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**“CONTRIBUTION OF OPTIMAL OPERATION OF LOGISTICS ON THE
ECONOMIC GROWTH OF EUROPEAN COUNTRIES DURING THE
CORONAVIRUS COVID-19 CRISIS”**

“ELENI G. TARATSA”

Patras, Greece, JANUARY, 2023

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*“Στις γυναίκες που αντιστάθηκαν και έγιναν ανάμνηση...
Στις γυναίκες που δεν αντιστάθηκαν και ζουν με την ανάμνηση...
Στις γυναίκες...”*

Abstract

Since the end of 2019 almost all humanity faces an unexpected crisis due to the coronavirus COVID-19. Subsequent lock-downs, abstention from labor, lack of PPE kits for personnel were the initial signs of the supply chain disruption in an international level. Logistic services could not facilitate product mobility and accurate package delivery. Inevitably, the inefficient flow of goods & the inability to solve the transportation obstacles magnified customers' unreliability to the quality and infrastructures of logistic services. This hindering of the efficient movement of goods directed most of the consumers either to consumption reductions or to product replacements. Additionally, possible restrictions that specific authorities placed in the path of trade due to lack of raw materials resulted in delivery delays and higher costs. As a consequence, economic growth was affected significantly by sudden logistics interruptions and abnormal operation of the supply chain all around the globe.

According to the literature and recent researches there is a lack of a formal and detailed research based on the influence of the optimal operation of the supply chain management and its impact on economic growth especially in Europe.

The aim of our research is to investigate, under a renewed perspective, the overall performance of the supply chain through specific indicators into the European countries and its contribution on European economic growth so far. Pandemic crisis of COVID-19 will be used as an example of forecasting economic growth due to future logistics disorders. New tasks that may arise related to the overall performance of the supply chain and the economic growth as results and proposals of this research, could introduce a renovating perspective on logistics model, well coordinated and probably robust enough to absorb any further unexpected fluctuation of the supply chain performance at least in European value chains in order to yield a positive growth in economy.

Keywords

Economic growth, Supply chain/Logistics indicators, GDP growth rate, COVID-19 crisis

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INTRODUCTION

Efficiency in supply chains can be considered as the cornerstone both to companies' and nations' success and profitability. As part of the competitive domain of commerce, supply chains have to be both efficient and responsive including innovative supply chain technologies, large warehouses that can operate as an accumulation of high demand products that can be dispatched in minimum delivery times. Reliable supply chains commonly depend on main logistics components that under well organized conditions enhance efficient transport services, flow of information, quality of trade infrastructure that boost a country's productivity and economic growth (Rajeev K., 2021).

Economic growth is considered the most important driver for the well-being of a country even though under the political view. Logistics performance is important for competitiveness and ultimately economic growth Puertas Medina et al. (2013). Marti (2017) indicate that for all the 26 EU countries, logistics was more important for exporting nations than importing nations in both 2005 and 2010 leading to increased export competitiveness. Prior studies by Arvis et al. (2018) indicate that efficient logistics performance connect firms to markets through reliable supply chain networks. More or less, all countries' growth trajectories are in front of unprecedented challenges during and after the recent coronavirus crisis. More specifically, individual countries have experienced market imperfections posed by post-coronavirus lockdowns, supply chain disruptions that occurred lack of medical and safety equipment converting residents' and firms' daily routine into a difficult situation. COVID-19 has strained logistics services worldwide (Chaudhary, M., Sodani, P.R. and Das, S. (2020).

The international logistics system has been surely disrupted in the past as well, especially during the 2008–2009 economic crash (Baldwin & Weder di Mauro, 2020). Although, this past experience could have been instructive for us today in order to face coronavirus crisis, there are a few qualitative differences. At that time, it was more a factor of demand than supply, whereas the current crisis has impacted both supply and demand significantly. Baldwin and Weber di Mauro (Baldwin & Weder di Mauro, 2020) mention global value chains (GVCs) that require parts of products to be manufactured in different countries before being assembled in another nation. COVID-19 initially impacted China, which is at the center of many GVCs, disrupting the supply chain (see Luo & Tsang, 2020). On the demand side, as the lockdown continues and consumers' physical spending is decreasing,

global demand continues to fall. However, this may have long term impacts as the new COVID-19 variants might impact lockdown policies, as well as the supply and demand. (Rajeev K., et al 2021). Supply chain performance is crucial to the smooth functioning of economies, and glitches can create bottlenecks with adverse implications for economic productivity and growth (see Salvatore, 2020). However, there are many dimensions to supply chains, and their coordinated (often sequential) functioning is crucial to the smooth on-time delivery of products to consumers and inputs to businesses (Elekdag, Muir, & Wu, 2015).

While supply chain challenges have been identified even in pre-COVID-19 era (see Alicke, Barriball, Lund, & Swan, 2020), the COVID-19 crisis has added urgency and uncertainty. A simulation exercise that discusses some supply chain disruption scenarios and their growth implications could be proved a useful method in nations planning for the challenges posed by the COVID-19 and other unexpected crises. So, coronavirus crisis emerged the task of underdeveloped formal research on the contribution of supply chain logistics in economic growth. Taking into consideration related data, we can examine the impact of various aspects of supply chain logistics, which may vary from country to country as well as the performance of logistics input and output dimensions, on economic growth.

Our analysis uses data from 2010 to 2018 for the European countries to investigate the relative impact of various aspects of supply chain logistics on economic growth. More specifically, our research focuses on quantitative approach by collecting data from the Logistics Performance Index of The World Bank of the 27 European nations using the software Gretl. Using pooled panel data (data collected over time on one particular economic unit) we aim to conduct multiple regression estimations, further analysis & correlations. The depend value will be the real per capital lnGDP growth rate across the 27 European countries correlated with various sub-components e.g. customs procedure, trade and transport infrastructure, arranging of international shipments, competence and quality of logistics sector services, tracking and traceability of consignments, timeliness of delivery and the overall performance of supply chain. Further parameters can be included such as landlocked countries, borderlength of countries etc in order to obtain more detailed outcomes.

Applying an empirical framework to a standard regression model, results will inform us about the possible improvements that supply chain logistics performance yield on economic dividends, especially dealing with the input and output of logistics performance.

While the size and time span of the sample are quite elaborate, formal cross-country information on the very recent logistics challenges from COVID-19 will take some time to emerge. This is one limitation faced by the present work.

This thesis is structured as follows:

- ✚ Chapter 1 reviews the econometrics modelling
- ✚ Chapter 2 describes the structure of the Logistics Performance Index (LPI) of World Bank
- ✚ Chapter 3 explains the model structure applied in our research as well as the sample and the variables used
- ✚ Chapter 4 presents the results of OLS estimation
- ✚ Chapter 5 examines the possible forecasting scenario based on our model
- ✚ Chapter 6 summarizes the main conclusions of the research

1. Econometric Modeling

1.1 Econometrics

Econometrics include a wide set of methods that interpret observations and analysis of economic reality as well as the estimation of economic trends in the future periods. Alternative approaches and multiple uses of econometrics techniques aim to investigate collected data, quantify economic actions of households, firms, governments and forecast future economic actions (Studenmund, 2017).

In economics we usually interpret the interactions between economic variables by formulating a mathematical function such as the following between income and consumption:

$$CONSUMPTION = f(INCOME)$$

Which demonstrates the consumption level as a function $f(*)$ of income (Hill, R.C. et al, 2011).

In more complicated systems we enrich the above mentioned linear function including a random error term e that express the possibility of false estimation or omitted factors. So, a typical equation of an econometric model can be:

$$CONSUMPTION = f(INCOME) + e$$

Apart from the linear equation type, we may need to interrelate a complex set of variables that do not describe the average behavior of a firm or a nation. Thus, a more extended econometric model is essential. Multilinear regression expressions usually include various components depending on the demand of each estimation. A typical equation of this is listed below:

$$Q^d = \beta_1 + \beta_2 * P_1 + \beta_2 * P_2 + \beta_3 * P_3 + \beta_4 * P_4 + e$$

The coefficients $\beta_1, \beta_2, \dots, \beta_4$ are parameters of the model under investigation via econometric techniques such as multiple regression. All these coefficients engage into a hypothesis that interrelate the independent variables in order to estimate the dependent tested variable. The random component e obscures our comprehension of the variable interaction and reflects every ambiguity that may arise (Hill, R.C. et al, 2011).

Generally, the scope of this kind of econometric formulas is to identify a functional equation including a systematic portion and an unobservable random component compatible with economic theory and the experimental data (Hill, R.C. et al, 2011).

1.2 Economic Data Types

An additional section of econometric models is economic data types that are differentiated according to the demand of estimation, the available data sources, the forecasting pursuits and testing hypotheses. Observing of an economic process we can acquire experimental data related to unknown parameters that facilitate scientists to specify key variables obtaining corresponding outcomes.

Data can arise by various levels of aggregation such as:

- Micro data derived by specific economic units e.g. competence and quality of logistics
- Macro data obtained from a pooling or aggregating index of consumers, households, companies, governments e.g. unemployment per year (Hill, R.C. et al, 2011)

Additionally, data can represent a flow or a stock:

- flow: a measured outcome during a time period such as the demand of a product during the last quarter of 2022.
- Stock: a measured outcome at a specific point in time, such as the quantity of returned shipments in a warehouse on December of 2022 (Hill, R.C. et al, 2011)

Moreover, data can be recorded either as quantitative or qualitative values:

- quantitative outcomes can be expressed in numerical values e.g. per capita income
- qualitative outcomes that interpret an “either-or” situation (Hill, R.C. et al, 2011)

Taking into consideration the dimension of time in our decision-making observations we can specify new data categories.

a) Time-series data

Time-series data involve a single entity over discrete points in time. Macroeconomic & supply-and demand data are better studied using time-series that can be recorded either in terms of lower frequency such as monthly, quarterly or at higher terms such as annually, two years period.

A time-series regression equation includes one entity and T different time intervals as listed below:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + e_t$$

where t runs from 1 to T. In other words, time-series data include the same economic quantity at a regular time periods (Studenmund, 2017).

b) Cross-section data

Cross-section of data can be collected across multiple sample subjects in a particular point in time e.g. GDP in Luxemburg during 2022.

A cross-sectional regression notation includes one time period and N different entities as listed below:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + e_i$$

where i runs from 1 to T (Studenmund, 2017).

c) Pooled data

Pooled data is actually a combination of time series of cross-sections referring to recording a characteristic that attributes of many subjects not necessarily with the same unit.

d) Panel or longitudinal data

Panel data include cross-sectional observations of the same units at multiple points in time. The subject of interest can be e.g. individuals, households, industries, regions and countries. So, in panel data we are connecting the time series data with cross-sectional data because we have one subject multiple time periods by recording its attribute over multiple time periods such as annually, biannually etc.

A panel data observation usually has two subscripts x_{it} where:

- i subscript refers to the cross-sectional unit between 1 to N sample size and shows the observed differences among the recording entities &
- t subscript refers to the time of the observation between 1 to T time span and refers to the observed differences of the tested subject over time (Studenmund, 2017).

Panel data index can be divided into

- Balanced panel, where each observation appears from 1 to N sample in each period from 1 to T
- Unbalanced panel, where each observation does not appear continuously (Studenmund, 2017).

Researches prefer panel data in order to have a larger sample size for observation and to obtain a better insight into the regression analysis in cases that time-series or cross-sectional data cannot correspond.

1.3 Regression analysis types

Apart from searching the essence on individual variables it is necessary to learn about the relationship among different types of variables. Thus, linear regression is a statistical method that contributes to this determination by combining a dependent variable Y and one or more explanatory variables X (Studenmund, 2017).

1.3.1 Simple linear regression analysis

To carry out a simple linear regression analysis, we have to assume that there is an influence in the dependent variable Y from a single independent variable X through a linear type of function as listed in the following equation:

$$Y = b_0 + b_1X + e$$

where Y is the dependent variable, X is the independent or explanatory variable, b_0 is the intercept (equals to Y when X equals to zero), b_1 is the coefficient that exhibits the slope of the linear relationship between Y & X variables or the influence on Y dependent variable that has every one-unit of change in X independent variable. The factor e is a random error component that refers to the difference that appears between the recorded Y value and the predicted Y value for a given X value of a specific sample. For a zero

random error component ($e=0$) we discuss on a deterministic linear relationship whilst for a none zero random error component ($e\neq 0$) we discuss on a probabilistic linear relationship (Hilmer, et al 2013).

1.3.2 Multiple linear regression analysis

Multiple linear regression analysis is a useful tool that allows us to express the linear relationship between a given dependent variable Y and potentially large numbers of independent variables X_i . The simplest multiple linear relationship between a given dependent variable Y and two independent variables X is the following:

$$Y_i = b_0 + b_1X_{1i} + b_2X_{2i}$$

where Y_i is the dependent variable, X_{1i} & X_{2i} are the independent variables, b_0 is the intercept equals to Y when X_{1i} & X_{2i} equals to zero, b_1 is the coefficient that represents the marginal effect where each one-unit of change in X_1 independent variable influence on Y_i dependent variable under the circumstances that all other independent variables remain constant, similarly, b_2 is the coefficient that represents the marginal effect where each one-unit of change in X_2 independent variable influence on Y_i dependent variable under the circumstances that all other independent variables remain constant (Hilmer,et al 2013).

The multiple linear regression equation between a given dependent variable Y and two independent variables X included the random error component is the following (Studenmund, 2017):

$$Y_i = b_0 + b_1X_{1i} + b_2X_{2i} + e$$

1.3.3 The Log-Linear Model

Log-linear Model can be considered a regression model that consists of a logged dependent variable and non logged independent variables. Commonly this kind of regression type is preferred to observe a nonlinear relationship between Y and X variables. The corresponding regression model between a given dependent variable Y and two independent variables X is listed below (Hill, R.C. et al, 2011):

$$Ln(Y_i) = b_0 + b_1X_{1i} + b_2X_{2i} + e$$

1.3.4 Missing data - Dummy & Categorical Variables

During the process of collecting data for every research we may encounter the absence of some observations. In these cases we have to select the optimal option to continue by dropping the missing observations and continue the estimation with non missing data. Another option is to introduce a dummy variable which can be equal to 1 for missing data values and 0 for non missing data values.

Dummy variables are a useful type of variable that facilitates the quantification of qualitative. Dummy variables can be expressed as binary values that can take the value of 1 for a true condition and 0 for a false condition. Additionally, in cases that we have more than two outcomes related with a qualitative variable we can use the type of categorical variables. Thus, each potential qualitative outcome is assigned with a numerical value such as 0, 1, 2, 3 e.t.c. (Hilmer,et al 2013).

1.4 Assumptions & Interpretation of Multiple linear regression analysis

1.4.1 Required Assumptions

Main components of our estimation attempt should be efficiency and unbiasedness. Up to this direction, selected estimators should have the minimum variance related to all unbiased estimators of a given sample so to be considered as the Best Linear Unbiased Estimators (BLUE). Likewise, a BLUE multiple regression analysis has to be complied with a series of required assumptions:

Assumption M1: Linearity of model parameters (Y_i & X_i) and accurate specification of regression model population should be implemented

Assumption M2: Data collecting should be through independent random sampling

Assumption M3: Elimination of data multicollinearity as value of the explanatory variables has to vary

Assumption M4: Error term must have zero mean so that the interpretation of the estimated intercept can have an informative value

Assumption M5: The error term does not appear any correlation with the rest of the independent variables and all of independent variables' functions

Assumption M6: The error term must have a constant variance for each independent homoskedasticity of the data. variable values that depicts

Summarizing the aforementioned, for a BLUE multiple linear regression the Assumptions M1 until M6 should be observed. The most common violation of the six assumptions appears when the error term does not have a constant variance and reflects heteroskedasticity of the data. (Hilmer,et al 2013).

1.4.2 Interpretation of Multiple linear regression analysis

Estimating the linear relationship between the tested variables should be followed by a well structured determination of the estimation that describes the degree of the goodness of Fit and if this estimation encounters the initial Null Hypothesis.

Initially, we re-write the multiple linear regression function between a given dependent variable Y and two independent variables X as it is described below:

$$Y_i = b_0 + b_1X_{1i} + b_2X_{2i}$$

where

b_0 is the estimated intercept that exhibits the predicted value for Y when X_{1i} and X_{2i} are equal to 0

b_1 is the estimated slope coefficient for the estimated linear regression between Y and X_{1i} whilst X_{2i} remains constant

b_2 is the estimated slope coefficient for the estimated linear regression between Y and X_{2i} whilst X_{1i} remains constant (Hilmer,et al 2013).

As far as the goodness-of-fit is concerned, we have to refer to least squares criterion (Studenmund, 2017). According to that, we aim to minimize the sum of squared residuals, the individual deviations from the predicted values of Y as can be depicted below:

$$\text{Minimize } \sum_{i=1}^n e_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n (y_i - (\hat{\beta}_0 + \hat{\beta}_1x_i))^2$$

After solving this minimization problem, we conclude to the following known regression function:

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

Or

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x.$$

Furthermore, best fitting of our estimation compared with the observed data depends on the calculation of different types of variation. A useful tool could be the Venn diagram where the explained and the unexplained variation in Y are measured. In our case we will use more convenient measures of goodness-of-fit such as R^2 and adjusted R^2 . The coefficient R^2 can be interpreted similarly for simple and multiple linear regression analysis where it takes values from 0 to 1 indicating the degree that the observed variation in X values describes the observed variation in Y with the value of 1 to depict the perfect fit. The only disadvantage of this measure of goodness-of-fit is that by adding more explanatory variables X_i to the regression model, that due to the nature of economic data they interrelate at least with the dependent variable Y, we obtain an increased R^2 because by definition increases the explained sum of squares (ESS) of the sample. In terms of interpretation, this method can lead to false results. Thus, the calculation of adjusted R^2 can poise the false estimation of R^2 measure. Namely, adjusted R^2 weights the R^2 for the number of the included explanatory variables in the sample regression function as listed in the following mathematical expression:

$$Adjusted R^2 = 1 - (1 - R^2) \left(\frac{n-1}{n-k-1} \right)$$

where n is the number of the observed data and k the number of the included explanatory variables in the sample regression function. It is considered as an informative measure that eliminates the excessive independent variable use with little statistical relationship with the dependent variable (Hilmer, et al 2013).

An integrated estimation on multiple regression should meet the initial Hypothesis testing. Hypothesis testing procedures compare an assumption about a given sample of data under an economic or a statistical view representing a statement about model parameters. Thus, after the estimation of the multiple regression that we examine, we conclude whether the initial hypothesis is true or not.

According to the multiple linear regression function between a given dependent variable Y and two independent variables X as it is described below:

$$Y_i = b_0 + b_1X_{1i} + b_2X_{2i}$$

We can discuss upon the Null and Alternative Hypothesis. In case the independent X_1 variable does not explain sufficiently the dependent variable Y then b_1 equals to 0, which depicts the null hypothesis. On the other hand, in case the independent X_1 variable explains at least the dependent variable Y then b_1 is different from 0, which depicts the alternative hypothesis. (Hilmer,et al 2013).

Accordingly, the null and alternative hypotheses for the slope parameter are the following:

$$H_0: b_j = 0$$

$$H_1: b_j \neq 0$$

where j is one of the k explanatory variables in the multiple regression model

A null hypothesis H_0 can be considered as the belief we insist until we are convinced by the sample evidence that it is not true. In this case, we reject the null hypothesis H_0 . Along with the null hypothesis H_0 follows the alternative hypothesis H_1 , as a complementary entity of the null hypothesis H_0 that will be accepted whether the null hypothesis is rejected. (Hilmer,et al 2013).

After the results of statistical hypothesis tests, we report the p-value (an abbreviation for probability value) of the test. Having the p-value of a test, we can specify the outcome of the test by comparing the p-value with the corresponding level of significance α .

The p-value rule is based on the following statements:

Reject the null hypothesis H_0 when the p-value is less than or equal to the level of confidence α .

$$\text{If } p \leq \alpha \text{ then reject } H_0$$

$$\text{If } p > \alpha \text{ then do not reject } H_0$$

1.5 Panel Data Analysis

Panel Data analysis can be assumed as a flexible method of regression as economists are able to implement various sets of data from a simple to a complex index. On the contrary to conventional cross-sectional or time series data, panel data analysis has a significant

advantage by increasing the researchers' degree of freedom to examine explanatory variables and relationships (Moffat, 2020).

Panel data analysis commonly can be divided into 2 categories

- Static panel data analysis
- Dynamic Panel data analysis

Following equation refers to static panel data analysis

$$Y_{it} = \alpha_i + \beta_1 X_{it}' + \varepsilon_{it}$$

where the dependent variable Y is explained by an intercept α , a set of independent variable X and an error term ε . The subscript i denotes the cross-sectional items while the subscript t denotes the time periods.

This mathematical expression represents an optimal analysis because through beta analysis we have both cross-sectional and time series information. Indeed, as we can interpret this equation we see the dependent variable to be explained by an intercept as a cross sectional item plus beta1 coefficient β_1 which represents the value for a set of independent variables for i cross-sectional items at t point in time and error term ε for i cross-sectional items at t point in time. (Hilmer 2013).

On the other hand, in a dynamic panel data analysis we have an additional independent variable that is the lag value of the dependent variable. The following equation refers to the dynamic panel data analysis where the dependent variable Y is explained by an intercept α , the lag value of the dependent variable, a set of independent variable X and an error term ε for i cross-sectional items at t point in time (Hill, R.C. et al, 2011).

$$Y_{it} = \alpha_i + Y_{i,t-1} + \beta_1 X_{it}' + \varepsilon_{it}$$

We will focus on the static panel data analysis where there are multiple models that can be used. Three of the most common methods used for setting static panel data analysis are the Fixed Effects Model, the Random Effects Model and the Pooled OLS Model. (Hilmer,et al 2013).

1.5.1 Fixed Effects Model

$$Y_{it} = \alpha_i + \beta_1 X_{it}' + \varepsilon_{it}$$

As we notice the equation we conclude that in the Fixed Effects Model the intercept of i cross-section item absorb all the variation across the cross-sectional effects so the variation across cross-sectional items is fixed (Hill, R.C. et al, 2011).

1.5.2 Random Effects Model

$$y_{it} = \alpha + \mu_{it} + \beta_1 x_{it}' + \varepsilon_{it}$$

In the Random Effects Model we have the dependent variable for i cross-sectional item at t point in time that is explained by an intercept α and by a common intercept μ_{it} which represents the variation across i cross-sectional unit and t point in time, a set of independent variable and the error term for i cross-sectional and t at point in time. The μ here represents the between eras, the between error term that will record the differences. (Hilmer 2013).

1.5.3 Pooled OLS Model

Above from the fixed effects and random effects model we can also use ordinary least square (OLS) in order to identify or to analyze a panel data that can be included in the following equation:

$$y = a + \beta_1 x' + \varepsilon$$

A pooled cross-section model is suitable for use when in the same regression model are estimated more than one time period of cross sectional data. During that estimation, as seen in the above regression function, we make no distinction between time periods and we omit the time-period identifier. While possible, if we estimate a pooled cross-section by OLS we may not exploit the significant advantages by the nature of panel data. However, taking into consideration the panel index contains observations for the same individuals over time we can resort to several empirical tools that can perform a remarkable estimation (Hilmer,et al 2013).

2. Logistics Performance Index (LPI) of World Bank

2.1 Literature of LPI

World Bank's Logistics Performance Index (LPI) considered as a very useful tool to realize and compare international trade dimensions and observe transport dynamics all around the world. Measurements of LPI depict in a value of score the performance of a country and how each country that engages actively into international trade can identify new challenges and opportunities they face in trade logistics and how they can improve their performance.

As logistics and transport play a main role in international trade relations, the LPI focuses on the differences between countries in terms of customs procedures, logistics costs and the quality of the infrastructure for overland and maritime transport. Domestic LPI is an investigation of the national logistic environment. It assesses four primary areas – services, reliability of supply chain, border procedures, and timeliness, and infrastructure (Domestic LPI, n.d.). The International LPI is an evaluation of a country based on trading partners (Arvis et al, 2018).

LPI 2018 ranks countries on six dimensions of trade including customs performance, infrastructure quality, and timeliness of shipments. These components cover the various areas that define LPI and it has been proved that they have a greater impact than distance and transport costs (Korinek and Sourdin, 2011). Specifically, they include elements of essential logistical value, such as the transparency of processes and their quality, as well as the predictability and reliability of services (Arvis et al, 2018). Each component of the aggregated LPI is chosen related to previous theoretical and empirical research and on the practical experience of logistics professionals involved in international freight forwarding. Each component is defined as follows (Marti 2014):

- Customs: entails everything that is related with the customs procedure such as efficiency in administration tasks, data exchanges, elimination of bureaucratic influence due to existing border legislation on bilateral trade, decline in customs taxes and generally efficient border management
- Infrastructure: encompasses the trade quality infrastructure, all the transport and distribution procedures that contribute to improved quality of export logistics, better standards of containerization and managing the volume of trade, optimal mobility of goods to the final destination

- International shipments: describes the arrangements of shipments at competitive prices including organizing, receiving, recording and sending shipments of goods (Marti 2017)
- Logistics quality and competence: related with the optimal operation of the logistics from all the parties that engage in supply chain. Depicts the quality of logistic services that comes from the organizational structure and the final impression that receive the customers. Represents the competence of the logistics and configure the relationship between organizations and consumers (Marti 2014)
- Tracking and tracing: depicts the well organized tracking and trace consignment based on information systems that identify the exact location of the dispatched freight, possible delays that may arise during the route of each consignment until the final destination to the customer, efficient package distribution and export promotion (Marti 2014)
- Timeliness: deals with the punctuality on delivery products. considered as a main component of the competitive logistic organisations due to the importance that accurate delivery times of shipments gain the best customers and increase the reliability of a firm and a country, focuses on time relationships as market globalization and modernization enhance (Marti 2014)

We should take into consideration that none of these components independently can guarantee an optimal level of logistics performance. The sum of these can configure a good logistic performance as recent reviews have demonstrated from empirical studies and extensive researches conducted by specialists on global freight transport.

The LPI uses standard statistical techniques to aggregate the data into a single indicator that can be used for cross-country comparisons (Olyanga 2022).

2.2 The LPI methodology

Due to the existence of multi-dimensional logistics, it is difficult to measure and summarize country performance. Looking at the time and costs related with logistics processes (shipments, customs managing, etc.) is a good starting point as this information is readily available despite the fact that cannot be easily aggregated into a coherent cross-country index due to differences in the structure of each country's supply chain. Moreover, a lot of key elements of good logistics, such as process transparency, quality of service,

predictability and reliability cannot be evaluated based on the parameters of time and cost information (Arvis et al, 2018).

2.2.1 Constructing the international LPI

The initial part of the LPI survey provides raw international LPI data. Each research participant rates his eight overseas markets on his six core components of logistics performance. Eight countries were randomly selected based on the major import and export markets of the country in which the respondent is located, and for landlocked countries, neighboring countries that are part of the land bridges connecting them to international markets. Randomly selected countries present a nonuniform probability so the chosen weights aim to develop the sample into uniform probabilities. In particular, country i is selected with probability $(N-n_i)/2N$, where n_i is the previous sample size for country i and N is the total sample size (Arvis et al, 2018).

The International LPI is a summary measure of the logistics sector's performance that combines data of six main performance components into one aggregated index. For some respondents with no provided information on all six components interpolation is used to replace the missing values by the country mean adjusted for the mean deviation of the respondent from the country mean of the questions answered (Arvis et al, 2018).

The six core components listed below:

- Customs efficiency and border managing tasks
- Trade and transport infrastructure
- Arranging of international shipments
- Competence and quality of logistics sector services
- Tracking and traceability of consignments
- Timeliness of shipments

The score of each aforementioned component rated from “very low” (1) to “very high” (5). LPI is constructed from these six measures using principal component analysis (PCA), a standard statistical technique to reduce the dimensionality of datasets. In LPI, the input to the PCA is the country scores for questions 10-15, averaged across all respondents providing data for a particular foreign market. Results are normalized by subtracting the sample mean and dividing by the standard deviation before running PCA. The output of

PCA is a single index (LPI) that is a weighted average of these scores. Weights are chosen to maximize the percentage of variation in the original six indicators of LPI explained by the summary (Arvis et al, 2018).

The PCA is re-run for each version of the LPI, but the weights remain fairly constant from year to year. This means that there is a high level of comparability between different LPI editions (Arvis et al, 2018).

3. Model Structure

3.1 Data source

Until now, data can be extracted by three broad sources such as private-use data, publicly available data and personal survey data. Academic researchers most commonly prefer government survey or firm-level data. (Hilmer, et al 2014).

Our research method contains quantitative and qualitative data by collecting time-series data from the Logistics Performance Index of The World Bank of the 27 European nations observed between 2010 & 2018. Complete data values can be found in Appendix A. The time span of our analysis is constrained by the logistics variables that are available every two years period from 2010 to 2018 (see –<https://lpi.worldbank.org/about>).

Assembling our data of interest is the next required process in order to convert received time series data to panel data as we want these time series data to correspond to various entities (e.g. countries). Harnessing insights from the literature, we need to include a number of independent variables as aspects of supply chain logistics in order to explain the interaction with economic growth. The dependent variable is a measure of total annual economic growth calculated as the log difference of real GDP per capital. The main explanatory variables constitute an index capturing the overall supply chain logistics performance. This index is constructed using several dimensions of supply chain logistics as well as several social & economic factors that influence the economic growth etc. (see <https://lpi.worldbank.org/about> for details; also see Arviset al., 2018). Qualitative regressors (geographic factors) were included as dummy variables.

3.2 Model Description

Determination of the framework of our research model should be formed according to the main principles on empirical research. Initially, we have to identify the question of sufficient interest in our case. Furthermore, we continue by determining the essential economic theory that corresponds to our question whilst collecting the suitable data can be assumed a significant contribution to our analysis.

The upshot of this discussion is based on the following hypothesis:

Hypothesis 1: Better supply chain performance increases economic growth?

A preliminary look at the data underlying the above hypothesis can be reflected in Fig. 1.

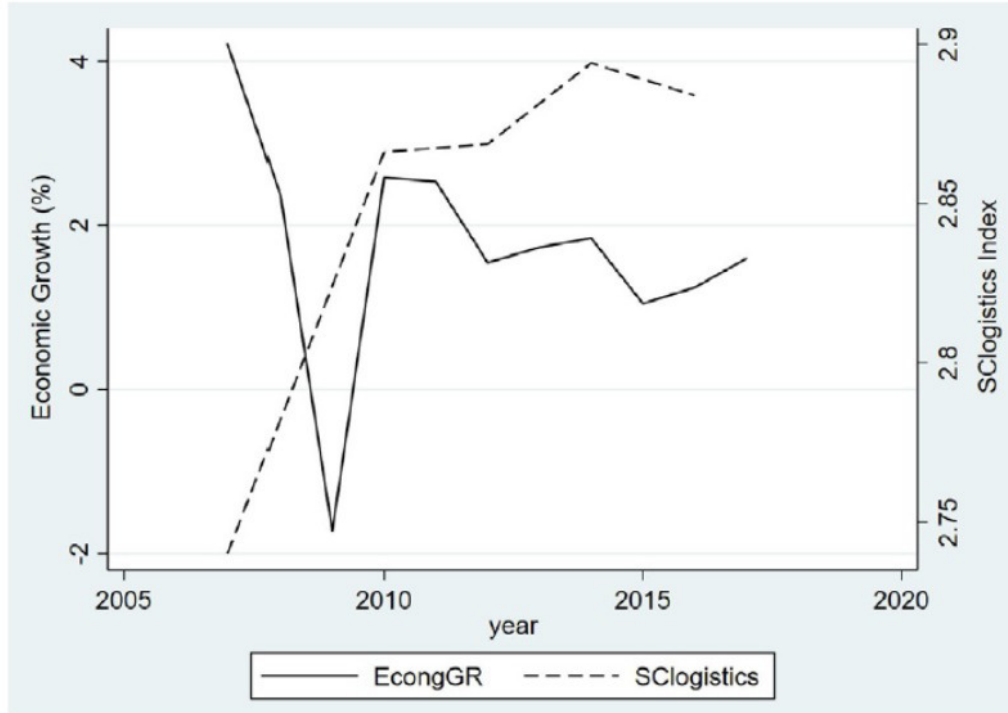


FIG. 3.1 SHOWS THE RELATION BETWEEN ECONGR AND SCLOGISTICS ACROSS THE SAMPLE COUNTRIES (BASED ON ANNUAL AVERAGES ACROSS AVAILABLE COUNTRIES)

The main concept of our Hypothesis is that a number of obstacles that deteriorate the normal operation of the supply chain network should be detected and eliminated. For instance, delivery times should be well controlled and monitored in order to obtain punctual delivery times of packages, high quality transport, reduced wastage during transportation etc. Complying with such improvements, economic growth can be ensured.

The general form of the estimated growth model, to test Hypothesis 1, with subscripts i for country and t for year is the following:

$$EconGR_{it} = f(Supply\ chain\ logistics_{itm}, Landlocked_i, BorderLength_i)$$

$$i = 1, \dots, 27; t = 2010, \dots, 2018; m = SClogistics, SCinput, SCoutput; g = GDP$$

The dependent variable is the real per capita annual GDP growth rate across the 27 European nations in our sample.

Initially, we formulate the main aggregate index of supply chain logistics performance (SClogistics) and we define them as micro econometrics variables. Moreover, we consider an additional index ($SC_{social\&econ.factors}$) with score values that represent social and economic

factors that influence the economic growth and we define them as macro econometrics variables. Dummy variables also used to describe the Landlocked countries in order to quantify the qualitative nature of this kind of observations. Finally, the quantitative variable of Border length of each country measured in km was also included in our index (see Appendix A). Definitions of the aforementioned variables are demonstrated at the Table 3.1.

TABLE 3.1 Variable definitions, sources and summary statistics.

Variable	Description [observations; mean; standard deviation]	Source
EconGR	Economic growth, measured as the log difference in real GDP per capital (at constant 2011 national prices in millions of 2011 US dollars)	LPI (2018)
SClogistics	Overall supply chain logistics performance index (LPI), measured as an unweighted average of the six sub-indicators including timeliness, tracking and tracing, logistics quality and competence, international shipments, infrastructure, and customs. The index is rated from 1 = “very low” to 5 = “very high”	LPI (2018)
SC _{social&econ.factors}	Supply chain logistics performance due to social & economic factors, measured by the Investment, Government expenditure, Unemployment, Inflation, Population Growth, rated from 1 = “very low” to 5 = “very high”	LPI (2018)
GDP	Log of real GDP per capita (at constant 2011 national prices in millions of 2011 US dollars. [2002; 9.279; 1.179]	LPI (2018)
LandLocked	Dummy variable equal to 1 for landlocked countries, and zero otherwise	Mayer and Zignago (2011)
BorderLength	The length of the country’s land border, measured in kilometers	

During our analysis we seek a relationship between the structural behavior of supply chain, measured by the LPI, and other economic and social factors. More specifically, the depend variable Y could be the ln- logarithm of the real per capital growth rate (lnGDP) across the 27 European countries correlated with specific sub-components in Supply Chain Management using them as independent variables. These variables can be divided into two categories related to their operational performance such as Macro and Micro operational variables as illustrated in Table 3.2.

TABLE 3.2 Definition of micro & macro variables

A/A	Micro-logistics operational variables	Macro-logistics operational variables
1	Customs: Customs efficiency and border managing tasks	INVESTMENT: Gross capital formation (% of GDP)
2	Infrastructure: Trade and transport infrastructure	GOVERNMENT EXPENDITURE: money spent by the public sector to purchase goods and provide services such as education, health care, social protection and defense (% of GDP)
3	International shipments: Arranging of international shipments	UNEMPLOYMENT: the number of unemployed people as a percentage of the labor force (% of total labor force)
4	Logistics quality and competence: Competence and quality of logistics sector services	INFLATION: measures how much more expensive a set of goods and services has become over a certain period, usually a year (annual %)
5	Tracking and tracing: Tracking and traceability of consignments	POPULATION GROWTH: the increase in the number of people in a population (annual %)
6	Timeliness: Timeliness of shipments	LandLocked: a country with no territory connected to an ocean
7		Border Length (km): the length of each country's land border

Binary dummy variables can be included such as landlocked countries etc in order to obtain more detailed outcomes.

The variable selection is very important/worthwhile issue before we start a linear regression especially a multiple linear regression. For instance, once we perform a simple linear regression we usually have a single independent variable X and we try to interpret its variance into the dependent variable Y . However, in the context of multiple linear regression we can include various independent variables X_i regarding their influence in our selected dependent variable Y .

3.3 Model Estimation

To estimate the baseline models for the overall and each dimension of supply chain logistics performance, we use Ordinary Least Squares (OLS) estimation and control for region specific effects and time effects with the useful software Gretl (see APENDIX B).

The criteria we choose the appropriate independent variables depends into the correlation they have in order to be a worthwhile part of our model. For instance, after the first analysis of each variable's X_i performance, we could decide which of them are significant or not worth having them in our model and continue with a new simulation excluding the most insignificant independent variable one at a time.

Our analysis focuses on examining the importance of each LPI component in economic growth taking into account all the macro variables that we mentioned into Table 2. Due to the fact that LPI components are markedly correlated, we aim to avoid estimation including all the components into the same regression equation in order not to encounter multicollinearity results and possible errors. Therefore, we formulate an individual multiple regression equation including each LPI index component separately. Hypothesis testing for each LPI multiple regression equation is also listed.

○ Model 1 – LnGDP & Customs

Our model includes a single Micro-logistics operational variable (e.g. Customs) and all the Macro-logistics operational variables as independent variables.

The Null Hypothesis of Customs can be as follows:

Does the improvement of Customs quality enhance the economic growth?

We run the first multiple regression setting as a dependent variable the lnGDP.

$$\begin{aligned} Ln(GDP_{it}) &= \beta_0 + \beta_1(Customs_{it}) + \beta_2(INVESTMENT_{it}) + \\ &\beta_3(GOVERNMENTEXPENDITURE_{it}) + \beta_4(UNEMPLOYMENT_{it}) + \\ &+ \beta_5(INFLATION_{it}) + \beta_6(POPULATIONGROWTH_{it}) + \beta_7(BorderLength_{it}) + \\ &\beta_8(LandLocked_{it}) + u_{ij} \end{aligned}$$

Results are listed in Chapter 4.1.

- Model 2 – LnGDP & Infrastructure

Our model includes a single Micro-logistics operational variable (e.g. Infrastructure) with all the Macro-logistics operational variables as independent variables.

The Null Hypothesis of Infrastructure can be as follows:

Does the improvement of Infrastructure quality enhance the economic growth?

We run the first multiple regression setting as a dependent variable the lnGDP.

$$\begin{aligned} \ln(GDP_{it}) = & \beta_0 + \beta_1(Infrastructure_{it}) + \beta_2(INVESTMENT_{it}) + \\ & \beta_3(GOVERNMENTEXPENDITURE_{it}) + \beta_4(UNEMPLOYMENT_{it}) + \\ & + \beta_5(INFLATION_{it}) + \beta_6(POPULATIONGROWTH_{it}) + \beta_7(BorderLength_{it}) + \\ & \beta_8(LandLocked_{it}) + u_{ij} \end{aligned}$$

Results are listed in Chapter 4.2.

- Model 3 – LnGDP & International shipments

Our model includes a single Micro-logistics operational variable (e.g. International shipments) with all the Macro-logistics operational variables as independent variables.

The Null Hypothesis of International shipments can be as follows:

Does the improvement of Infrastructure quality enhance the economic growth?

We run the first multiple regression setting as a dependent variable the lnGDP.

$$\begin{aligned} \ln(GDP_{it}) = & \beta_0 + \beta_1(International\ shipments_{it}) + \beta_2(INVESTMENT_{it}) + \\ & \beta_3(GOVERNMENTEXPENDITURE_{it}) + \beta_4(UNEMPLOYMENT_{it}) + \\ & + \beta_5(INFLATION_{it}) + \beta_6(POPULATIONGROWTH_{it}) + \beta_7(BorderLength_{it}) + \\ & \beta_8(LandLocked_{it}) + u_{ij} \end{aligned}$$

Results are listed in Chapter 4.3.

- Model 4 – LnGDP & Logistics quality and competence

Our model includes a single Micro-logistics operational variable (e.g. Logistics quality and competence) with all the Macro-logistics operational variables as independent variables.

The Null Hypothesis of Logistics quality and competence can be as follows:

Does the improvement of Logistics quality and competence enhance the economic growth?

We run the first multiple regression setting as a dependent variable the LnGDP.

$$\begin{aligned} \ln(GDP_{it}) = & \beta_0 + \beta_1(\text{Logisticsquality\&competence}_{it}) + \beta_2(\text{INVESTMENT}_{it}) + \\ & \beta_3(\text{GOVERNMENTEXPENDITURE}_{it}) + \beta_4(\text{UNEMPLOYMENT}_{it}) + \\ & + \beta_5(\text{INFLATION}_{it}) + \beta_6(\text{POPULATIONGROWTH}_{it}) + \beta_7(\text{BorderLength}_{it}) + \\ & \beta_8(\text{LandLocked}_{it}) + u_{ij} \end{aligned}$$

Results are listed in Chapter 4.4.

- Model 5 – LnGDP & Tracking and tracing

Our model includes a single Micro-logistics operational variable (e.g. Tracking and tracing) with all the Macro-logistics operational variables as independent variables.

The Null Hypothesis of Tracking and tracing can be as follows:

Does the improvement of Tracking and tracing enhance the economic growth?

We run the first multiple regression setting as a dependent variable the LnGDP.

$$\begin{aligned} \ln(GDP_{it}) = & \beta_0 + \beta_1(\text{Tracking\&tracing}_{it}) + \beta_2(\text{INVESTMENT}_{it}) + \\ & \beta_3(\text{GOVERNMENTEXPENDITURE}_{it}) + \beta_4(\text{UNEMPLOYMENT}_{it}) + \\ & + \beta_5(\text{INFLATION}_{it}) + \beta_6(\text{POPULATIONGROWTH}_{it}) + \beta_7(\text{BorderLength}_{it}) + \\ & \beta_8(\text{LandLocked}_{it}) + u_{ij} \end{aligned}$$

Results are listed in Chapter 4.5.

- Model 6 – LnGDP & Timeliness

Our model includes a single Micro-logistics operational variable (e.g. Timeliness) with all the Macro-logistics operational variables as independent variables.

The Null Hypothesis of Timeliness can be as follows:

Does the improvement of Timeliness enhance the economic growth?

We run the first multiple regression setting as a dependent variable the lnGDP.

$$\begin{aligned} \ln(GDP_{it}) = & \beta_0 + \beta_1(Timeliness_{it}) + \beta_2(INVESTMENT_{it}) + \\ & \beta_3(GOVERNMENTEXPENDITURE_{it}) + \beta_4(UNEMPLOYMENT_{it}) + \\ & + \beta_5(INFLATION_{it}) + \beta_6(POPULATIONGROWTH_{it}) + \beta_7(BorderLength_{it}) + \\ & \beta_8(LandLocked_{it}) + u_{ij} \end{aligned}$$

Results are listed in Chapter 4.6.

- Model 7 – LnGDP & Overall LPI score

Our model includes a single Micro-logistics operational variable (f.i. overall LPI score) with all the Macro-logistics operational variables as independent variables.

The Null Hypothesis of overall LPI score can be as follows:

Does the increase of the overall LPI score enhance the economic growth?

We run the first multiple regression setting as a dependent variable the lnGDP.

$$\begin{aligned} \ln(GDP_{it}) = & \beta_0 + \beta_1(OverallLPI_{it}) + \beta_2(INVESTMENT_{it}) + \\ & \beta_3(GOVERNMENTEXPENDITURE_{it}) + \beta_4(UNEMPLOYMENT_{it}) + \\ & + \beta_5(INFLATION_{it}) + \beta_6(POPULATIONGROWTH_{it}) + \beta_7(BorderLength_{it}) + \\ & \beta_8(LandLocked_{it}) + u_{ij} \end{aligned}$$

Results are listed in Chapter 4.7.

In our strategy we focus on the overall performance of the model and examine the influence of each individual variable to the model's performance, explain their variance and try to forecast unobserved values of the dependent variable.

As we mentioned, we follow the technique of backward elimination to discard any independent variable that does not have a statistically significant relationship with the dependent variable. In order to determine the existence of any statistically significant relationship we must initially decide the desired confidence level. So, if we determine a 5% statistic significance level (which means a confidence level of 95%), then we can use some indicators such as the p-value in order to continue our assumptions. For values of p-value higher than 5% we will discard the particular variable. At the end of this approach, we will have a clean model where all the variables have statistically significant coefficients at least up to the 5% level.

Summarizing, after conducting the first multiple linear regression we discard the independent variable with the highest p-value and we repeat the regression. We continue with this method in order to obtain all the independent variables with p-value $< 5\%$. We use this repeatable method discarding one variable per regression trial in order to have more accurate monitoring.

4. Results of OLS estimation

4.1 Model 1 - LnGDP & Customs

Implementing the first multiple regression setting as dependent variable the lnGDP and independent variable the Customs including the macro-variables of INVESTMENT, GOVERNMENT EXPENDITURE, UNEMPLOYMENT, INFLATION, POPULATION GROWTH, BorderLength (km) & Landlocked we have the following Table 4.1.1.

TABLE 4.1.1 Initial Model Pooled OLS between lnGDP & Customs

	coefficient	std. error	t-ratio	p-value
const	7.24811	0.282852	25.63	8.26e-052
Customs	0.904551	0.0723140	12.51	7.74e-024
INVESTMENT	-0.00854155	0.00731771	-1.167	0.2453
GOVERNMENTEXPENDI	0.00585742	0.00899538	0.6512	0.5161
~				
UNEMPLOYMENT	0.00888891	0.00620044	1.434	0.1542
INFLATION	0.0383079	0.0174606	2.194	0.0301
POPULATIONGROWTH	0.321308	0.0382983	8.390	8.42e-014
BorderLength (km)	-0.000130113	2.83859e-05	-4.584	1.08e-05
LandLocked	0.0785911	0.0638812	1.230	0.2209
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	9.008677	S.E. of regression	0.267390	
R-squared	0.836949	Adjusted R-squared	0.826596	
F(8, 126)	80.84547	P-value(F)	6.44e-46	
Log-likelihood	-8.828359	Akaike criterion	35.65672	
Schwarz criterion	61.80419	Hannan-Quinn	46.28232	
Rho	0.394070	Durbin-Watson	0.947717	

We exclude successively the variables GOVERNMENTEXPENDITURE, Landlocked, INVESTMENT, according to its highest p-value and test statistic significance at 5% level.

Following the procedure of excluding the variables with the highest p-value we obtain the final Model Table 4.1.2.

TABLE 4.1.2 Final Model Pooled OLS between lnGDP & Customs

	coefficient	std. error	t-ratio	p-value
const	7.10273	0.212704	33.39	2.43e-065
Customs	0.922156	0.0591663	15.59	1.89e-031
UNEMPLOYMENT	0.0117508	0.00551004	2.133	0.0349
INFLATION	0.0401025	0.0168247	2.384	0.0186
POPULATIONGROWTH	0.332341	0.0366580	9.066	1.73e-015
BorderLength (km)	-0.000127720	2.77544e-05	-4.602	9.89e-06
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	9.222019	S.E. of regression	0.267373	
R-squared	0.833088	Adjusted R-squared	0.826618	
F(5, 129)	128.7720	P-value(F)	2.17e-48	
Log-likelihood	-10.40825	Akaike criterion	32.81650	
Schwarz criterion	50.24815	Hannan-Quinn	39.90023	
Rho	0.397041	Durbin-Watson	0.930119	

*** Note: * denote test statistic significance at the 5% level

The final mathematical equation that corresponds to our last multiple regression above is:

$$\ln GDP = 7.10 + 0.922 * Customs + 0.0118 * UNEMPLOYMENT + 0.0401 * INFLATION + 0.332 * POPULATIONGROWTH - 0.000128 * BorderLengthkm$$

for sample size of $n = 135$ & $R\text{-squared} = 0.833$

According to the resulting equation we examine if the model is statistically significant that at least one of the independent variables can have a linear relationship with the dependent variable.

More specifically, we examine the following hypothesis:

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$$

$$H_1: \text{At least one } \beta_i \text{ is not equal to } 0$$

Using as test statistic significance at the 5% level ($\alpha=5\%$), at least one beta coefficient cannot be equal to 0, the model is able to appear validity in a specific degree. So, if we examine the GDP value we have the following tasks:

- 1) $\beta_1 = 0.922$ which means that for an increase of Customs services by 1 unit, GDP increases by $\exp(0.922)=2.51$ units with the rest independent variables remaining unchanged
- 2) $\beta_2 = 0.0118$ which means that for an increase of 1 unit at the level of Unemployment, GDP increases by $\exp(0.0118)=1.01$ units with the rest independent variables remaining unchanged

- 3) $\beta_3 = 0.0401$ which means that for an increase of 1 unit at the level of Inflation, the GDP increases by $\exp(0.04)=1.04$ units with the rest independent variables remaining unchanged
- 4) $\beta_4 = 0.332$ which means that for an increase of 1 unit at the level of Population Growth, the GDP increases by $\exp(0.332)= 1.39$ units with the rest independent variables remaining unchanged
- 5) $\beta_5 = - 0.000128$ which means that for an increase of 1000km at the Border Length of a country, the GDP decreases by $\exp(-0.128)= 0.88$ units with the rest independent variables remaining unchanged. We can see that this decrease is around zero so the impact of the variable of Border Length (km) is meaningless to the dependent variable of $\ln\text{GDP}$

The adjusted R^2 is equal to 0.8266 similar to the initial value and depicts that 82.66% of the variation in $\ln\text{GDP}$ can be explained by the independent variables adjusted by the given sample size.

The next normal probability plot depicts that the residual estimation errors do not deviate significantly from the normal distribution.

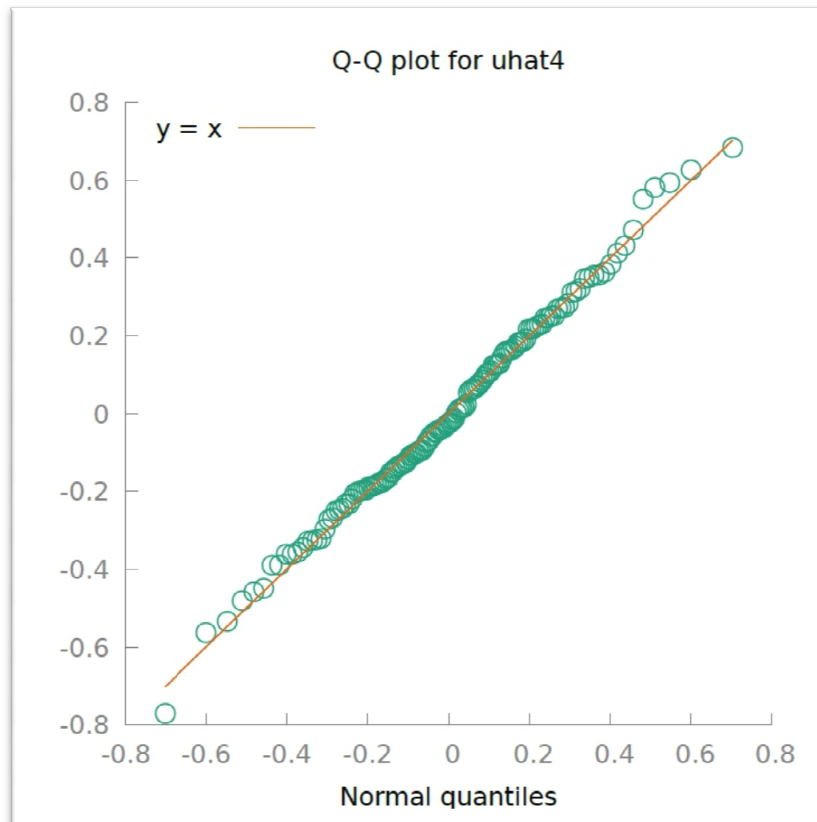


FIG. 4.1 NORMAL PROBABILITY PLOT BETWEEN $\ln\text{GDP}$ & CUSTOMS

According to the above plot we can check the hypotheses of the independence and the homoskedasticity of the residuals.

Summarizing, we conclude that the economic growth increases in a satisfying level as:

- ✓ the Customs services improve
- ✓ the Population Growth increases

The increase of the level of Inflation does not influence economic growth so much. On the other hand, we notice a reduction of economic growth as the Border length of a country increases.

4.2 Model 2 - LnGDP & Infrastructure

Implementing the first multiple regression setting as dependent variable the LnGDP and independent variable the Infrastructure including the macro-variables of INVESTMENT, GOVERNMENT EXPENDITURE, UNEMPLOYMENT, INFLATION, POPULATION GROWTH, BorderLength (km) & Landlocked we have the following Table 4.2.1.

TABLE 4.2.1 Initial Model Pooled OLS between lnGDP & Infrastructure

	coefficient	std. error	t-ratio	p-value
const	7.60256	0.264963	28.69	4.25e-057
Infrastructure	0.813194	0.0628656	12.94	7.09e-025
INVESTMENT	-0.00147917	0.00717969	-0.2060	0.8371
GOVERNMENTEXPENDI	-0.00449221	0.00925724	-0.4853	0.6283
~				
UNEMPLOYMENT	0.00417199	0.00604175	0.6905	0.4911
INFLATION	0.0205284	0.0167324	1.227	0.2222
POPULATIONGROWTH	0.282692	0.0388017	7.286	3.08e-011
BorderLength (km)	-0.000138591	2.80132e-05	-4.947	2.36e-06
LandLocked	0.0306791	0.0626569	0.4896	0.6252
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	8.675174	S.E. of regression	0.262394	
R-squared	0.842985	Adjusted R-squared	0.833016	
F(8, 126)	84.55893	P-value(F)	6.11e-47	
Log-likelihood	-6.282065	Akaike criterion	30.56413	
Schwarz criterion	56.71160	Hannan-Quinn	41.18973	
Rho	0.464813	Durbin-Watson	0.895059	

We exclude successively the variables INVESTMENT, Landlocked, GOVERNMENTEXPENDITURE, UNEMPLOYMENT, INFLATION according to its highest p-value and test statistic significance at 5% level.

Following the procedure of excluding the variables with the highest p-value we obtain the final Model Table 4.2.2.

TABLE 4.2.2 Final Model Pooled OLS between lnGDP & Infrastructure

	coefficient	std. error	t-ratio	p-value
const	7.65472	0.158450	48.31	2.36e-085
Infrastructure	0.782573	0.0480294	16.29	2.66e-033
POPULATIONGROWTH	0.283047	0.0335085	8.447	4.95e-014
BorderLength (km)	-0.000135032	2.60974e-05	-5.174	8.38e-07
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	8.835216	S.E. of regression	0.259701	
R-squared	0.840088	Adjusted R-squared	0.836426	
F(3, 131)	229.4009	P-value(F)	6.03e-52	
Log-likelihood	-7.515976	Akaike criterion	23.03195	
Schwarz criterion	34.65305	Hannan-Quinn	27.75444	
Rho	0.500766	Durbin-Watson	0.846051	

*** Note: denote test statistic significance at the 5% level

The final mathematical equation that corresponds to our last multiple regression above is:

$$\ln GDP = 7.65 + 0.783 * \text{Infrastructure} + 0.283 * \text{POPULATIONGROWTH} - 0.000135 * \text{BorderLengthkm}$$

for sample size of $n = 135$ & $R\text{-squared} = 0.840$

According to the resulting equation we examine if the model is statistically significant that at least one of the independent variables can have a linear relationship with the dependent variable.

More specifically we examine the following hypothesis:

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$$

$$H_1: \text{At least one } \beta_i \text{ is not equal to } 0$$

Using as test statistic significance at the 5% level ($\alpha=5\%$), at least one beta coefficient cannot be equal to 0, the model is able to appear validity in a specific degree. So, if we examine the GDP value we have the following tasks:

- 1) $\beta_1 = 0.783$ which means that for an increase of Infrastructure domain by 1 unit, GDP increases by $\exp(0.783) = 2.19$ units with the rest independent variables remaining unchanged

- 2) $\beta_2 = 0.283$ which means that for an increase of 1 unit at the level of Population Growth, the GDP increases by $\exp(0.283) = 1.33$ units with the rest independent variables remaining unchanged
- 3) $\beta_3 = -0.000135$ which means that for an increase of 1000km at the Border Length of a country, the GDP decreases by $\exp(-0.135) = 0.87$ units with the rest independent variables remaining unchanged. We can see that this decrease is around zero so the impact of the variable of Border Length (km) is meaningless to the dependent variable of $\ln\text{GDP}$

The adjusted R^2 is equal to 0.8364 similar to the initial value and depicts that 83.64% of the variation in $\ln\text{GDP}$ can be explained by the independent variables adjusted by the given sample size.

The next normal probability plot depicts that the residual estimation errors do not deviate significantly from the normal distribution.

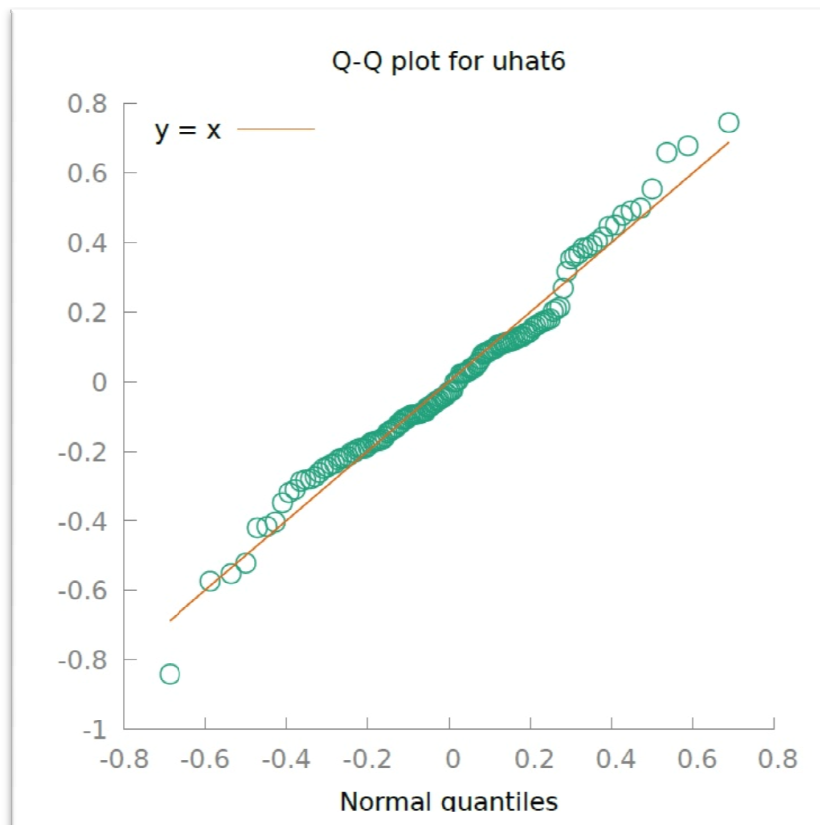


FIG. 4.2 NORMAL PROBABILITY PLOT BETWEEN $\ln\text{GDP}$ & INFRASTRUCTURE

According to the above plot we can check the hypotheses of the independence and the homoskedasticity of the residuals.

Summarizing, we conclude that the economic growth increases in a satisfying level as:

- ✓ the Infrastructure facilities improve
- ✓ the Population Growth increases

On the other hand, we notice a reduction of economic growth as the Border length of a country increases.

4.3 Model 3 - LnGDP & International shipments

Implementing the first multiple regression setting as dependent variable the LnGDP and independent variable the International shipments including the macro-variables of INVESTMENT, GOVERNMENT EXPENDITURE, UNEMPLOYMENT, INFLATION, POPULATION GROWTH, BorderLength(km) & Landlocked we have the following Table 4.3.1.

TABLE 4.3.1 Initial Model Pooled OLS between lnGDP & International shipments

	coefficient	std. error	t-ratio	p-value
const	6.96772	0.416419	16.73	8.28e-034
International shipments	0.754784	0.105403	7.161	5.89e-011
INVESTMENT	-0.00872117	0.00924542	-0.9433	0.3473
GOVERNMENTEXPENDI	0.0428285	0.0100795	4.249	4.14e-05
~				
UNEMPLOYMENT	0.00645971	0.00784074	0.8239	0.4116
INFLATION	0.00885216	0.0216281	0.4093	0.6830
POPULATIONGROWTH	0.418162	0.0462318	9.045	2.28e-015
BorderLength (km)	-9.58449e-05	3.55875e-05	-2.693	0.0080
LandLocked	0.0259630	0.0806374	0.3220	0.7480
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	14.35395	S.E. of regression	0.337521	
R-squared	0.740203	Adjusted R-squared	0.723708	
F(8, 126)	44.87425	P-value(F)	2.50e-33	
Log-likelihood	-40.27235	Akaike criterion	98.54469	
Schwarz criterion	124.6922	Hannan-Quinn	109.1703	
Rho	0.677496	Durbin-Watson	0.593648	

We exclude successively the variables Landlocked, INFLATION, UNEMPLOYMENT, INVESTMENT according to its highest p-value and test statistic significance at 5% level.

Following the procedure of excluding the variables with the highest p-value we obtain the final Model Table 4.3.2.

TABLE 4.3.2 Final Model Pooled OLS between lnGDP & International shipments

	coefficient	std. error	t-ratio	p-value
const	6.95691	0.317378	21.92	1.71e-045
International shipments	0.720736	0.100124	7.198	4.35e-011
GOVERNMENTEXPENDI~	0.0444000	0.00971386	4.571	1.12e-05
POPULATIONGROWTH	0.404431	0.0415830	9.726	3.92e-017
BorderLength (km)	-0.000103089	3.40851e-05	-3.024	0.0030
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	14.66724	S.E. of regression	0.335894	
R-squared	0.734533	Adjusted R-squared	0.726364	
F(4, 130)	89.92557	P-value(F)	1.77e-36	
Log-likelihood	-41.72977	Akaike criterion	93.45954	
Schwarz criterion	107.9859	Hannan-Quinn	99.36265	
Rho	0.706670	Durbin-Watson	0.535985	

*** Note: * denote test statistic significance at the 5% level

The final mathematical equation that corresponds to our last multiple regression above is:

$$\ln GDP = 6.96 + 0.721 * \text{International shipments} + 0.0444 * \text{GOVERNMENTEXPENDITURE} + 0.404 * \text{POPULATIONGROWTH} - 0.000103 * \text{BorderLength km}$$

for sample size of $n = 135$ & $R\text{-squared} = 0.735$

According to the resulting equation we examine if the model is statistically significant that at least one of the independent variables can have a linear relationship with the dependent variable.

More specifically we examine the following hypothesis:

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$$

$$H_1: \text{At least one } \beta_i \text{ is not equal to } 0$$

Using as test statistic significance at the 5% level ($\alpha=5\%$), at least one beta coefficient cannot be equal to 0, the model is able to appear validity in a specific degree. So, if we examine the GDP value we have the following tasks:

- 1) $\beta_1 = 0.721$ which means that for an increase of the value of International shipments by 1 unit, GDP increases by $\exp(0.721) = 2.06$ units with the rest independent variables remaining unchanged

- 2) $\beta_2 = 0.0444$ which means that for an increase of 1 unit at the level of GOVERNMENTEXPENDITURE, GDP increases by $\exp(0.0444) = 1.05$ units with the rest independent variables remaining unchanged
- 3) $\beta_3 = 0.404$ which means that for an increase of 1 unit at the level of Population Growth, the GDP increases by $\exp(0.404) = 1.50$ units with the rest independent variables remaining unchanged
- 4) $\beta_4 = -0.000103$ which means that for an increase of 1000km at the Border Length of a country, the GDP decreases by $\exp(-0.103) = 0.90$ units with the rest independent variables remaining unchanged. We can see that this decrease is around zero so the impact of the variable of Border Length (km) is meaningless to the dependent variable of $\ln\text{GDP}$

The adjusted R^2 is equal to 0.7264 similar to the initial value and depicts that 72.64% of the variation in $\ln\text{GDP}$ can be explained by the independent variables adjusted by the given sample size.

The next normal probability plot depicts that the residual estimation errors do not deviate significantly from the normal distribution.

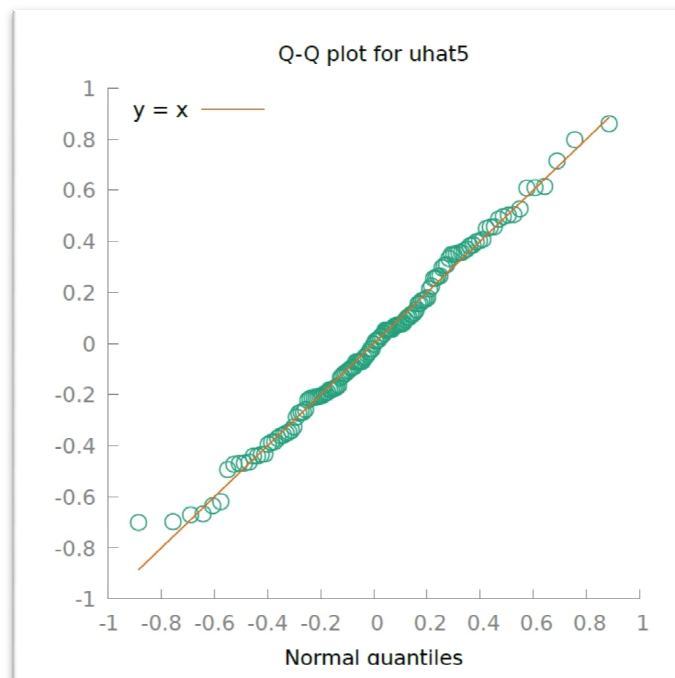


FIG. 4.3 NORMAL PROBABILITY PLOT BETWEEN $\ln\text{GDP}$ & INTERNATIONAL SHIPMENTS

According to the above plot we can check the hypotheses of the independence and the homoskedasticity of the residuals.

Summarizing, we conclude that the economic growth increases in a satisfying level as:

- ✓ the International shipments improve
- ✓ the Population Growth increases

The increase of the amount of Government Expenditure does not influence economic growth so much. On the other hand, we notice a reduction of economic growth as the Border length of a country increases.

4.4 Model 4 - LnGDP & Logistics Quality & Competence

Implementing the first multiple regression setting as dependent variable the lnGDP and independent variable the Logistics Quality & Competence including the macro-variables of INVESTMENT, GOVERNMENT EXPENDITURE, UNEMPLOYMENT, INFLATION, POPULATION GROWTH, BorderLength (km) & Landlocked we have the following Table 4.4.1.

TABLE 4.4.1 Initial Model Pooled OLS between lnGDP & LOGISTICS QUALITY & COMPETENCE

	coefficient	std. error	t-ratio	p-value
const	7.33203	0.287847	25.47	1.56e-051
LOGISTICS QUALITY & COMPETENCE	0.850952	0.0711404	11.96	1.68e-022
INVESTMENT	-0.00823531	0.00749678	-1.099	0.2741
GOVERNMENTEXPENDI	0.00706102	0.00922026	0.7658	0.4452
UNEMPLOYMENT	0.00745560	0.00633905	1.176	0.2418
INFLATION	0.0220729	0.0175376	1.259	0.2105
POPULATIONGROWTH	0.330906	0.0390487	8.474	5.30e-014
BorderLength (km)	-0.000146980	2.95688e-05	-4.971	2.13e-06
LandLocked	0.0476805	0.0654037	0.7290	0.4673
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	9.456871	S.E. of regression	0.273961	
R-squared	0.828837	Adjusted R-squared	0.817969	
F(8, 126)	76.26747	P-value(F)	1.33e-44	
Log-likelihood	-12.10571	Akaike criterion	42.21142	
Schwarz criterion	68.35889	Hannan-Quinn	52.83702	
Rho	0.523665	Durbin-Watson	0.734530	

We exclude successively the variables Landlocked, GOVERNMENTEXPENDITURE, INVESTMENT, INFLATION, UNEMPLOYMENT according to its highest p-value and test statistic significance at 5% level.

Following the procedure of excluding the variables with the highest p-value we obtain the final Model Table 4.4.2.

TABLE 4.4.2 Final Model Pooled OLS between lnGDP & LOGISTICS QUALITY & COMPETENCE

	coefficient	std. error	t-ratio	p-value
const	7.40230	0.189702	39.02	5.42e-074
LOGISTICS QUALITY & COMPETENCE	0.856228	0.0576415	14.85	7.12e-030
POPULATIONGROWTH	0.312690	0.0349014	8.959	2.83e-015
BorderLength (km)	-0.000154475	2.81554e-05	-5.487	2.04e-07
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	9.961570	S.E. of regression	0.275758	
R-squared	0.819702	Adjusted R-squared	0.815573	
F(3, 131)	198.5251	P-value(F)	1.54e-48	
Log-likelihood	-15.61525	Akaike criterion	39.23049	
Schwarz criterion	50.85159	Hannan-Quinn	43.95298	
Rho	0.551163	Durbin-Watson	0.687419	

*** Note: * denote test statistic significance at the 5% level

The final mathematical equation that corresponds to our last multiple regression above is:

$$\ln GDP = 7.40 + 0.856 * \text{Logistics quality and competence} + 0.313 * \text{POPULATIONGROWTH} - 0.000154 * \text{BorderLength km}$$

for sample size of $n = 135$ & $R\text{-squared} = 0.820$

According to the resulting equation we examine if the model is statistically significant that at least one of the independent variables can have a linear relationship with the dependent variable.

More specifically we examine the following hypothesis:

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$$

$$H_1: \text{At least one } \beta_i \text{ is not equal to } 0$$

Using as test statistic significance at the 5% level ($\alpha=5\%$), at least one beta coefficient cannot be equal to 0, the model is able to appear validity in a specific degree. So, if we examine the GDP value we have the following tasks:

- 1) $\beta_1 = 0.856$ which means that for an increase on the advance of Logistics quality and competence by 1 unit, GDP increases by $\exp(0.856) = 2.35$ units with the rest independent variables remaining unchanged

- 2) $\beta_2 = 0.313$ which means that for an increase of 1 unit at the level of Population Growth, the GDP increases by $\exp(0.313) = 1.37$ units with the rest independent variables remaining unchanged
- 3) $\beta_3 = -0.000154$ which means that for an increase of 1000km at the Border Length of a country, the GDP decreases by $\exp(-0.154) = 0.86$ units with the rest independent variables remaining unchanged. We can see that this decrease is around zero so the impact of the variable of Border Length (km) is meaningless to the dependent variable of $\ln\text{GDP}$

The adjusted R^2 is equal to 0.8156 similar to the initial value and depicts that 81.56% of the variation in $\ln\text{GDP}$ can be explained by the independent variables adjusted by the given sample size.

The next normal probability plot depicts that the residual estimation errors do not deviate significantly from the normal distribution.

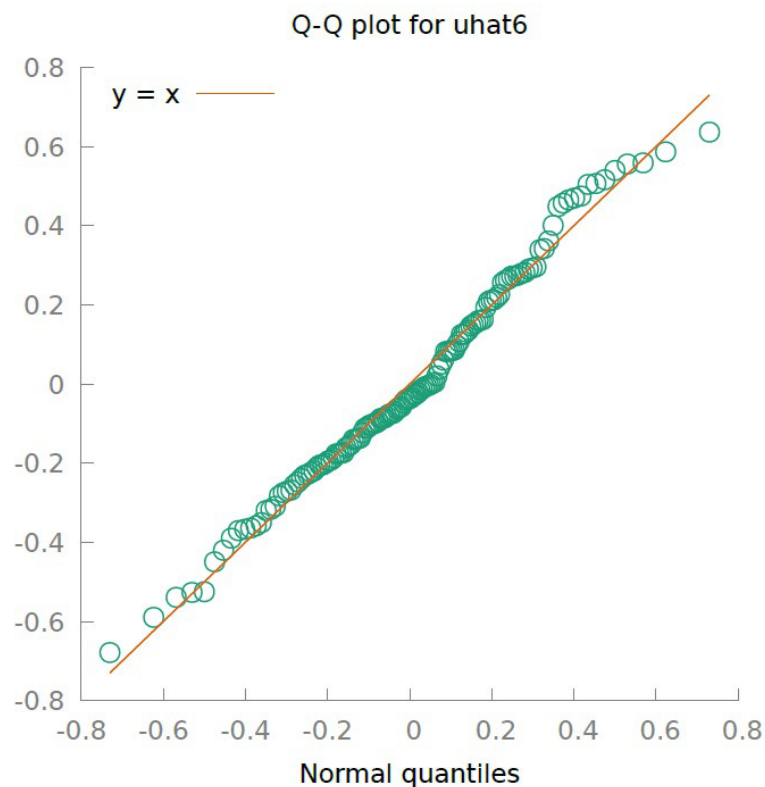


FIG. 4.4 NORMAL PROBABILITY PLOT BETWEEN LNGDP & LOGISTICS QUALITY & COMPETENCE

According to the above plot we can check the hypotheses of the independence and the homoskedasticity of the residuals.

Summarizing, we conclude that the economic growth increases in a satisfying level as:

- ✓ the advance of Logistics quality and competence enhances
- ✓ the Population Growth increases

On the other hand, we notice a reduction of economic growth as the Border length of a country increases.

4.5 Model 5 - LnGDP & Tracking & Tracing

Implementing the first multiple regression setting as dependent variable the LnGDP and independent variable the Tracking & Tracing including the macro-variables of INVESTMENT, GOVERNMENT EXPENDITURE, UNEMPLOYMENT, INFLATION, POPULATION GROWTH, BorderLength (km) & Landlocked we have the following Table 4.5.1.

TABLE 4.5.1 Initial Model Pooled OLS between lnGDP & TRACKING AND TRACING

	coefficient	std. error	t-ratio	p-value
const	7.49837	0.308079	24.34	1.84e-049
TRACKING AND TRACING	0.748238	0.0728021	10.28	2.28e-018
INVESTMENT	-0.0122717	0.00810672	-1.514	0.1326
GOVERNMENTEXPENDI	0.0195266	0.00952666	2.050	0.0425
~				
UNEMPLOYMENT	0.00164811	0.00678646	0.2429	0.8085
INFLATION	0.00413197	0.0186058	0.2221	0.8246
POPULATIONGROWTH	0.370945	0.0411295	9.019	2.64e-015
BorderLength (km)	-0.000125177	3.14690e-05	-3.978	0.0001
LandLocked	0.0419346	0.0704953	0.5949	0.5530
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	10.98578	S.E. of regression	0.295277	
R-squared	0.801165	Adjusted R-squared	0.788540	
F(8, 126)	63.46122	P-value(F)	1.52e-40	
Log-likelihood	-22.22130	Akaike criterion	62.44259	
Schwarz criterion	88.59006	Hannan-Quinn	73.06819	
Rho	0.488214	Durbin-Watson	0.867050	

We exclude successively the variables INFLATION, UNEMPLOYMENT, Landlocked, INVESTMENT according to its highest p-value and test statistic significance at 5% level.

Following the procedure of excluding the variables with the highest p-value we obtain the final Model Table 4.5.2.

TABLE 4.5.2 Final Model Pooled OLS between lnGDP & TRACKING AND TRACING

	coefficient	std. error	t-ratio	p-value
const	7.30567	0.219745	33.25	2.04e-065
TRACKING AND TRACING	0.732617	0.0710647	10.31	1.40e-018
GOVERNMENTEXPENDI~	0.0206363	0.00924320	2.233	0.0273
POPULATIONGROWTH	0.368707	0.0366274	10.07	5.62e-018
BorderLength (km)	-0.000129492	3.01364e-05	-4.297	3.37e-05
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	11.28648	S.E. of regression	0.294651	
R-squared	0.795722	Adjusted R-squared	0.789437	
F(4, 131)	126.5971	P-value(F)	7.70e-44	
Log-likelihood	-24.04401	Akaike criterion	58.08802	
Schwarz criterion	72.61440	Hannan-Quinn	63.99113	
Rho	0.514456	Durbin-Watson	0.811575	

*** *Note:* denote test statistic significance at the 5% level

The final mathematical equation that corresponds to our last multiple regression above is:

$$\ln GDP = 7.31 + 0.733 * \text{Trackingandtracing} + 0.0206 * \text{GOVERNMENTEXPENDITURE} + 0.369 * \text{POPULATIONGROWTH} - 0.000129 * \text{BorderLengthkm}$$

for sample size of $n = 135$ & $R\text{-squared} = 0.796$

According to the resulting equation we examine if the model is statistically significant that at least one of the independent variables can have a linear relationship with the dependent variable.

More specifically we examine the following hypothesis:

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$$

$$H_1: \text{At least one } \beta_1 \text{ is not equal to } 0$$

Using as test statistic significance at the 5% level ($\alpha=5\%$), at least one beta coefficient cannot be equal to 0, the model is able to appear validity in a specific degree. So, if we examine the GDP value we have the following tasks:

- 1) $\beta_1 = 0.733$ which means that for an increase of Tracking and tracing performance by 1 unit, GDP increases by $\exp(0.733) = 2.08$ units with the rest independent variables remaining unchanged

- 2) $\beta_2 = 0.0206$ which means that for an increase of 1 unit at the value of GOVERNMENT EXPENDITURE, GDP increases by $\exp(0.0206) = 1.02$ units with the rest independent variables remaining unchanged
- 3) $\beta_3 = 0.369$ which means that for an increase of 1% at the level of Population Growth, the GDP increases by $\exp(0.369) = 1.45$ units with the rest independent variables remaining unchanged
- 4) $\beta_4 = -0.000129$ which means that for an increase of 1000km at the Border Length of a country, the GDP decreases by $\exp(-0.129) = 0.88$ with the rest independent variables remaining unchanged. We can see that this decrease is around zero so the impact of the variable of Border Length (km) is meaningless to the dependent variable of $\ln\text{GDP}$

The adjusted R^2 is equal to 0.7894 similar to the initial value and depicts that 78.94% of the variation in $\ln\text{GDP}$ can be explained by the independent variables adjusted by the given sample size.

The next normal probability plot depicts that the residual estimation errors do not deviate significantly from the normal distribution.

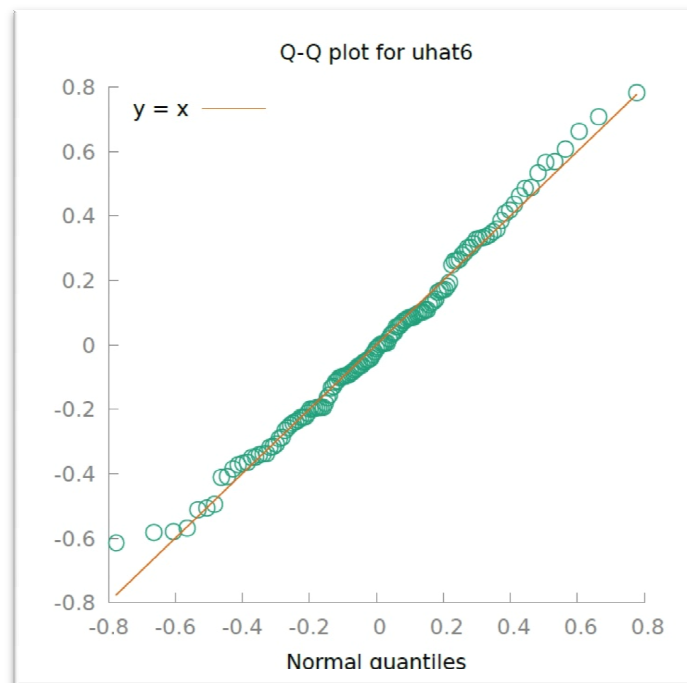


FIG. 4.5 NORMAL PROBABILITY PLOT BETWEEN $\ln\text{GDP}$ & TRACKING & TRACING

According to the above plot we can check the hypotheses of the independence and the homoskedasticity of the residuals.

Summarizing, we conclude that the economic growth increases in a satisfying level as:

- ✓ the Tracking and tracing performance improves
- ✓ the Population Growth increases

The increase of the amount of Government expenditure does not influence economic growth so much. On the other hand, we notice a reduction of economic growth as the Border length of a country increases.

4.6 Model 6 - LnGDP & Timeliness

Implementing the first multiple regression setting as dependent variable the LnGDP and independent variable the Timeliness including the macro-variables of INVESTMENT, GOVERNMENT EXPENDITURE, UNEMPLOYMENT, INFLATION, POPULATION GROWTH, BorderLength (km) & Landlocked we have the following Table 4.6.1.

TABLE 4.6.1 Initial Model Pooled OLS between lnGDP & TIMELINESS

	coefficient	std. error	t-ratio	p-value
const	7.00785	0.403927	17.35	3.40e-035
TIMELINESS	0.641775	0.0863773	7.430	1.45e-011
INVESTMENT	-0.00304796	0.00913196	-0.3338	0.7391
GOVERNMENTEXPENDI	0.0388842	0.0101385	3.835	0.0002
~				
UNEMPLOYMENT	0.00288255	0.00769220	0.3747	0.7085
INFLATION	0.00383322	0.0211994	0.1808	0.8568
POPULATIONGROWTH	0.429638	0.0451871	9.508	1.73e-016
BorderLength (km)	-9.16141e-05	3.50003e-05	-2.618	0.0099
LandLocked	0.0102544	0.0798637	0.1284	0.8980
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	14.04305	S.E. of regression	0.333845	
R-squared	0.745830	Adjusted R-squared	0.729692	
F(8, 126)	46.21641	P-value(F)	6.43e-34	
Log-likelihood	-38.79427	Akaike criterion	95.58854	
Schwarz criterion	121.7360	Hannan-Quinn	106.2141	
Rho	0.653858	Durbin-Watson	0.593911	

We exclude successively the variables Landlocked, INFLATION, INVESTMENT, INVESTMENT, UNEMPLOYMENT according to its highest p-value and test statistic significance at 5% level.

Following the procedure of excluding the variables with the highest p-value we obtain the final Model Table 4.6.2

TABLE 4.6.2 Final Model Pooled OLS between lnGDP & TIMELINESS

	coefficient	std. error	t-ratio	p-value
const	6.99353	0.298271	23.45	1.56e-048
TIMELINESS	0.637640	0.0828632	7.695	3.12e-012
GOVERNMENTEXPENDI~	0.0392427	0.00971096	4.041	9.05e-05
POPULATIONGROWTH	0.421850	0.0395877	10.66	1.92e-019
BorderLength (km)	-9.54887e-05	3.30213e-05	-2.892	0.0045
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	14.09382	S.E. of regression	0.329263	
R-squared	0.744911	Adjusted R-squared	0.737062	
F(4, 130)	94.90659	P-value(F)	1.35e-37	
Log-likelihood	-39.03785	Akaike criterion	88.07570	
Schwarz criterion	102.6021	Hannan-Quinn	93.97881	
Rho	0.657779	Durbin-Watson	0.587625	

*** Note: denote test statistic significance at the 5% level

The final mathematical equation that corresponds to our last multiple regression above is:

$$\ln GDP = 6.99 + 0.638 * Timeliness + 0.0392 * GOVERNMENTEXPENDITURE + 0.422 * POPULATIONGROWTH - 9.55e-05 * BorderLengthkm$$

for sample size of $n = 135$ & $R\text{-squared} = 0.745$

According to the resulting equation we examine if the model is statistically significant that at least one of the independent variables can have a linear relationship with the dependent variable.

More specifically we examine the following hypothesis:

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$$

$$H_1: \text{At least one } \beta_i \text{ is not equal to } 0$$

Using as test statistic significance at the 5% level ($\alpha=5\%$), at least one beta coefficient cannot be equal to 0, the model is able to appear validity in a specific degree. So, if we examine the GDP value we have the following tasks:

- 1) $\beta_1 = 0.638$ which means that for an enhancement of Timeliness advance by 1 unit, GDP increases by $\exp(0.638) = 1.89$ units with the rest independent variables remaining unchanged
- 2) $\beta_2 = 0.0392$ which means that for an increase of 1 unit at the amount of GOVERNMENT EXPENDITURE, GDP increases by $\exp(0.0392) = 1.04$ units with the rest independent variables remaining unchanged

3) $\beta_3 = 0.422$ which means that for an increase of 1 unit at the level of Population Growth, the GDP increases by $\exp(0.422) = 1.53$ units with the rest independent variables remaining unchanged

4) $\beta_4 = -9.55e-05$ we observe that the coefficient is around zero so the impact of the variable of Border Length(km) is meaningless to the dependent variable of GDP

The adjusted R^2 is equal to 0.7371 similar to the initial value and depicts that 73.71% of the variation in $\ln GDP$ can be explained by the independent variables adjusted by the given sample size.

The next normal probability plot depicts that the residual estimation errors do not deviate significantly from the normal distribution.

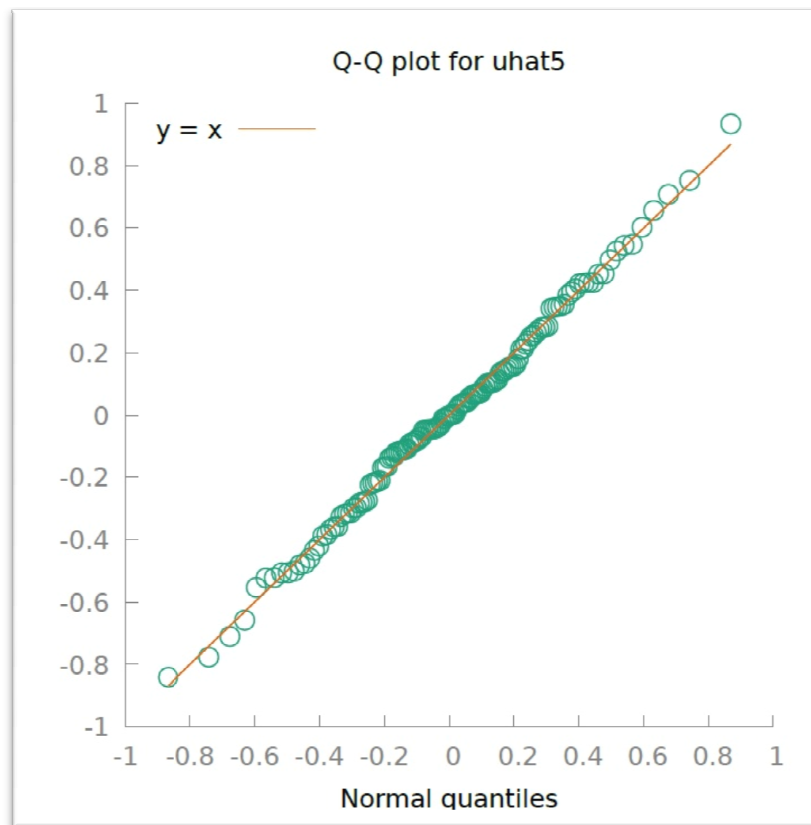


FIG. 4.6 NORMAL PROBABILITY PLOT BETWEEN LNGDP & TIMELINESS

According to the above plot we can check the hypotheses of the independence and the homoskedasticity of the residuals.

Summarizing, we conclude that the economic growth increases in a satisfying level as:

- ✓ the advance of Timeliness enhances
- ✓ the Population Growth increases

The increase of the amount of Government expenditure does not influence economic growth so much. On the other hand, we conclude that the impact of the Border Length (km) parameter is meaningless into the economic growth.

4.7 Model 7 - LnGDP & Overall LPI

Implementing the first multiple regression setting as dependent variable the lnGDP and independent variable the Overall LPI including the macro-variables of INVESTMENT, GOVERNMENT EXPENDITURE, UNEMPLOYMENT, INFLATION, POPULATION GROWTH, BorderLength (km) & Landlocked we have the following Table 4.7.1.

TABLE 4.7.1 Initial Model Pooled OLS between lnGDP & overall LPI

	coefficient	std. error	t-ratio	p-value
const	6.80822	0.303789	22.41	8.70e-046
overallLPIscore	0.978105	0.0792102	12.35	1.91e-023
INVESTMENT	-0.00763421	0.00736736	-1.036	0.3021
GOVERNMENTEXPENDI	0.00816207	0.00897198	0.9097	0.3647
~				
UNEMPLOYMENT	0.00707757	0.00622587	1.137	0.2578
INFLATION	0.0264636	0.0173149	1.528	0.1289
POPULATIONGROWTH	0.326971	0.0384221	8.510	4.36e-014
BorderLength (km)	-0.000141634	2.88807e-05	-4.904	2.84e-06
LandLocked	0.0342299	0.0643005	0.5323	0.5954
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	9.137695	S.E. of regression	0.269298	
R-squared	0.834614	Adjusted R-squared	0.824113	
F(8, 126)	79.48160	P-value(F)	1.56e-45	
Log-likelihood	-9.788207	Akaike criterion	37.57641	
Schwarz criterion	63.72389	Hannan-Quinn	48.20201	
Rho	0.494156	Durbin-Watson	0.843365	

We exclude successively the variables Landlocked, GOVERNMENTEXPENDITURE, INVESTMENT, INFLATION, UNEMPLOYMENT according to its highest p-value and test statistic significance at 5% level.

Following the procedure of excluding the variables with the highest p-value we obtain the final Model Table 4.7.2.

TABLE 4.7.2 Final Model Pooled OLS between lnGDP & overall LPI

	coefficient	std. error	t-ratio	p-value
const	6.89819	0.217479	31.72	2.49e-063
overallLPIscore	0.987487	0.0649027	15.21	9.66e-031
POPULATIONGROWTH	0.307944	0.0344558	8.937	3.20e-015
BorderLength (km)	-0.000148836	2.75950e-05	-5.394	3.12e-07
Mean dependent var	10.20493	S.D. dependent var	0.642120	
Sum squared resid	9.663645	S.E. of regression	0.271603	
R-squared	0.825094	Adjusted R-squared	0.821089	
F(5, 129)	205.9918	P-value(F)	2.12e-49	
Log-likelihood	-13.56569	Akaike criterion	35.13138	
Schwarz criterion	46.75248	Hannan-Quinn	39.85387	
Rho	0.503113	Durbin-Watson	0.830739	

*** *Note:* denote test statistic significance at the 5% level

The final mathematical equation that corresponds to our last multiple regression above is:

$$\ln gdp = 6.90 + 0.987 * overallLPIscore + 0.308 * POPULATIONGROWTH - 0.000149 * BorderLengthkm$$

for sample size of $n = 135$ & $R\text{-squared} = 0.825$

According to the resulting equation we examine if the model is statistically significant that at least one of the independent variables can have a linear relationship with the dependent variable.

More specifically we examine the following hypothesis:

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$$

$$H_1: \text{At least one } \beta_i \text{ is not equal to } 0$$

Using as test statistic significance at the 5% level ($\alpha=5\%$), at least one beta coefficient cannot be equal to 0, the model is able to appear validity in a specific degree. So, if we examine the GDP value we have the following tasks:

- 1) $\beta_1 = 0.987$ which means that for an increase of the overall LPI score by 1 unit, GDP increases by $\exp(0.987) = 2.68$ units with the rest independent variables remaining unchanged
- 2) $\beta_2 = 0.308$ which means that for an increase of 1 unit at the level of Population Growth, the GDP increases by $\exp(0.308) = 1.36$ units with the rest independent variables remaining unchanged

- 3) $\beta_3 = -0.000149$ which means that for an increase of 1000km at the Border Length of a country, the GDP decreases by $\exp(-0.149) = 0.86$ units with the rest independent variables remaining unchanged. We can see that this decrease is around zero so the impact of the variable of Border Length(km) is meaningless to the dependent variable of lnGDP

The adjusted R^2 is equal to 0.8210 similar to the initial value and depicts that 82.10% of the variation in lnGDP can be explained by the independent variables adjusted by the given sample size.

The next normal probability plot depicts that the residual estimation errors do not deviate significantly from the normal distribution.

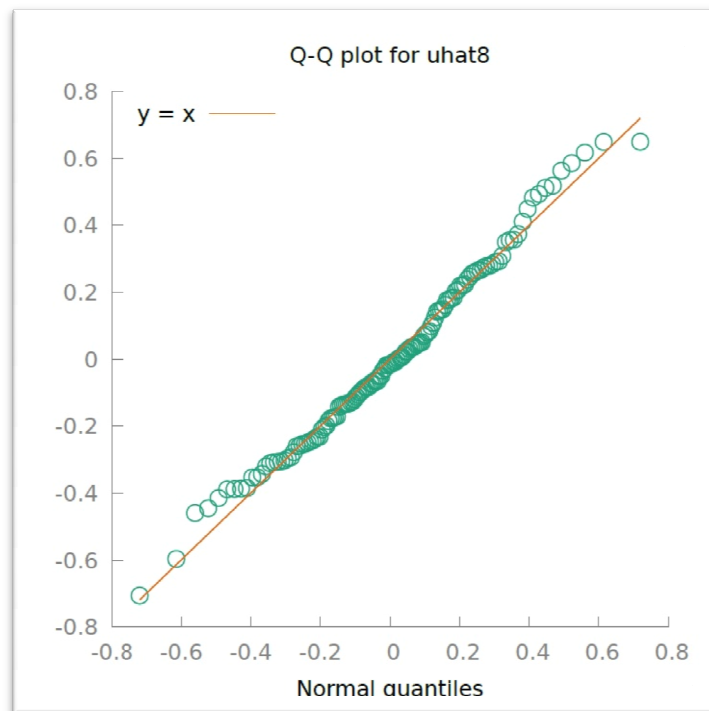


FIG. 4.7 NORMAL PROBABILITY PLOT BETWEEN LNGDP & OVERALL LPI

According to the above plot we can check the hypotheses of the independence and the homoskedasticity of the residuals. Summarizing, we conclude that the economic growth increases in a satisfying level as

- ✓ the overall LPI score increases
- ✓ the Population Growth increases

On the other hand, we notice a reduction of economic growth as the Border length of a country increases.

5. Simulated impact of supply chain disruptions due to COVID-19

Our ultimate goal of our analysis was the possibility to approach to some extent the disorder that occurred into the supply chain services during the pandemic period of COVID-19. More specifically, the disruptions from the stage of the production, the workforce and the transportation, created the huge demand from the financial and political point of view of an accurate model that could contribute to a better managing of future sudden trade shutdown in a national or a global level.

Accordingly, in this section, we could assume a forecasting scenario for the country of Greece that is related to the next 3 successive years of 2019, 2020 & 2021 where the coronavirus transmission was intense and exerted influence in the economic growth at a maximum level. More specifically, we could search the overall LPI score in case of the given GDP per capita values respectively to each reference year and to what extent the forecasting results match our simulation model that we discussed. Up to this concept, we could get a feedback of the level of the well or not well operation of the supply chain structures in Greece during and after the spread of the coronavirus. The following index depicts our scenarios:

COUNTRY	REFERENCE	YEAR	GDP	LnGDP	Overall LPI score
22	GREECE	2010	26690,607	10,192	2,96
22	GREECE	2012	21914,252	9,995	2,83
22	GREECE	2014	21587,958	9,980	3,20
22	GREECE	2016	17911,799	9,793	3,24
22	GREECE	2018	19747,343	9,891	3,20
22	GREECE	2019	19144,30	9.860	???
22	GREECE	2020	17658,90	9.779	???
22	GREECE	2021	20192,60	9.913	???

According to current observations and limited time period of researches, we cannot be sure for the reliability of any possible forecasting structure due to multi-parameters that are engaged with the social & economic phenomenon of COVID-19 and logistics domain that we have omitted from our analysis. A representative sample of these omitted factors

could be individual factors that constitute the performance of a supply chain such as immobility of labor, discontinuation of operation for small or bigger intervals. Moreover, it is worth noting a country's (e.g. Greece) dependence level of China and other global supply chains in raw materials or semi-assembled items. Indeed, we have examined specific parameters of which we had reliable data at our disposal. As the consequences of COVID-19 are still unfolding, there is a big gap of ascertained data of significant parameters that influence the economic growth during coronavirus period. The case of a non integrated supply chain network that could inhibit large-scale economic consequences could be an interesting task for further analysis.

Taking into consideration the aforementioned concerns we suggest further research up to this direction in a ten-year time horizon.

6. Conclusions

Due to limitations on our specific topic of research because we continue to face the pandemic crisis and its consequences, we relied on published researches on this topic (Rajeev K., et al Supply chain performance and economic growth: The impact of COVID-19 disruptions), the literature on regression and panel models methodology (Hill, R.C. et al, 2011) and other researches that have been published during the completion of this dissertation.

The basic aims of this research included the following tasks:

- examine the contribution on economic growth of different economic & social parameters such as Inflation, Unemployment e.t.c. as well as the dimensions of supply chain logistics such as Customs cost, Timeliness e.t.c. . The consideration of these aspects enabled us to observe differing growth results, positive or negative impact on economic growth and to detect possible advances in logistics dimensions for further improvement in supply chain operation in a more coordinated and reconsidered manner.
- Identification of logistics performance variety across the 27 European countries with different growth rates through the Logistics Performance Index (LPI) published by the World Bank in 2010, 2012, 2014, 2016 and 2018.
- impact exploration of both supply and demand drivers during coronavirus crisis on economic chains
- forecasting probability of the uncertain period after the ongoing crisis as an interesting domain for research through simulation models in order to estimate future crises under uncertain conditions

According to our outcomes we conclude that the improvement of each LPI component enhances the economic growth as well as the improvement of the total performance of the logistics services. Based on our analysis, further outcomes emerged that exhibit economic growth enhancement as the population growth increases. On the contrary, we notice a small reduction on economic growth as the border length of a country increases.

References

Adam Slater Lead Economist “The new post-Covid long-term looks much like the old one”
OXFORD ECONOMICS, OCTOBER 2021

Alicke, K., Barriball, E., Lund, S., & Swan, D. (2020). Is your supply chain risk blind – or risk resilient? McKinsey & Company. <https://www.mckinsey.com/business-functions/operations/our-insights/is-your-supply-chain-risk-blind-or-risk-resilient>
<https://www.rdocumentation.org/packages/pwt9/versions/9.1-0/topics/pwt9.1>
<http://chartsbin.com/view/mp2>

Arvis, J.-F., Ojala, L., Wiederer, C., Shepherd, B., Raj, A., Dairabayeva, K. and Kiiski, T. (2018), Connecting to Compete 2018 Trade Logistics in the Global Economy. The Logistics Performance Index and its Indicators.

Baldwin, R., & Weder di Mauro, B. (Eds.). (2020). *Economics in the Time of COVID-19*. Centre for Economic Policy Research, London: CEPR Press.
<http://acdc2007.free.fr/ceprcorona.pdf>

Chaudhary, M., Sodani, P.R. and Das, S. (2020) “Effect of covid-19 on economy in India: Some reflections for policy and Programme,” *Journal of Health Management*, 22(2), pp. 169–180. Available at: <https://doi.org/10.1177/0972063420935541>.

Christiana Hilmer, Michael Hilmer - Practical Econometrics (The McGraw-hill_Irwin Series in Economics)-McGraw-Hill Education (2013)

Elekdag, S., Muir, D., & Wu, Y. (2015). Trade linkages, balance sheets, and spillovers: The Germany-Central European Supply Chain. *Journal of Policy Modeling*, 37(2), 374–387.
CONNECTING TO COMPETE 2014 TRADE LOGISTICS IN THE GLOBAL ECONOMY –

Hill, R.C., Griffiths, W.E. and Lim, G.C. (2011) *Principles of econometrics*. Hoboken, NJ: Wiley.

Hilmer, C.E. and Hilmer, M.J. (2014) *Practical econometrics: Data collection, analysis, and application*. New York: McGraw-Hill Education.

Korinek, J. and Sourdin, P. (2011) To what extent are high-quality logistics services trade facilitating?, *OECD Trade Policy Working Papers* 108. OECD Publishing.

Luo, S., & Tsang, K. P. (2020). China and world output impact of the Hubei lockdown during the Coronavirus outbreak. *Contemporary Economic Policy*, 38(4), 583–592.

Martí L. R. Puertasb and L. Garcíac (2014) - IMPORTANCE OF THE LOGISTICS PERFORMANCE INDEX IN INTERNATIONAL TRADE

Marti, L., Mart_in, J.C. and Puertas, R. (2017), “A dea-logistics performance index”, *Journal of Applied Economics*, Vol. 20 No. 1, pp. 169-192, doi: [10.1016/S1514-0326\(17\)30008-9](https://doi.org/10.1016/S1514-0326(17)30008-9).

Marti, L. and Puertas, R. (2017), “The importance of export logistics and trade costs in emerging economies”, Maritime Economics and Logistics, Valencia, Spain. doi: [10.1057/mel.2015.31](https://doi.org/10.1057/mel.2015.31).

Mayer, T., & Zignago, S. (2011). Notes on CEPII’s distance measures: The GeoDist database. In CEPII Working Paper#2011-25.. https://mpra.ub.unimuenchen.de/36347/2/MPPA_paper_36347.pdf

Moffatt Mike. "What Is Panel Data?" ThoughtCo, Aug. 26, 2020, [thoughtco.com/panel-data-definition-in-economic-research-1147034](https://www.thoughtco.com/panel-data-definition-in-economic-research-1147034).

Olyanga, A.M. *et al.* (2022) “Export Logistics Infrastructure and export competitiveness in the East African Community,” *Modern Supply Chain Research and Applications*, 4(1), pp. 39–61. Available at: <https://doi.org/10.1108/mscra-09-2021-0017>.

Puertas Medina, R.M., Mart_1 Selva, M.L. and Garcia Menendez, L. (2013), “Logistics performance and export competitiveness: European experience”, *Empirica*, pp. 1-14, doi: [10.1007/s10663-013-9241-z](https://doi.org/10.1007/s10663-013-9241-z).

Rajeev K., et all , Supply chain performance and economic growth:The impact of COVID-19 disruptions, 28 January 2021

Salvatore, D. (2020). Growth and trade in the United States and the world economy: Overview. *Journal of Policy Modeling*,42(4), 750–759.

Studenmund, A.H. (2017) Using econometrics a practical guide. Boston: Pearson.

<https://proxy.eap.gr/login?url=https://www.proquest.com/newspapers/growthslows-19-european-countries/docview/2624100798/se-2?accountid=16059>

<https://www.wikipedia.org/>

<https://lpi.worldbank.org/international>

Appendix A: DATASET OF MICRO & MACRO-VARIABLES

A/A	REFERENCE	YEAR	GDP	lnGDP	overall LPI score	Customs	Infrastructure	International shipments	Logistics quality and competence	Tracking and tracing	Timeliness	INVESTMENT	GOVERNMENT EXPENDITURE	UNEMPLOYMENT	INFLATION	POLPULATION GROWTH	Border Length (km)	Land-Locked
1	GERMANY	2010	41531,934	10,634218	4,11	4,00	4,34	3,66	4,14	4,18	4,48	20,0657854	19,56321167	6,96999979	1,103809	-0,153198447	3621	0
1	GERMANY	2012	43858,363	10,688721	4,03	3,87	4,26	3,67	4,09	4,05	4,32	19,7159884	19,27687584	5,380000114	2,008491	0,187727801	3621	0
1	GERMANY	2014	47959,993	10,778122	4,12	4,10	4,32	3,74	4,12	4,17	4,36	20,3702907	19,58902519	4,980000019	0,906798	0,416877359	3621	0
1	GERMANY	2016	42107,517	10,647982	4,23	4,12	4,44	3,86	4,28	4,27	4,45	19,9674295	19,90120393	4,119999886	0,491749	0,807218539	3621	0
1	GERMANY	2018	47950,181	10,777918	4,20	4,09	4,37	3,86	4,31	4,24	4,39	21,9046516	19,90480602	3,380000114	1,732168	0,300526702	3621	0
2	NETHERLANDS	2010	50950,034	10,838601	4,07	3,98	4,25	3,61	4,15	4,12	4,41	20,2216253	26,24333724	4,989999771	1,275306	0,512923101	1027	0
2	NETHERLANDS	2012	50073,006	10,821237	4,02	3,85	4,15	3,86	4,05	4,12	4,15	18,7247115	26,02662313	5,820000172	2,455548	0,370055035	1027	0
2	NETHERLANDS	2014	52830,174	10,874838	4,05	3,96	4,23	3,64	4,13	4,07	4,34	17,9126214	25,68124963	7,420000076	0,976035	0,359828173	1027	0
2	NETHERLANDS	2016	46007,853	10,736567	4,19	4,12	4,29	3,94	4,22	4,17	4,41	20,4875645	24,6834487	6,010000229	0,316667	0,53217888	1027	0
2	NETHERLANDS	2018	53018,629	10,878399	4,02	3,92	4,21	3,68	4,09	4,02	4,25	20,9575871	24,36875555	3,829999924	1,703498	0,583933409	1027	0
3	BELGIUM	2010	44141,878	10,695164	3,94	3,83	4,01	3,31	4,13	4,22	4,29	23,1267767	23,73268609	8,289999962	2,189299	0,913639392	1385	0
3	BELGIUM	2012	44673,116	10,707127	3,98	3,85	4,12	3,73	3,98	4,05	4,20	23,6899258	24,30335286	7,539999962	2,839663	0,620163579	1385	0
3	BELGIUM	2014	47700,54	10,772698	4,04	3,80	4,10	3,80	4,11	4,11	4,39	23,1361877	24,23389585	8,520000458	0,340003	0,443929288	1385	0
3	BELGIUM	2016	41984,103	10,645046	4,11	3,83	4,05	4,05	4,07	4,22	4,43	24,2522123	23,26203662	7,829999924	1,973853	0,506300002	1385	0
3	BELGIUM	2018	47519,553	10,768897	4,04	3,66	3,98	3,99	4,13	4,05	4,41	25,3687916	23,09132851	5,949999809	2,053165	0,455184695	1385	0
4	SWEDEN	2010	52869,044	10,875573	4,08	3,88	4,03	3,83	4,22	4,22	4,32	22,9620372	25,03236949	8,609999657	1,157988	0,852524629	2233	0
4	SWEDEN	2012	58037,821	10,96885	3,85	3,68	4,13	3,39	3,90	3,82	4,26	22,5912255	25,75016978	7,980000019	0,888378	0,739763272	2233	0
4	SWEDEN	2014	60020,36	11,002439	3,96	3,75	4,09	3,76	3,98	3,98	4,26	23,5041187	26,08433328	7,949999809	-0,179638	0,992219729	2233	0
4	SWEDEN	2016	51965,157	10,858329	4,20	3,92	4,27	4,00	4,25	4,38	4,45	24,715387	26,36538679	6,989999771	0,984269	1,256453985	2233	0
4	SWEDEN	2018	54589,06	10,907589	4,05	4,05	4,24	3,92	3,98	3,88	4,28	26,0083971	26,05938812	6,360000134	1,953535	1,16164516	2233	0
5	LUXEMBOURG	2010	110777,91	11,615283	3,98	4,04	4,06	3,67	3,67	3,92	4,58	18,0831935	15,78580051	4,360000134	2,273679	1,825405804	359	1
5	LUXEMBOURG	2012	112591,12	11,631518	3,82	3,54	3,79	3,70	3,82	3,91	4,19	18,7523049	16,30409061	5,139999866	2,662842	2,4015419	359	1
5	LUXEMBOURG	2014	123514,2	11,724111	3,95	3,82	3,91	3,82	3,78	3,68	4,71	19,0935868	16,05145356	5,849999905	0,628544	2,356978705	359	1

5	LUXEMBOUR G	2016	106826,73	11,578963	4,22	3,90	4,24	4,24	4,01	4,12	4,80	17,9319133	15,6742178	6,289999962	0,290833	2,155311988	359	1
5	LUXEMBOUR G	2018	117197,48	11,671616	3,63	3,53	3,63	3,37	3,76	3,61	3,90	17,0955581	16,74251269	5,590000153	1,528195	1,928837514	359	1
6	IRELAND	2010	48607,941	10,791542	3,89	3,60	3,76	3,70	3,82	4,02	4,47	17,2801975	18,66869674	14,52999973	-0,922096	0,544884384	360	0
6	IRELAND	2012	49028,827	10,800164	3,52	3,40	3,35	3,40	3,54	3,65	3,77	20,1867609	18,17516531	15,44999981	1,696209	0,423743803	360	0
6	IRELAND	2014	55525,897	10,924605	3,87	3,80	3,84	3,44	3,94	4,13	4,13	22,2323864	16,3755193	11,85999966	0,182542	0,731001377	360	0
6	IRELAND	2016	62818,966	11,048012	3,79	3,47	3,77	3,83	3,79	3,98	3,94	37,5726174	12,72974366	8,369999886	0,008306	1,128834064	360	0
6	IRELAND	2018	79068,975	11,278076	3,51	3,36	3,29	3,42	3,60	3,62	3,76	28,5518355	11,90427924	5,739999771	0,48837	1,238875453	360	0
7	FRANCE	2010	40638,335	10,612467	3,84	3,63	4,00	3,30	3,87	4,01	4,37	21,9462945	23,98925669	8,869999886	1,531123	0,494040603	4,4	0
7	FRANCE	2012	40874,7	10,618267	3,85	3,64	3,96	3,73	3,82	3,97	4,02	22,6266323	23,9504999	9,399999619	1,954195	0,483998961	4,4	0
7	FRANCE	2014	43011,263	10,669217	3,85	3,65	3,98	3,68	3,75	3,89	4,17	22,7098311	24,12589283	10,28999996	0,507759	0,473706908	4,4	0
7	FRANCE	2016	37037,374	10,519683	3,90	3,71	4,01	3,64	3,82	4,02	4,25	22,6093927	23,73238072	10,05000019	0,183335	0,263868789	4,4	0
7	FRANCE	2018	41572,485	10,635194	3,84	3,59	4,00	3,55	3,84	4,00	4,15	23,8572576	23,27159496	9,020000458	1,850815	0,274451849	4,4	0
8	DENMARK	2010	58041,398	10,968912	3,85	3,58	3,99	3,46	3,83	3,94	4,38	18,0760462	27,36584798	7,75	2,310924	0,444197155	68	0
8	DENMARK	2012	58507,508	10,97691	4,02	3,93	4,07	3,70	4,14	4,10	4,21	19,4663909	26,47145553	7,800000191	2,397915	0,376272243	68	0
8	DENMARK	2014	62548,985	11,043705	3,78	3,79	3,82	3,65	3,74	3,36	4,39	20,0910206	25,78565204	6,929999828	0,564021	0,507053283	68	0
8	DENMARK	2016	54663,998	10,908961	3,82	3,82	3,75	3,66	4,01	3,74	3,92	21,7753957	24,86850637	5,989999771	0,25	0,780392644	68	0
8	DENMARK	2018	61591,929	11,028286	3,99	3,92	3,96	3,53	4,01	4,18	4,41	22,5992898	24,27535142	5,130000114	0,813609	0,495838926	68	0
9	SPAIN	2010	30502,72	10,325571	3,63	3,47	3,58	3,11	3,62	3,96	4,12	22,3030663	20,63290231	19,86000061	1,799881	0,460408305	1917,8	0
9	SPAIN	2012	28324,429	10,25148	3,70	3,40	3,74	3,68	3,69	3,67	4,02	18,4356691	19,97693723	24,79000092	2,446	0,064925963	1917,8	0
9	SPAIN	2014	29461,55	10,290841	3,72	3,63	3,77	3,51	3,83	3,54	4,07	17,9020073	19,63633475	24,44000053	-0,15087	-0,298951059	1917,8	0
9	SPAIN	2016	26505,343	10,185102	3,73	3,48	3,72	3,63	3,73	3,82	4,00	18,7533218	19,05821303	19,62999916	-0,202672	0,08443015	1917,8	0
9	SPAIN	2018	30349,752	10,320544	3,83	3,62	3,84	3,83	3,80	3,83	4,06	20,4779686	18,67336957	15,25	1,675068	0,437982994	1917,8	0
10	ITALY	2010	36000,52	10,491289	3,64	3,38	3,72	3,21	3,74	3,83	4,08	20,5797952	20,55298417	8,359999657	1,525516	0,307591222	1899,2	0
10	ITALY	2012	35053,526	10,464631	3,67	3,34	3,74	3,53	3,65	3,73	4,05	17,7895129	19,80806333	10,64999962	3,041363	0,26954124	1899,2	0
10	ITALY	2014	35518,415	10,477807	3,69	3,36	3,78	3,54	3,62	3,84	4,05	16,9592018	19,53901351	12,68000031	0,241047	0,917504096	1899,2	0
10	ITALY	2016	30939,714	10,339796	3,76	3,45	3,79	3,65	3,77	3,86	4,03	17,5610283	19,02656631	11,68999958	-0,094017	-0,169884073	1899,2	0
10	ITALY	2018	34605,263	10,451761	3,74	3,47	3,85	3,51	3,66	3,85	4,13	18,5274602	18,88086607	10,60999966	1,137488	-0,19006364	1899,2	0
11	AUSTRIA	2010	46858,043	10,754878	3,76	3,49	3,68	3,78	3,70	3,83	4,08	22,6078471	20,49254767	4,820000172	1,813534	0,2403943	2562	1
11	AUSTRIA	2012	48567,695	10,790714	3,89	3,77	4,05	3,71	4,10	3,97	3,79	23,9771069	19,86069237	4,869999886	2,485676	0,455937472	2562	1

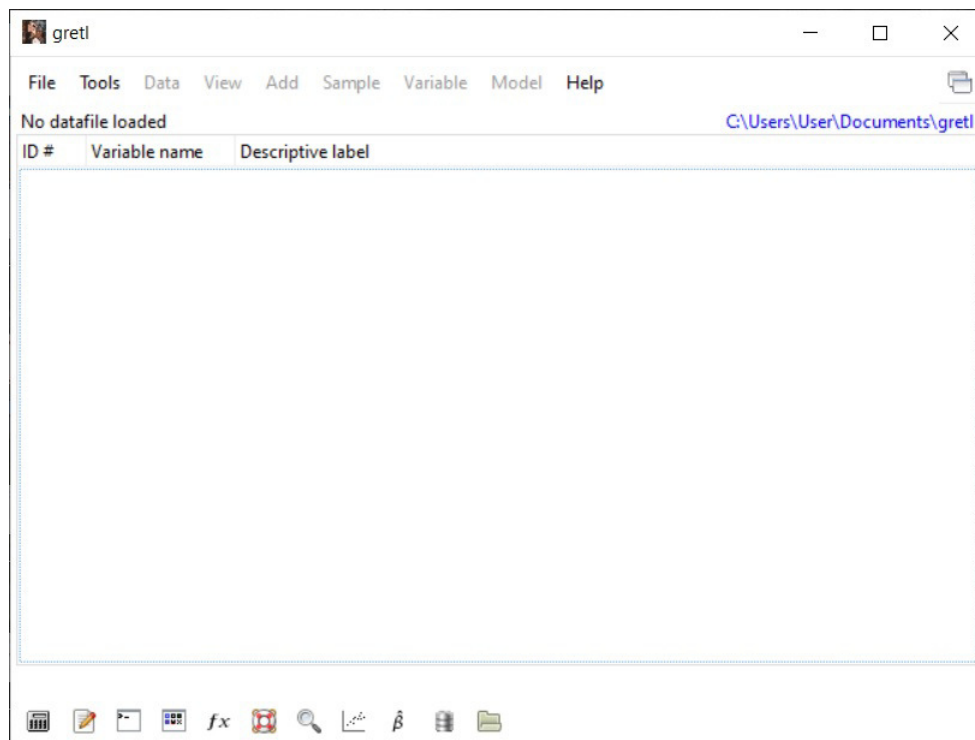
11	AUSTRIA	2014	51717,496	10,853551	3,65	3,53	3,64	3,26	3,56	3,93	4,04	23,5315428	19,80284204	5,619999886	1,605812	0,781541633	2562	1
11	AUSTRIA	2016	45276,831	10,720551	4,10	3,79	4,08	3,85	4,18	4,36	4,37	24,256326	19,65110116	6,010000229	0,891592	1,081396299	2562	1
11	AUSTRIA	2018	51461,433	10,848588	4,03	3,71	4,18	3,88	4,08	4,09	4,25	25,7225323	19,331863	4,849999905	1,99838	0,487071925	2562	1
12	FINLAND	2010	46459,973	10,746346	3,89	3,86	4,08	3,41	3,92	4,09	4,08	22,0826712	23,68623866	8,390000343	1,184135	0,457494535	2654	0
12	FINLAND	2012	47710,79	10,772913	4,05	3,98	4,12	3,85	4,14	4,14	4,10	23,3907191	24,09705676	7,690000057	2,808336	0,475809487	2654	0
12	FINLAND	2014	50260,3	10,824971	3,62	3,89	3,52	3,52	3,72	3,31	3,80	21,9210525	24,50736357	8,659999847	1,041196	0,413560208	2654	0
12	FINLAND	2016	43784,284	10,68703	3,92	4,01	4,01	3,51	3,88	4,04	4,14	23,2748554	23,67114446	8,819999695	0,356685	0,287421402	2654	0
12	FINLAND	2018	49964,5	10,819068	3,97	3,82	4,00	3,56	3,89	4,32	4,28	25,2574229	22,91191941	7,360000134	1,083821	0,132641041	2654	0
13	PORTUGAL	2010	22498,691	10,021212	3,34	3,31	3,17	3,02	3,31	3,38	3,84	21,126001	20,59315438	10,77000046	1,402573	0,045910037	1214	0
13	PORTUGAL	2012	20564,89	9,9313405	3,50	3,19	3,42	3,43	3,48	3,60	3,88	15,7019476	18,33549284	15,52999973	2,773339	-0,405421788	1214	0
13	PORTUGAL	2014	22074,301	10,002169	3,56	3,26	3,37	3,43	3,71	3,71	3,87	15,3166181	18,39846456	13,89000034	-0,278153	-0,539190467	1214	0
13	PORTUGAL	2016	19978,401	9,902407	3,41	3,37	3,09	3,24	3,15	3,65	3,95	15,8325245	17,58787723	11,06999969	0,607397	-0,315459017	1214	0
13	PORTUGAL	2018	23551,048	10,066926	3,64	3,17	3,25	3,83	3,71	3,72	4,13	18,2904716	16,97712782	6,989999771	0,993716	-0,160104021	1214	0
14	POLAND	2010	12613,011	9,4424842	3,44	3,12	2,98	3,22	3,26	3,45	4,52	21,5063269	19,17511494	9,640000343	2,580694	-0,285609122	3047	0
14	POLAND	2012	13097,271	9,4801592	3,43	3,30	3,10	3,47	3,30	3,32	4,04	21,2526225	18,07825595	10,09000015	3,560372	-0,000239076	3047	0
14	POLAND	2014	14271,306	9,5660062	3,49	3,26	3,08	3,46	3,47	3,54	4,13	20,6556751	18,31498021	8,989999771	0,053821	-0,074846229	3047	0
14	POLAND	2016	12447,44	9,4292702	3,43	3,27	3,17	3,44	3,39	3,46	3,80	19,6980177	17,91823608	6,159999847	-0,664767	-0,042985131	3047	0
14	POLAND	2018	15468,482	9,6465598	3,54	3,25	3,21	3,68	3,58	3,51	3,95	20,7654291	17,73468046	3,849999905	1,812952	-0,000200133	3047	0
15	CZECH REPUBLIC	2010	19960,068	9,901489	3,51	3,31	3,25	3,42	3,27	3,60	4,16	27,359869	20,53370132	7,28000021	1,472727	0,291361674	1989	1
15	CZECH REPUBLIC	2012	19870,801	9,8970067	3,14	2,95	2,96	3,01	3,34	3,17	3,40	26,3598483	19,45255853	6,980000019	3,287623	0,139925656	1989	1
15	CZECH REPUBLIC	2014	19890,92	9,8980186	3,49	3,24	3,29	3,59	3,51	3,56	3,73	26,0101211	19,33226501	6,110000134	0,343989	0,105277582	1989	1
15	CZECH REPUBLIC	2016	18575,232	9,8295844	3,67	3,58	3,36	3,65	3,65	3,84	3,94	26,0239744	18,96218641	3,950000048	0,683504	0,192048416	1989	1
15	CZECH REPUBLIC	2018	23419,736	10,061334	3,68	3,29	3,46	3,75	3,72	3,70	4,13	27,2023499	19,3889825	2,24000001	2,149495	0,334427262	1989	1
16	HUNGARY	2010	13223,083	9,4897193	2,99	2,83	3,08	2,78	2,87	2,87	3,52	21,1753828	21,39136514	11,17000008	4,855558	-0,226013876	2185	1
16	HUNGARY	2012	12989,18	9,471872	3,17	2,82	3,14	2,99	3,18	3,52	3,41	20,1540002	19,94931038	11	5,652145	-0,516437607	2185	1
16	HUNGARY	2014	14298,834	9,5679333	3,46	2,97	3,18	3,40	3,33	3,82	4,06	24,0478111	19,98809272	7,730000019	-0,227566	-0,269378767	2185	1
16	HUNGARY	2016	13107,378	9,4809306	3,43	3,02	3,48	3,44	3,35	3,40	3,88	21,5441591	19,95702719	5,110000134	0,394769	-0,295110605	2185	1
16	HUNGARY	2018	16427,373	9,7067043	3,42	3,35	3,27	3,22	3,21	3,67	3,79	26,8069993	19,68799355	3,710000038	2,850248	-0,126786952	2185	1
17	LATVIA	2010	11420,994	9,3432085	3,25	2,94	2,88	3,38	2,96	3,55	3,72	20,3779858	18,40733459	19,47999954	-1,084636	-2,08130509	1382	0

17	LATVIA	2012	13847,338	9,5358483	2,78	2,71	2,52	2,72	2,64	2,97	3,08	27,5086336	17,50234156	15,05000019	2,257789	-1,240359153	1382	0
17	LATVIA	2014	15721,452	9,6627814	3,40	3,22	3,03	3,38	3,21	3,50	4,06	23,8890557	17,97443744	10,85000038	0,620491	-0,941743354	1382	0
17	LATVIA	2016	14322,023	9,5695537	3,33	3,11	3,24	3,28	3,29	3,42	3,62	21,1805777	18,13640471	9,640000343	0,140633	-0,913885332	1382	0
17	LATVIA	2018	17856,307	9,7901121	2,81	2,80	2,98	2,74	2,69	2,79	2,88	23,2663075	18,18736623	7,409999847	2,534454	-0,779138396	1382	0
18	SLOVENIA	2010	23509,543	10,065162	2,87	2,59	2,65	2,84	2,90	3,16	3,10	22,3616416	20,4195374	7,239999771	1,80117	0,436079485	1086	0
18	SLOVENIA	2012	22643,1	10,02761	3,29	3,05	3,24	3,34	3,25	3,20	3,60	18,7592667	20,35539854	8,840000153	2,597414	0,210024306	1086	0
18	SLOVENIA	2014	24214,922	10,094724	3,38	3,11	3,35	3,05	3,51	3,51	3,82	19,3740246	18,88801043	9,670000076	0,199344	0,098351922	1086	0
18	SLOVENIA	2016	21663,643	9,9833907	3,18	2,88	3,19	3,10	3,20	3,27	3,47	18,4268675	19,0355604	8	-0,055	0,073197207	1086	0
18	SLOVENIA	2018	26104,103	10,169848	3,31	3,42	3,26	3,19	3,05	3,27	3,70	21,237945	18,27252639	5,110000134	1,738609	0,362584395	1086	0
19	ESTONIA	2010	14663,045	9,5930856	3,16	3,14	2,75	3,17	3,17	2,95	3,68	21,691389	19,56253206	16,709999908	2,972045	-0,228057969	633	0
19	ESTONIA	2012	17404,201	9,7644669	2,86	2,51	2,79	2,82	2,82	3,00	3,23	29,361547	18,19515466	10,02000046	3,9334	-0,357944411	633	0
19	ESTONIA	2014	20234,117	9,9151254	3,35	3,40	3,34	3,34	3,27	3,20	3,55	27,0987019	18,73089419	7,349999905	-0,106175	-0,262256175	633	0
19	ESTONIA	2016	18282,923	9,8137228	3,36	3,41	3,18	3,07	3,18	3,25	4,08	25,1187126	19,72445628	6,760000229	0,148685	0,029112226	633	0
19	ESTONIA	2018	23052,301	10,045521	3,31	3,32	3,10	3,26	3,15	3,21	3,80	26,9134178	19,2003649	5,369999886	3,436327	0,348039138	633	0
20	ROMANIA	2010	8214,0769	9,0136047	2,84	2,36	2,25	3,24	2,68	2,90	3,45	27,1292462	15,4673902	6,960000038	6,091417	-0,593959184	2508	0
20	ROMANIA	2012	8507,1048	9,0486569	3,00	2,65	2,51	2,99	2,83	3,10	3,82	27,0423189	14,56926852	6,789999962	3,334923	-0,445177936	2508	0
20	ROMANIA	2014	10043,677	9,2146986	3,26	2,83	2,77	3,32	3,20	3,39	4,00	24,7696482	14,503111	6,800000191	1,06831	-0,374575498	2508	0
20	ROMANIA	2016	9548,5874	9,1641485	2,99	3,00	2,88	3,06	2,82	2,95	3,22	23,410766	15,08563123	5,900000095	-1,544797	-0,573660845	2508	0
20	ROMANIA	2018	12398,982	9,4253696	3,12	2,58	2,91	3,18	3,07	3,26	3,68	22,7769579	16,82719389	4,190000057	4,625484	-0,587493307	2508	0
21	SLOVAK REPUBLIC	2010	16825,352	9,7306421	3,24	2,79	3,00	3,05	3,15	3,54	3,92	24,1778002	19,27226399	14,38000011	0,957018	0,093191273	1474	1
21	SLOVAK REPUBLIC	2012	17430,827	9,7659956	3,03	2,88	2,99	2,84	3,07	2,84	3,57	20,4149641	17,89228597	13,96000004	3,606103	0,170183855	1474	1
21	SLOVAK REPUBLIC	2014	18630,976	9,8325808	3,25	2,89	3,22	3,30	3,16	3,02	3,94	21,5611108	18,42119363	13,18000031	-0,076165	0,097045422	1474	1
21	SLOVAK REPUBLIC	2016	16501,084	9,7111813	3,34	3,28	3,24	3,41	3,12	3,12	3,81	23,0110105	18,93873315	9,670000076	-0,52001	0,12892233	1474	1
21	SLOVAK REPUBLIC	2018	19380,514	9,8720234	3,03	2,79	3,00	3,10	3,14	2,99	3,14	23,100426	18,62767657	6,539999962	2,514037	0,13850816	1474	1
22	GREECE	2010	26690,607	10,192067	2,96	2,48	2,94	2,85	2,69	3,31	3,49	17,9862597	22,35690747	12,71000004	4,712973	0,128880433	1228	0
22	GREECE	2012	21914,252	9,9948925	2,83	2,38	2,88	2,69	2,76	2,98	3,32	12,0979313	22,26069297	24,44000053	1,501528	-0,540752951	1228	0
22	GREECE	2014	21587,958	9,9798909	3,20	3,36	3,17	2,97	3,23	3,03	3,50	11,8922837	20,5865958	26,48999977	-1,311211	-0,66611329	1228	0
22	GREECE	2016	17911,799	9,793215	3,24	2,85	3,32	2,97	2,91	3,59	3,85	12,8368978	20,61262606	23,54000092	-0,825652	-0,415913028	1228	0
22	GREECE	2018	19747,343	9,8907742	3,20	2,84	3,17	3,30	3,06	3,18	3,66	13,1500555	19,77554833	19,29000092	0,625629	-0,202880238	1228	0

23	LITHUANIA	2010	11987,508	9,3916204	3,13	2,79	2,72	3,19	2,85	3,27	3,92	18,1257055	19,84499587	17,809999947	1,319214	-2,09694342	1574	0
23	LITHUANIA	2012	14367,709	9,5727386	2,95	2,73	2,58	2,97	2,91	2,73	3,70	19,760167	17,45475172	13,359999966	3,089983	-1,341201988	1574	0
23	LITHUANIA	2014	16551,018	9,7142029	3,18	3,04	3,18	3,10	2,99	3,17	3,60	19,6225909	16,61376488	10,699999981	0,103758	-0,859827343	1574	0
23	LITHUANIA	2016	14998,125	9,6156805	3,63	3,42	3,57	3,49	3,49	3,68	4,14	19,2082502	16,99889807	7,860000134	0,905525	-1,270694533	1574	0
23	LITHUANIA	2018	19176,812	9,8614571	3,02	2,85	2,73	2,79	2,96	3,12	3,65	20,3525323	16,37097276	6,150000095	2,697928	-0,954190459	1574	0
24	BULGARIA	2010	6853,0029	8,8324422	2,83	2,50	2,30	3,07	2,85	2,96	3,18	22,5209524	16,50446634	10,27999973	2,438991	-0,658275447	1808	0
24	BULGARIA	2012	7432,4788	8,9136147	3,21	2,97	3,20	3,25	3,10	3,16	3,56	21,8862701	15,79052344	12,27000046	2,954568	-0,579220596	1808	0
24	BULGARIA	2014	7901,7859	8,9748441	3,16	2,75	2,94	3,31	3,00	2,88	4,04	21,5071661	16,83265399	11,42000008	-1,418184	-0,568389264	1808	0
24	BULGARIA	2016	7569,4788	8,9318795	2,81	2,40	2,35	2,93	3,06	2,72	3,31	18,9542719	15,58277019	7,570000172	-0,79865	-0,701382098	1808	0
24	BULGARIA	2018	9446,7008	9,1534208	3,03	2,94	2,76	3,23	2,88	3,02	3,31	21,214296	16,41437166	5,210000038	2,814545	-0,722080405	1808	0
25	MALTA	2010	21799,174	9,9896274	2,82	2,65	2,89	2,91	2,89	2,56	3,02	22,2767466	19,06336474	6,849999905	1,515635	0,491182811	219	0
25	MALTA	2012	22527,637	10,022498	3,16	2,81	3,10	3,17	3,01	3,05	3,79	17,155414	19,83290696	6,199999809	2,375821	0,899209212	219	0
25	MALTA	2014	26754,268	10,194449	3,11	3,00	3,08	3,23	3,00	3,15	3,15	15,6642443	18,51165716	5,71999979	0,310306	1,996754408	219	0
25	MALTA	2016	25741,446	10,155858	3,07	2,78	2,94	3,09	2,85	3,12	3,61	24,7267937	15,92195722	4,690000057	0,642703	2,288615441	219	0
25	MALTA	2018	30672,292	10,331115	2,81	2,70	2,90	2,70	2,80	2,80	3,01	21,732425	15,97581233	3,660000086	1,157824	3,491955403	219	0
26	CROATIA	2010	14067,523	9,5516241	2,77	2,62	2,36	2,97	2,53	2,82	3,22	20,9404128	21,26554389	11,61999989	1,030555	-0,226821271	1982	0
26	CROATIA	2012	13401,657	9,5031336	3,16	3,06	3,35	2,95	2,92	3,20	3,54	18,6200816	21,5754244	15,93000031	3,412073	-0,305655945	1982	0
26	CROATIA	2014	13762,373	9,5296935	3,05	2,95	2,92	2,98	3,00	3,11	3,37	18,766699	21,8428721	17,29000092	-0,215196	-0,407343185	1982	0
26	CROATIA	2016	12527,74	9,4357007	3,16	3,07	2,99	3,12	3,21	3,16	3,39	20,7335244	20,68268389	13,10000038	-1,125	-0,698383457	1982	0
26	CROATIA	2018	15227,56	9,6308622	3,10	2,98	3,01	2,93	3,10	3,01	3,59	23,1780152	20,60206729	8,430000305	1,500125	-0,893486928	1982	0
27	CYPRUS	2010	31023,638	10,342505	3,13	2,92	2,94	3,13	2,82	3,51	3,44	24,0254984	18,51985994	6,260000229	2,430041	1,31435018	150,4	0
27	CYPRUS	2012	28912,157	10,272017	3,24	3,02	3,17	3,21	3,17	3,36	3,54	16,2028606	18,81406283	11,80000019	2,389054	0,903504248	150,4	0
27	CYPRUS	2014	27163,333	10,209623	3,00	2,88	2,87	3,01	2,92	3,00	3,31	13,5649063	16,78699353	16,09000015	-1,354989	0,734358832	150,4	0
27	CYPRUS	2016	24605,921	10,110742	3,00	3,11	3,00	2,80	2,72	2,54	3,79	17,4397575	15,24670168	12,94999981	-1,429167	0,789476882	150,4	0
27	CYPRUS	2018	29334,111	10,286506	3,15	3,05	2,89	3,15	3,00	3,15	3,62	19,3419875	14,5771693	8,369999886	1,435491	0,808549298	150,4	0

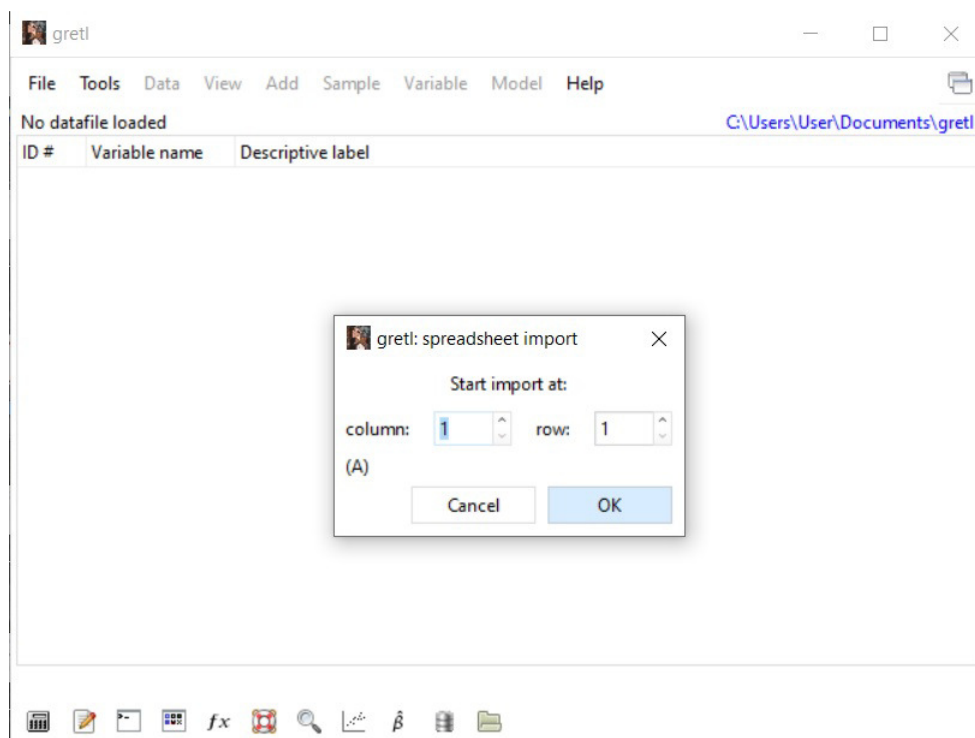
Appendix B: OLS via Gretl software

Beginning with Gretl software we encounter the following homepage in Picture B.1.



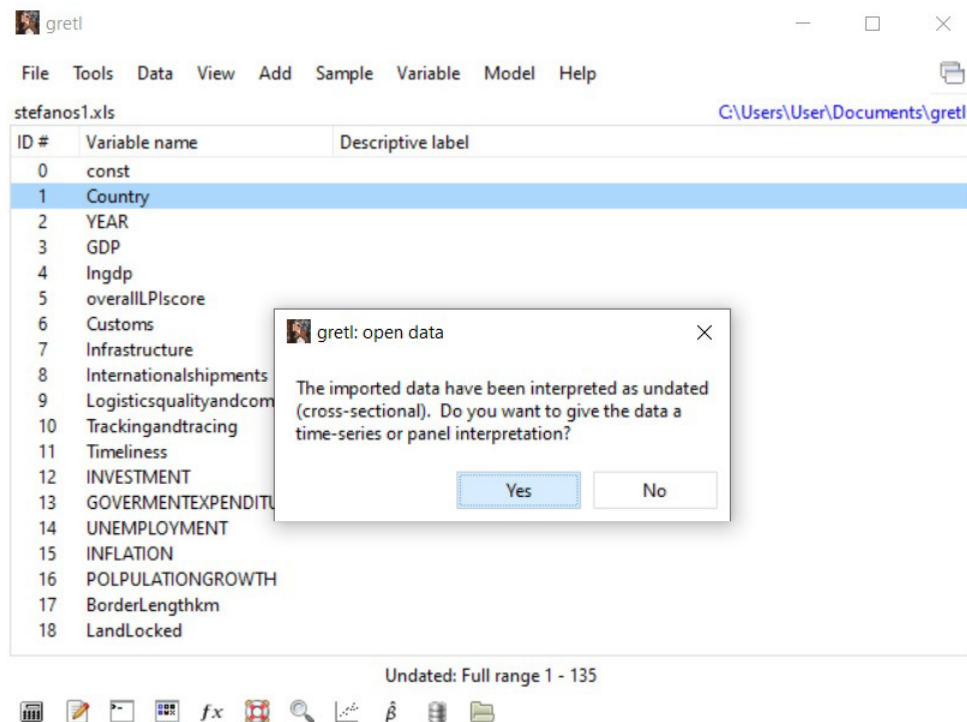
Picture B.1 Gretl homepage

By clicking File & Open data we select our data file (Excel, ASCII etc) and the following dialogue text appears in Picture B.2.

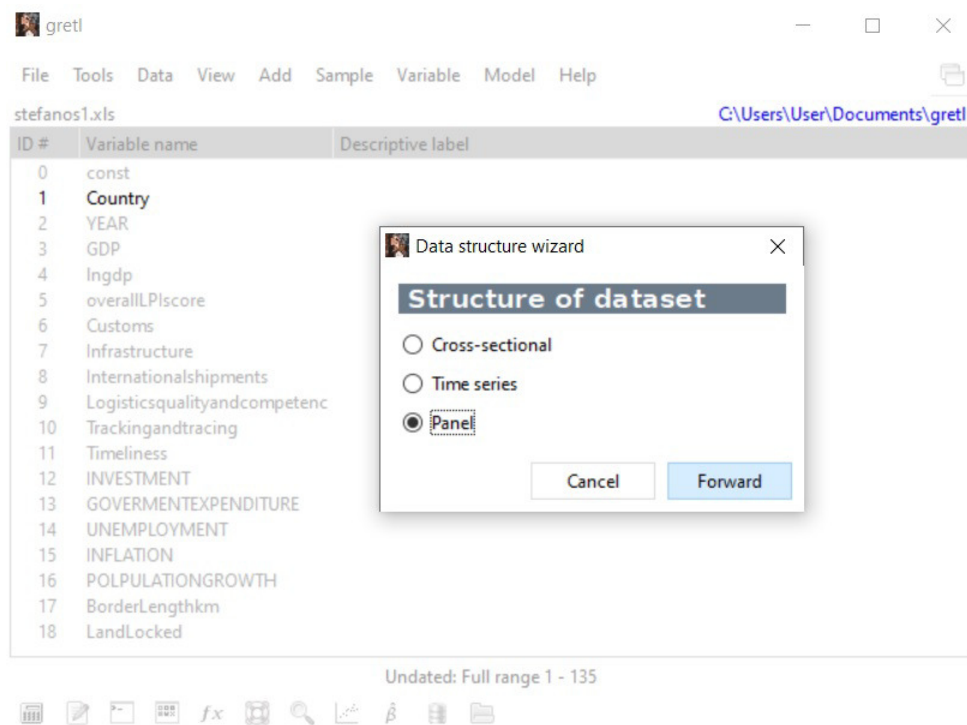


Picture B.2 Excel data input in Gretl

It is required by Gretl to define the dimensions (initial column and row) of our data file as well as the interpretation of our dataset (cross-sectional, time series, panel data) as shown in Pictures B.3 & B.4.

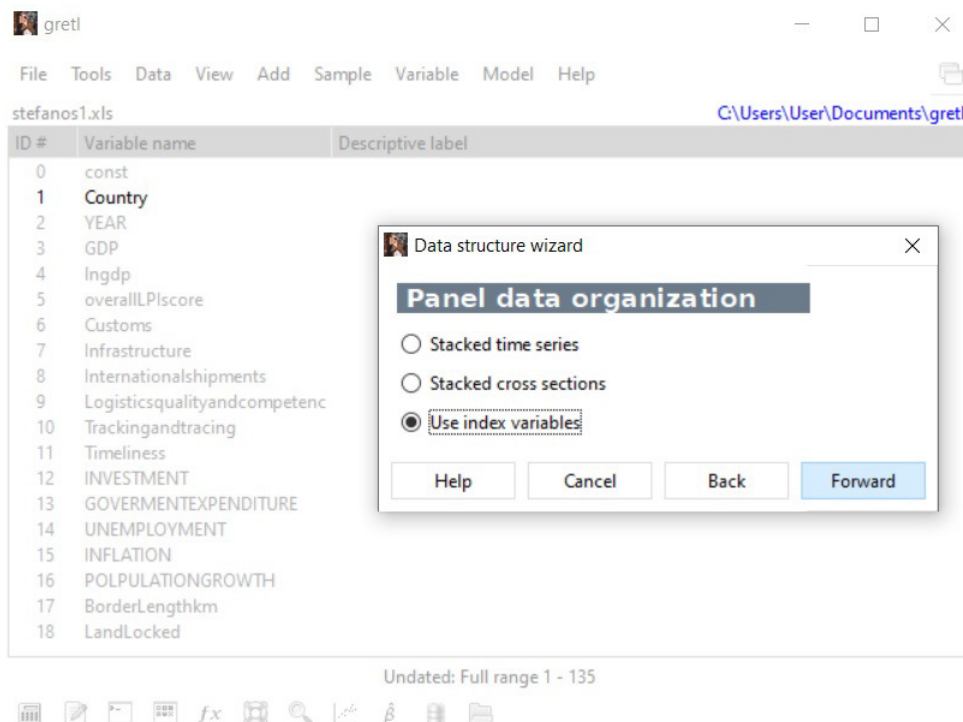


Picture B.3 Data characterization as time-series or panel

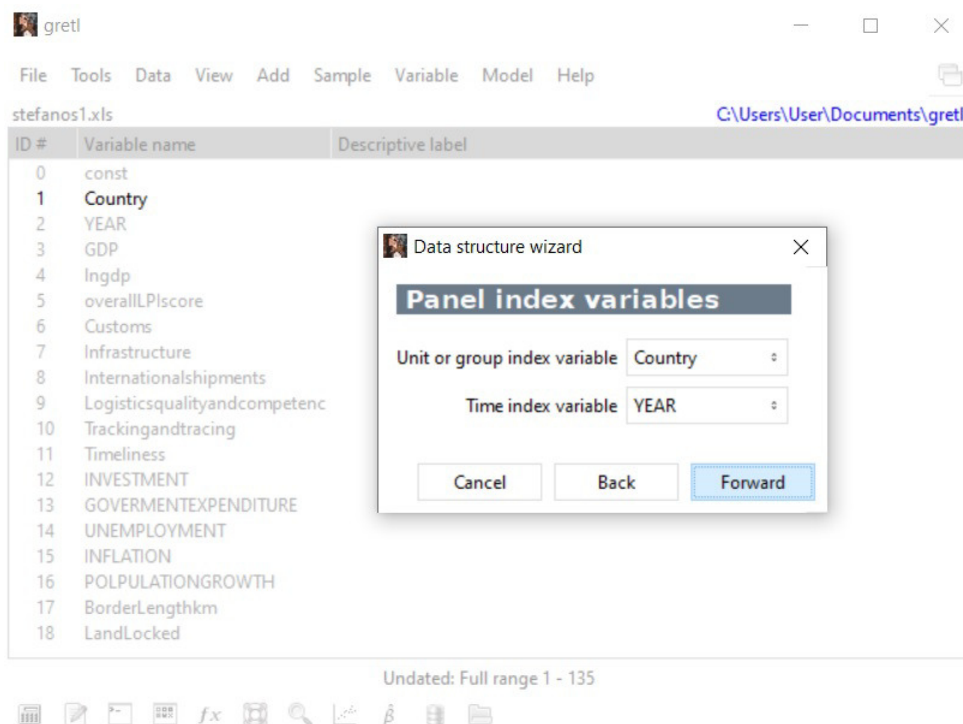


Picture B.4 Structure of dataset

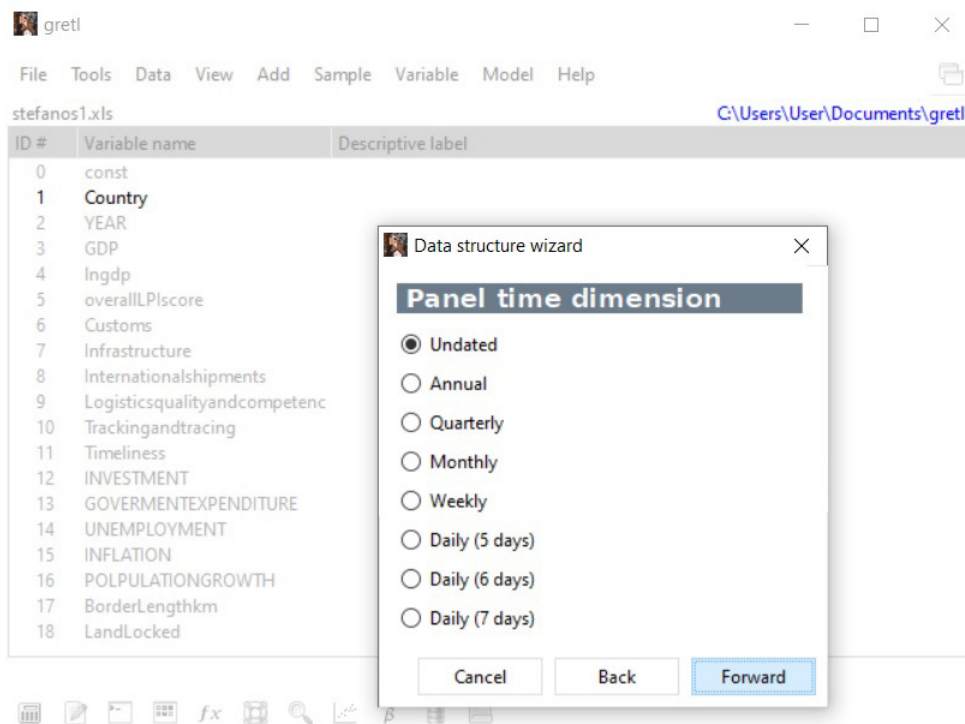
Moreover, Gretl program requires additional information about panel data organization, panel index variables & panel time dimension in order to be confirmed the inserted dataset structure as demonstrated in Pictures B.5, B.6, B.7 & B.8.



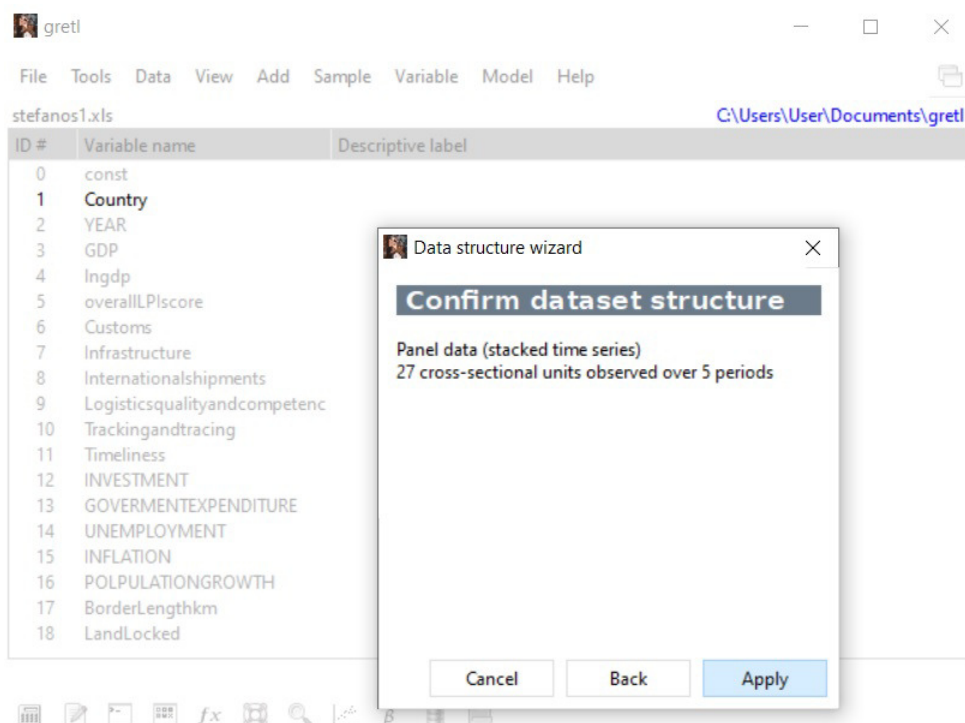
Picture B.5 Panel data organization



Picture B.6 Panel index variables

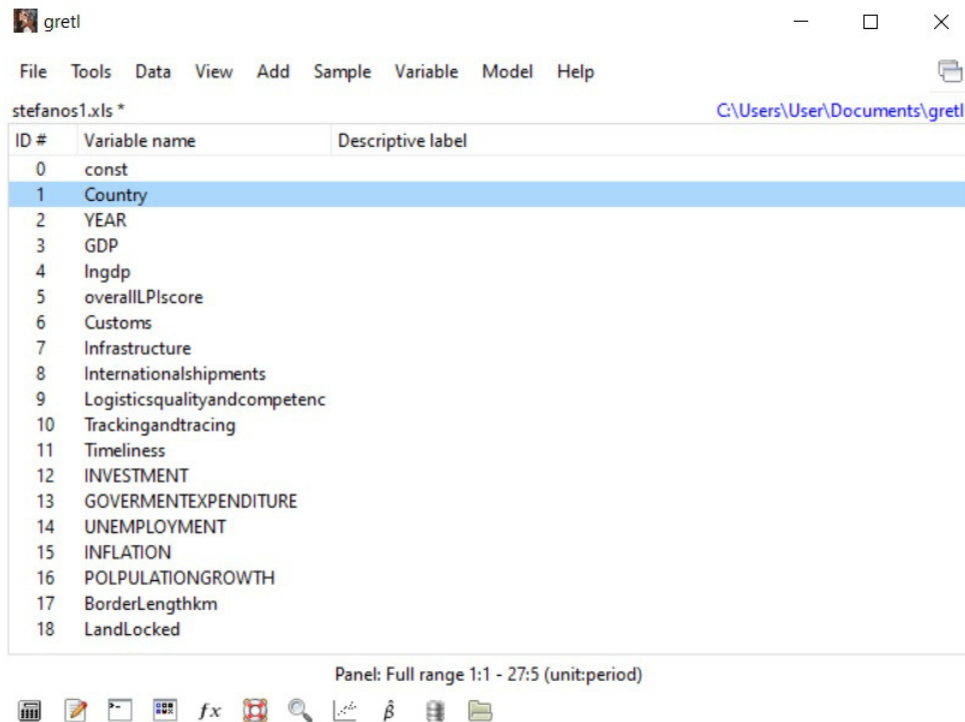


Picture B.7 Panel time dimension



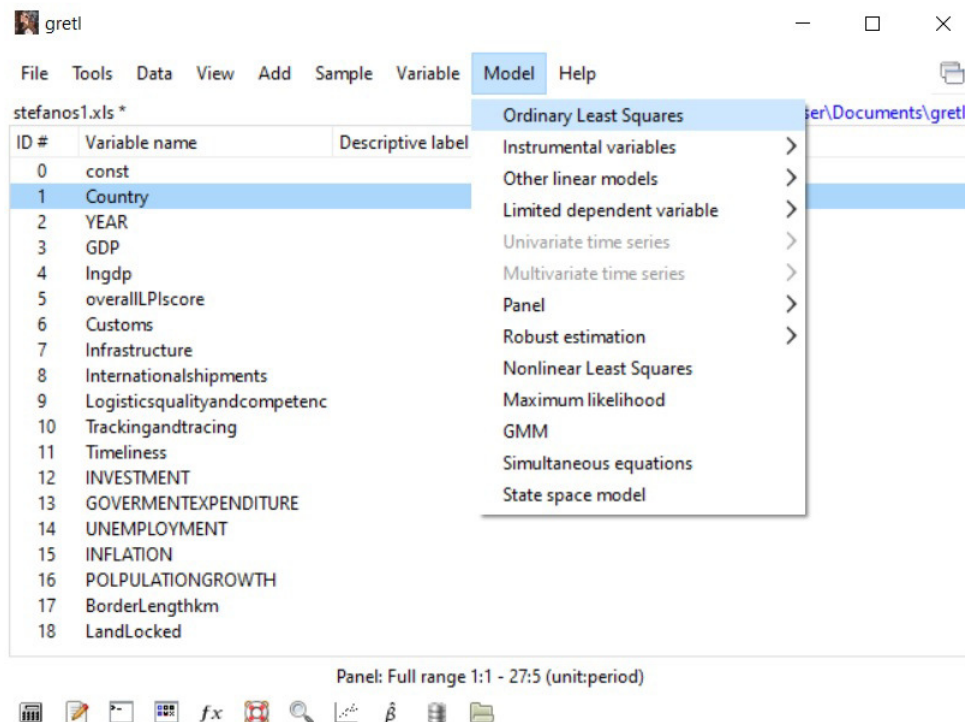
Picture B.8 Confirmation of dataset structure

According to the above steps, we encounter the Gretl homepage including our dataset structure as shown in Picture B.9.



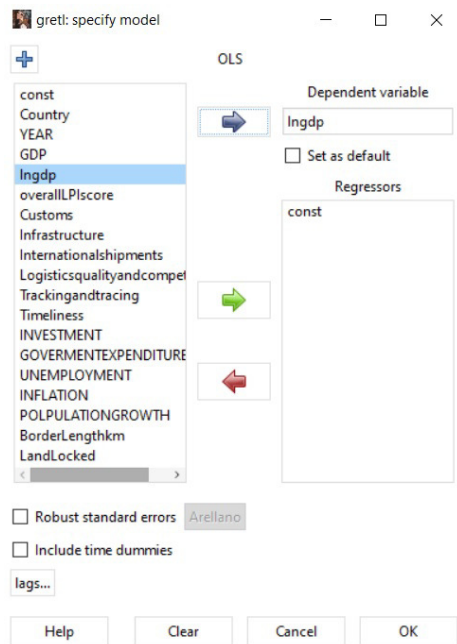
Picture B.9 Gretl homepage including dataset structure

By clicking Model we can select the type of simulation that we want to conduct. Here, we select the option of Ordinary Least Squares as shown in Picture B.10.

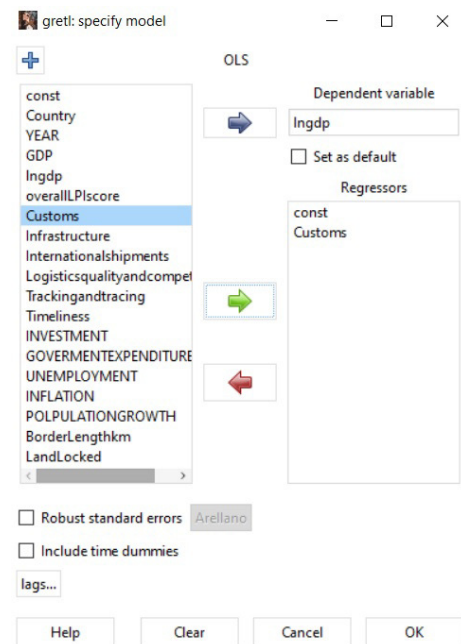


Picture B.10 Modeling options - Ordinary Least Squares

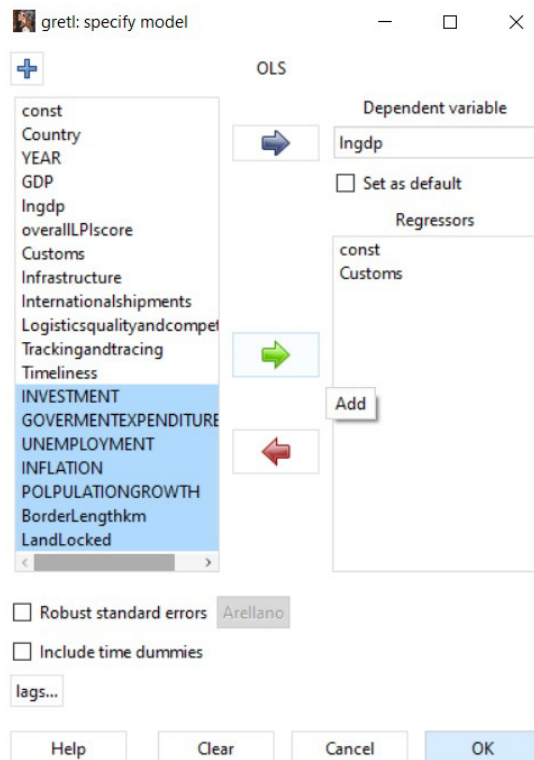
Complying with the corresponding dialog boards we can set the dependent variable and the independent variables as regressors and click OK so that the multiple regression can be conducted as shown in Pictures B.11, B.12, B.13 & B.14.



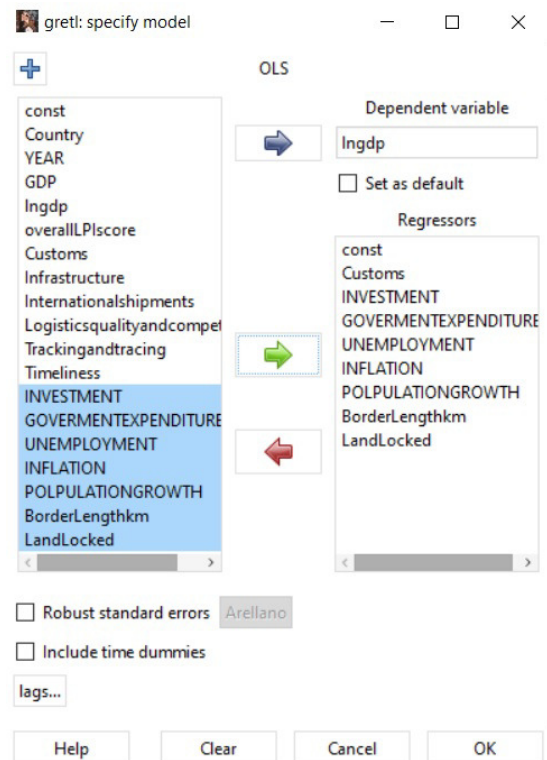
Picture B.11 Model specification - Dependent variable input



Picture B.12 Model specification - Micro-variable input

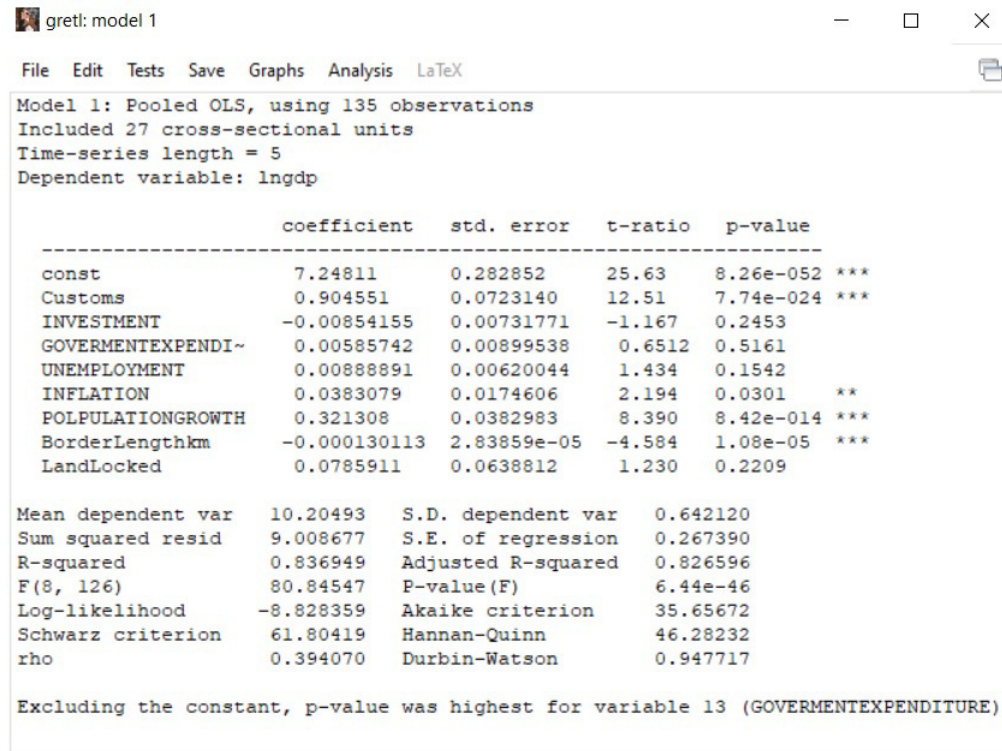


Picture B.13 Model specification - Macro-variables input



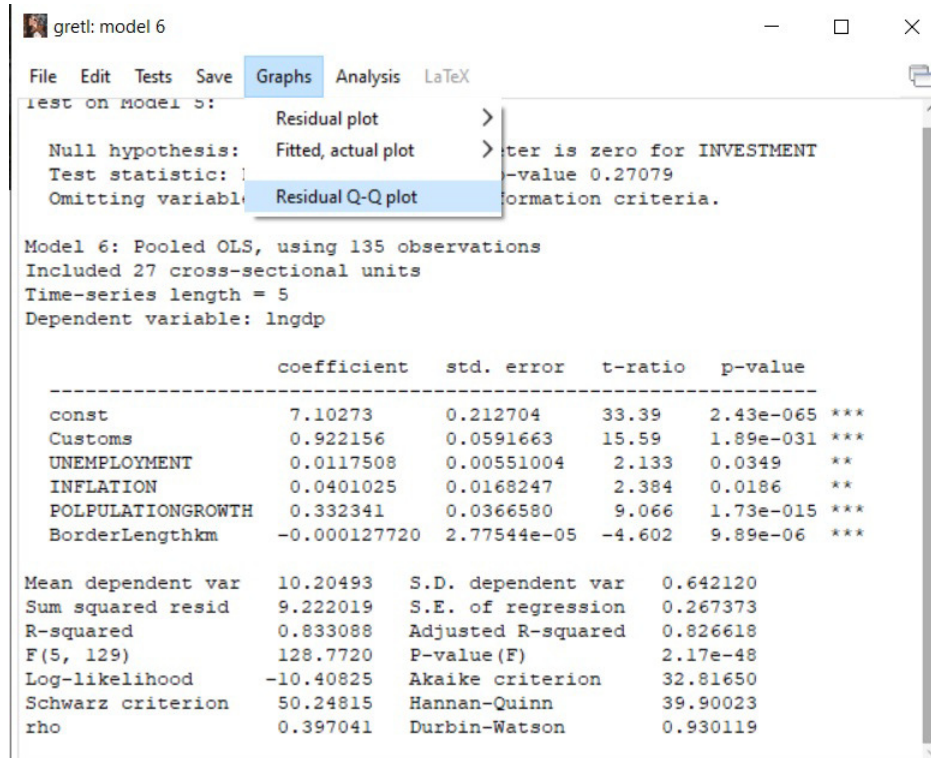
Picture B.14 Model specification - Macro-variables setting

Details of the OLS modeling are listed in the Picture B.15 where the researcher can find the required indicators and draw conclusions such as reschedule the regressors and repeat the multiple regression.



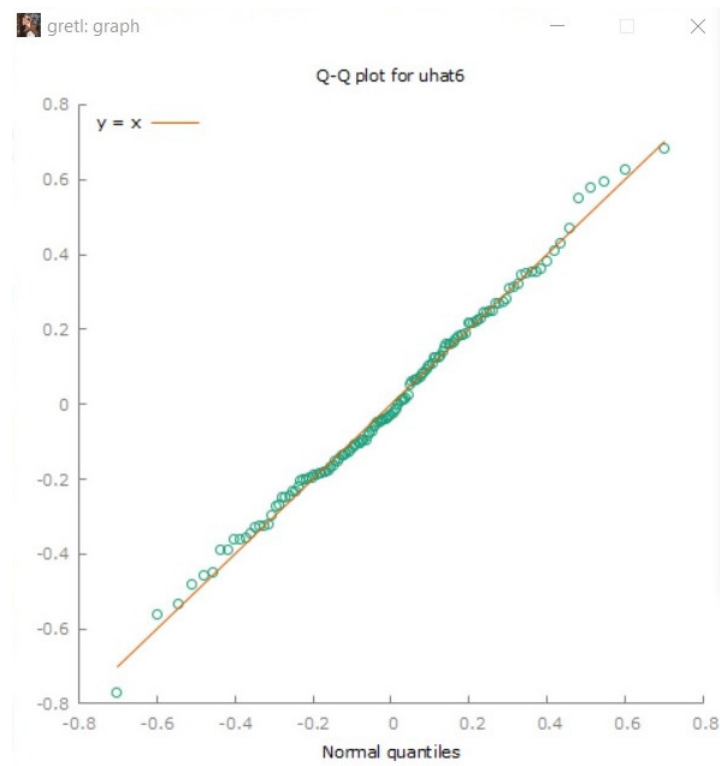
Picture B.15 Pooled OLS results

Gretl provides several types of plot through Graphs option as shown in Picture B.16.



Picture B.16 Exporting Residual Q-Q plot

In our analysis we preferred the Residual Q-Q plot that was suitable for our case as shown in Picture B.17.



Picture B.17 Residual Q-Q plot

Author'sStatement:

I hereby expressly declare that, according to the article 8 of Law 1559/1986, this dissertation is solely the product of my personal work, does not infringe any intellectual property, personality and personal data rights of third parties, does not contain works/contributions from third parties for which the permission of the authors/beneficiaries is required, is not the product of partial or total plagiarism, and that the sources used are limited to the literature references alone and meet the rules of scientific citations.