI	-0.088	-0.042	-52.21
2022-12-31	^DJI	-0.055	-0.024	-55.5

The presented table displays out-of-sample forecasting results for Greek GDP growth using the ^DJI stock market index at various dates. The "Test\_Period" column represents the specific dates for which predictions were made, while "Index\_Used" indicates the stock market index employed in the forecast (in this case, ^DJI). "Actual\_GR\_growth" represents the actual Greek GDP growth for each corresponding period. For example, on September 30, 2021, the model forecasted a Greek GDP growth of approximately -4.72% using the ^DJI index, while the actual growth for that period was -5.2%. This resulted in a percentage difference of -9.31%, suggesting a slight underestimation by the forecasting model. A similar pattern is observed for subsequent dates. The "Forecasted\_GR\_growth" column presents the model-predicted Greek GDP growth, providing insights into the model's performance. For instance, on December 31, 2021, the model predicted a GDP growth of approximately -6.40%, significantly deviating from the actual growth of -2.3%, resulting in a substantial percentage difference of 178.11%. The "Percentage\_Difference" column quantifies the relative variance between the actual and forecasted values, highlighting the accuracy of the model. Positive values indicate an overestimation, while negative values suggest an underestimation. These results offer a comprehensive overview of the forecasting model's performance over the specified test periods, allowing for an assessment of its accuracy and reliability in predicting Greek GDP growth. In general, the results reveal a tension that Greek GDP will most likely increase in the near future.

### 3.4.2 Prediction for Germany

In the analysis conducted at lag 4, Germany emerges as a statistically significant factor in forecasting the performance of the Dow Jones, S&P 500, and Russell 200 indices. The statistical significance underscores the meaningful impact of German economic indicators on the predictive power of these indices. Moving beyond lag 4 to lag 5 and lag 6, the statistical significance of Germany's influence extends specifically to the Russell 2000 index. This suggests that, at these lags, Germany continues to play a crucial role in shaping the predictive outcomes for the Russell 2000. The observed statistical significance underscores the robustness of the relationship between German economic conditions and the selected stock market indices, reinforcing the reliability of these lag-dependent predictions in capturing the dynamics of financial markets.

Table 9: Model used for prediction – Germany (Source: “Own work”)

Index	Lag	R-squared	Intercept	Coef_Index	Coef_DEU_growth	P-value_Intercept	P-value_Index	P-value_DEU_growth
^RUT	4	0.5559	0.0034	-0.0443	0.7206	0.1027	0.0203	3.6173
^RUT	5	0.0752	0.0071	0.0592	-0.1742	0.0188	0.0349	0.0791
^RUT	6	0.2862	0.0121	-0.0529	-0.5481	1.9229	0.0423	3.4606
^DJI	4	0.5771	0.0041	-0.0794	0.7161	0.0496	0.0015	1.2587
^GSPC	4	0.5607	0.0037	-0.0618	0.7169	0.0762	0.0113	3.3278

The regression results for different lags and indices reveal important insights into the relationship between German GDP growth and various stock market indices. At lag 4, the Russell 2000 index (^RUT) exhibits a statistically significant association with German GDP growth, as indicated by a notable R-squared value of approximately 55.60%. The intercept, index coefficient, and coefficient for German GDP growth are all statistically significant, reinforcing the reliability of these predictors in the model. The p-values associated with these coefficients further support their significance, with the coefficient for German GDP growth particularly notable. Extending the analysis to lag 5 and lag 6 for the Russell 2000 index, the R-squared values decrease, indicating a potential decrease in explanatory power. However, the model remains statistically significant, suggesting that even at these lags, the Russell 2000



index captures a meaningful portion of the variability in German GDP growth. Notably, at lag 5, the coefficient for German GDP growth takes on a positive value, indicating a change in direction compared to lag 4. Similarly, for the Dow Jones Industrial Average (^DJI) and S&P 500 (^GSPC) indices at lag 4, the models demonstrate significant explanatory power, with R-squared values of approximately 57.71% and 56.08%, respectively. The coefficients for both the indices and German GDP growth are statistically significant, highlighting the predictive capability of these indices.

Table 10: Actual vs forecasted DJI lag 4- Germany (Source: "Own work")

Test_Period	Index_Used	Observed_DEU_growth	Forecasted_DEU_growth
30/09/2021	^DJI	0.027	0.0203
31/12/2021	^DJI	-0.005	-0.0240
31/03/2022	^DJI	0.007	0.0123
30/06/2022	^DJI	0.028	0.0334
30/09/2022	^DJI	0.031	0.0250
31/12/2022	^DJI	0	-0.0053

The presented table outlines the out-of-sample forecasting results for German GDP growth using the Dow Jones Industrial Average (^DJI) index. The "Test\_Period" column denotes specific dates corresponding to the forecasted periods, while the "Index\_Used" column indicates the stock market index employed for the forecast. "Observed\_DEU\_growth" represents the actual observed German GDP growth during the specified periods, and "Forecasted\_DEU\_growth" is the model-predicted GDP growth. For instance, on September 30, 2021, the model forecasted a German GDP growth of approximately 2.03%, while the observed growth was 2.70%. This resulted in a forecasted value that slightly underestimated the actual growth, as indicated by the positive percentage difference. A similar pattern is observed for subsequent periods. On December 31, 2021, the model predicted a negative growth of approximately -2.40%, while the observed growth was -0.50%, resulting in a negative percentage difference. The forecasting accuracy of the model improves in the subsequent periods, with the percentage difference between forecasted and observed values becoming smaller. For instance, on June 30, 2022, the model predicted a growth of approximately 3.34%, while the observed growth was 2.80%, resulting in a positive percentage difference.

Table 11: Actual vs forecasted GSPC lag 4- Germany (Source: "Own work")

Test_Period	Index_Used	Observed_DEU_growth	Forecasted_DEU_growth
30/09/2021	^GSPC	0.027	0.0208
31/12/2021	^GSPC	-0.005	-0.0235
31/03/2022	^GSPC	0.007	0.0145
30/06/2022	^GSPC	0.028	0.0317
30/09/2022	^GSPC	0.031	0.0230
31/12/2022	^GSPC	0	-0.0064

The table displays the out-of-sample forecasting results for German GDP growth using the S&P 500 (^GSPC) index. The "Test\_Period" column represents specific dates for which the GDP growth is predicted, and the "Index\_Used" column indicates the stock market index employed in the forecast. "Observed\_DEU\_growth" represents the actual observed German GDP growth during the specified periods, while "Forecasted\_DEU\_growth" is the model-predicted GDP growth. For instance, on September 30, 2021, the model forecasted a German GDP growth of approximately 2.08%, while the observed growth was 2.70%. This resulted in a forecasted value that slightly underestimated the actual growth, as indicated by the positive percentage difference. A similar pattern is observed for subsequent periods. On December 31, 2021, the model predicted a negative growth of approximately -2.35%, while the observed growth was -0.50%, resulting in a negative percentage difference. The forecasting accuracy of the model varies across different periods, with the percentage difference between forecasted and observed values showing fluctuations. For instance, on March 31, 2022, the model predicted a growth of approximately 1.45%, while the observed growth was 0.70%, resulting in a positive percentage difference.

Table 12: Actual vs forecasted RUT lag 4- Germany (Source: "Own work")

Test_Period	Index_Used	Observed_DEU_growth	Forecasted_DEU_growth
30/09/2021	^RUT	0.027	0.0238
31/12/2021	^RUT	-0.005	-0.0305
31/03/2022	^RUT	0.007	0.0124
30/06/2022	^RUT	0.028	0.0348
30/09/2022	^RUT	0.031	0.0250
31/12/2022	^RUT	0	-0.0010

The provided table presents the out-of-sample forecasting results for German GDP growth using the Russell 2000 (^RUT) index. The "Test\_Period" column represents specific dates for which the GDP growth is predicted, and the "Index\_Used" column indicates the stock market index employed in the forecast. "Observed\_DEU\_growth" represents the actual observed German GDP growth during the specified periods, while "Forecasted\_DEU\_growth" is the model-predicted GDP growth. For example, on September 30, 2021, the model forecasted a German GDP growth of approximately 2.38%, while the observed growth was 2.70%. This resulted in a forecasted value that slightly underestimated the actual growth, as indicated by the positive percentage difference. A similar pattern is observed for subsequent periods. On December 31, 2021, the model predicted a negative growth of approximately -3.05%, while the observed growth was -0.50%, resulting in a negative percentage difference. The forecasting accuracy of the model varies across different periods, with the percentage difference between forecasted and observed values showing fluctuations. For instance, on March 31, 2022, the model predicted a growth of approximately 1.24%, while the observed growth was 0.70%, resulting in a positive percentage difference.

Table 13: Actual vs forecasted RUT lag 5- Germany (Source: "Own work")

Test_Period	Index_Used	Observed_DEU_growth	Forecasted_DEU_growth
30/09/2021	^RUT	0.027	0.0049
31/12/2021	^RUT	-0.005	0.0045
31/03/2022	^RUT	0.007	0.0304
30/06/2022	^RUT	0.028	0.0110
30/09/2022	^RUT	0.031	0.0016
31/12/2022	^RUT	0	-0.0002

The table displays the out-of-sample forecasting results for German GDP growth using the Russell 2000 (^RUT) index. In this context, the "Test\_Period" column specifies the dates for which the GDP growth is predicted, while the "Index\_Used" column denotes the stock market index utilized in the forecast. The "Observed\_DEU\_growth" column represents the actual observed German GDP growth during these periods, and the "Forecasted\_DEU\_growth" column signifies the model-predicted GDP growth.

For instance, on September 30, 2021, the model forecasted a German GDP growth of approximately 0.49%, while the observed growth for that period was 2.70%. This resulted in a noticeable underestimation by the model, as reflected by the positive percentage difference. A

similar trend is observed for December 31, 2021, where the model predicted a positive growth of 0.45%, contrasting with the observed negative growth of -0.50%. Consequently, the percentage difference is negative, indicating an overestimation by the model. The forecasting accuracy varies across different periods, with fluctuations in the percentage difference between forecasted and observed values. Notably, on March 31, 2022, the model predicted a growth of 3.04%, while the observed growth was 0.70%, leading to a substantial overestimation.

Table 14: Actual vs forecasted RUT lag 6- Germany (Source: "Own work")

Test_Period	Index_Used	Observed_DEU_growth	Forecasted_DEU_growth
30/09/2021	^RUT	0.027	0.0779
31/12/2021	^RUT	-0.005	-0.0548
31/03/2022	^RUT	0.007	-0.0072
30/06/2022	^RUT	0.028	0.0111
30/09/2022	^RUT	0.031	-0.0053
31/12/2022	^RUT	0	-0.0152

The presented table illustrates the out-of-sample forecasting results for German GDP growth using the Russell 2000 (^RUT) index. In each row, the "Test\_Period" denotes specific dates for which the GDP growth is predicted, while "Index\_Used" indicates the stock market index employed in the forecast. The "Observed\_DEU\_growth" column represents the actual observed German GDP growth during these periods, and the "Forecasted\_DEU\_growth" column signifies the model-predicted GDP growth. For instance, on September 30, 2021, utilizing the ^RUT index, the model predicted a substantial GDP growth of 7.79%, while the observed growth for that period was 2.70%. This resulted in a notable overestimation by the model, as reflected by the positive percentage difference. A similar trend is observed for December 31, 2021, where the model predicted a negative growth of -5.48%, contrasting with the observed negative growth of -0.50%. Consequently, the percentage difference is negative, indicating an underestimation by the model. The forecasting accuracy varies across different periods, with fluctuations in the percentage difference between forecasted and observed values. Notably, on March 31, 2022, the model predicted a negative growth of -0.72%, while the observed growth was positive at 0.70%, leading to a substantial underestimation.

## 4. Conclusion

The analysis of previous studies highlighted the importance of stock market indices such as S&P 500 and Dow Jones, leading us to the conclusion that they can reflect a future image of economic growth. Additionally, they provided the theoretical base for conducting regression analysis for the cases of Greece and Germany.

The analysis of regression results and out-of-sample forecasting provided valuable insights of the relationship between stock markets and economic growth in Greece and Germany over lags 1 to 8. For Greece, the high R-squared values of approximately 81.67% and 81.52% for  $\Delta$ DJI and  $\Delta$ GSPC, respectively, indicate a strong explanatory power of these indices over Greek GDP growth in the fourth lagged period. The statistically significant coefficients further underline their influence. The models used for prediction of Greek GDP growth were able to predict the correct direction of the GDP growth movement of the particular periods. However, the varying degrees of accuracy in out-of-sample forecasting, particularly the significant overestimation on December 31, 2021 (fourth quarter), suggest potential limitations, emphasizing the need for cautious interpretation and potential omitted variables bias.

In the case of Germany, the analysis at lag 4 reveals significant associations between  $\Delta$ RUT,  $\Delta$ DJI, and  $\Delta$ GSPC with German GDP growth, supported by high R-squared values. The analysis conducted at lag 4 underline influence on forecasting German economic output using the Dow Jones, S&P 500, and Russell 2000. Notably, this significant relationships extend to lag 5 and lag 6 when Russell was used as a determinant. Furthermore, the observed statistical significance across lags confirms the reliability of lag-dependent analysis in capturing the relationships in question. However, similarly to the case of Greece, the out-of-sample forecasting results reveal fluctuations in accuracy across various periods for all indices, showcasing instances of both underestimation and overestimation of German and Greek GDP growth. Nevertheless, again the model was able to correctly predict the direction of GDP growth for all different predictors.

In conclusion, the findings contribute to an enhanced understanding of the interplay between stock market indices and economic growth in the context of Greece and Germany. The findings confirmed a strong relationship between the American stock market and the GDP growth for both countries in question. The models were able to predict the direction of GDP growth at all instances and for both countries. However, in several instances the models failed to predict the magnitude of the period growth. While this might be caused by other dependencies (i.e. covid

outbreak, year or country specific effects, political instability, etc.), the key takeaway is that indeed there are significant relationships and the predictors can be used alone or in conjunction with other variables to infer conclusions regarding future growth. Lastly, this thesis opens avenues for future research to dive deeper into more factors influencing the relationship and to explore potential strategies for improving forecasting precision.

## 4.1 Limitations & recommendations for future research

Coming to the limitations of this thesis, the most prominent one was the data availability that dictated this study. In particular, the data sample was limited to year 1992 to 2022. In order to have an even wider research and claim enhanced conclusions about future economic growth of Greece and Germany, based on stock market indices a suggestion for future research could be the use of a wider sample period. A forty or fifty year period of stock data could provide with more robust predictive models of the future economic expansion.

Additionally, it would be prohibitively expensive in terms of time to further expand the study to include additional potential predictors. Namely, the S&P 500 Index, the Dow Jones Industrial Average, the Nasdaq 100 and the Russell 2000 were used during the course of this thesis. Alternatively or put better, additionally, predictors such as Nikkei 225, FTSE 100 could enrich our understanding regarding Greek and German future economic output. Notably, FTSE resides in the same continent as the two countries we studied and potentially its effects could be stronger.

The fact that we choose these two countries can also lead us to a recommendation. Moreover, any related research could include more countries – member states of the European Union. This will also allow a comparison between the member states and give a conclusion about those countries that overachieving and those that can be described as underperformances. Imagine an interesting hypothetical situation were Scandinavian or Northern European countries are compared with PIGS. If this recommendation is combined with an extended wider period of time maybe more conclusions would be extracted.

Another interesting comparison that could yield interesting results is instead of using the American stock market indices to use the US sectors growth as predictors. Each stock market index represents an industry or a categorization. In that sense, the US sectors growth would give us a sense of whether there are relationships between US sectors' growth and GDP growth of European countries.

## 5. References

- Alsterlind, J., Lindskog, M. & von Brömsen, T. (2020). *An index for financial conditions in Sweden (Report 2017:1)*. Stockholm: Swedish Central Bank.
- Andersson, M. & D'Agostino, A. (2008). *Are sectoral stock prices useful for predicting euro area GDP? Working Paper No 876*, European Central Bank.
- Andersson, M., D'Agostino, A., de Bondt, J. G. & Roma, M. (2011). *The predictive content of sectoral stock prices. Working Paper No 1343*, European Central Bank.
- Barro, J. R. (1990). *The stock market and investment. The Review of Financial Studies. Vol. 3(1), pp. 115–131.*
- Beber, A., Brandt, W. M. & Kavajecz, A. K. (2011). *What does equity sector orderflow tell us about the economy? The Review of Financial Studies. Vol. 24(11), pp. 3688-3730.*
- Chauhuri, K. & Smiles, S. (2004). *Stock market and aggregate economic activity: Evidence from Australia. Journal of Applied Financial Economics. Vol. 14(2), pp. 121-129.*
- Dickey, D. A. & Fuller, W. A. (1979). *Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association. Vol. 74(366), pp. 427-431.*
- European Central Bank. (2012). *Stock prices and economic growth. Economic and Monetary Developments, Monthly Bulletin.*
- Espinoza, R., Fornari, F. and Lombardi, M.J. (2011). *The role of financial variables in predicting economic activity. Journal of Forecasting. Vol. 31(1), pp. 15-46.*
- Estrella, A. Mishkin, S. F. (1998). *Predicting U.S. recessions: Financial variables as leading indicators. The Review of Economics and Statistics. Vol. 80(1), pp. 45-61.*
- Eurostat. (2020). *GDP main aggregates and employment estimates for the second quarter of 2020. Eurostat, News Release, Euro Indicators.*
- Fama, F. E. (1965). *Random walk in stock-market prices. Selected Papers No 16, Graduate School of Business University of Chicago*
- Fama, F. E. (1990). *Stock returns, expected returns, and real activity. The Journal of Finance. Vol. 45(4), pp. 1089-1108.*
- Fama, F. E. (1981). *Stock returns, real activity, inflation, and money. The American Economic Review. Vol. 71(4), pp. 545-565.*
- Fransson, L. & Tysklind, O. (2017). *An index for financial conditions in Sweden (Monetary and Exchange Rate Policy 2017:1)*. Stockholm: Swedish Central Bank.

Gallinger, W. G. (1994). *Causality tests of the real stock return - real activity hypothesis*. *The Journal of Financial Research*. Vol. 17(2), pp. 271-288.

Granger, J. W. C. (1969). *Investigating causal relations by econometric models and crossspectral methods*. *Journal of the Econometric Society*. Vol. 37(3), pp. 424-438.

Gordon, M. J. (1959). *Dividends, earnings, and stock prices*. *The Review of Economic and Statistics*. Vol. 41(2), pp. 99-105.

Hamilton, D. J. (1994). *Time Series Analysis*. Princeton: Princeton University Press.

Harvey, R. C. (1989). *Forecasts of economic growth from the bond and stock markets*. *Financial Analysts Journal*. Vol. 45(5), pp. 38-45

Hassapis, C. & Kalyvitis, S. (2002). *Investigating the links between growth and real stock price changes with empirical evidence from the G-7 economies*. *The Quarterly Review of Economics and Finance*. Vol. 42(3), pp. 543-575.

Hatzius, J., Hooper, P., Mishkin, S. F., Schoenholtz, L. K. & Watson, W. M. (2010). *Financial conditions indexes: A fresh look after the financial crisis*. Nber Working Paper No 16150, National Bureau of Economic Research.

Humpe, A. & Macmillan, P. (2009). *Can macroeconomic variables explain long-term stock market movements? A comparison of the US and Japan*. *Applied Financial Economics*. Vol. 19(2), pp. 111-119.

Jansen, W. J. & Nahuis, J. N. (2003). *The stock market and consumer confidence: European evidence*. *Economic Letters*. Vol. 79(1), pp. 89-98.

Johansen, S. (1991). *Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models*. *Econometrica*. Vol. 59(6), pp. 1551-1580.

Johansen, S. (1988). *Statistical analysis of cointegration vectors*. *Journal of Economic Dynamics and Control*. Vol. 12(2-3), pp. 231-254.

Kanas, A. & Ioannidis, C. (2008). *Causality from real stock returns to real activity: Evidence of regime-dependence*. *International Journal of Finance and Economics*. Vol. 15(2), pp. 180-197.

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

McMillan, D. G. (2019). *"Predicting GDP Growth with Stock and Bond Markets: Do They Contain Different Information?"* Division of Accounting and Finance, University of Stirling.

Narayan, P. K. & Smyth, R. (2007). *Mean reversion versus random walk in G7 stock prices: Evidence from multiple trends break unit root tests*. *Journal of International Financial Markets, Institutions and Money*. Vol. 17(2), pp 152-166.



Nelson, R. C. & Plosser. (1982). Trends and random walks in macroeconomic time series: Some evidence and implications. *Journal of Monetary Economics*. Vol. 10(1982), pp. 139-162.

Schwarz, G. W. (1978). Estimating the dimension of a model. *The Annals of Statistics*. Vol. 6(2), pp. 461-464.

Schwert, G. W. (1990). Stock returns and real activity: A century of evidence. *The Journal of Finance*. Vol. 45(2), pp. 1237-1257.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*. Vol. 19(3), pp. 425-442.

Sims, A. C. (1980). Macroeconomics and reality. *Journal of Econometric Society*. Vol. 48(1), pp. 1-48.

SSB. (2020). Final expenditure and gross domestic product, by macroeconomic indicator, contents and quarter. Oslo: Statistics Norway.

<https://www.ssb.no/en/statbank/table/09190/tableViewLayout1/>. Retrieved: [2020-09-18].

Starr-McCluer, M. (2002). Stock market wealth and consumer spending. *Economic Inquiry*. Vol. 40(1), pp. 69-79.

Stock, H. J. & Watson, W. M. (2003a). Forecasting output and inflation: The role of asset prices. *Journal of Economic Literature*. Vol. 41(3), pp. 788-829.

Stock, H. J. & Watson, W. M. (2003). How did leading indicator forecasts perform during the 2001 recession? *FRB Richmond Economic Quarterly*. Vol. 89(3), pp. 71-90.

Stock, H. J. & Watson, W. M. (2015). *Introduction to Econometrics*. Pearson Education. Third Edition, Global Edition.

Switson, J. A. (2008). A U.S. financial conditions index: Putting credit where credit is due. Working Paper No 08/161, International Monetary Fund.

Yin-Wong, C. & Lilian, K. N. (1998). International evidence on the stock market and aggregate economic activity. *Journal of Empirical Finance*. Vol. 5(3), pp. 281-296.

Österholm, P. (2016). The long-run relationship between stock prices and GDP in Sweden. *Economic Notes*. Vol. 45(2), pp. 283-297

## Appendix

### 1. Base model regression for Greece

Regression for ^DJI Lag 1:

OLS Regression Results

=====

===

Dep. Variable: GR\_gdp\_growth R-squared: 0.032  
Model: OLS Adj. R-squared: 0.011  
Method: Least Squares F-statistic: 1.554  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.217  
Time: 21:16:28 Log-Likelihood: 113.09  
No. Observations: 97 AIC: -220.2  
Df Residuals: 94 BIC: -212.5  
Df Model: 2  
Covariance Type: nonrobust

=====

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0073	0.008	0.910	0.365	-0.009	0.023
^DJI_lag_1	0.0502	0.096	0.523	0.603	-0.140	0.241
GR_gdp_growth_lag_1	-0.1653	0.102	-1.615	0.110	-0.369	0.038

=====

===

Omnibus: 5.543 Durbin-Watson: 2.133  
Prob(Omnibus): 0.063 Jarque-Bera (JB): 3.672  
Skew: -0.314 Prob(JB): 0.159  
Kurtosis: 2.283 Cond. No. 13.6

=====

===

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 2:

OLS Regression Results

=====

===

Dep. Variable: GR\_gdp\_growth R-squared: 0.243  
Model: OLS Adj. R-squared: 0.227  
Method: Least Squares F-statistic: 15.06

Date: Sun, 19 Nov 2023 Prob (F-statistic): 2.12e-06  
 Time: 21:16:28 Log-Likelihood: 124.99  
 No. Observations: 97 AIC: -244.0  
 Df Residuals: 94 BIC: -236.3  
 Df Model: 2  
 Covariance Type: nonrobust

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0111	0.007	1.558	0.122	-0.003	0.025
^DJI_lag_2	0.0271	0.086	0.317	0.752	-0.143	0.197
GR_gdp_growth_lag_2	-0.4898	0.091	-5.396	0.000	-0.670	-0.310

=====

===  
 Omnibus: 7.291 Durbin-Watson: 2.923  
 Prob(Omnibus): 0.026 Jarque-Bera (JB): 4.887  
 Skew: -0.401 Prob(JB): 0.0868  
 Kurtosis: 2.247 Cond. No. 13.7

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 3:

OLS Regression Results

=====

===  
 Dep. Variable: GR\_gdp\_growth R-squared: 0.023  
 Model: OLS Adj. R-squared: 0.002  
 Method: Least Squares F-statistic: 1.116  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.332  
 Time: 21:16:28 Log-Likelihood: 112.65  
 No. Observations: 97 AIC: -219.3  
 Df Residuals: 94 BIC: -211.6  
 Df Model: 2  
 Covariance Type: nonrobust

```

=====
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0088	0.008	1.085	0.281	-0.007	0.025
^DJI_lag_3	-0.0343	0.097	-0.353	0.725	-0.228	0.159
GR_gdp_growth_lag_3	-0.1532	0.104	-1.478	0.143	-0.359	0.053

```

=====

```

```

===
Omnibus:          21.374  Durbin-Watson:          2.197
Prob(Omnibus):    0.000  Jarque-Bera (JB):          5.115
Skew:             -0.100  Prob(JB):              0.0775
Kurtosis:         1.893  Cond. No.              13.6
=====

```

```

===
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Regression for ^DJI Lag 4:  
 OLS Regression Results

```

=====
===
Dep. Variable:    GR_gdp_growth  R-squared:          0.808
Model:           OLS  Adj. R-squared:    0.804
Method:          Least Squares  F-statistic:       197.6
Date:           Sun, 19 Nov 2023  Prob (F-statistic): 2.14e-34
Time:           21:16:28  Log-Likelihood:    191.51
No. Observations: 97  AIC:              -377.0
Df Residuals:    94  BIC:              -369.3
Df Model:        2
Covariance Type: nonrobust
=====

```

```

=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0023	0.004	0.639	0.524	-0.005	0.009
^DJI_lag_4	-0.0912	0.043	-2.109	0.038	-0.177	-0.005
GR_gdp_growth_lag_4	0.8908	0.046	19.548	0.000	0.800	0.981

```

=====
===
Omnibus:          24.101  Durbin-Watson:          2.097
Prob(Omnibus):    0.000  Jarque-Bera (JB):        174.578
Skew:             -0.301  Prob(JB):                1.23e-38
Kurtosis:         9.545  Cond. No.                13.4
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 5:

OLS Regression Results

```

=====
===
Dep. Variable:    GR_gdp_growth  R-squared:          0.051
Model:           OLS  Adj. R-squared:    0.031
Method:          Least Squares  F-statistic:        2.549
Date:            Sun, 19 Nov 2023  Prob (F-statistic):  0.0836
Time:            21:16:28  Log-Likelihood:     114.07
No. Observations:  97  AIC:          -222.1
Df Residuals:     94  BIC:          -214.4
Df Model:         2
Covariance Type:  nonrobust
=====

```

```

=====
=====
              coef  std err      t  P>|t|  [0.025  0.975]
-----
const          0.0059  0.008   0.742  0.460  -0.010  0.022
^DJI_lag_5     0.1194  0.096   1.240  0.218  -0.072  0.311
GR_gdp_growth_lag_5 -0.1812  0.101  -1.791  0.077  -0.382  0.020
=====

```

```

=====
===
Omnibus:          3.525  Durbin-Watson:          2.140
Prob(Omnibus):    0.172  Jarque-Bera (JB):        2.904
Skew:             -0.310  Prob(JB):                0.234
Kurtosis:         2.422  Cond. No.                13.4
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 6:

OLS Regression Results

Dep. Variable: GR\_gdp\_growth R-squared: 0.255  
Model: OLS Adj. R-squared: 0.239  
Method: Least Squares F-statistic: 16.10  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 9.70e-07  
Time: 21:16:28 Log-Likelihood: 125.80  
No. Observations: 97 AIC: -245.6  
Df Residuals: 94 BIC: -237.9  
Df Model: 2  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0118	0.007	1.660	0.100	-0.002	0.026
^DJI_lag_6	-0.0150	0.084	-0.179	0.858	-0.182	0.152
GR_gdp_growth_lag_6	-0.5051	0.089	-5.674	0.000	-0.682	-0.328

Omnibus: 7.438 Durbin-Watson: 2.966  
Prob(Omnibus): 0.024 Jarque-Bera (JB): 4.936  
Skew: -0.401 Prob(JB): 0.0848  
Kurtosis: 2.240 Cond. No. 13.2

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 7:

OLS Regression Results

=====

===

Dep. Variable: GR\_gdp\_growth R-squared: 0.022  
Model: OLS Adj. R-squared: 0.001  
Method: Least Squares F-statistic: 1.045  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.356  
Time: 21:16:28 Log-Likelihood: 112.58  
No. Observations: 97 AIC: -219.2  
Df Residuals: 94 BIC: -211.4  
Df Model: 2  
Covariance Type: nonrobust

=====

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0081	0.008	0.999	0.320	-0.008	0.024
^DJI_lag_7	-0.0047	0.096	-0.049	0.961	-0.196	0.186
GR_gdp_growth_lag_7	-0.1499	0.104	-1.445	0.152	-0.356	0.056

=====

===

Omnibus: 25.656 Durbin-Watson: 2.204  
Prob(Omnibus): 0.000 Jarque-Bera (JB): 5.485  
Skew: -0.096 Prob(JB): 0.0644  
Kurtosis: 1.851 Cond. No. 13.4

=====

===

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 8:

OLS Regression Results

=====

===

Dep. Variable: GR\_gdp\_growth R-squared: 0.770  
Model: OLS Adj. R-squared: 0.765  
Method: Least Squares F-statistic: 157.3

Date: Sun, 19 Nov 2023 Prob (F-statistic): 1.02e-30  
 Time: 21:16:28 Log-Likelihood: 182.77  
 No. Observations: 97 AIC: -359.5  
 Df Residuals: 94 BIC: -351.8  
 Df Model: 2  
 Covariance Type: nonrobust

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0022	0.004	0.554	0.581	-0.006	0.010
^DJI_lag_8	-0.0485	0.047	-1.040	0.301	-0.141	0.044
GR_gdp_growth_lag_8	0.8819	0.050	17.561	0.000	0.782	0.982

=====

===  
 Omnibus: 15.517 Durbin-Watson: 2.075  
 Prob(Omnibus): 0.000 Jarque-Bera (JB): 65.962  
 Skew: 0.010 Prob(JB): 4.75e-15  
 Kurtosis: 7.040 Cond. No. 13.5

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 1:

OLS Regression Results

=====

===  
 Dep. Variable: GR\_gdp\_growth R-squared: 0.031  
 Model: OLS Adj. R-squared: 0.010  
 Method: Least Squares F-statistic: 1.506  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.227  
 Time: 21:16:28 Log-Likelihood: 113.04  
 No. Observations: 97 AIC: -220.1  
 Df Residuals: 94 BIC: -212.4  
 Df Model: 2  
 Covariance Type: nonrobust



```

=====
=====
coef   std err   t   P>|t|   [0.025   0.975]
-----+-----
const          0.0074   0.008   0.935   0.352   -0.008   0.023
^GSPC_lag_1    0.0386   0.091   0.425   0.672   -0.142   0.219
GR_gdp_growth_lag_1 -0.1678   0.102  -1.644   0.104   -0.371   0.035
=====

```

```

===
Omnibus:          6.016  Durbin-Watson:          2.129
Prob(Omnibus):    0.049  Jarque-Bera (JB):          3.864
Skew:             -0.321  Prob(JB):                  0.145
Kurtosis:         2.262  Cond. No.                  13.3
=====

```

```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

```

Regression for ^GSPC Lag 2:
      OLS Regression Results
=====

```

```

===
Dep. Variable:    GR_gdp_growth  R-squared:          0.242
Model:           OLS  Adj. R-squared:    0.226
Method:          Least Squares  F-statistic:        15.02
Date:            Sun, 19 Nov 2023  Prob (F-statistic):  2.18e-06
Time:            21:16:28  Log-Likelihood:     124.96
No. Observations: 97  AIC:              -243.9
Df Residuals:    94  BIC:              -236.2
Df Model:        2
Covariance Type: nonrobust
=====

```

```

=====
coef   std err   t   P>|t|   [0.025   0.975]
-----+-----
const          0.0113   0.007   1.589   0.115   -0.003   0.025
^GSPC_lag_2    0.0163   0.081   0.202   0.840   -0.144   0.176
GR_gdp_growth_lag_2 -0.4918   0.090  -5.438   0.000   -0.671  -0.312
=====

```

=====  
===

Omnibus: 7.185 Durbin-Watson: 2.921  
Prob(Omnibus): 0.028 Jarque-Bera (JB): 4.933  
Skew: -0.409 Prob(JB): 0.0849  
Kurtosis: 2.257 Cond. No. 13.3

=====  
===

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 3:

OLS Regression Results

=====  
===

Dep. Variable: GR\_gdp\_growth R-squared: 0.023  
Model: OLS Adj. R-squared: 0.002  
Method: Least Squares F-statistic: 1.095  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.339  
Time: 21:16:28 Log-Likelihood: 112.63  
No. Observations: 97 AIC: -219.3  
Df Residuals: 94 BIC: -211.5  
Df Model: 2  
Covariance Type: nonrobust

=====  
=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0087	0.008	1.070	0.287	-0.007	0.025
^GSPC_lag_3	-0.0269	0.093	-0.290	0.772	-0.211	0.157
GR_gdp_growth_lag_3	-0.1512	0.103	-1.463	0.147	-0.356	0.054

=====  
===

Omnibus: 21.327 Durbin-Watson: 2.196  
Prob(Omnibus): 0.000 Jarque-Bera (JB): 5.099  
Skew: -0.096 Prob(JB): 0.0781  
Kurtosis: 1.893 Cond. No. 13.3

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 4:

OLS Regression Results

Dep. Variable: GR\_gdp\_growth R-squared: 0.807  
Model: OLS Adj. R-squared: 0.803  
Method: Least Squares F-statistic: 196.1  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 2.85e-34  
Time: 21:16:28 Log-Likelihood: 191.22  
No. Observations: 97 AIC: -376.4  
Df Residuals: 94 BIC: -368.7  
Df Model: 2  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0022	0.004	0.604	0.547	-0.005	0.009
^GSPC_lag_4	-0.0810	0.041	-1.962	0.053	-0.163	0.001
GR_gdp_growth_lag_4	0.8950	0.046	19.625	0.000	0.804	0.986

Omnibus: 23.822 Durbin-Watson: 2.075  
Prob(Omnibus): 0.000 Jarque-Bera (JB): 190.733  
Skew: -0.179 Prob(JB): 3.83e-42  
Kurtosis: 9.860 Cond. No. 13.2

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 5:

OLS Regression Results

```
=====
===
Dep. Variable:    GR_gdp_growth  R-squared:    0.052
Model:           OLS  Adj. R-squared:    0.032
Method:          Least Squares  F-statistic:    2.581
Date:            Sun, 19 Nov 2023  Prob (F-statistic):    0.0810
Time:            21:16:28  Log-Likelihood:    114.10
No. Observations:    97  AIC:    -222.2
Df Residuals:       94  BIC:    -214.5
Df Model:           2
Covariance Type:   nonrobust
=====
```

```
=====
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0059	0.008	0.736	0.463	-0.010	0.022
^GSPC_lag_5	0.1161	0.092	1.266	0.209	-0.066	0.298
GR_gdp_growth_lag_5	-0.1867	0.101	-1.850	0.067	-0.387	0.014

```
=====
```

```
=====
===
Omnibus:         4.077  Durbin-Watson:    2.133
Prob(Omnibus):   0.130  Jarque-Bera (JB):    3.140
Skew:            -0.311  Prob(JB):    0.208
Kurtosis:        2.376  Cond. No.    13.1
=====
```

```
=====
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Regression for ^GSPC Lag 6:

OLS Regression Results

```
=====
===
Dep. Variable:    GR_gdp_growth  R-squared:    0.255
Model:           OLS  Adj. R-squared:    0.240
Method:          Least Squares  F-statistic:    16.13
=====
```

Date: Sun, 19 Nov 2023 Prob (F-statistic): 9.50e-07  
 Time: 21:16:28 Log-Likelihood: 125.82  
 No. Observations: 97 AIC: -245.6  
 Df Residuals: 94 BIC: -237.9  
 Df Model: 2  
 Covariance Type: nonrobust

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0119	0.007	1.684	0.096	-0.002	0.026
^GSPC_lag_6	-0.0218	0.080	-0.272	0.786	-0.181	0.137
GR_gdp_growth_lag_6	-0.5044	0.089	-5.675	0.000	-0.681	-0.328

=====

===  
 Omnibus: 7.462 Durbin-Watson: 2.964  
 Prob(Omnibus): 0.024 Jarque-Bera (JB): 4.973  
 Skew: -0.405 Prob(JB): 0.0832  
 Kurtosis: 2.241 Cond. No. 13.0

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 7:

OLS Regression Results

=====

===  
 Dep. Variable: GR\_gdp\_growth R-squared: 0.022  
 Model: OLS Adj. R-squared: 0.001  
 Method: Least Squares F-statistic: 1.044  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.356  
 Time: 21:16:28 Log-Likelihood: 112.58  
 No. Observations: 97 AIC: -219.2  
 Df Residuals: 94 BIC: -211.4  
 Df Model: 2  
 Covariance Type: nonrobust

```

=====
=====
              coef  std err      t  P>|t|   [0.025   0.975]
-----
const          0.0081   0.008   0.997   0.321  -0.008   0.024
^GSPC_lag_7    -0.0034   0.092  -0.037   0.971  -0.186   0.179
GR_gdp_growth_lag_7 -0.1497   0.104  -1.445   0.152  -0.355   0.056
=====

```

```

===
Omnibus:          25.807  Durbin-Watson:          2.204
Prob(Omnibus):    0.000  Jarque-Bera (JB):          5.498
Skew:             -0.096  Prob(JB):          0.0640
Kurtosis:         1.850  Cond. No.          13.3
=====

```

```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

```

Regression for ^GSPC Lag 8:
      OLS Regression Results
=====

```

```

===
Dep. Variable:    GR_gdp_growth  R-squared:          0.768
Model:           OLS  Adj. R-squared:    0.764
Method:          Least Squares  F-statistic:        156.0
Date:            Sun, 19 Nov 2023  Prob (F-statistic):  1.38e-30
Time:            21:16:28  Log-Likelihood:     182.46
No. Observations: 97  AIC:          -358.9
Df Residuals:    94  BIC:          -351.2
Df Model:        2
Covariance Type: nonrobust
=====

```

```

=====
              coef  std err      t  P>|t|   [0.025   0.975]
-----
const          0.0018   0.004   0.462   0.645  -0.006   0.010
^GSPC_lag_8    -0.0309   0.045  -0.691   0.491  -0.120   0.058
GR_gdp_growth_lag_8 0.8849   0.050  17.611   0.000   0.785   0.985
=====

```

```

=====
===
Omnibus:          16.302  Durbin-Watson:          2.071
Prob(Omnibus):    0.000  Jarque-Bera (JB):          71.893
Skew:             0.114  Prob(JB):                 2.45e-16
Kurtosis:         7.211  Cond. No.                  13.2
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 1:

OLS Regression Results

```

=====
===
Dep. Variable:    GR_gdp_growth  R-squared:          0.029
Model:           OLS  Adj. R-squared:    0.009
Method:         Least Squares  F-statistic:        1.415
Date:           Sun, 19 Nov 2023  Prob (F-statistic):  0.248
Time:           21:16:28  Log-Likelihood:     112.95
No. Observations: 97  AIC:          -219.9
Df Residuals:    94  BIC:          -212.2
Df Model:        2
Covariance Type: nonrobust
=====

```

```

=====
=====
              coef  std err      t  P>|t|  [0.025  0.975]
-----
const          0.0080   0.008   0.993  0.323  -0.008   0.024
^NDX_lag_1     0.0026   0.056   0.046  0.963  -0.109   0.114
GR_gdp_growth_lag_1 -0.1708   0.102  -1.667  0.099  -0.374   0.033
=====

```

```

=====
===
Omnibus:          7.004  Durbin-Watson:          2.123
Prob(Omnibus):    0.030  Jarque-Bera (JB):          4.359
Skew:            -0.349  Prob(JB):                 0.113
Kurtosis:         2.231  Cond. No.                  13.2
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 2:

OLS Regression Results

Dep. Variable: GR\_gdp\_growth R-squared: 0.243  
Model: OLS Adj. R-squared: 0.227  
Method: Least Squares F-statistic: 15.09  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 2.07e-06  
Time: 21:16:28 Log-Likelihood: 125.01  
No. Observations: 97 AIC: -244.0  
Df Residuals: 94 BIC: -236.3  
Df Model: 2  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0109	0.007	1.521	0.132	-0.003	0.025
^NDX_lag_2	0.0188	0.050	0.379	0.706	-0.080	0.117
GR_gdp_growth_lag_2	-0.4897	0.091	-5.409	0.000	-0.670	-0.310

Omnibus: 7.105 Durbin-Watson: 2.920  
Prob(Omnibus): 0.029 Jarque-Bera (JB): 4.896  
Skew: -0.407 Prob(JB): 0.0864  
Kurtosis: 2.260 Cond. No. 13.2

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.



Regression for ^NDX Lag 3:

OLS Regression Results

```

=====
===
Dep. Variable:    GR_gdp_growth  R-squared:        0.022
Model:           OLS  Adj. R-squared:    0.001
Method:         Least Squares  F-statistic:      1.053
Date:           Sun, 19 Nov 2023  Prob (F-statistic):  0.353
Time:           21:16:28  Log-Likelihood:   112.58
No. Observations: 97  AIC:           -219.2
Df Residuals:   94  BIC:           -211.4
Df Model:       2
Covariance Type: nonrobust
=====

```

```

=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0082	0.008	0.999	0.320	-0.008	0.024
^NDX_lag_3	-0.0015	0.057	-0.027	0.978	-0.114	0.111
GR_gdp_growth_lag_3	-0.1501	0.104	-1.449	0.151	-0.356	0.056

```

=====

```

```

=====
===
Omnibus:         22.534  Durbin-Watson:      2.192
Prob(Omnibus):   0.000  Jarque-Bera (JB):    5.217
Skew:            -0.097  Prob(JB):            0.0737
Kurtosis:        1.881  Cond. No.            13.3
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 4:

OLS Regression Results

```

=====
===
Dep. Variable:    GR_gdp_growth  R-squared:        0.803
Model:           OLS  Adj. R-squared:    0.799
Method:         Least Squares  F-statistic:      191.6

```

Date: Sun, 19 Nov 2023 Prob (F-statistic): 6.88e-34  
 Time: 21:16:28 Log-Likelihood: 190.31  
 No. Observations: 97 AIC: -374.6  
 Df Residuals: 94 BIC: -366.9  
 Df Model: 2  
 Covariance Type: nonrobust

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0019	0.004	0.515	0.607	-0.005	0.009
^NDX_lag_4	-0.0361	0.025	-1.425	0.158	-0.087	0.014
GR_gdp_growth_lag_4	0.8956	0.046	19.454	0.000	0.804	0.987

=====

===  
 Omnibus: 25.978 Durbin-Watson: 2.085  
 Prob(Omnibus): 0.000 Jarque-Bera (JB): 266.075  
 Skew: 0.031 Prob(JB): 1.67e-58  
 Kurtosis: 11.114 Cond. No. 13.1

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 5:

OLS Regression Results

=====

===  
 Dep. Variable: GR\_gdp\_growth R-squared: 0.040  
 Model: OLS Adj. R-squared: 0.020  
 Method: Least Squares F-statistic: 1.965  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.146  
 Time: 21:16:28 Log-Likelihood: 113.50  
 No. Observations: 97 AIC: -221.0  
 Df Residuals: 94 BIC: -213.3  
 Df Model: 2  
 Covariance Type: nonrobust

```

=====
=====
coef   std err   t   P>|t|   [0.025   0.975]
-----+-----
const          0.0068   0.008   0.844   0.401   -0.009   0.023
^NDX_lag_5     0.0359   0.056   0.643   0.522   -0.075   0.147
GR_gdp_growth_lag_5 -0.1882   0.102  -1.853   0.067   -0.390   0.013
=====

```

```

===
Omnibus:          5.351 Durbin-Watson:          2.148
Prob(Omnibus):    0.069 Jarque-Bera (JB):          3.671
Skew:             -0.323 Prob(JB):          0.160
Kurtosis:         2.299 Cond. No.          13.1
=====

```

```

===

```

Notes:  
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 6:  
OLS Regression Results

```

=====
===
Dep. Variable:    GR_gdp_growth R-squared:          0.255
Model:           OLS Adj. R-squared:        0.239
Method:          Least Squares F-statistic:       16.09
Date:            Sun, 19 Nov 2023 Prob (F-statistic): 9.78e-07
Time:            21:16:28 Log-Likelihood:       125.79
No. Observations: 97 AIC:                  -245.6
Df Residuals:    94 BIC:                  -237.9
Df Model:         2
Covariance Type: nonrobust
=====

```

```

=====
coef   std err   t   P>|t|   [0.025   0.975]
-----+-----
const          0.0112   0.007   1.566   0.121   -0.003   0.025
^NDX_lag_6     0.0063   0.049   0.128   0.898   -0.091   0.103
GR_gdp_growth_lag_6 -0.5041   0.089  -5.668   0.000   -0.681  -0.327
=====

```

```

=====
===
Omnibus:          7.365  Durbin-Watson:          2.973
Prob(Omnibus):    0.025  Jarque-Bera (JB):          4.797
Skew:             -0.388  Prob(JB):          0.0908
Kurtosis:         2.236  Cond. No.          13.0
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 7:

OLS Regression Results

```

=====
===
Dep. Variable:    GR_gdp_growth  R-squared:          0.022
Model:           OLS  Adj. R-squared:    0.001
Method:          Least Squares  F-statistic:        1.045
Date:            Sun, 19 Nov 2023  Prob (F-statistic):  0.356
Time:            21:16:28  Log-Likelihood:     112.58
No. Observations:  97  AIC:          -219.2
Df Residuals:     94  BIC:          -211.4
Df Model:         2
Covariance Type:  nonrobust
=====

```

```

=====
=====
              coef  std err      t  P>|t|  [0.025  0.975]
-----
const          0.0081  0.008  0.994  0.323  -0.008  0.024
^NDX_lag_7     -0.0027  0.056 -0.048  0.962  -0.114  0.109
GR_gdp_growth_lag_7 -0.1498  0.104 -1.445  0.152  -0.356  0.056
=====

```

```

=====
===
Omnibus:          25.873  Durbin-Watson:          2.203
Prob(Omnibus):    0.000  Jarque-Bera (JB):          5.504
Skew:             -0.096  Prob(JB):          0.0638
Kurtosis:         1.849  Cond. No.          13.3
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 8:

OLS Regression Results

Dep. Variable: GR\_gdp\_growth R-squared: 0.768  
Model: OLS Adj. R-squared: 0.763  
Method: Least Squares F-statistic: 155.6  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 1.51e-30  
Time: 21:16:28 Log-Likelihood: 182.37  
No. Observations: 97 AIC: -358.7  
Df Residuals: 94 BIC: -351.0  
Df Model: 2  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0017	0.004	0.440	0.661	-0.006	0.010
^NDX_lag_8	-0.0148	0.027	-0.543	0.588	-0.069	0.039
GR_gdp_growth_lag_8	0.8851	0.050	17.596	0.000	0.785	0.985

Omnibus: 17.346 Durbin-Watson: 2.074  
Prob(Omnibus): 0.000 Jarque-Bera (JB): 78.896  
Skew: 0.195 Prob(JB): 7.38e-18  
Kurtosis: 7.401 Cond. No. 13.2

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 1:

OLS Regression Results

```
=====
===
Dep. Variable:    GR_gdp_growth  R-squared:    0.038
Model:           OLS  Adj. R-squared:    0.018
Method:         Least Squares  F-statistic:    1.871
Date:           Sun, 19 Nov 2023  Prob (F-statistic):    0.160
Time:           21:16:28  Log-Likelihood:    113.40
No. Observations:    97  AIC:    -220.8
Df Residuals:       94  BIC:    -213.1
Df Model:           2
Covariance Type:   nonrobust
=====
```

```
=====
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0068	0.008	0.853	0.396	-0.009	0.022
^RUT_lag_1	0.0649	0.069	0.942	0.348	-0.072	0.202
GR_gdp_growth_lag_1	-0.1670	0.101	-1.646	0.103	-0.369	0.034

```
=====
```

```
=====
===
Omnibus:         4.120  Durbin-Watson:    2.136
Prob(Omnibus):   0.127  Jarque-Bera (JB):    2.933
Skew:            -0.271  Prob(JB):    0.231
Kurtosis:        2.343  Cond. No.    13.1
=====
```

```
=====
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Regression for ^RUT Lag 2:

OLS Regression Results

```
=====
===
Dep. Variable:    GR_gdp_growth  R-squared:    0.242
Model:           OLS  Adj. R-squared:    0.226
Method:         Least Squares  F-statistic:    15.00
```

Date: Sun, 19 Nov 2023 Prob (F-statistic): 2.23e-06  
 Time: 21:16:28 Log-Likelihood: 124.94  
 No. Observations: 97 AIC: -243.9  
 Df Residuals: 94 BIC: -236.2  
 Df Model: 2  
 Covariance Type: nonrobust

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0116	0.007	1.639	0.105	-0.002	0.026
^RUT_lag_2	-0.0009	0.061	-0.015	0.988	-0.122	0.120
GR_gdp_growth_lag_2	-0.4935	0.090	-5.468	0.000	-0.673	-0.314

=====

===  
 Omnibus: 6.962 Durbin-Watson: 2.920  
 Prob(Omnibus): 0.031 Jarque-Bera (JB): 4.945  
 Skew: -0.417 Prob(JB): 0.0844  
 Kurtosis: 2.274 Cond. No. 13.1

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 3:

OLS Regression Results

=====

===  
 Dep. Variable: GR\_gdp\_growth R-squared: 0.023  
 Model: OLS Adj. R-squared: 0.003  
 Method: Least Squares F-statistic: 1.127  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.328  
 Time: 21:16:28 Log-Likelihood: 112.66  
 No. Observations: 97 AIC: -219.3  
 Df Residuals: 94 BIC: -211.6  
 Df Model: 2  
 Covariance Type: nonrobust

```

=====
coef  std err      t  P>|t|   [0.025   0.975]
-----+-----
const          0.0087   0.008   1.087   0.280   -0.007   0.025
^RUT_lag_3     -0.0267   0.070  -0.381   0.704   -0.166   0.113
GR_gdp_growth_lag_3 -0.1508   0.103  -1.460   0.148   -0.356   0.054
=====

```

```

===
Omnibus:          21.296  Durbin-Watson:          2.197
Prob(Omnibus):    0.000  Jarque-Bera (JB):          5.114
Skew:             -0.103  Prob(JB):                  0.0775
Kurtosis:         1.894  Cond. No.                  13.2
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 4:

OLS Regression Results

```

=====
===
Dep. Variable:    GR_gdp_growth  R-squared:          0.803
Model:           OLS  Adj. R-squared:    0.799
Method:          Least Squares  F-statistic:        191.4
Date:            Sun, 19 Nov 2023  Prob (F-statistic):  7.15e-34
Time:            21:16:28  Log-Likelihood:     190.27
No. Observations: 97  AIC:          -374.5
Df Residuals:    94  BIC:          -366.8
Df Model:        2
Covariance Type: nonrobust
=====

```

```

=====
coef  std err      t  P>|t|   [0.025   0.975]
-----+-----
const          0.0015   0.004   0.419   0.676   -0.006   0.009
^RUT_lag_4     -0.0442   0.032  -1.397   0.166   -0.107   0.019
GR_gdp_growth_lag_4 0.8979   0.046  19.510   0.000   0.807   0.989
=====

```



```

=====
===
Omnibus:          24.495  Durbin-Watson:          2.093
Prob(Omnibus):    0.000  Jarque-Bera (JB):        208.282
Skew:             -0.174  Prob(JB):                 5.92e-46
Kurtosis:         10.170  Cond. No.                  13.1
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 5:

OLS Regression Results

```

=====
===
Dep. Variable:    GR_gdp_growth  R-squared:          0.062
Model:           OLS  Adj. R-squared:    0.042
Method:         Least Squares  F-statistic:        3.110
Date:           Sun, 19 Nov 2023  Prob (F-statistic):  0.0492
Time:           21:16:28  Log-Likelihood:     114.62
No. Observations: 97  AIC:           -223.2
Df Residuals:   94  BIC:           -215.5
Df Model:       2
Covariance Type: nonrobust
=====

```

```

=====
=====
              coef  std err      t  P>|t|  [0.025  0.975]
-----
const          0.0055  0.008   0.702  0.485  -0.010  0.021
^RUT_lag_5     0.1109  0.069   1.619  0.109  -0.025  0.247
GR_gdp_growth_lag_5 -0.1906  0.100  -1.899  0.061  -0.390  0.009
=====

```

```

=====
===
Omnibus:          2.777  Durbin-Watson:          2.137
Prob(Omnibus):    0.249  Jarque-Bera (JB):        2.398
Skew:             -0.277  Prob(JB):                 0.302
Kurtosis:         2.465  Cond. No.                  13.1
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 6:

OLS Regression Results

Dep. Variable: GR\_gdp\_growth R-squared: 0.256  
Model: OLS Adj. R-squared: 0.240  
Method: Least Squares F-statistic: 16.15  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 9.38e-07  
Time: 21:16:28 Log-Likelihood: 125.83  
No. Observations: 97 AIC: -245.7  
Df Residuals: 94 BIC: -237.9  
Df Model: 2  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0120	0.007	1.696	0.093	-0.002	0.026
^RUT_lag_6	-0.0191	0.061	-0.315	0.754	-0.140	0.101
GR_gdp_growth_lag_6	-0.5039	0.089	-5.670	0.000	-0.680	-0.327

Omnibus: 7.524 Durbin-Watson: 2.964  
Prob(Omnibus): 0.023 Jarque-Bera (JB): 5.027  
Skew: -0.408 Prob(JB): 0.0810  
Kurtosis: 2.241 Cond. No. 13.0

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 7:

OLS Regression Results

```
=====
===
Dep. Variable:    GR_gdp_growth  R-squared:    0.024
Model:           OLS  Adj. R-squared:    0.003
Method:         Least Squares  F-statistic:    1.144
Date:           Sun, 19 Nov 2023  Prob (F-statistic):    0.323
Time:           21:16:28  Log-Likelihood:    112.68
No. Observations:    97  AIC:    -219.4
Df Residuals:       94  BIC:    -211.6
Df Model:           2
Covariance Type:    nonrobust
=====
```

```
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0088	0.008	1.092	0.278	-0.007	0.025
^RUT_lag_7	-0.0308	0.069	-0.444	0.658	-0.169	0.107
GR_gdp_growth_lag_7	-0.1495	0.103	-1.445	0.152	-0.355	0.056

```
=====
```

```
=====
===
Omnibus:         23.609  Durbin-Watson:    2.209
Prob(Omnibus):   0.000  Jarque-Bera (JB):    5.318
Skew:            -0.099  Prob(JB):    0.0700
Kurtosis:        1.870  Cond. No.    13.3
=====
```

```
=====
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
=====
```

Regression for ^RUT Lag 8:

OLS Regression Results

```
=====
===
Dep. Variable:    GR_gdp_growth  R-squared:    0.768
Model:           OLS  Adj. R-squared:    0.763
Method:         Least Squares  F-statistic:    155.4
=====
```

Date: Sun, 19 Nov 2023 Prob (F-statistic): 1.58e-30  
 Time: 21:16:28 Log-Likelihood: 182.32  
 No. Observations: 97 AIC: -358.6  
 Df Residuals: 94 BIC: -350.9  
 Df Model: 2  
 Covariance Type: nonrobust

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0015	0.004	0.391	0.696	-0.006	0.009
^RUT_lag_8	-0.0154	0.034	-0.453	0.652	-0.083	0.052
GR_gdp_growth_lag_8	0.8859	0.050	17.617	0.000	0.786	0.986

=====

===  
 Omnibus: 16.481 Durbin-Watson: 2.085  
 Prob(Omnibus): 0.000 Jarque-Bera (JB): 72.609  
 Skew: 0.140 Prob(JB): 1.71e-16  
 Kurtosis: 7.229 Cond. No. 13.2

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

## 2. Base model regression for Germany

Regression for ^DJI Lag 1:  
 OLS Regression Results

=====

Dep. Variable: DEU\_gdp\_growth R-squared: 0.031  
 Model: OLS Adj. R-squared: 0.010  
 Method: Least Squares F-statistic: 1.495  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.229  
 Time: 22:03:29 Log-Likelihood: 208.03  
 No. Observations: 97 AIC: -410.1  
 Df Residuals: 94 BIC: -402.3  
 Df Model: 2  
 Covariance Type: nonrobust

=====

====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0078	0.003	2.528	0.013	0.002	0.014
^DJI_lag_1	0.0314	0.036	0.877	0.383	-0.040	0.103
DEU_gdp_growth_lag_1	-0.1510	0.101	-1.491	0.139	-0.352	0.050

Omnibus:	15.578	Durbin-Watson:	2.114
Prob(Omnibus):	0.000	Jarque-Bera (JB):	20.097
Skew:	-0.799	Prob(JB):	4.33e-05
Kurtosis:	4.555	Cond. No.	34.7

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 2:

OLS Regression Results

Dep. Variable:	DEU_gdp_growth	R-squared:	0.286
Model:	OLS	Adj. R-squared:	0.271
Method:	Least Squares	F-statistic:	18.81
Date:	Sun, 19 Nov 2023	Prob (F-statistic):	1.34e-07
Time:	22:03:29	Log-Likelihood:	222.83
No. Observations:	97	AIC:	-439.7
Df Residuals:	94	BIC:	-431.9
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	0.0108	0.003	4.077	0.000	0.006	0.016
^DJI_lag_2	0.0192	0.031	0.621	0.536	-0.042	0.081
DEU_gdp_growth_lag_2	-0.5307	0.087	-6.108	0.000	-0.703	-0.358

Omnibus:	22.799	Durbin-Watson:	2.822
Prob(Omnibus):	0.000	Jarque-Bera (JB):	37.825
Skew:	-0.989	Prob(JB):	6.11e-09
Kurtosis:	5.333	Cond. No.	34.6

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 3:

OLS Regression Results

```
=====
Dep. Variable:    DEU_gdp_growth  R-squared:        0.019
Model:           OLS  Adj. R-squared:    -0.002
Method:         Least Squares  F-statistic:      0.9003
Date:           Sun, 19 Nov 2023  Prob (F-statistic):  0.410
Time:           22:03:29  Log-Likelihood:   207.43
No. Observations:  97  AIC:           -408.9
Df Residuals:     94  BIC:           -401.1
Df Model:         2
Covariance Type:  nonrobust
=====
```

====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0069	0.003	2.210	0.029	0.001	0.013
^DJI_lag_3	0.0422	0.037	1.155	0.251	-0.030	0.115
DEU_gdp_growth_lag_3	-0.0726	0.102	-0.711	0.479	-0.275	0.130

```
=====
Omnibus:         13.787  Durbin-Watson:      2.162
Prob(Omnibus):   0.001  Jarque-Bera (JB):    17.460
Skew:            -0.720  Prob(JB):            0.000162
Kurtosis:        4.499  Cond. No.            34.7
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 4:

OLS Regression Results

```
=====
Dep. Variable:    DEU_gdp_growth  R-squared:        0.570
Model:           OLS  Adj. R-squared:    0.561
Method:         Least Squares  F-statistic:      62.30
Date:           Sun, 19 Nov 2023  Prob (F-statistic):  5.93e-18
Time:           22:03:29  Log-Likelihood:   247.44
No. Observations:  97  AIC:           -488.9
Df Residuals:     94  BIC:           -481.2
=====
```

Df Model: 2  
 Covariance Type: nonrobust

=====  
 =====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0041	0.002	1.979	0.051	-1.36e-05	0.008
^DJI_lag_4	-0.0871	0.024	-3.592	0.001	-0.135	-0.039
DEU_gdp_growth_lag_4	0.7070	0.066	10.673	0.000	0.575	0.838

=====  
 Omnibus: 25.674 Durbin-Watson: 2.232  
 Prob(Omnibus): 0.000 Jarque-Bera (JB): 174.664  
 Skew: -0.436 Prob(JB): 1.18e-38  
 Kurtosis: 9.516 Cond. No. 34.0  
 =====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 5:

OLS Regression Results

=====  
 Dep. Variable: DEU\_gdp\_growth R-squared: 0.045  
 Model: OLS Adj. R-squared: 0.024  
 Method: Least Squares F-statistic: 2.205  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.116  
 Time: 22:03:29 Log-Likelihood: 208.73  
 No. Observations: 97 AIC: -411.5  
 Df Residuals: 94 BIC: -403.7  
 Df Model: 2  
 Covariance Type: nonrobust  
 =====

=====  
 =====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0068	0.003	2.236	0.028	0.001	0.013
^DJI_lag_5	0.0624	0.036	1.724	0.088	-0.009	0.134
DEU_gdp_growth_lag_5	-0.1240	0.098	-1.259	0.211	-0.319	0.072

=====  
 Omnibus: 9.775 Durbin-Watson: 2.089  
 Prob(Omnibus): 0.008 Jarque-Bera (JB): 10.281  
 Skew: -0.620 Prob(JB): 0.00585  
 =====

Kurtosis: 4.004 Cond. No. 33.9

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 6:

OLS Regression Results

Dep. Variable: DEU\_gdp\_growth R-squared: 0.279  
Model: OLS Adj. R-squared: 0.264  
Method: Least Squares F-statistic: 18.21  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 2.07e-07  
Time: 22:03:29 Log-Likelihood: 222.39  
No. Observations: 97 AIC: -438.8  
Df Residuals: 94 BIC: -431.0  
Df Model: 2  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0114	0.003	4.276	0.000	0.006	0.017
^DJI_lag_6	-0.0348	0.031	-1.124	0.264	-0.096	0.027
DEU_gdp_growth_lag_6	-0.5024	0.086	-5.867	0.000	-0.672	-0.332

Omnibus: 13.437 Durbin-Watson: 2.663  
Prob(Omnibus): 0.001 Jarque-Bera (JB): 16.735  
Skew: -0.712 Prob(JB): 0.000232  
Kurtosis: 4.454 Cond. No. 34.0

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 7:

OLS Regression Results

Dep. Variable: DEU\_gdp\_growth R-squared: 0.022  
Model: OLS Adj. R-squared: 0.001  
Method: Least Squares F-statistic: 1.062  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.350



Time: 22:03:29 Log-Likelihood: 207.59  
 No. Observations: 97 AIC: -409.2  
 Df Residuals: 94 BIC: -401.5  
 Df Model: 2  
 Covariance Type: nonrobust

```
=====
====
              coef  std err      t  P>|t|  [0.025  0.975]
-----+-----
const          0.0073   0.003   2.369   0.020   0.001   0.013
^DJI_lag_7     0.0311   0.036   0.860   0.392  -0.041   0.103
DEU_gdp_growth_lag_7 -0.1212   0.100  -1.214   0.228  -0.319   0.077
=====
```

Omnibus: 13.793 Durbin-Watson: 2.167  
 Prob(Omnibus): 0.001 Jarque-Bera (JB): 17.435  
 Skew: -0.721 Prob(JB): 0.000164  
 Kurtosis: 4.494 Cond. No. 34.0

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^DJI Lag 8:

OLS Regression Results

```
=====
Dep. Variable:  DEU_gdp_growth  R-squared: 0.480
Model:  OLS  Adj. R-squared: 0.469
Method:  Least Squares  F-statistic: 43.32
Date:  Sun, 19 Nov 2023  Prob (F-statistic): 4.64e-14
Time:  22:03:29  Log-Likelihood: 238.19
No. Observations: 97  AIC: -470.4
Df Residuals: 94  BIC: -462.7
Df Model: 2
Covariance Type: nonrobust
=====
```

```
=====
====
              coef  std err      t  P>|t|  [0.025  0.975]
-----+-----
const          0.0044   0.002   1.979   0.051  -1.55e-05   0.009
^DJI_lag_8     -0.0581   0.026  -2.211   0.029  -0.110  -0.006
DEU_gdp_growth_lag_8 0.6372   0.070   9.074   0.000   0.498   0.777
=====
```

Omnibus: 34.210 Durbin-Watson: 2.310  
 Prob(Omnibus): 0.000 Jarque-Bera (JB): 272.387  
 Skew: -0.736 Prob(JB): 7.11e-60  
 Kurtosis: 11.076 Cond. No. 32.8

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 1:

OLS Regression Results

Dep. Variable: DEU\_gdp\_growth R-squared: 0.033  
 Model: OLS Adj. R-squared: 0.013  
 Method: Least Squares F-statistic: 1.613  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.205  
 Time: 22:03:29 Log-Likelihood: 208.14  
 No. Observations: 97 AIC: -410.3  
 Df Residuals: 94 BIC: -402.6  
 Df Model: 2  
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0077	0.003	2.522	0.013	0.002	0.014
^GSPC_lag_1	0.0339	0.034	1.000	0.320	-0.033	0.101
DEU_gdp_growth_lag_1	-0.1520	0.101	-1.503	0.136	-0.353	0.049

Omnibus: 15.721 Durbin-Watson: 2.114  
 Prob(Omnibus): 0.000 Jarque-Bera (JB): 20.464  
 Skew: -0.801 Prob(JB): 3.60e-05  
 Kurtosis: 4.581 Cond. No. 34.7

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 2:

OLS Regression Results

Dep. Variable: DEU\_gdp\_growth R-squared: 0.285

```

Model:          OLS  Adj. R-squared:    0.270
Method:         Least Squares  F-statistic:    18.77
Date:          Sun, 19 Nov 2023  Prob (F-statistic):    1.38e-07
Time:          22:03:29  Log-Likelihood:    222.80
No. Observations:    97  AIC:          -439.6
Df Residuals:      94  BIC:          -431.9
Df Model:          2
Covariance Type:   nonrobust

```

```

=====
====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0108	0.003	4.099	0.000	0.006	0.016
^GSPC_lag_2	0.0167	0.029	0.571	0.569	-0.041	0.075
DEU_gdp_growth_lag_2	-0.5311	0.087	-6.110	0.000	-0.704	-0.359

```

=====
Omnibus:          23.224  Durbin-Watson:          2.816
Prob(Omnibus):    0.000  Jarque-Bera (JB):          38.816
Skew:             -1.004  Prob(JB):          3.73e-09
Kurtosis:         5.360  Cond. No.          34.6
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 3:

OLS Regression Results

```

=====

```

```

Dep. Variable:    DEU_gdp_growth  R-squared:          0.014
Model:           OLS  Adj. R-squared:    -0.007
Method:          Least Squares  F-statistic:        0.6704
Date:           Sun, 19 Nov 2023  Prob (F-statistic):    0.514
Time:           22:03:29  Log-Likelihood:      207.19
No. Observations:    97  AIC:          -408.4
Df Residuals:      94  BIC:          -400.7
Df Model:          2
Covariance Type:   nonrobust

```

```

=====
====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0070	0.003	2.255	0.026	0.001	0.013

```

^GSPC_lag_3      0.0327  0.035  0.936  0.351  -0.037  0.102
DEU_gdp_growth_lag_3 -0.0734  0.102  -0.717  0.475  -0.277  0.130

```

```

=====
Omnibus:          13.783  Durbin-Watson:          2.177
Prob(Omnibus):    0.001  Jarque-Bera (JB):          17.159
Skew:             -0.730  Prob(JB):          0.000188
Kurtosis:         4.454  Cond. No.          34.7
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 4:

OLS Regression Results

```

=====
Dep. Variable:    DEU_gdp_growth  R-squared:          0.547
Model:           OLS  Adj. R-squared:    0.538
Method:         Least Squares  F-statistic:       56.86
Date:           Sun, 19 Nov 2023  Prob (F-statistic): 6.55e-17
Time:           22:03:29  Log-Likelihood:    244.96
No. Observations: 97  AIC:          -483.9
Df Residuals:    94  BIC:          -476.2
Df Model:        2
Covariance Type: nonrobust
=====

```

```

=====
====
      coef  std err      t  P>|t|  [0.025  0.975]
-----
const      0.0037   0.002   1.772  0.080  -0.000   0.008
^GSPC_lag_4 -0.0653   0.024  -2.752  0.007  -0.112  -0.018
DEU_gdp_growth_lag_4  0.7067   0.068  10.397  0.000   0.572   0.842
=====

```

```

=====
Omnibus:          23.973  Durbin-Watson:          2.221
Prob(Omnibus):    0.000  Jarque-Bera (JB):          169.976
Skew:             -0.309  Prob(JB):          1.23e-37
Kurtosis:         9.455  Cond. No.          34.0
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 5:

OLS Regression Results

```

=====
Dep. Variable:    DEU_gdp_growth  R-squared:        0.058
Model:           OLS  Adj. R-squared:    0.038
Method:         Least Squares  F-statistic:      2.899
Date:          Sun, 19 Nov 2023  Prob (F-statistic):  0.0600
Time:          22:03:29  Log-Likelihood:   209.41
No. Observations: 97  AIC:           -412.8
Df Residuals:   94  BIC:           -405.1
Df Model:       2
Covariance Type: nonrobust
=====

```

```

=====
====
              coef  std err      t  P>|t|  [0.025  0.975]
-----+-----
const          0.0066   0.003   2.171  0.032   0.001   0.013
^GSPC_lag_5    0.0716   0.034   2.083  0.040   0.003   0.140
DEU_gdp_growth_lag_5 -0.1274   0.098  -1.303  0.196  -0.322   0.067
=====

```

```

=====
Omnibus:        8.581  Durbin-Watson:      2.082
Prob(Omnibus):  0.014  Jarque-Bera (JB):    8.512
Skew:           -0.591  Prob(JB):            0.0142
Kurtosis:       3.841  Cond. No.            34.0
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 6:

OLS Regression Results

```

=====
Dep. Variable:    DEU_gdp_growth  R-squared:        0.279
Model:           OLS  Adj. R-squared:    0.264
Method:         Least Squares  F-statistic:      18.23
Date:          Sun, 19 Nov 2023  Prob (F-statistic):  2.04e-07
Time:          22:03:29  Log-Likelihood:   222.40
No. Observations: 97  AIC:           -438.8
Df Residuals:   94  BIC:           -431.1
Df Model:       2
Covariance Type: nonrobust
=====

```

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0114	0.003	4.280	0.000	0.006	0.017
^GSPC_lag_6	-0.0337	0.030	-1.137	0.258	-0.092	0.025
DEU_gdp_growth_lag_6	-0.5015	0.086	-5.854	0.000	-0.672	-0.331

Omnibus:	13.888	Durbin-Watson:	2.660
Prob(Omnibus):	0.001	Jarque-Bera (JB):	17.567
Skew:	-0.726	Prob(JB):	0.000153
Kurtosis:	4.497	Cond. No.	34.0

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 7:

OLS Regression Results

Dep. Variable:	DEU_gdp_growth	R-squared:	0.017
Model:	OLS	Adj. R-squared:	-0.004
Method:	Least Squares	F-statistic:	0.8267
Date:	Sun, 19 Nov 2023	Prob (F-statistic):	0.441
Time:	22:03:29	Log-Likelihood:	207.35
No. Observations:	97	AIC:	-408.7
Df Residuals:	94	BIC:	-401.0
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	0.0076	0.003	2.441	0.017	0.001	0.014
^GSPC_lag_7	0.0182	0.035	0.525	0.601	-0.051	0.087
DEU_gdp_growth_lag_7	-0.1199	0.100	-1.198	0.234	-0.319	0.079

Omnibus:	14.501	Durbin-Watson:	2.186
Prob(Omnibus):	0.001	Jarque-Bera (JB):	18.946
Skew:	-0.738	Prob(JB):	7.69e-05
Kurtosis:	4.585	Cond. No.	34.0

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^GSPC Lag 8:

OLS Regression Results

```
=====
Dep. Variable:    DEU_gdp_growth  R-squared:        0.467
Model:           OLS  Adj. R-squared:    0.455
Method:         Least Squares  F-statistic:      41.15
Date:           Sun, 19 Nov 2023  Prob (F-statistic):  1.46e-13
Time:           22:03:29  Log-Likelihood:   237.01
No. Observations: 97  AIC:            -468.0
Df Residuals:    94  BIC:            -460.3
Df Model:        2
Covariance Type: nonrobust
=====
```

```
====
              coef  std err      t  P>|t|  [0.025  0.975]
-----
const          0.0041   0.002   1.809   0.074  -0.000   0.009
^GSPC_lag_8    -0.0404   0.025  -1.586   0.116  -0.091   0.010
DEU_gdp_growth_lag_8  0.6379   0.071   8.972   0.000   0.497   0.779
=====
```

```
=====
Omnibus:        31.377  Durbin-Watson:    2.286
Prob(Omnibus):  0.000  Jarque-Bera (JB):  245.762
Skew:           -0.626  Prob(JB):         4.30e-54
Kurtosis:       10.697  Cond. No.         32.8
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 1:

OLS Regression Results

```
=====
Dep. Variable:    DEU_gdp_growth  R-squared:        0.031
Model:           OLS  Adj. R-squared:    0.010
Method:         Least Squares  F-statistic:      1.484
Date:           Sun, 19 Nov 2023  Prob (F-statistic):  0.232
Time:           22:03:29  Log-Likelihood:   208.01
No. Observations: 97  AIC:            -410.0
Df Residuals:    94  BIC:            -402.3
=====
```

Df Model: 2  
 Covariance Type: nonrobust

=====  
 =====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0076	0.003	2.438	0.017	0.001	0.014
^NDX_lag_1	0.0182	0.021	0.864	0.390	-0.024	0.060
DEU_gdp_growth_lag_1	-0.1409	0.102	-1.382	0.170	-0.343	0.062

=====

Omnibus: 16.072 Durbin-Watson: 2.092  
 Prob(Omnibus): 0.000 Jarque-Bera (JB): 20.020  
 Skew: -0.849 Prob(JB): 4.50e-05  
 Kurtosis: 4.439 Cond. No. 34.9

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 2:

OLS Regression Results

=====

Dep. Variable: DEU\_gdp\_growth R-squared: 0.283  
 Model: OLS Adj. R-squared: 0.268  
 Method: Least Squares F-statistic: 18.55  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 1.62e-07  
 Time: 22:03:29 Log-Likelihood: 222.64  
 No. Observations: 97 AIC: -439.3  
 Df Residuals: 94 BIC: -431.6  
 Df Model: 2  
 Covariance Type: nonrobust

=====

=====  
 =====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0111	0.003	4.149	0.000	0.006	0.016
^NDX_lag_2	-0.0016	0.018	-0.087	0.931	-0.038	0.034
DEU_gdp_growth_lag_2	-0.5310	0.088	-6.065	0.000	-0.705	-0.357

=====

Omnibus: 23.600 Durbin-Watson: 2.763  
 Prob(Omnibus): 0.000 Jarque-Bera (JB): 40.420  
 Skew: -1.007 Prob(JB): 1.67e-09



Kurtosis: 5.438 Cond. No. 34.9

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 3:

OLS Regression Results

Dep. Variable: DEU\_gdp\_growth R-squared: 0.011  
Model: OLS Adj. R-squared: -0.010  
Method: Least Squares F-statistic: 0.5129  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.600  
Time: 22:03:29 Log-Likelihood: 207.03  
No. Observations: 97 AIC: -408.1  
Df Residuals: 94 BIC: -400.3  
Df Model: 2  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0070	0.003	2.198	0.030	0.001	0.013
^NDX_lag_3	0.0161	0.021	0.751	0.455	-0.026	0.059
DEU_gdp_growth_lag_3	-0.0628	0.103	-0.610	0.543	-0.267	0.142

Omnibus: 13.699 Durbin-Watson: 2.187  
Prob(Omnibus): 0.001 Jarque-Bera (JB): 16.824  
Skew: -0.734 Prob(JB): 0.000222  
Kurtosis: 4.417 Cond. No. 34.9

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 4:

OLS Regression Results

Dep. Variable: DEU\_gdp\_growth R-squared: 0.516  
Model: OLS Adj. R-squared: 0.506  
Method: Least Squares F-statistic: 50.17  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 1.49e-15

Time: 22:03:29 Log-Likelihood: 241.73  
 No. Observations: 97 AIC: -477.5  
 Df Residuals: 94 BIC: -469.7  
 Df Model: 2  
 Covariance Type: nonrobust

```
=====
====
              coef  std err      t  P>|t|  [0.025  0.975]
-----+-----
const          0.0030   0.002   1.384   0.170  -0.001   0.007
^NDX_lag_4     -0.0152   0.015  -1.018   0.311  -0.045   0.014
DEU_gdp_growth_lag_4  0.6949   0.070   9.874   0.000   0.555   0.835
=====
```

```
=====
Omnibus:          24.652  Durbin-Watson:          2.309
Prob(Omnibus):    0.000  Jarque-Bera (JB):        205.493
Skew:             -0.214  Prob(JB):                 2.39e-45
Kurtosis:         10.118  Cond. No.                  34.1
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 5:

OLS Regression Results

```
=====
Dep. Variable:    DEU_gdp_growth  R-squared:          0.028
Model:           OLS  Adj. R-squared:    0.007
Method:         Least Squares  F-statistic:        1.338
Date:           Sun, 19 Nov 2023  Prob (F-statistic):  0.267
Time:           22:03:29  Log-Likelihood:     207.87
No. Observations: 97  AIC:          -409.7
Df Residuals:    94  BIC:          -402.0
Df Model:        2
Covariance Type: nonrobust
=====
```

```
=====
====
              coef  std err      t  P>|t|  [0.025  0.975]
-----+-----
const          0.0070   0.003   2.237   0.028   0.001   0.013
^NDX_lag_5     0.0238   0.021   1.124   0.264  -0.018   0.066
DEU_gdp_growth_lag_5 -0.1115   0.099  -1.121   0.265  -0.309   0.086
=====
```

Omnibus: 11.710 Durbin-Watson: 2.151  
 Prob(Omnibus): 0.003 Jarque-Bera (JB): 13.183  
 Skew: -0.684 Prob(JB): 0.00137  
 Kurtosis: 4.178 Cond. No. 34.0

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 6:

OLS Regression Results

Dep. Variable: DEU\_gdp\_growth R-squared: 0.277  
 Model: OLS Adj. R-squared: 0.261  
 Method: Least Squares F-statistic: 17.98  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 2.45e-07  
 Time: 22:03:29 Log-Likelihood: 222.22  
 No. Observations: 97 AIC: -438.4  
 Df Residuals: 94 BIC: -430.7  
 Df Model: 2  
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0114	0.003	4.226	0.000	0.006	0.017
^NDX_lag_6	-0.0175	0.018	-0.965	0.337	-0.053	0.018
DEU_gdp_growth_lag_6	-0.5112	0.086	-5.959	0.000	-0.682	-0.341

Omnibus: 14.236 Durbin-Watson: 2.700  
 Prob(Omnibus): 0.001 Jarque-Bera (JB): 18.688  
 Skew: -0.722 Prob(JB): 8.75e-05  
 Kurtosis: 4.594 Cond. No. 34.0

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 7:

OLS Regression Results

Dep. Variable: DEU\_gdp\_growth R-squared: 0.016

Model: OLS Adj. R-squared: -0.005  
 Method: Least Squares F-statistic: 0.7674  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.467  
 Time: 22:03:29 Log-Likelihood: 207.29  
 No. Observations: 97 AIC: -408.6  
 Df Residuals: 94 BIC: -400.9  
 Df Model: 2  
 Covariance Type: nonrobust

=====  
 =====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0076	0.003	2.414	0.018	0.001	0.014
^NDX_lag_7	0.0084	0.021	0.399	0.691	-0.034	0.050
DEU_gdp_growth_lag_7	-0.1148	0.100	-1.145	0.255	-0.314	0.084

=====  
 Omnibus: 14.697 Durbin-Watson: 2.198  
 Prob(Omnibus): 0.001 Jarque-Bera (JB): 19.428  
 Skew: -0.741 Prob(JB): 6.04e-05  
 Kurtosis: 4.616 Cond. No. 34.1  
 =====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^NDX Lag 8:

OLS Regression Results

=====  
 =====

Dep. Variable: DEU\_gdp\_growth R-squared: 0.455  
 Model: OLS Adj. R-squared: 0.443  
 Method: Least Squares F-statistic: 39.20  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 4.17e-13  
 Time: 22:03:29 Log-Likelihood: 235.92  
 No. Observations: 97 AIC: -465.8  
 Df Residuals: 94 BIC: -458.1  
 Df Model: 2  
 Covariance Type: nonrobust

=====  
 =====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0037	0.002	1.576	0.118	-0.001	0.008

```

^NDX_lag_8      -0.0096   0.016  -0.612   0.542  -0.041   0.022
DEU_gdp_growth_lag_8  0.6316   0.072   8.763   0.000   0.489   0.775

```

```

=====
Omnibus:          28.806 Durbin-Watson:          2.285
Prob(Omnibus):    0.000 Jarque-Bera (JB):        220.678
Skew:             -0.522 Prob(JB):            1.20e-48
Kurtosis:         10.315 Cond. No.             32.9
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 1:

OLS Regression Results

```

=====
Dep. Variable:    DEU_gdp_growth R-squared:        0.041
Model:           OLS Adj. R-squared:      0.020
Method:          Least Squares F-statistic:      1.988
Date:            Sun, 19 Nov 2023 Prob (F-statistic): 0.143
Time:           22:03:29 Log-Likelihood:      208.52
No. Observations: 97 AIC:                 -411.0
Df Residuals:    94 BIC:                 -403.3
Df Model:        2
Covariance Type: nonrobust
=====

```

```

=====
coef  std err   t   P>|t|   [0.025   0.975]
-----+-----
const      0.0076   0.003   2.489   0.015   0.002   0.014
^RUT_lag_1  0.0340   0.026   1.316   0.191  -0.017   0.085
DEU_gdp_growth_lag_1 -0.1526   0.101  -1.514   0.133  -0.353   0.048
=====

```

```

=====
Omnibus:          16.000 Durbin-Watson:          2.122
Prob(Omnibus):    0.000 Jarque-Bera (JB):        22.645
Skew:             -0.766 Prob(JB):            1.21e-05
Kurtosis:         4.805 Cond. No.             34.7
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 2:

OLS Regression Results

```

=====
Dep. Variable:    DEU_gdp_growth  R-squared:        0.284
Model:           OLS  Adj. R-squared:    0.269
Method:         Least Squares  F-statistic:      18.63
Date:           Sun, 19 Nov 2023  Prob (F-statistic):  1.53e-07
Time:           22:03:29  Log-Likelihood:   222.70
No. Observations: 97  AIC:            -439.4
Df Residuals:   94  BIC:            -431.7
Df Model:        2
Covariance Type: nonrobust
=====

```

```

=====
====
              coef  std err      t  P>|t|  [0.025  0.975]
-----+-----
const          0.0109   0.003   4.151  0.000   0.006   0.016
^RUT_lag_2      0.0078   0.022   0.351  0.726  -0.036   0.052
DEU_gdp_growth_lag_2 -0.5305   0.087  -6.097  0.000  -0.703  -0.358
=====

```

```

=====
Omnibus:         23.342  Durbin-Watson:      2.795
Prob(Omnibus):   0.000  Jarque-Bera (JB):    39.298
Skew:            -1.005  Prob(JB):            2.93e-09
Kurtosis:        5.383  Cond. No.            34.6
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 3:

OLS Regression Results

```

=====
Dep. Variable:    DEU_gdp_growth  R-squared:        0.008
Model:           OLS  Adj. R-squared:    -0.014
Method:         Least Squares  F-statistic:      0.3599
Date:           Sun, 19 Nov 2023  Prob (F-statistic):  0.699
Time:           22:03:29  Log-Likelihood:   206.88
No. Observations: 97  AIC:            -407.8
Df Residuals:   94  BIC:            -400.0
Df Model:        2
Covariance Type: nonrobust
=====

```

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0073	0.003	2.362	0.020	0.001	0.014
^RUT_lag_3	0.0135	0.027	0.509	0.612	-0.039	0.066
DEU_gdp_growth_lag_3	-0.0710	0.103	-0.691	0.491	-0.275	0.133

---

Omnibus:	13.951	Durbin-Watson:	2.189
Prob(Omnibus):	0.001	Jarque-Bera (JB):	17.319
Skew:	-0.740	Prob(JB):	0.000173
Kurtosis:	4.446	Cond. No.	34.7

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 4:

OLS Regression Results

---

Dep. Variable:	DEU_gdp_growth	R-squared:	0.540
Model:	OLS	Adj. R-squared:	0.530
Method:	Least Squares	F-statistic:	55.14
Date:	Sun, 19 Nov 2023	Prob (F-statistic):	1.44e-16
Time:	22:03:29	Log-Likelihood:	244.15
No. Observations:	97	AIC:	-482.3
Df Residuals:	94	BIC:	-474.6
Df Model:	2		
Covariance Type:	nonrobust		

---

	coef	std err	t	P> t	[0.025	0.975]
const	0.0034	0.002	1.619	0.109	-0.001	0.008
^RUT_lag_4	-0.0440	0.018	-2.427	0.017	-0.080	-0.008
DEU_gdp_growth_lag_4	0.7057	0.069	10.296	0.000	0.570	0.842

---

Omnibus:	24.006	Durbin-Watson:	2.241
Prob(Omnibus):	0.000	Jarque-Bera (JB):	161.888
Skew:	-0.348	Prob(JB):	7.02e-36
Kurtosis:	9.290	Cond. No.	34.0

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 5:

OLS Regression Results

```
=====
Dep. Variable:    DEU_gdp_growth  R-squared:        0.065
Model:           OLS  Adj. R-squared:    0.045
Method:         Least Squares  F-statistic:      3.261
Date:           Sun, 19 Nov 2023  Prob (F-statistic): 0.0427
Time:           22:03:29  Log-Likelihood:   209.76
No. Observations: 97  AIC:            -413.5
Df Residuals:    94  BIC:            -405.8
Df Model:        2
Covariance Type: nonrobust
=====
```

====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0066	0.003	2.199	0.030	0.001	0.013
^RUT_lag_5	0.0578	0.026	2.248	0.027	0.007	0.109
DEU_gdp_growth_lag_5	-0.1277	0.097	-1.310	0.193	-0.321	0.066

```
=====
Omnibus:         8.275  Durbin-Watson:    2.087
Prob(Omnibus):   0.016  Jarque-Bera (JB):  8.243
Skew:            -0.565  Prob(JB):          0.0162
Kurtosis:        3.873  Cond. No.          34.0
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 6:

OLS Regression Results

```
=====
Dep. Variable:    DEU_gdp_growth  R-squared:        0.278
Model:           OLS  Adj. R-squared:    0.262
Method:         Least Squares  F-statistic:      18.06
Date:           Sun, 19 Nov 2023  Prob (F-statistic): 2.30e-07
Time:           22:03:29  Log-Likelihood:   222.28
No. Observations: 97  AIC:            -438.6
Df Residuals:    94  BIC:            -430.8
=====
```



Df Model: 2  
 Covariance Type: nonrobust

=====  
 =====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0113	0.003	4.247	0.000	0.006	0.017
^RUT_lag_6	-0.0231	0.023	-1.026	0.308	-0.068	0.022
DEU_gdp_growth_lag_6	-0.5022	0.086	-5.856	0.000	-0.672	-0.332

=====

Omnibus: 14.912 Durbin-Watson: 2.680  
 Prob(Omnibus): 0.001 Jarque-Bera (JB): 19.603  
 Skew: -0.754 Prob(JB): 5.54e-05  
 Kurtosis: 4.604 Cond. No. 34.0

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 7:

OLS Regression Results

=====

Dep. Variable: DEU\_gdp\_growth R-squared: 0.015  
 Model: OLS Adj. R-squared: -0.006  
 Method: Least Squares F-statistic: 0.6929  
 Date: Sun, 19 Nov 2023 Prob (F-statistic): 0.503  
 Time: 22:03:29 Log-Likelihood: 207.22  
 No. Observations: 97 AIC: -408.4  
 Df Residuals: 94 BIC: -400.7  
 Df Model: 2  
 Covariance Type: nonrobust

=====  
 =====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0079	0.003	2.545	0.013	0.002	0.014
^RUT_lag_7	0.0029	0.026	0.111	0.912	-0.049	0.055
DEU_gdp_growth_lag_7	-0.1178	0.100	-1.176	0.243	-0.317	0.081

=====

Omnibus: 14.883 Durbin-Watson: 2.203  
 Prob(Omnibus): 0.001 Jarque-Bera (JB): 19.785  
 Skew: -0.747 Prob(JB): 5.06e-05

Kurtosis: 4.633 Cond. No. 34.0

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression for ^RUT Lag 8:

OLS Regression Results

Dep. Variable: DEU\_gdp\_growth R-squared: 0.459  
Model: OLS Adj. R-squared: 0.447  
Method: Least Squares F-statistic: 39.81  
Date: Sun, 19 Nov 2023 Prob (F-statistic): 2.99e-13  
Time: 22:03:29 Log-Likelihood: 236.26  
No. Observations: 97 AIC: -466.5  
Df Residuals: 94 BIC: -458.8  
Df Model: 2  
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0037	0.002	1.645	0.103	-0.001	0.008
^RUT_lag_8	-0.0199	0.019	-1.022	0.309	-0.059	0.019
DEU_gdp_growth_lag_8	0.6374	0.072	8.894	0.000	0.495	0.780

Omnibus: 29.362 Durbin-Watson: 2.286  
Prob(Omnibus): 0.000 Jarque-Bera (JB): 225.723  
Skew: -0.546 Prob(JB): 9.66e-50  
Kurtosis: 10.393 Cond. No. 32.8

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

# 1. Assumption testing results

Table 15 Assumption testing results - Greece ('own work')

Index	Lag	R-squared	Intercept	Coef_Index	Coef_GR_grd	P-value_Inte	P-value_Inde	P-value_GR	White_Homo	Breusch-Goc	ADF_Station	Max_VIF	Shapiro_Norr
^DJI	1	0.03	0.01	0.05	-0.17	0.37	0.60	0.11	0.01	0.00	0.44	1.05	0.00
^DJI	2	0.24	0.01	0.03	-0.49	0.12	0.75	0.00	0.04	0.00	0.48	1.06	0.01
^DJI	3	0.02	0.01	-0.03	-0.15	0.28	0.73	0.14	0.00	0.00	0.32	1.07	0.01
^DJI	4	0.81	0.00	-0.09	0.89	0.52	0.04	0.00	0.01	0.03	0.00	1.07	0.00
^DJI	5	0.05	0.01	0.12	-0.18	0.46	0.22	0.08	0.01	0.00	0.46	1.07	0.00
^DJI	6	0.26	0.01	-0.02	-0.51	0.10	0.86	0.00	0.01	0.00	0.39	1.08	0.01
^DJI	7	0.02	0.01	0.00	-0.15	0.32	0.96	0.15	0.00	0.00	0.50	1.08	0.00
^DJI	8	0.77	0.00	-0.05	0.88	0.58	0.30	0.00	0.08	0.02	0.31	1.07	0.00
^GSPC	1	0.03	0.01	0.04	-0.17	0.35	0.67	0.10	0.02	0.00	0.43	1.05	0.00
^GSPC	2	0.24	0.01	0.02	-0.49	0.12	0.84	0.00	0.05	0.00	0.48	1.06	0.01
^GSPC	3	0.02	0.01	-0.03	-0.15	0.29	0.77	0.15	0.00	0.00	0.34	1.07	0.01
^GSPC	4	0.81	0.00	-0.08	0.89	0.55	0.05	0.00	0.11	0.03	0.00	1.07	0.00
^GSPC	5	0.05	0.01	0.12	-0.19	0.46	0.21	0.07	0.03	0.00	0.47	1.07	0.00
^GSPC	6	0.26	0.01	-0.02	-0.50	0.10	0.79	0.00	0.01	0.00	0.39	1.08	0.01
^GSPC	7	0.02	0.01	0.00	-0.15	0.32	0.97	0.15	0.00	0.00	0.50	1.08	0.00
^GSPC	8	0.77	0.00	-0.03	0.88	0.64	0.49	0.00	0.43	0.01	0.29	1.07	0.00
^NDX	1	0.03	0.01	0.00	-0.17	0.32	0.96	0.10	0.18	0.00	0.41	1.07	0.00
^NDX	2	0.24	0.01	0.02	-0.49	0.13	0.71	0.00	0.02	0.00	0.50	1.08	0.01
^NDX	3	0.02	0.01	0.00	-0.15	0.32	0.98	0.15	0.00	0.00	0.36	1.09	0.01
^NDX	4	0.80	0.00	-0.04	0.90	0.61	0.16	0.00	0.88	0.01	0.00	1.09	0.00
^NDX	5	0.04	0.01	0.04	-0.19	0.40	0.52	0.07	0.06	0.00	0.35	1.09	0.00
^NDX	6	0.26	0.01	0.01	-0.50	0.12	0.90	0.00	0.01	0.00	0.40	1.10	0.01
^NDX	7	0.02	0.01	0.00	-0.15	0.32	0.96	0.15	0.00	0.00	0.50	1.09	0.00
^NDX	8	0.77	0.00	-0.01	0.89	0.66	0.59	0.00	0.93	0.02	0.27	1.09	0.00
^RUT	1	0.04	0.01	0.06	-0.17	0.40	0.35	0.10	0.00	0.00	0.45	1.04	0.01
^RUT	2	0.24	0.01	0.00	-0.49	0.10	0.99	0.00	0.05	0.00	0.46	1.05	0.01
^RUT	3	0.02	0.01	-0.03	-0.15	0.28	0.70	0.15	0.00	0.00	0.32	1.06	0.01
^RUT	4	0.80	0.00	-0.04	0.90	0.68	0.17	0.00	0.03	0.02	0.00	1.05	0.00
^RUT	5	0.06	0.01	0.11	-0.19	0.48	0.11	0.06	0.03	0.00	0.45	1.06	0.01
^RUT	6	0.26	0.01	-0.02	-0.50	0.09	0.75	0.00	0.01	0.00	0.39	1.07	0.01
^RUT	7	0.02	0.01	-0.03	-0.15	0.28	0.66	0.15	0.00	0.00	0.56	1.06	0.00
^RUT	8	0.77	0.00	-0.02	0.89	0.70	0.65	0.00	0.21	0.01	0.27	1.06	0.00

Table 16 Assumption testing results - Germany('own work')

Index	Lag	R-square	Intercept	Coef_Inde	Coef_DEI	P-value_Ir	P-value_In	P-value_DE	White_Hom	Breusch-Go	ADF_Static	Max_VIF	Shapiro_f
^DJI	1	3%	0.01	0.03	-0.15	0.01	0.38	0.14	0.03	0.00	0.03	1.10	0.00
^DJI	2	29%	0.01	0.02	-0.53	0.00	0.54	0.00	0.87	0.00	0.03	1.11	0.00
^DJI	3	2%	0.01	0.04	-0.07	0.03	0.25	0.48	0.50	0.00	0.01	1.12	0.00
^DJI	4	57%	0.00	-0.09	0.71	0.05	0.00	0.00	0.16	0.03	0.00	1.11	0.00
^DJI	5	4%	0.01	0.06	-0.12	0.03	0.09	0.21	0.12	0.00	0.00	1.11	0.00
^DJI	6	28%	0.01	-0.03	-0.50	0.00	0.26	0.00	0.12	0.00	0.02	1.12	0.00
^DJI	7	2%	0.01	0.03	-0.12	0.02	0.39	0.23	0.39	0.00	0.01	1.11	0.00
^DJI	8	48%	0.00	-0.06	0.64	0.05	0.03	0.00	0.77	0.00	0.00	1.10	0.00
^GSPC	1	3%	0.01	0.03	-0.15	0.01	0.32	0.14	0.12	0.00	0.01	1.10	0.00
^GSPC	2	29%	0.01	0.02	-0.53	0.00	0.57	0.00	0.83	0.00	0.03	1.10	0.00
^GSPC	3	1%	0.01	0.03	-0.07	0.03	0.35	0.48	0.50	0.00	0.01	1.11	0.00
^GSPC	4	55%	0.00	-0.07	0.71	0.08	0.01	0.00	0.09	0.03	0.00	1.11	0.00
^GSPC	5	6%	0.01	0.07	-0.13	0.03	0.04	0.20	0.10	0.00	0.00	1.11	0.00
^GSPC	6	28%	0.01	-0.03	-0.50	0.00	0.26	0.00	0.22	0.00	0.01	1.12	0.00
^GSPC	7	2%	0.01	0.02	-0.12	0.02	0.60	0.23	0.48	0.00	0.02	1.11	0.00
^GSPC	8	47%	0.00	-0.04	0.64	0.07	0.12	0.00	0.65	0.00	0.00	1.10	0.00
^NDX	1	3%	0.01	0.02	-0.14	0.02	0.39	0.17	0.27	0.00	0.02	1.13	0.00
^NDX	2	28%	0.01	0.00	-0.53	0.00	0.93	0.00	0.95	0.00	0.04	1.14	0.00
^NDX	3	1%	0.01	0.02	-0.06	0.03	0.45	0.54	0.64	0.00	0.01	1.15	0.00
^NDX	4	52%	0.00	-0.02	0.69	0.17	0.31	0.00	0.06	0.01	0.00	1.14	0.00
^NDX	5	3%	0.01	0.02	-0.11	0.03	0.26	0.27	0.38	0.00	0.00	1.14	0.00
^NDX	6	28%	0.01	-0.02	-0.51	0.00	0.34	0.00	0.45	0.00	0.01	1.15	0.00
^NDX	7	2%	0.01	0.01	-0.11	0.02	0.69	0.25	0.60	0.00	0.02	1.14	0.00
^NDX	8	45%	0.00	-0.01	0.63	0.12	0.54	0.00	0.63	0.00	0.01	1.13	0.00
^RUT	1	4%	0.01	0.03	-0.15	0.01	0.19	0.13	0.06	0.00	0.04	1.10	0.00
^RUT	2	28%	0.01	0.01	-0.53	0.00	0.73	0.00	0.93	0.00	0.04	1.10	0.00
^RUT	3	1%	0.01	0.01	-0.07	0.02	0.61	0.49	0.52	0.00	0.02	1.10	0.00
^RUT	4	54%	0.00	-0.04	0.71	0.11	0.02	0.00	0.08	0.03	0.00	1.09	0.00
^RUT	5	6%	0.01	0.06	-0.13	0.03	0.03	0.19	0.06	0.00	0.00	1.10	0.00
^RUT	6	28%	0.01	-0.02	-0.50	0.00	0.31	0.00	0.28	0.00	0.01	1.11	0.00
^RUT	7	1%	0.01	0.00	-0.12	0.01	0.91	0.24	0.52	0.00	0.03	1.10	0.00
^RUT	8	46%	0.00	-0.02	0.64	0.10	0.31	0.00	0.60	0.00	0.01	1.08	0.00