DEPARTMENT OF ENVIRONMENTAL AND CIVIL ENGINEERING

REGIONAL SPATIO-TEMPORAL EXPLANATORY MODELLING of MACROSCOPIC TRANSPORTATION INFORMATION for SUPPORTING DECISION-MAKING PROCESSES

DOCTOR OF PHILOSOPHY DISSERTATION

PARASKEVAS NIKOLAOU

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University of Cyprus

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The present doctoral dissertation was submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy of the University of Cyprus. It is a product of original work of my own, unless otherwise mentioned through references, notes, or any other statements.

Paraskevas Nikolaou

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Abstract in Greek

Οι μεταφορές είναι ζωτικής σημασίας σε πολλές πτυχές, από τις κοινωνικές αλληλεπιδράσεις έως τις οικονομικές συναλλαγές των παγκόσμιων κοινοτήτων. Η μελέτη ενός φαινομένου μεταφοράς απαιτεί μια σειρά από ενέργειες που είναι απαραίτητες για την πλήρη κατανόηση του φαινομένου. Αυτές οι ενέργειες ξεκινούν από τη συλλογή δεδομένων και καταλήγουν στην χάραξη πολιτικής. Σε κάθε μελέτη υπάρχει συνεχής ανησυχία για το: Ποια δεδομένα πρέπει να συλλέγονται επαρκώς για την καταγραφή ενός φαινομένου μεταφοράς; Ακόμα και όταν συλλέγονται τα δεδομένα, υπάρχει μια σειρά ενεργειών που πρέπει να ακολουθούνται για την ανάλυση των δεδομένων και τον εντοπισμό πιθανών προβλημάτων. Ο καθαρισμός των δεδομένων από αυτά τα προβλήματα και η παρακολούθηση τους για εύρεση πιθανών τάσεων είναι ένα καλό προκαταρκτικό βήμα για την προετοιμασία του δείγματος και την ανάπτυξη των μοντέλων. Ωστόσο, ακόμα και όταν το δείγμα προετοιμάζεται για διερευνητική ανάλυση, προκύπτουν και πάλι αμέτρητα ερωτήματα: Ποια μέθοδος είναι πιο κατάλληλη για το κάθε φαινόμενο μεταφοράς; Είναι το μέγεθος του δείγματος κατάλληλο για την ανάλυση; Αυτά και πολλά άλλα ερωτήματα προκύπτουν ειδικά όταν υπάρχει ποικιλία μεθόδων, εργαλείων και τεχνικών που καθιστούν πιο περίπλοκη τη διαδικασία ανάλυσης. Αυτή η διατριβή ανέπτυξε μια καινοτόμα ιδέα σύλληψης περιφερειακών και διεθνών φαινομένων μεταφοράς με τη χρήση μακροσκοπικών πληροφοριών σε μια δισδιάστατη ανάλυση (ως προς τον χρόνος και τον χώρο). Αναλυτικά παρέχει μια, βήμα προς βήμα, μεθοδολογική διαδικασία που ξεκινά από τη συλλογή και ανάλυση μακροσκοπικών και τεχνικών πληροφοριών περιφερειακών και διεθνών μονάδων, συνεχίζει με την ερμηνεία δύο φαινομένων μεταφοράς, που είναι το φαινόμενο των θανατηφόρων τροχαίων ατυχημάτων και των πολυτροπικών εμπορευματικών μεταφορών, από την μελέτη των γραμμικών επιδράσεων μακροσκοπικών παραγόντων στα φαινόμενα μεταφοράς. Ακολουθήθηκε η ενσωμάτωση του χρόνου για την ανάλυση της δυναμικής των φαινομένων με την πάροδο του χρόνου. Στη συνέχεια, ερευνήθηκε η διάσταση του χώρου και οι χωρικές συνδέσεις μεταξύ των μονάδων και τέλος, η μεθοδολογία χρησιμοποιεί μια δισδιάστατη προσέγγιση για την παροχή μιας ρεαλιστικής ερμηνείας των φαινομένων. Τέλος αλλά εξίσου σημαντικό, είναι ότι η παρούσα Διατριβή παρέχει ερμηνεία των αποτελεσμάτων που προέκυψαν από τις μεθοδολογικές εφαρμογές για την υποστήριξη της λήψης αποφάσεων και χάραξης πολιτικής. Όπως αποκαλύφθηκε από τα ευρήματα αυτής της διατριβής, αυτό το

μεθοδολογικό πλαίσιο μπορεί να εφαρμοστεί όχι μόνο σε ένα φαινόμενο μεταφοράς αλλά και σε όλα τα φαινόμενα μεταφοράς σε μακρο-επίπεδο.

Abstract

Transportation is of vital importance in a multitude of aspects, from the social interactions to the economic transactions of the global communities. Studying a transportation phenomenon requires a series of tasks that are necessary for the full understanding of the phenomenon. These tasks start from the data collection and end up with the policy-making procedures. In every study, there is a continuous concern of What data should be collected for capturing a transportation phenomenon, adequately? Even when the data are collected, there is a series of procedures that must be followed for analyzing the data and identifying possible data inflations. Cleaning the data from data inflations and observing any possible trends is a good preliminary step for preparing the sample for the models' development. Even when the sample is prepared for exploratory analysis then countless questions arise: What method is more appropriate for the respective transportation phenomenon? Is the size of the sample adequate for the analysis? These and several more questions arise especially when there is a variety of methods, tools, and techniques that make more complex the procedure of analysis. This Thesis has developed a novel idea of capturing regional and international transportation phenomena by the use of macroscopic information in a two-dimensional analysis (time and space). In detail it provides a step-by-step methodological procedure that starts from the collection and analysis of macroscopic and technical information of regional and international units, it continues with the interpretation of two transportation phenomena, namely road traffic fatalities, and multimodal freight transports, by studying the linear effects of macroscopic factors on the transportation phenomena. The incorporation of time is followed for analyzing the dynamics of the phenomena over time. Then the dimension of space and the spatial connections between the units are investigated and finally, the methodology uses a two-dimensional approach for providing a realistic interpretation of the phenomena. Last but not least, this Thesis provides interpretations of the results obtained from the methodological applications for the support of decision and policy-making. As it was revealed from the findings of this Thesis this methodological framework applies not only to one transportation phenomenon but also to all macro-level transportation phenomena.

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Table of Contents

List of Figures

List of Tables

CHAPTER 1: INTRODUCTION

In the time of increasing mobility in the global community, transportation seems to still lack conceptual understanding. Transportation is of vital importance from the social interactions to the economic transactions of the global communities. For example, the global economic crisis (2007-2013) and the pandemic of COVID-19 (2019-2020) have affected several global transportation phenomena and therefore attracted the attention of countless researchers. However, these effects have a different manifestation in transportation phenomena based on the level of approach (macro, meso, micro). The choice of the level of approach depends on the transportation phenomenon and the purpose of the study.

The study of a transportation phenomenon requires following some standard procedures before the models' development. These, procedures can be characterized as data collection-data analysis. Though despite the era we are covering widespread available information, much of this information is not open (free) and is sometimes inconsistent. Additionally, collecting information to analyze a transportation phenomenon does not necessarily mean that it is also important (in terms of statistical meaning). However, when it is required to study a phenomenon on a large scale and simultaneously use free information then the macro-level approach is preferred.

An additional concern of studying a transportation phenomenon is the extent of the investigation. Investigating a transportation phenomenon at a national, regional, or even international level requires the respective collection of information.

It has been evited over the years that transportation changes are timely and spatially related fact that can be confirmed form the changes that occurred before, during, and after the economic crisis and COVID-19. These dimensions (time and space) therefore play a vital role, especially when investigating transportation phenomena.

Having in mind all the above concerns and by observing the changes of different transportation phenomena on a national, regional, and international level over the dimensions of time and space the following "research question" has emerged:

Is there an integrated methodological framework that could encompass simultaneously macro-level spatio-temporal information for analyzing different transportation phenomena?

This Thesis develops a step-by-step procedure for providing a sufficient answer to the above question.

1.2. Scope

This Thesis has been developed for filling the gaps in the literature that exists on the concept of developing a methodology that can be used for investigating different transportation phenomena on a national, regional, or even global scale using macro-level information on a Spatio-temporal context. In detail the current Thesis tries to implement the following individual scopes:

- Descriptive Analysis
  - Collect and pre-process/visualize representative and robust information that can explain adequately a transportation phenomenon on a national, regional, or international scale.
- Exploratory Analysis
  - Analyze a transportation phenomenon and its behavior over time and provide significant interpretations of the factors that seem to affect it. Can an economically unstable time series affect transportation phenomenon modeling?
  - Analyze the transportation phenomenon over space, i.e., can neighboring units (e.g. cities, countries) and their connections affect the way the phenomenon is captured?
  - The incorporation of time and space in a Spatio-temporal structure and the interpretation of the fluctuations of the phenomenon over time and space. Are different and varied transportation phenomena multi-dimensional?
- Explanatory Analysis
  - Evaluation of different units (e.g. countries) concerning their performance based on different transportation phenomena and identifying best and under-performing units.

- Investigate and measure the effects that different factors have on the units' performance.
- Setting short-term and long-term targets.

The overall scope of this Thesis is to develop a methodological framework that can adequately address all the above individual objectives. However, for validating the multi-dimensionality in different transportation phenomena we develop a methodology over two different nature transportation phenomena. The first phenomenon was based on human mobility (Road Traffic Fatalities) and the second phenomenon was based on the movement of goods (Multimodal Freight Mobility Flows).

1.2. Methodological Approach

For addressing all the objectives of this Thesis is of high importance the selection and development of a robust methodology able to provide suitable quantitative means for Transport Policy purposes, by incorporating three important elements:

- Time
- Space
- Multiple socio-economic and demographic measurements

The concept idea followed for developing this methodological framework was based on the ability to use macro-level information on a national, regional, or international scale and incorporating time and space components. For validating the assumption of transportation phenomena multi-dimensionality, the proposed methodology was based on two entirely different transportation phenomena: Road Traffic Fatalities and Multimodal Freight Flows, using macro-level information.

1.2.1. Data

As described earlier, for analyzing and understanding different transportation phenomena it is important the collection of information that can adequately capture and interpret them. This collection stands for a tedious task, especially when looking for robust sources of information and continuous sets of observations. However, despite the countless pieces of information, several issues arise prior to, during, and after the collection. The issues that occur prior to the data collection are concerning the scale of analysis and the sources where the data are collected. For example, when our analysis is concerning different transportation phenomena inside the country then our search for information should focus on national sources. When our analysis is focusing on a larger scale (e.g., regional or international) then our data can be collected from global organizations (e.g., Eurostat, World Bank, World Health Organization, etc.). Besides, the variety of information that these global organizations are providing, still there is missing information. However, the benefit of collecting data from global organizations is that we can have a significant amount of exposure factors at no cost, a fact that encourages researchers for incorporating this information.

The issues that occur during the analysis are issues of inconsistency and data inflation. These issues occur in the scenario when a countless number of sources are used for collecting information. The issues that occur after the data collection processes are based on statistical significance. Therefore, prior to the exploratory and explanatory approaches, every study should focus on data interpretations through descriptive analysis.

Descriptive analysis is based on the two pillars of the qualitative and quantitative understanding of the data. In detail, qualitative analysis (data visualization) presents the information where is possible to identify data inconsistencies. Furthermore, quantitative analysis (statistical analysis) presents any possible data inflations in the dataset (e.g. collinearities) and also homogeneities or heterogeneities of the data.

Overall, the collection and analysis of data, are of significant importance in the analysis and interpretation of different transportation phenomena.

1.2.2. Proof of Concept on Road Traffic Fatalities

The first transportation phenomenon concerned the field of human mobility and in particular the vital phenomenon of road traffic fatalities. The phenomenon of road traffic fatalities concerned and still concerns a significant body of researchers for understanding and interpreting the phenomenon in order to reduce it or even eliminate it.

The challenge that arises when studying road traffic fatalities is the collection of data. The availability of finding a number of fatalities sometimes comes with a cost especially when these fatalities have detailed information behind them (geographic location of the accident, time of the accident, etc.). As mentioned above for collecting the data that will help study, thoroughly, road traffic fatalities we must look at the phenomenon on a larger scale, in a macro-level approach. Macro-level information on road traffic fatalities is limited for some countries or for some time periods, but always available in some global organizations' datasets, likewise in World Health Organization (W.H.O.).

The methodological approaches for studying road traffic fatalities should be able to provide us the "picture" of how and to what extent road traffic fatalities are affected by different factors. Thus, the challenge is on both the exploratory as well as the explanatory phase of the analysis. Based on the scope of this Thesis, the methodological framework that will be developed should be able to capture the changes in road traffic fatalities over time.

Besides time there also the dimension of space. This dimension concerns the spatial correlation between under investigation units (e.g., connections between countries or cities, etc). This correlation depends on the spatial connection of neighboring under-investigation units. Therefore, the methodology should be also able to capture and incorporate these connections.

The methodological framework developed should be also able to incorporate both dimensions of time and space and observe how road traffic fatalities can be interpreted. Notwithstanding the significant information obtained from all the approaches, the methodology continues by developing an explanatory analysis, which interprets the results obtained from all the approaches and provides support to decision-making processes.

1.2.3. Proof of Concept on Multimodal Freight Transportation

The second transportation phenomenon concerned in this Thesis was the mobility of goods and in particular the multimodal freight flow transportation. Studying this phenomenon is important for selecting information that will be able to interpret the phenomenon, adequately. The information concerning freights is more available in contrast with the information on road fatalities. However, this information is not open to the public. Notwithstanding, this fact there is also free available information when looking at the phenomenon to a larger scale (macro-level approach). Therefore, as in road traffic fatalities also multimodal freight transportation is investigated using macro-level information.

The methodology that was developed for analyzing this phenomenon should also be able to incorporate time variants of the phenomenon and the spatial connections between the under-investigation units.

It must be mentioned that the nature of the two transportation phenomena (road traffic fatalities and multimodal freight transportation) is different and thus the methodological framework developed differs in some points. Additionally, the methodologies developed will be able to capture and interpret the phenomenon from the perspectives of interpretation and policymaking.

1.3. Contribution

This thesis contributes to the existing methodological framework by capturing regional and international transportation phenomena using macro-level information and developing a methodological framework for analyzing the effects of time and space on different transportation phenomena, separately and by combining these two dimensions. The step-by-step approaches developed to provide answers to the different transportation phenomena (such as what factors are affecting them), support the procedures followed by the policymakers.

Additionally, this Thesis is evident of the hypothesis that macro-level information can be adequately explained larger in scale transportation phenomena and that multidimensional analysis of these larger in scale transportation phenomena is providing a better "picture" of the phenomena. This methodological framework is suggested to be followed in other researches for analyzing macro-level transportation phenomena.

1.4. Summary

The current Thesis has developed a novel idea of capturing regional and international transportation phenomena using macroscopic information in a two-dimensional analysis. In detail it provides a step-by-step methodological procedure that starts from the collection and analysis of macroscopic and technical information of regional and international units, it continues with the interpretation of two transportation phenomena (road traffic fatalities and multimodal freight transports) by studying the linear effects of the phenomenon. The incorporation of time is followed for analyzing the dynamics of the phenomenon over time. Then the dimension of space and the spatial connections between the units are investigated and finally, the methodology uses a two-dimensional approach for providing a realistic interpretation of the phenomena. The methodological framework of the Thesis ends with the analysis of a policymaking approach.

The rest of this Thesis will develop a thorough investigation of the existing literature on the approaches made for analyzing the two different transportation phenomena, namely, Road Safety and Multimodal Freight Transportation (Chapter 2). Then the methodological framework will be developed (Chapter 3) and the results that were generated will be presented (Chapter 4). Finally, the conclusions of this Thesis will be provided (Chapter 5).

CHAPTER 2: LITERATURE REVIEW

The ongoing social, economic, demographic, technological, and environmental changes the coincidence of which are bringing far-reaching changes to macro-level transportation phenomena. The countless and various approaches and methods that are followed, from time to time, for incorporating the changes of macro-level transportation phenomena, created a created uncertainty of which method is more suitable for the analysis of these phenomena.

This Chapter provides a background review of macro-level transportation phenomena analyses, from the data collection to the models' selection approaches. The scope is the investigation and identification of an integrated methodological framework that could encompass simultaneously macro-level Spatio-temporal information for analyzing regional and global transportation phenomena. The following sections provide a methodological investigation of all published sources bearing information on related research topics/subjects.

2.1. Data Collection for Studying Macro-Level Transportation Phenomena

Studying a macro-level transportation phenomenon also requires the collection of macro-level information, which will capture the different aspects of the phenomenon over time and space. According to the literature search, socio-economic and demographic factors can adequately capture different transportation macro-level phenomena. For instance, *(Dimitriou, et al., 2017; Nikolaou & Dimitriou, 2018)* presented that socio-economic and demographic factors are related to the macro-level transportation phenomenon of road fatalities, which appeared well capturing the phenomenon. *Wang, et al., (2016)* used the socio-economic data of Connecticut, USA for describing the safety performance functions for local road intersections and segments. This contention stands even when the scale of analysis is different, i.e., from a local to a national, regional, and even global scale of analysis *(Lloyd, et al., 2015)*. Some other cases of the incorporation of macro-level factors for investigating a transportation phenomenon on a regional scale are of *Yannis, et al., (2014) and Antoniou, et al., (2016)* who used economic factors such as Gross Domestic Product (GDP) for analyzing a macro-level transportation phenomenon (road traffic fatalities) in European.

Despite the fact that macro-level information is available and accessible through Global Organizations (e.g. World Health Organization, World Bank, Eurostat, and other) the collection of this information must be conducted wisely, while collecting data from different data sources may lead to errors and misleading results due to data inflations and information inconsistencies *(Hellerstein, 2008)*. The detection of these errors can vary from a descriptive to an exploratory analysis.

Many studies have been developed for addressing data inconsistencies. For instance, *Ma, et al., (2009)* developed a method for information inconsistencies detection for real-time information in dynamic decision-making. Furthermore, *Fomina, et al., (2014)* presented some methods and approaches to deal with inconsistent and noisy databases used for the inductive notion formation. *Deb & Liew, (2016)* developed a methodology for imputing missing data of numerical or categorical values in a traffic accident historical database. A preliminary investigation of data behaviours, data inconsistencies and data inflations can be obtained from a descriptive analysis which will give a first "taste" of the data.

2.2. Data Analysis

Data analysis is commonly used for identifying and describing the basic features of the data. Data analysis that can be also referred to as descriptive analysis is developed in many studies for presenting the qualitative and quantitative descriptions of the data in a manageable form. In the qualitative analysis, data visualization procedures are attached and in the quantitative analysis, preliminary measures of the data are obtained.

Often the most effective way to describe, explore, and summarize a set of numbers, even a very large set, is to look at pictures of those numbers. For a visual representation of the sets there are several types of reports (e.g., charts, diagrams, bars, maps, and other) *(Tufte, 2007)*. Scientific visualization approaches provide a visual representation of analyses of the collected data and of the calculation results for obtaining an understanding insight of data *(Chaolong, et al., 2016)*. For instance, *Baur, et al., (2015)* collected biomarkers of aging analytical, anthropometric and demographic data from about 3000 volunteers in the MARK-AGE database and applied a data visualization method, among other methods, for dealing with errors in the database. However, the data visualization approach is not 100% efficient way for identifying data inconsistencies, or data homogeneities/heterogeneities, or data inflations (e.g. collinearities), even if the phenomenon seems to be stationary and robust over the years.

Therefore, for identifying more efficiently possible data inconsistencies or homogeneities or collinearities, several researchers used multivariate exploratory techniques, for preliminary analyses, such as correlation and cluster analysis.

Identifying homogeneous groups of under-investigation units based on the collected information is an important task in the preliminary analysis of the data. Cluster analysis is also important in the decision-making procedures for addressing different transportation phenomena based on homogeneous sets of under-investigation units *(Depaire, et al., 2008)*.

One of the common pitfalls of model development lurks in the existence of collinear variables. Macro-level variables are often susceptible to this issue, and therefore a step of explicitly considering this possibility preceded the modeling effort. For dealing with this issue prior to the models' development, in the descriptive analysis, is by developing quantitative analyses that will be able to identify these data inflations (collinearities). In detail, the correlation analysis will provide a "picture" of the variables that are highly correlated with the different transportation phenomena. Correlation analysis is suitable for identifying multicollinearities in a collected data sample. The multicollinearity problem can usually be eliminated by removing one of the exogenous variables in question from the set of exogenous variables *(Bertsimas & Freund, 2005)*.

2.3. Investigations of Direct and Indirect Effects on Different Transportation Phenomena

Analyzing different transportation phenomena can provide significant, in meaning, findings that can be considered in the overall procedures of decision making. These findings can be reflected through the direct and indirect effects of macro-level socio-economic and demographic factors on the different transportation phenomena.

Direct effects of macro-level factors on a transportation phenomenon can be estimated using linear regression analyses suitable to the transportation phenomenon's nature. For example, when analyzing a non-negative transportation phenomenon (e.g. road traffic fatalities) a suitable linear regression model that takes this under control is the Negative Binomial *(Poch & Mannering, 1996).* For instance, *Mohammadi, et al., (2014)* explored the effects of temporal correlation in crash frequency at the highway segment level using a negative binomial regression. *Zou, et al., (2014)* analyzed different functional forms of the varying weight parameters by using NB regression models. In addition, *Zou, et al., (2015)* used NB model in comparison with a Sichel model to determine whether the dispersion term of the Sichel model can be used as an alternative to the NB model. Furthermore, *Coruh, et al., (2015)* analyzed the factors that are affecting the frequency of accident counts in 81 cities with monthly data using random parameters NB panel count data models.

An additional approach for estimating the direct linear relationships between the explanatory effects and the transportation phenomenon is the Ordinary Least Square (OLS) model *(Jeong & Yoon, 2018).*

Collecting data and forming extensive datasets, especially when the study focuses on a global scale, creates speculation of latent constructs inside the sample. Identifying the possible existence of latent constructs inside the samples can be achieved in several ways, namely, Principal Component Analysis and Factor Analysis. Additionally, these techniques have the ability to identify addressing data inflations inside the sample *(Saha, et al., 2016)*.

An alternative technique for identifying latent constructs in the sample and for addressing data inflations is Factor Analysis. Several studies have been conducted by applying Factor Analysis over a variety of fields, such as health *(Chen, et al., 2016)*, where Exploratory Factor Analysis was implemented to explore the structure of nursing students mentors' behavior. An alternative field of study was the work of *Kim, et al., (2017)* who used Exploratory Factor Analysis for evaluating the water quality of the monitoring network of Nakdong River, Korea. Another implementation of Factor Analysis is presented by *Law, et al., (2017)*, where Exploratory Factor Analysis is used to compute the safety performance index for each risk domain in order to measure and compare intercity bus safety.

Overall, Factor Analysis and Principal Component Analysis were approved to be trustworthy techniques for not only identifying data anomalies but also identifying latent structures inside extensive datasets. These latent structures have an effect on the different transportation phenomenon, which cannot be integrated by using a simple linear regression model (such as Negative Binomial or Ordinary Least Square). The appropriate method for incorporating these latent structures and measuring their effects on transportation phenomena is the Structural Equation Modeling (SEM). "*By segregating measurement errors from the true score of attributes, SEM provides a methodology to model the latent variables directly*" *(Yuan & Bentler, 2006)*.

SEM has been widely used in several fields, such as in economics *(e.g. Tahmasebi & Rocca, 2015)*, health *(e.g. Lai, et al., 2015)*, psychology *(e.g. Al-Refaie, 2013)*, road safety (*e.g. Chen, et al., 2016; Hassan, et al., 2013*) and other. For instance, *Wong, et al., (2018)* used SEM to evaluate the model's assumptions. In detail, they tested the construct of the Multilevel Older Persons Transportation and Road Safety model and its ability to account for variation in older adult's driving self-regulation. Furthermore, *Lee, et al., (2008)* implemented SEM to estimate the relationship between exogenous factors and traffic accident size. For this purpose, they used accident data occurred on highways in Korea. Another case of SEM application is of the work of *Hassan & Abdel-Aty, (2011)*, where they investigated drivers' responses under low visibility conditions and quantify the impacts and values of various factors related to drivers' compliance and satisfaction with variable speed limit and variable message signs instructions in different visibility and traffic conditions, covering two types of roadways. In their research the relationship between socio-economic factors and road traffic fatalities was studied by the implementation of SEM not in an operational level, but rather on a macro level.

Based on the literature SEM method has different mathematical formations the Partial Least Square SEM (PLS-SEM) and the Covariance-Based SEM (CB-SEM). Using PLS-SEM or CB-SEM may produce similar results *(e.g., Amaro, et al., 2015)*, however, PLS-SEM is preferred by certain researchers because CB-SEM requires larger samples than PLS-SEM *(e.g. Hair, et al., 2011; Astrachan, et al., 2014)*. For instance, *Vidal Vieira & Fransoo, (2015)* studied the interactions between freight distribution constructs, such as regulations, collaboration, detour, load-unload interfaces, and logistics performance by using the PLS-SEM model. Furthermore, *Shen, et al., (2016)* evaluated the rail transit passenger satisfaction level and identified the factors that affect passengers' satisfaction in China by applying PLS-SEM. Similarly, *Sarstedt, et al., (2014)* developed the PLS-SEM model to investigate the relationship between family business theories and theories in other practices (e.g., marketing). *Zahoor, et al., (2015)* explored the causal relationship of safety climate and safety performance on building projects using PLS-SEM models.

However, linear regression and the Structural Equation Modeling methods are not able to integrate the component of time and therefore in case the sample is time variant then the creation of the models is based on a repetitio capturing each different time instance. Most of the times these models have the same structure of included variables, and thus the selection of the most statistically significant models is a necessary procedure.

The complexity of SEM makes model selection harder than with simpler modeling approaches. Therefore, a lot of attention is given on the model Goodness-of-Fit (GoF) criteria and overall selection procedure that were introduced from several researchers *(*e.g., *Hooper, et al., 2008)*. *Preacher & Merkle, (2012)* discussed the problems stemming from sampling variability in selection indices and show that selection decisions using information criteria (specifically the Bayesian information criterion) can be highly unstable over repeated sampling, even in large samples.

Overall, the background review presented in this section reveals the methods applied for capturing the effects that different macro-level socio-economic and demographic factors have on different transportation phenomena. Additionally, this section presents the tools that are appropriate for identifying data errors and latent structures. It is showed that these latent structures can be incorporated in a model and affect the transportation phenomenon. This model is Structural Equation Modeling. The selection of statistically robust models is a straightforward procedure that takes under consideration GoF indices.

2.4. Integrating Dimensional Components on Transportation Phenomena Investigations

As *Tobler, (1979)* stated in his first law of geography: "Everything is related to everything else, but closer things more so" and because classic regression models do not take the spatial influences into account, therefore it is important to emphasize on the spatial lags of the transportation phenomenon and the spatial relationships between the different under investigation units. Several, spatial models have been developed in several fields, including road safety *(e.g., Irumba, 2014)*, spatial statistics *(e.g., Du, et al., 2018)* and other.

Similar implementations of spatial analysis showed the importance of taking into account spatial dependencies and thus several researchers have incorporated the spatial autocorrelation in their studies. For instance, *Truong, et al., (2016)* explored the factors associated with traffic crash fatalities in 63 provinces of Vietnam during the period from 2012 to 2014. In detail, they implemented the ST-CAR model for accounting the spatiotemporal autocorrelation in the data. Additionally*, Jia, et al., (2018)* identified a spatial correlation of crash data for the case of Suzhou Industrial Park, China. *Krisztin, (2018)* incorporated the spatial dependence of freight generation models by using a Spatial Autoregressive model

(SAR), which appeared that indeed spatial dependence plays a key role in European Freight generation modeling. Also, *Saha, et al., (2018)* implemented a spatial analysis of bicycle crashes at census block groups in Florida. For assessing the possible existence of spatial autocorrelation across the census block groups, they examined two model specifications (e.g. Besag's model and Leroux's model).

Additionally, *Rhee, et al., (2016)* investigated traffic crashes in a large metropolitan area in Seoul by implementing standard spatial regression models (e.g. spatial error model and spatial lag model). *Xie, et al., (2019)* accounted for the spatial autocorrelation of neighbouring sites and the inherent correlation across different crash types by the development of the multivariate conditional autoregressive model. *Alkaabi & Debbage, (2011)* analyzed the geography of air freight demand and suggested a substantial spatial concentration and hierarchy of air freight volume.

As it was observed from the literature, spatial component is indeed important in the analysis of any macro-level transportation phenomenon. However, this spatial dependence is more obvious when their spatial connections between the under-investigation units exist. These, spatial connections might be also relevant with the homogeneity of the units and therefore is considered for investigation in this Thesis.

Besides the dimension of space in transportation phenomena we also have the dimension of time which is also important for incorporation. So far, in the literature review besides from the time-series and pattern models, there was not a methodology that can incorporate both dimensions in the same model's structure. In detail, the multi-dimensional characteristics of transportation phenomena due to their variation over time and space, leads to a respective analysis of both components for capturing each different phenomenon adequately.

Several studies have also been developed for modeling both spatial and temporal variability in a different study area e.g., environment *(Romić, et al., 2020)*. However, as far as we know this approach is novel for the analysis of macro-level transportation phenomena. Countless methods, tools, and models have been developed for incorporating this multi-dimensional information. However, few methods can incorporate the repetition of observations based on time and space variants and provide non-biased results. One of these methods is the Linear Mixed Model (LMM). Based on the literature review Mixed model has been applied to several studies likewise psychology *(e.g., Meteyard & Davies, 2020)*, hydrology *(e.g. Mellor & Cey, 2015)* and other.

2.5. Evaluation Procedures of Transportation Phenomena

From the collection of data to their analysis (descriptive and exploratory) is a procedure that provides insights both on the data and on the different transportation phenomena. All the above procedures can capture any different macro-level transportation phenomenon by estimating the effects of the macro-level information on the phenomena and by integrating the dimensional components of time and space. However, in every macro-level transportation phenomenon there is a procedure of evaluation identifying under and best-performing (in terms of the transportation phenomenon that is under investigation) units, targeting the under-performing and measuring the effects of macro-level information on their performance. The improved performance on transportation phenomena can be useful for validating the applied policies and strategies *(Jung, et al., 2016)*. Therefore, it is important identifying the under and best-performing units by implementing a benchmark analysis and attend them by following the policy strategies of best-performing countries. According to relevant literature reviews on macro-level transportation phenomena, many studies were presented by using benchmark analysis on a national level *(e.g. Aarts & Houwing, 2015; Bastos, et al., 2015)* or international level *(e.g. Hermans, et al., 2009)* towards policy/decision making.

One of the most popular benchmarking methods is Data Envelopment Analysis (DEA). The findings from DEA have the ability of providing clear directions for policymakers about what actions are needed in order to improve the performance of a unit (country, city and other) based on the transportation phenomenon. Furthermore, many researchers have used DEA method for implementing benchmarking analysis. For instance, *Alper, et al., (2015)*, estimated the relative efficiency of 197 local municipalities in traffic safety in Israel during 2004-2009. Additionally, *Egilmez & McAvoy, (2013)*, implemented DEA based Malmquist index model for assessing the relative efficiency and productivity of U.S. States in reducing the number of fatal crashes. Moreover, *Wu, et al., (2015)*, analysed the effectiveness of maritime safety control along the Yangtze River. *Shen, et al., (2012)*, implemented DEA as a performance measurement technique for providing an overall perspective on a country's road safety condition. A study by *Pal & Mitra, (2016)*, evaluated the efficiency of 37 Indian State Road Transport Undertakings by using desirable and undesirable outputs (e.g. number of accidents). For this evaluation, the directional distance function of DEA was used. *Merkert & Assaf,* *(2015)*, used DEA for the purpose of investigation of the impact that airport quality might have on airport profit. In the following section, the application of DEA for benchmark analysis of the road safety levels in EU23 countries is proposed, starting from a preliminary investigation of the dataset used for that purpose.

In the work of *Bray, et al., (2014)*, they explored the Fuzzy theory-based DEA model in order to find the efficiency values for transportation system considering uncertainty in data. The method is then applied for evaluating the container ports of Mediterranean Sea.
Regarding the literature, several studies were implemented for evaluating ports efficiency by using the technically sound DEA method. For instance, *MARTÍNEZ-BUDRÍA, et al., (1999)* used the DEA method for evaluating the efficiency of all the Spanish Port Authorities during the time period 1993-1997. Another implementation of the DEA method was from *(Rios & Maçada, 2006)*, where they analysed the efficiency of operations in container terminals of Mercosur, concerning the years 2002, 2003 and 2004. In *Barros, (2006)* paper, the DEA method was implemented for evaluating the performance of Italian ports from 2002 to 2003, combining operational and financial variables. DEA method was also developed in *Schøyen & Odeck, (2013)* study, where they evaluated the efficiency of Norwegian container ports comparing to some Nordic and UK container ports.

As it appeared from the literature review the DEA method is widely used in the field of transportation. An additional, formation of DEA This research uses a basic DEA method, namely DEA-CCR from Charnes, Cooper and Rhodes who proposed it. For instance, *Barros & Athanassiou, (2004)* used DEA-CCR and DEA-BCC, for evaluating the efficiency of Greek and Portuges ports. Furthermore, *Elsayed & Shabaan Khalil, (2017)* used DEA-CCR and DEA-BCC models for assessing the comparative efficiency of SAFAGA port (Egypt) during the time period 2004-2013.

Evaluating the performance of a country or a city or of any unit is important as the best-performing and under-performing units will be identified. However, all this information is deficient when there is no information on which factors are affecting the most this performance of both under and best-performers.

For analyzing and identifying the effects of different components on transportation phenomenon a suitable regression model was developed, namely, Tobit, which is introduced by *Tobin, (1958)*. The combination of the DEA method and Tobit regression has also been developed in several research. For instance, *Tasnim & Afzal, (2018)* used Tobit regression model for observing what macro factors affect the efficiency of the knowledge spillover theory of entrepreneurship. For identifying the efficiency of 59 countries DEA method was developed. Another study used DEA for measuring the efficiency of 30 university science parks and Tobit regression model for analyzing the impact of possible influential factors *(Wu, et al., 2010)*.

As it was proved from other research, the investigation of the factors that affect both under and best-performers on the different transportation phenomena is a task that can be achieved from DEA-Tobit. However, in case the investigation concerns only the under-performers and not the best-performers. In that case, we would be talking about a sample-selection method that can take advantage of the findings from DEA, incorporate the macro-level explanatory factors, and measure the effectiveness of these explanatory factors on transportation phenomena.

Based on the literature, the model that can accommodate sample selection approaches is the Heckit model from *(Alkaabi & Debbage, 2011)*. Implementations of Heckman's model were used in several studies, namely, in health *(e.g., Mishra & Monica, 2019; Morrissey, et al., 2016)*, in agricultural science *(e.g., Abdullah, et al., 2019)*, marketing and management *(e.g. Lyu & Noh, 2017)*, economics *(e.g. Sellers-Rubio & Nicolau-Gonzalbez, 2016)*. For instance, *(Tsekeris & Dimitriou, 2008)* implemented the Two-Part and Double-Hurdle Heckit models for estimating the probability of selecting a specific mode in interurban public transportation.

Overall, the procedures presented in the literature that were applied form previous researchers for the evaluation procedures of the units under consideration in every macro-level transportation phenomenon showed a robust technique that considered in the developed methodological framework of this Thesis.

2.6. Deciding the Proof of Concept Macro-Level Transportation Phenomena

This Chapter presented all the techniques and mechanisms that previous studies implemented for studying different macro-level transportation phenomena. This Thesis takes advantage of the applications of existing methodologies from the literature and creates a new methodological framework that combines all the above methods, mechanisms, techniques in a novel way and develops a new approach to transportation. Notwithstanding the range of fields of different transportation phenomena this Thesis provides proof of concept for the proposed methodological framework on two major fields of macro-level transportation phenomena, namely: Road Traffic Fatalities and Multimodal Freight Transportation.

2.6.1. Why Road Traffic Fatalities

Road traffic injuries have nowadays been recognized as one of the most important public health issues that require concerted efforts for effective and sustainable prevention. Worldwide, an estimated 1.35 million people are killed in road accidents, with road traffic injuries being the leading cause of death for children and young people aged between 5 and 29 years old and the number of road traffic fatalities continues to climb, reaching 1.35 million in 2016 *(WHO, 2018)*.

As the decade of Action for Road Safety (2011-2020) is coming to its end the divergence from the United Nations' goal becomes apparent. This goal is nothing less than the decrease of road traffic fatalities.

In 2010, the European Commission adopted the "Road Safety Program", which aimed to halve road deaths in Europe in the decade 2011-2020. Besides the efforts and the progress that has been made with reducing the number of fatalities still, this target has not been reached yet *(EC, 2019)*. Additionally, based on European Road Safety Observatory's annual accident report 2018 25,600 deaths were recorded within the Member States of the European Union in 2016, a number that highlights the importance of investigating and understanding the phenomenon and finally supporting the overall effort of policymakers *(European Road Safety Observatory, 2018)*.

Therefore, road safety is a major issue worldwide because of the negative impact on victims, their families, and society. Strategic road safety policies are essential to the effort of road traffic fatalities' reduction.

2.6.2. Why Multimodal Freight Transportation

The role of the maritime sector in the European region is recognized as of paramount importance. Indicatively, 74% of goods are entering or leaving Europe by the sea, a fact highlighting the importance of the maritime system, especially that of containerized cargo, in economic development *(European Commission, 2018)*. Accordingly, container port terminals, corresponds to a critical part of the European supply chain since acts as gateways from/to the system of the international trade. The last decades, important developments are taking place in the ownership, management, organization and technological development of container terminals, where vast effort (and capital) is invested throughout the European market of cargo handling and especially in container terminals, fostering competition among them in attracting cargo. These investments concern all elements that effect on port performance, such as terminals organization structure, equipment, and infrastructure.

World trade can play a major role in national development, in terms of economic growth. Therefore, it is important identifying the factors that mostly affect freight demand. As referred to *(WTO, 2017)* in 2017 Asia recorded the highest increase in freight volume with the growth of 8.1% and Europe recorder the second smallest increase in volume, with the growth of 3%, while Middle East region recorded a -2.2% decrease in volume growth. However, the European Union remains a significant 'player' in the global freight system, accounting for a third of world exports in 2017.

2.7. Summary

This Chapter presents a thorough investigation of the existing literature based on the analysis of macro-level transportation phenomena. As it was appeared from the literature, the data collection procedure is important, and thus for capturing the different transportation phenomena is important collecting and integrating macro-level information which is correlated with macro-level transportation phenomena.

A descriptive analysis of the data including data visualization, correlation analysis appeared form the literature able to reveal, in a preliminary analysis, facts of the data or of the phenomenon or even of the units that are considered, either countries or cities or other. Following this founding from the literature the most expected step was the exploratory analysis where researchers implement several methods for investigating the factors and the effect on the different transportation phenomena. Some of the most robust methods are Ordinary Least Square and Negative Binomial.

As also revealed from the literature, when collecting extensive data sample, it is highly possible that these sample might contain latent structures that have an unobserved effect on the phenomena. These, latent structures were identified from the methods of Principal Component Analysis and Factor Analysis. In case that indeed latent structures were included in the sample they were incorporated by using Structural Equation Modeling.

Based on the literature, analysing macro-level transportation phenomena in a space that homogeneity exists it is possible that the phenomenon is spatially related. Therefore, this spatial correlation can and was incorporated by the implementation of Spatial Autocorrelation Model. However, space is not the only dimension of transportation that is affecting the phenomena. Time is also an important component that affects the different transportation phenomena. For integrating the dimensional aspects of transportation phenomena, the existing literature favoured the method of Linear Mixed Model.

When investigating a macro-level transportation phenomenon, the last step should be the support on decision-making processes for improving the conditions of this phenomenon. Therefore, the background review shed light to a benchmarking analysis method namely, Data Envelopment Analysis (DEA). In addition, to the evaluation that DEA can provide it is also important measuring the effects that macro-level explanatory data have on the transportation performances.

All the background review not only showed appropriate and most suitable techniques but also covered all the missing points that appear to be when analyzing a transportation phenomenon and not considering all the aspects that this phenomenon might have. Thus, based on the literature the methodological framework of this Thesis was developed. However, for providing proof to the concept of this Thesis two macro-level transportation phenomena where analyzed, namely, Road Traffic Fatalities and Multimodal Freight Transportation, for the reasons mentioned in this Chapter.

CHAPTER 3: METHODOLOGICAL FRAMEWORK

This chapter presents a straightforward methodology that aims the analysis of transport phenomena. The methodological implementations introduced in this Thesis follow a step-by-step approach for developing a context of a descriptive, exploratory, and explanatory analysis. Each section of this chapter achieves a balance between depth and breadth of theory and applications in transportation. **Figure 1** presents an overview of this Thesis' methodological framework followed.

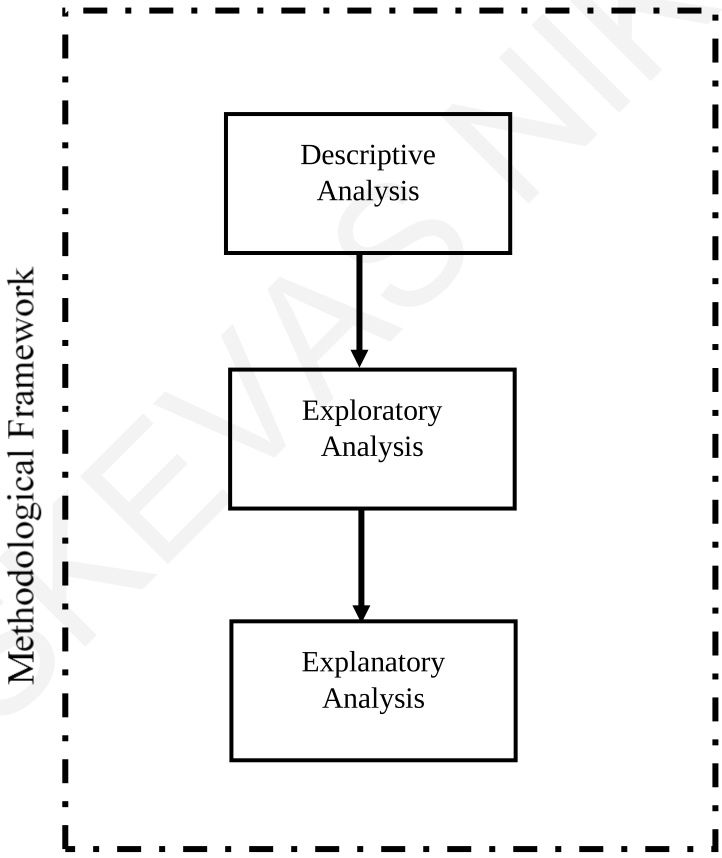


Figure 1. Overview of the methodological framework's structure

The descriptive analysis includes a throughout investigation of data behaviours throughout qualitative (visual) and quantitative (statistical) analysis. The exploratory analysis introduces methodological frameworks suitable for measuring unobserved structures in data and observing and analysing temporal and spatial sequences in outcomes, including different transportation phenomena. When analysing macro-level transportation phenomena, explanatory procedures are vital, especially when supporting policy and decision-making is strategies. Therefore, these explanatory procedures are based on the findings from the descriptive and exploratory analysis.

Figure 2 presents the flow chart of the detailed proposed methodological framework when analysing different transportation phenomena on a macro-level analysis. As can be seen, the methodological framework starts by having the transportation phenomenon of interest and the declaration of the under-study Decision Making Units (DMUs). However, most of the time the availability of data in the data collection procedure affects the under-selection DMUs, and therefore this procedure is repeated until we come up with collecting the available and open information of the DMUs.

The methodological approaches start from the descriptive analysis with a qualitative (data visualization) and quantitative (correlation and cluster analysis) analysis are implemented. At this stage data dissimilarities or similarities will be revealed with data inflations (e.g., collinearities). Cluster analysis which is added in the quantitative analysis it is possible to be seen also at the explanatory stage of analysis due to the capability of the method of grouping homogeneous sets of DMUs that are possible to be addressed with the same approaches in the decision-making procedures.

Moreover, at the second stage of analysis, which is the exploratory analysis, different macro-level factors were investigated for their effects on the different transportation phenomena by developing linear regression models, such as Ordinary Least Square and Negative Binomial. However, interpreting a model requires the statistical check of the model through the use of Good-Of-Fit indices or Stepwise regression analysis.

Obtaining these estimates does not say a lot especially when it is highly possible that these factors may have some latent structures that are not visible to the naked eye and therefore require the use of techniques that can reveal this information. These techniques are namely, Principal Component Analysis and Factor Analysis. For incorporating this latent information suitable Structural Equation Models (SEM) are revealed, namely, Partial Least Square-SEM and Covariance Based-SEM.

Analysing, different transportation phenomena can be considered as incomplete when we are not considering spatial autocorrelation between the DMUs. Therefore, at this stage, the investigation of spatial dependence was conducted for identifying possible spatial dependence in the transportation phenomena. To quantify this spatial dependence, the Spatial Autoregressive model was introduced. It must be noted that in all the above-mentioned approaches the temporal component was incorporated in the models through a repetition of the model based on the difference in years' data.

Therefore, one of the important approaches of the exploratory analysis is the dimensional analysis of the transportation phenomena by incorporating time and space which can be achieved through the development of an extended form of Linear Mixed Model which was named as Spatio-Temporal Linear Mixed Model. With this implementation exploratory analysis was able to quantify the effects that different factors have on different transportation phenomena.

The finally, step of the exploratory analysis was the support the decision-making procedures of local, regional, and global authorities based on the performance of the DMUs in the different transportation phenomena. In order to make it happen a benchmarking analysis was constructed namely Data Envelopment Analysis (DEA) and DEA-Cross Efficiency for evaluating the DMUs' performance. The performance of the DMUs was presented as an efficiency score for each DMU ranking either from 0 to 1 in case of a minimization of the output or from 1 and above in case of maximization of the output. However, for quantifying the effect that different factors have on the DMUs' performance a censored regression model was introduced, namely, Tobit. However, Tobit model provided the effects of the factors on both best and under-performing. Moreover, for studying and measuring the effects that these factors have only on the under-performing DMUs a selection sample-based model, namely, Heckit was introduced. In addition to the above a target setting approach was included in the methodology and thus targets are set for under-performing DMUs in order to improve their performance based on the performance of best-performing DMUs. At this point it must be highlighted that time component was incorporated by "*n*" observations of the factors each one representing a different time instance of the "**T**" period (see **Fig.2**).

Overall, this methodological framework concludes with an explanatory analysis which provides answers to several aspects of different transportation phenomena and also robust results for understanding, interpreting, and addressing different in nature transportation phenomena.

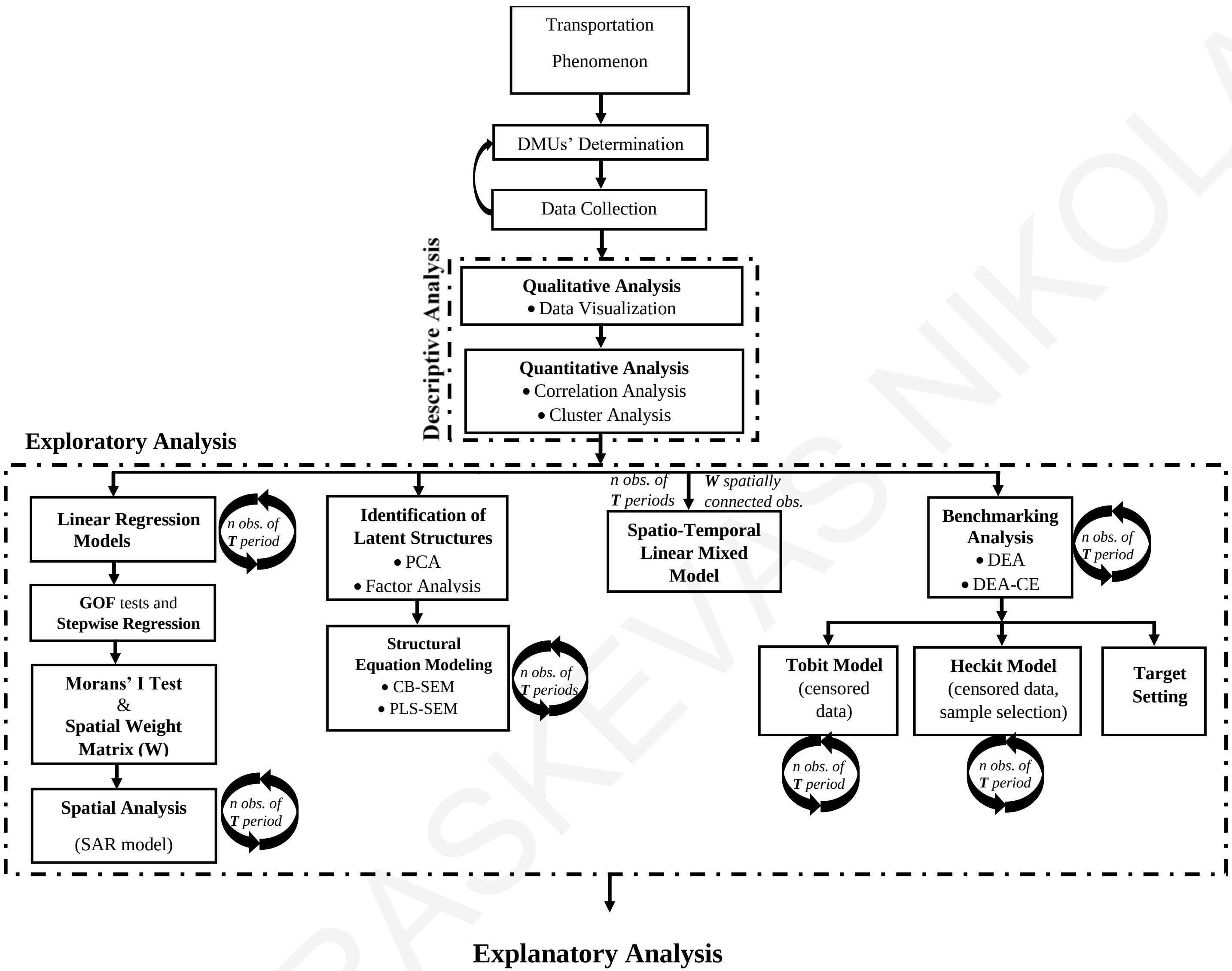


Figure 2. Chart flow of the detailed methodological framework

3.1. Descriptive Analysis

This section describes some of the methods/techniques commonly used in transportation data analysis through the concepts of descriptive analysis. When the collected data are in large amounts and need to be interpreted, descriptive analysis (qualitative and quantitative) is used for organizing and summarizing them. For example, suppose data are collected concerning a transportation phenomenon for a time period, for several factors and for tens to hundreds of observations, which from now will be named as Decision Making Units (DMUs). Then the data can be analyzed with descriptive analysis to answer questions such as "What is the performance of the DMUs over the time period and for each factor separately?" or "Are there any data inflations that must be addressed?". This section provides answers to such questions. The discussion begins with the qualitative analysis of the collected information and in particular the data visualization analysis and continues with the quantitative analysis of the data which is the statistical analysis.

3.1.1. Data Visualization

Data visualization analysis is a process of combining science and art and presenting graphics of complex information. These graphic displays should aim to:

- Show the data
- Encourage the eye to compare different perspectives of the data
- Identify lacks of information
- Identify homogeneities and heterogeneities
- Identify consistencies and inconsistencies
- Observe the spatial and temporal relations of factors and DMUs

At the same time, the graphic displays should be aesthetically pleasing and avoid distorting what the information wants to say. There are countless types of visualizations (e.g. box plots, pies charts, bar charts, maps, etc.) that offer different aspects of the data. All the feature aspects of a graph are characterized as aesthetics.

Aesthetics describe every aspect of a given graphical element. These elements are:

- Position

- Shape/type
- Color
- Size/width

The position of the graph elements might be the geographic position of the elements or a visualization between x and y factors in a 2D dimensional space or a visualization between x, y, and z in a 3D dimensional space. The shape of the graph elements usually denotes the different DMUs that the data are referring to. As for the elements color and size are also features that describe different classifications of the information or different DMUs.

The ways of visualizing the data vary based on the nature of the data. For example, if we would like to observe spatial dependencies on the data the best way to identify this is by drawing a map. However, besides the important information that visualization processes offer in the descriptive data analysis, it is important also justifying the outcomes of this approach from statistical tests (quantitative analysis).

3.1.2. Statistical Analysis

This section examines methods and techniques for statistically summarizing and interpreting data in the transition from a thorough data visualization approach. The statistical analysis begins with the examination of a numerical descriptive measure of association (correlation analysis) and data homogeneities/similarities and heterogeneities/dissimilarities.

3.1.2.1. Correlation Analysis

Correlation analysis belongs to the statistical measures that provide useful information regarding possible relationships between variables. Correlation between two variables is the measure of the linear relationship between them. The population linear correlation parameter "ρ" is a commonly used measure of how well two variables are linearly related. The correlation parameter lies between the limit interval of [-1,1], where $\rho=0$ indicates zero linear relationships between the variables, $\rho > 1$ indicates a positive linear relationship between the variables and $\rho < 0$ indicates a negative linear relationship between the variables.

Correlation stems directly from another measure of association, the covariance. If we consider two random variables, X and Y, both normally distributed with population means

$\boldsymbol{\mu_X}$ and $\boldsymbol{\mu_Y}$, and population standard deviations $\boldsymbol{\sigma_X}$ and $\boldsymbol{\sigma_Y}$, respectively. The population and the sample covariance between X and Y are defined, respectively, in **Equation 1** and **Equation 2**:

$$COV_p(X,Y) = \frac{\sum_{i=1}^{N}(x_i - \mu_X)(y_i - \mu_Y)}{N} \quad \textbf{(1)}$$

$$COV_s(X,Y) = \frac{\sum_{i=1}^{n}(x_i - \bar{X})(y_i - \bar{Y})}{n-1} \quad \textbf{(2)}$$

Based on the above equations the covariance is positive when two variables increase together, negative when two variables move in opposite directions, and it is zero when two variables are not linearly related.

As a measure of association, the covariance suffers from a major drawback. It is usually difficult to interpret the degree of linear association between two variables using the covariance because its magnitude depends on the magnitudes of the standard deviations of X and Y and thus it is not standardized. For this reason, the covariance is divided by the standard deviations to obtain a measure (either called as Pearson product-moment correlation parameter or correlation parameter) that is constrained to the range of values [-1,1]. The population "ρ" and the sample "r" correlation parameter of X and Y are defined in **Equation 3** and **Equation 4**, respectively *(Washington, et al., 2003)*.

$$\rho = \frac{COV(X,Y)}{\sigma_X \sigma_Y} \quad \textbf{(3)}$$

$$r = \frac{COV(X,Y)}{s_X s_Y} \quad \textbf{(4)}$$

Where, s_X and s_Y are the sample standard deviations.

Correlation analysis is a strong statistical measure for identifying not only the independent variables that have a strong relationship (either positive or negative) with the dependent variable/s but also for identifying data inflations (collinearities). In detail, in case two independent variables have a strong relationship between them (i.e., r > |±0.7|) then the variables are considered as identical. Therefore, in this case, one of the variables must be omitted from the sample due to this collinearity. Either way including both variables may create bias in the modeling development approach.

3.1.2.2. Cluster Analysis

Cluster analysis is commonly used for finding out which DMUs are similar or dissimilar based on specific factors in a set. The main reason for making cluster analysis so useful tools is the need for researchers to obtain continually classifications of DMUs in a way that will help to understand the data and for supporting decision making, planning, or managing procedures.

While applying cluster analysis there exists a question that should be taken under concern “What is the optimal number of clusters-classifications?”. Based on the set of factors that are used for the classification in the cluster analysis we obtain different groups of DMUs. Therefore, prior to the cluster analysis, it is important of identifying the optimum number of clusters. This identification can be gained through some techniques. Some of the techniques are the Average Silhouette Method and the Elbow Method.

The average silhouette method measures the average silhouette of observations for different values of “K”. The optimal number of clusters “K” is the one that maximizes the average silhouette over a range of possible values for “K”. As for the Elbow method, it looks at the total within-cluster sum of square as a function of the number of clusters.

Clustering analysis has several approaches for identifying similar groups. The basic approaches are:

- Centroid-Based Clustering, and

In the case of centroid-based clustering, the number of “K” is fixed and known based on the Average Silhouette and Elbow methods. The idea behind the K-means method (centroid-based clustering) is the identification of “K” centroids in order to represent all the DMUs in an optimal manner.

The k-means formation can be seen in **Equation 5**:

$$S(D, \boldsymbol{m}_1, \ldots, \boldsymbol{m}_K) = \sum_{i=1}^{n} d\left(x_i, \boldsymbol{m}_{C(i)}\right),$$
$$c(i) = argmin\, d\left(x_i, \boldsymbol{m}_j\right), i = 1, \ldots, n, j \in \{1, \ldots, K\} \quad \textbf{(5)}$$

Where, $\boldsymbol{m}_1, \ldots, \boldsymbol{m}_K$ are “K” centroids and d is a dissimilarity measure. The centroids $\boldsymbol{m}_1, \ldots, \boldsymbol{m}_K$ may be required to be the objects in D (where in this case they are sometimes called exemplars), or they may stem from the data space X. For the K-means method, $\boldsymbol{x}_1, \dots, \boldsymbol{x}_n \in R^p, \boldsymbol{m}_1, \dots, \boldsymbol{m}_K$ are not required to be exemplars, and d is the squared Euclidean distance, which implied that $\boldsymbol{m}_1, \dots, \boldsymbol{m}_K$ have to be mean vectors of their respective cluster in order to minimize **Equation 1,** and thus the name of the equation is K-means *(Hennig, et al., 2015)*. In detail, K-means clustering requires that very DMU will be close to the centroid point, a fact that restricts the shapes of the clusters.

- Agglomerative Hierarchical Methods

Agglomerative hierarchical clustering method has two ways of building a hierarchy. The one is the agglomerative and the other one is divise. Agglomerative hierarchical clustering begins from a clustering in which every DMU forms its own cluster, creating "n" clusters. In every step, every most similar cluster is merged and thus a new cluster is created, and also the number of clusters is reduced by one (n-1). In the end, all similar DMUs are merged into the same cluster. The different agglomerative hierarchical methods can be varied based on the different ways of computing the dissimilarity "D" between two clusters (e.g. C1, C2) from the dissimilarities "d" between the merged DMUs (e.g. x1, x2). The most famous methods are:

- Nearest Neighbor presented in **Equation 6**

$$D(C1, C2) = \min_{x1 \in C1, x2 \in C2} d(x1, x2) \tag{6}$$

- Furthest Neighbor presented in **Equation 7**

$$D(C1, C2) = \max_{x1 \in C1, x2 \in C2} d(x1, x2) \tag{7}$$

Partitions in "K" clusters can be obtained from hierarchies by cutting the hierarchy at the appropriate level. In some respects the different agglomerative hierarchical methods are quite different from each other, emphasizing, for instance, separation of clusters over homogeneity in the most extreme manner (Nearest Neighbor), or the opposite (Furthest Neighbor), but on the other hand, the agglomerative process makes partitions obtained by them rather more similar on some datasets than to what can be obtained from other clustering approaches *(Hennig, et al., 2015)*.

Divise hierarchical methods start with all objects in a single cluster and proceed by splitting up on of the clusters at each step finding the most similar DMUs. Computationally, it is much more difficult to find optimal splits as required for divise clustering than to find optimal merges as required for agglomerative clustering, and thus agglomerative hierarchical clustering is much more widely used.

3.2. Exploratory Analysis

Having prepared the descriptive analysis, useful outcomes will occur about the originally collected data. However, besides this information, it is important obtaining the information or effects that this information has on transportation. A classic way of measuring these effects is by quantifying it in a linear regression analysis. However, this information has some insight structures that are not visible to the naked eye and therefore require a thorough look for defining them. Furthermore, investigating different transportation phenomena requires also the understanding of these phenomena on different dimensions. These dimensional concerns mainly the time evolution and the space dependence of these phenomena.

Therefore, this section implements different methodologies for measuring relationships between different variables with transportation phenomena, illustrating, structures in data (e.g. latent structures), and analyzing temporal and spatial variations on different transportation phenomena.

3.2.1. Linear Regression Models

The objective of a linear regression model is to analyze the relationships between a dependent variable (Y) with one or more independent variables (X). The ability to say whether an X variable is affecting the Y variable is through the coefficients (beta parameters). Thus, the regression works by estimating the beta parameters through a population of given information on both dependent and independent variables. The most famous procedures that are followed for estimating the parameters are the least-squares and maximum likelihood.

3.2.1.1. Negative Binomial Regression Model

Failing to satisfy the property of the Poisson distribution, which is the restriction that the mean should be equal to variance, results to a common analysis error. Thus, if this equality does not hold the data are to be either under-dispersed or over-dispersed, and the parameter vector is biased if corrective measures are not taken *(Washington, et al., 2003)*.

The negative binomial model for observation «i» is depicted in **Equation 8**:

$$\lambda_i = EXP(\boldsymbol{bX}_i + e_i) \quad \textbf{(8)}$$

Where $\boldsymbol{X_i}$ is a vector of explanatory variables, $\boldsymbol{\beta}$ is a vector of estimable parameters and $\boldsymbol{EXP}(\boldsymbol{\varepsilon_i})$ is a Gamma-distributed disturbance term with mean 1 and variance a. The addition of this term allows the variance to differ from the mean as depicted in **Equation 9**:

$$VAR[y_i] = E[y_i]\big[1 + aE[y_i]\big] = E[y_i] + aE[y_i]^2 \quad \textbf{(9)}$$

3.2.1.2. Least Square Estimations-OLS

Least square estimations often referred as to Ordinary Least Square (OLS) is a method for estimating regression model parameters given the sample data. The mathematical form of the OLS model is given below (**Equation 10**):

$$\boldsymbol{\hat{Y}} = \boldsymbol{X\beta} + \varepsilon \quad \textbf{(10)}$$

Where Y with a hat is the predicted value of the dependent variables given the constant parameters (β) of the independent variables (X) and the error terms (ε). OLS requires a minimum (least) solution of the squared disturbances, i.e., OLS seeks a solution that minimizes the function Q in **Equation 11**:

$$Q_{min} = \sum_{i=1}^{n} (Y_i - \widehat{Y}_i)^2_{min}$$

$$= \sum_{i=1}^{n} (Y_i - [\beta_0 + \beta_1 X_i])^2_{min} \qquad \textbf{(11)}$$

$$= \sum_{i=1}^{n} (Y_i - \beta_0 - \beta_1 X_i)^2_{min}$$

Where the values of β_0 and β_1 which minimize the function, Q are the least-squares estimated parameters and they are unknown. Thus, estimators B_0 and B_1 are obtained, which are random variables that vary from sample to sample. By setting the partial derivatives of Q with respect to β_0 and β_1 equal to zero, the least square estimators B_0 and B_1 can be obtained using β_0 and β_1 with hat, and thus the following equations can be formed (**Equation 12**, **Equation 13**) *(Washington, et al., 2003).*

$$\widehat{\beta}_1 = \frac{\sum_{i=1}^{n} (X_i - \overline{X})(Y_i - \overline{Y})}{\sum_{i=1}^{n} (X_i - \overline{X})^2} \qquad \textbf{(12)}$$

$$\widehat{\beta}_0 = \overline{Y} - \widehat{\beta}_1 \overline{\overline{X}} \qquad \textbf{(13)}$$

The derivation of the matrix algebra equivalent of the least-squares normal equations for the simple regression case is straightforward. In the simple regression case, the expression Y=Xβ consists of the matrices in **Equation 14**. The beta vector is shown as $\boldsymbol{\beta}$ with a hat since it is the estimated vector of betas for the true beta vector $\boldsymbol{\beta}$ *(Washington, et al., 2003)*.

$$\boldsymbol{Y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \boldsymbol{X\beta} = \begin{bmatrix} 1 & x_1 \\ 1 & \vdots \\ 1 & x_n \end{bmatrix} \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{bmatrix} \qquad \textbf{(14)}$$

Therefore, the following steps are used for solving the betas:

- Step 1: $\boldsymbol{Y = X\beta}$
- Step 2: $\boldsymbol{X^T Y = X^T X B}$
- Step 3: $(\boldsymbol{X^T X})^{-\mathbf{1}} \boldsymbol{X^T Y} = (\boldsymbol{X^T X})^{-\mathbf{1}} \boldsymbol{X^T X B} = \boldsymbol{B}$

3.2.1.3. Maximum Likelihood Estimation

An alternative estimation method of the beta parameters is Maximum Likelihood (ML), which results in the maximum likelihood estimates. For the regression model, the likelihood function for a sample of n independent, identically, and normally distributed disturbances is given by **Equation 15**:

$$L = (2\pi\sigma^2)^{-\frac{n}{2}} EXP\left[-\frac{1}{2\sigma^2}\sum_{i=1}^{n}(\boldsymbol{Y_i} - \boldsymbol{X_i^T\beta})^2\right]$$
$$= (2\pi\sigma^2)^{-\frac{n}{2}} EXP\left[-\tfrac{1}{2\sigma^2}\textstyle\sum_{i=1}^{n}(\boldsymbol{Y} - \boldsymbol{X\beta})^T(\boldsymbol{Y} - \boldsymbol{X\beta})\right] \quad \textbf{(15)}$$

As is usually the case, the logarithm of **Equation 13**, or the log-likelihood, is simpler to solve than the likelihood function itself and thus taking the log of L yields **Equation 16**:

$$LN(L) = LL = -\frac{n}{2}LN(2\pi) - \frac{n}{2}LN(\sigma^2) - \frac{1}{2\sigma^2}(\boldsymbol{Y} - \boldsymbol{X\beta})^{\boldsymbol{T}}(\boldsymbol{Y} - \boldsymbol{X\beta}) \quad \textbf{(16)}$$

Maximizing the log-likelihood with respect to β and σ^2 reveals a solution for the estimates of the betas that is equivalent to the OLS estimates and therefore the ML and OLS estimates are equivalent to the regression model. Additionally, it turns out that the ML estimates for the variance is biased toward zero and is a result of small sample bias fact that makes ML estimates consistent *(Washington, et al., 2003)*.

3.2.1.4. Goodness of Fit Measures

Goodness-Of-Fit (GOF) measures are useful for comparing multiple models of the same study and for providing information about the uncertainty involved with the transportation phenomenon of interest. Different methods use different GOF measures or indices for the comparison mentioned above. Some of the most known measures are the Sum of Squared Errors (SSE) (**Equation 17**), Akaike's Information Criterion (AIC) (**Equation 18**), and Bayesian Information Criterion (BIC) (**Equation 19**).

$$SSE = \sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad \textbf{(17)}$$

$$AIC(p,q) = \log\left(\hat{\sigma}_{p,q}^2\right) + 2\frac{p+q+1}{n+1} \quad \textbf{(18)}$$

$$BIC(p,q) = \log\left(\hat{\sigma}_{p,q}^2\right) + \frac{(p+q)\log{(n+1)}}{n+1} \quad \textbf{(19)}$$

3.2.1.5. Stepwise Regression

Stepwise regression is a procedure that relies on a user-selected criterion (e.g. AIC), for selecting the best model's formation. Stepwise regression is divided into two procedures, backward or forward.

Backward stepwise regression starts by comparing models with an extensive formation including a large number o independent variables and it operates by removing one independent variable at the time based on the GOF measure selected as a criterion, i.e., the variable that is removed is the one contributing the least at the GOF of the model.

Forward stepwise regression works in the opposite direction of the backward stepwise regression. In detail, we start at a very simple form of the regression model and sequentially we continue by adding independent variables by the GOF criterion.

Overall stepwise regression does not have a specific mathematic formation, but it is a mechanical procedure that results in many models and finally to the model that has the best GOF based on the GOF criterion selected.

3.2.2. Latent Data Structures and Models

Latent data structures in transportation include attitudes towards transportation policies, intentions towards transportation means to use, socio-economic and demographic status, etc. It is essential for identifying these latent structures for better understanding and interpreting different transportation phenomena. These structures can be used for formulating and specifying statistical models. For uncovering the data structures two most popular methods are illustrated: Principal Component Analysis (PCA) and Factor Analysis (FA). For dealing with the latent constructs in transportation phenomena a formal modeling framework is introduced, namely, Structural Equation Modeling (SEM).

3.2.2.1. Principal Component Analysis

Principal Component Analysis (PCA) is well known for the ability to reduce relatively large datasets and for interpreting data structures and variables importance. PCA works by explaining the variance-covariance structure using a few linear combinations of the originally measured data.

The reduction of the originally collected data works by choosing some principal components that explain a large proportion (70%-90%) of the total population, without losing much of the information. Additionally, PCA is suitable for original variables that are correlated (but not collinear) due to the capability of PCA describing adequately these variables with less principal components fact that can assist the data reduction procedure. Therefore, in this case, randomize treatments on original data affect the performance of PCA in the data reduction process.

Consider a dataset of "n" observations and "P" variables or measurements upon them, is expressed in an n x P matrix **X** (**Equation 20**).

$$\boldsymbol{X}_{n\times P} = \begin{bmatrix} x_{11} & \dots & x_{1P} \\ \vdots & \ddots & \vdots \\ x_{n1} & \dots & x_{nP} \end{bmatrix} \quad \textbf{(20)}$$

PCA does not provide any distinction between dependent and independent variables and in particular, it provides K < n principal component having the formation in **Equation 21**, which maximizes the variability across individuals, subject to the constrain in **Equation 22**. Given this constraint, the variation of Z_1 (VAR[Z_1]) is maximized.

$$Z_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1P}x_P \quad \textbf{(21)}$$

$$a_{11}^2 + a_{12}^2 + \cdots + a_{1P}^2 = 1 \quad \textbf{(22)}$$

Continuously, a second principal component is then sought which maximizes the variability across the individual subject to the constraint of **Equation 23** and the correlation of Z_1 and Z_2 is zero (COR[Z_1,Z_2]=0). Then a third principal component is added subject to the same constraint on the a_{ij} values, with the additional constraint that correlation Z_1, Z_2, and Z_3

(COR[Z_1, Z_2, Z_3]=0). Additional principal components are added up to *P* (number of originally collected variables) *(Washington, et al., 2003)*.

$$a_{21}^2 + a_{22}^2 + \cdots + a_{2P}^2 = 1 \tag{23}$$

The eigenvalues of the sample variance-covariance matrix X are the variances of the principal components. The corresponding eigenvector provides the coefficients to satisfy **Equation 22**. The P x P symmetric variance-covariance matrix is given in **Equation 24**:

$$S^2[\boldsymbol{X}] = \begin{bmatrix} s^2(x_1) & s(x_1, x_2) & \dots & s(x_1, x_P) \\ \vdots & \dots & \ddots & s(x_2, x_P) \\ s(x_P, x_1) & s(x_P, x_2) & \dots & s^2(x_P) \end{bmatrix} \tag{24}$$

The diagonal elements of the above equation represent the estimated variances of the random variables (from 1 to P), while the off-diagonal elements represent the estimated covariances between variables. The sum of the eigenvalues λP of the sample variance-covariance matrix is equal to the sum of the diagonal elements in **Equation 24**, or the sum of the variances of the P variables in matrix X that is (**Equation 25**) *(Washington, et al., 2003)*:

$$\boldsymbol{\lambda_1 + \lambda_2 + \cdots + \lambda_P = VAR(x_1) + VAR(x_2) + \cdots + VAR(x_P)} \tag{25}$$

Because the sum of the diagonal elements represents the total sample variance, and the sum of the eigenvalues is equal to the trace of **Equation 26**, then the variance in the principal components accounts for all of the variations in the collected original variables. There are P eigenvalues, and the proportion of the total variance explained by the j^{th} principal components is given by **Equation 27** *(Washington, et al., 2003)*:

$$VAR_j = \frac{\lambda_j}{\lambda_1 + \lambda_2 + \cdots + \lambda_P}, j = 1,2, \dots, P \tag{27}$$

To avoid excessive influence of measurement units, the principal components analysis is carried out on a standardized variance-covariance matrix, or the correlation matrix. The correlation matrix is the variance-covariance matrix as obtained by using the standardized variables instead of the original variables, such that **Equation 28** replaces the original $\mathbf{X}_{ij}$'s.

Because the correlation matrix is often used, variables used in principal components analysis are restricted to interval and ratio scales unless corrections are made. Using the correlation matrix, the sum of the diagonal terms, and the sum of eigenvalues, is equal to P.

$$Z_{ij} = X_{ij} - \overline{X_j}/\sigma_j;\ i = 1,2,\dots,n; j = 1,2,\dots,P \tag{28}$$

Overall, PCA is a significant tool in the exploratory analysis which offers insights from capturing the underlying dimensions of variables inside the datasets.

3.2.2.2. Factor Analysis

Factor Analysis (FA) is a relative tool of PCA which also has the target of reducing the number of collected variables with a smaller set of parsimonious by describing the covariance among many variables in terms of few unobservable factors (latent variables). However, the basic difference between FA and PCA is that FA is based on a specific statistical model and PCA is not. FA relies on the correlation matrix fact that makes it suitable for variables measured on interval and ratio scale. The FA model in matrix notation is given in **Equation 29**:

$$(\boldsymbol{X} - \boldsymbol{\mu})_{p\times 1} = \boldsymbol{L}_{p\times m}\boldsymbol{F}_{m\times 1} + \boldsymbol{\varepsilon}_{p\times 1} \tag{29}$$

Where, $\boldsymbol{F}$'s are the factors and $\boldsymbol{L_{ij}}$'s are the factor loadings, $\boldsymbol{\varepsilon}$ is the vector of residuals, X is the vector of measurements and μ is the vector of means. Here, p represents the number of measurements on a subject or item and m represents the number of common factors. Therefore, with p equations and $p + m$ unknowns, the unknowns cannot be directly solved without additional information. To solve the unknown factor loading and errors, restrictions are imposed. The factor rotation method used determines the type of the FA model, orthogonal, or oblique. A Factor loading that is close to either one suggests that a variable X_i is largely influenced by F_j. In contrast, a factor loading close to zero suggests that a variable X_i is not substantively influenced by F_j. A collection of factor loadings, that is as diverse as possible, is sought, leading to easy interpretation. The orthogonal factor analysis model satisfies the conditions in **Equation 30** (Washington, et al., 2003).

$$
\begin{aligned}
E[\boldsymbol{F}] &= 0 \\
COV[\boldsymbol{F}] &= \boldsymbol{I} \\
E[\boldsymbol{\varepsilon}] &= 0 \\
COV[\boldsymbol{\varepsilon}] &= \boldsymbol{\psi}
\end{aligned}
\tag{30}
$$

Where **ψ** is a diagonal matrix and **F** and **ε** are independent. Varimax rotation, which maximizes the sum of the variances of the factor loadings, is a common method for conducting an orthogonal rotation although there are many other methods. The oblique factor analysis model relaxes the restriction of uncorrelated factor loadings, resulting in factors that are nonorthogonal. Oblique FA is conducted with the intent to achieve a more interpretable structure. Specifically, computational strategies have been developed to rotate factors so as to best represent clusters of variables, without the constraint of orthogonality. However, the oblique factors produced by such rotations are often not easily interpreted, sometimes resulting in factors with less-than-obvious meaning *(Washington, et al., 2003)*.

Overall, in FA highly influential variables for describing the factors (latent variables) are those with high loadings and those with low loadings are the variables that act as less influential in describing the factors. Therefore, variables with high loadings are those which better determine the underlying latent constructs inside a dataset.

3.2.3. Structural Equation Modeling

Structural Equation Modeling (SEM) is designed to measure unobserved or latent variables, such as attitude, by using one or more observed variables. The framework of SEM has the potential of accommodating a latent variable as a factor described by a set of observed variables. Additionally, SEM provides information about the direct and indirect relationships between observed and unobserved variables, enabling a researcher to test a set of regression equations simultaneously. Overall, the benefits of using SEM compared to other multivariate procedures are of the ability of the SEM of incorporating both observed and latent variables (unobserved factors) and because SEM can provide a unifying framework that fits numerous linear models *(Malkanthie, 2015)*.

SEM illustrates relationships with specific shapes and path diagrams. Ovals and circles represent latent-unobserved variables, while rectangles or squares represent measured-observed variables. Residuals are always unobserved, so they are represented by ovals or circles. Correlations between observed and unobserved variables are represented by bidirectional arrows. Causal effects are represented by single-headed arrows.

The SEM model is known to be described by two sub-models: the structural model (the relationship between latent variables) and the measurement model (the relationship between each latent variable with their observed variables). The structural model considers the connection between each latent variable. Latent variables can be grouped into two categories, exogenous and endogenous, where exogenous latent variables do not have any prior latent variable connected with them in the model and endogenous latent variables refer to all other variables. The measurement model depends on the relationship that observed variables have with their respective latent variables.

SEM has different extensions of formation based on the datasets characteristics (e.g. size). These SEM extensions are: Partial Least Square and Covariance Based. PLS-SEM is using a regression-based Ordinary Least Square (OLS) estimation method so as to explain the latent constructs' variance *(Astrachan, et al., 2014)*. In contrast, CB-SEM follows a maximum likelihood estimation procedure.

3.2.3.1. Partial Least Square SEM

PLS-SEM is a commonly-applied method in several research fields such as Health and Safety *(e.g. Alolah, et al., 2014)*, Management *(e.g. Streukens & Leroi-Werelds, 2016; Nitzl, 2016)*, Transportation *(e.g. Schoenau & Müller, 2017)*, etc. PLS-SEM is also known as a Variance-Based SEM and the objective of this method is to minimize the amount of unexplained variance. The estimation procedure for the PLS-SEM method is an Ordinary Least Square (OLS) regression-based method instead of Maximum Likelihood (ML) in the CB-SEM estimation procedure. The structural (inner) model of the PLS-SEM method can be written as in **Equation 31**:

$$\boldsymbol{\xi} = \boldsymbol{B\xi} + \boldsymbol{\zeta} \qquad \textbf{(31)}$$

Where ξ is the vector of latent variables, **B** denotes the matrix of coefficients of their relationships, and ζ represents the structural model residuals. The basic PLS-SEM design assumes a recursive structural model that is subject to predictor specifications.

3.2.3.2. Covariance Based SEM

CB-SEM is a common and traditional method currently used by researchers. The CB-SEM path model component in correlation to latent construct variables can be expressed as in **Equation 32** *(Klingler, 2015)*:

$$\boldsymbol{\eta} = \boldsymbol{B\eta} + \boldsymbol{\Gamma\xi} + \boldsymbol{\zeta} \tag{32}$$

Where **B** is a $k \times k$ matrix of path coefficients describing the relationship between endogenous latent variables, **Γ** is a $k \times j$ matrix of path coefficients that describe the linear effects of exogenous variables on endogenous variables and ζ is a $k \times 1$ vector of errors of endogenous variables.

The measurement model components of the CB-SEM model can be written as in

Equation 33 *(Klingler, 2015)*:

$$\begin{aligned} \boldsymbol{x} &= \boldsymbol{\Lambda_x \xi} + \boldsymbol{\delta} \\ \boldsymbol{y} &= \boldsymbol{\Lambda_y \eta} + \boldsymbol{\varepsilon} \end{aligned} \tag{33}$$

Where $\boldsymbol{\Lambda_x}$ is a $p \times j$ matrix of factor loadings relating $\boldsymbol{x}$ to $\boldsymbol{\xi}$, $\boldsymbol{x}$ is a $p \times 1$vector of observed exogenous variables, $\boldsymbol{\delta}$ is a $p \times 1$ vector of measurement error, $\boldsymbol{\varepsilon}$ is a $k \times 1$ vector of endogenous latent variables, $\boldsymbol{\Lambda_y}$ is a $q \times k$ matrix of factor loading relating $\boldsymbol{y}$ to $\boldsymbol{\eta}$ and $\boldsymbol{y}$ is a $q \times 1$ vector of observed endogenous variables. Overall, the CB-SEM is a common method for estimating parameters by the use of Maximum Likelihood.

3.2.4. Temporal Analysis

Temporal analysis has been the focus of countless research topics, including transportation phenomena, and the tool for an insightful investigation of variables behavior over time and the outcome on different transportation phenomena.

The different structures of time series analysis are based on the transportation phenomenon and on the research objectives. For instance, when the research scope is the prediction of the transportation phenomenon then a forecasting model is more suitable for this case.

This Thesis implements a temporal analysis without developing a specific time series model but using time-variant data on the above and below methodological content described. This approach concentrates on gaining an improved understanding of the data generating mechanism and modeling the behaviour of data over time. Therefore, this section does not describe a specific methodological framework.

3.2.5. Spatial Dependence Analysis

Analyzing different transportation phenomena also includes the spatial considerations. In detail, it is strongly believed that transportation evolves also in space. These evolutions are not directly obvious and require the development of a methodology that can identify possible spatial relations and quantify them.

For identifying the spatial dependence of a transportation phenomenon is important first to create the structure of which independent variables are affecting this phenomenon by a simple linear regression model (e.g., OLS). For identifying spatial dependence in the DMUs based on the transportation phenomenon it is required that we know the spatial relationship between the DMUs expressed through the phenomenon. The relationships are also called connections and are drawn into a spatial weight matrix ($\boldsymbol{W}$) which can present the DMUs connections. The spatial weight matrix differs based on the nature of the transportation phenomenon, DMUs, etc. Generally, the specification of the neighbouring set is quite arbitrary, while some criteria for creating the spatial weights matrix such are: Rook criterion (two units are close to one another if they share a side); Queen criterion (two units are close if they share a side or an edge); and the distance-based criterion (two units are close if they are within the chosen distance).

Therefore, having the relationship between independent variables with the phenomenon and the spatial relationships between the DMUs we are able to test whether or not there exists a spatial dependence. This can be identified using a well-known test, namely, Moran’s I Test. In case a spatial dependence exists then the spatial dimension of the transportation phenomenon should be measured through a suitable spatial model called a Spatial Autoregressive Model.

3.2.4.1. Moran's I Test

Moran's I test was originally developed as a two-dimensional analog of the test of significance of the serial correlation coefficient in univariate time-series (**Equation 34**).

$$I = \left(\frac{e'We}{e'e}\right) \tag{34}$$

Where, e=y-**X**β is a vector of OLS residuals $\beta = (X'X)^{-1}X'y$, $\boldsymbol{W}$ is the row standardized spatial weights matrix *(Anselin & Bera, 1995)*. For implementing the Moran's I Test it is required that the relationship of dependent and independent variables is set through a regression analysis, likewise the OLS, and also the spatial weight matrix ($\boldsymbol{W}$).

The $\boldsymbol{W}$ matrix is of $N \times N$ dimensions and for each location in the system, it specifies which of the other locations in the system affect the value of that location. The weights matrix is binary, with $w_{ij} = 1$ when i and j are connected and $w_{ij} = 0$ when they are not. For instance, the diagonal elements $w_{ii} = 0$. For computational simplicity, the weights are always standardized such that the elements in each row sum to 1 *(Anselin, et al., 2008; Anselin, 2001)*.

The results of the Moran's I test show whether the null hypothesis is rejected or not, i.e., if the *p*-value of the Moran's I test is lower than 0.05 it means that the transportation phenomenon for the specific DMUs is spatially auto-correlated, i.e., the spatial dependence of the phenomenon exists.

3.2.4.2. Spatial Autoregressive Analysis

Regarding the Spatial Autoregressive model (SAR), it says that what happens in one region (in terms of the dependent variable, e.g., a transportation phenomenon) is related to what happens in a neighbouring region. The formal model is presented in **Equation 35**:

$$y = \lambda \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\beta + u \tag{35}$$

Where u are spatially correlated residuals. Note that $\lambda\boldsymbol{W}\boldsymbol{y}$ makes sense since the diagonal elements $\boldsymbol{W}$ are zero, which implies that we do not have the circular specification that the neighbor y_j is influenced by the neighbor y_i *(Viton, 2010)*. Additionally, $\lambda\boldsymbol{W}\boldsymbol{y}$ is the spatial component that takes account of the spatial influence in the transportation phenomenon.

Overall, SAR models provide the information on how and to what extent spatial component affects a transportation phenomenon in the are that the DMUs are located. This information is essential especially when the spatial dependence is evident through different tests such as Moran's I Test.

3.2.6. Spatio-Temporal Linear Mixed Effect Model

As has been referred collecting information related to transportation phenomena with time variations creates the need for a temporal analysis that can reveal trends over time. However, the time variations of the variables for each DMU are analyzed as a repetition of each variable. For instance, if the DMUs are from 1 to n and the under-study time period is referring from 1 to k years then the variable would take the following form (**Equation 36**):

$$Variable = \begin{bmatrix} DMU_1^1 \\ \vdots \\ DMU_1^k \\ DMU_2^1 \\ \vdots \\ DMU_2^k \\ \vdots \\ DMU_n^1 \\ \vdots \\ DMU_n^k \end{bmatrix} \qquad \textbf{(36)}$$

Therefore, in case the variable is formed as above in a single model analysis for analyzing the time dynamics of the factors to the transportation phenomenon then this will obtain bias results. In detail, treating each observation as an independent sample point, ignoring this repetition, will obtain a false sense of security in our inference, i.e., will lead to inflated estimates of the within-DMUs variability.

Furthermore, for analyzing the spatial dependence between the DMUs in a transportation phenomenon with relation to the temporal dynamics of the phenomenon it requires the ability to handle the above issue. Therefore, for incorporating this repetition a straightforward methodological development, namely, the Linear Mixed Effect model (LME) was concerned. LME model consists of a fixed effect and a random effect model. The fixed-effect model accounts for the DMUs' effects, but it does not provide a useful representation of the DMUs' data, i.e., it estimates the within-DMU variability. As for the random-effect model, it provides estimates of the between-DMUs variability. When inferences are confined to the

effects in the model, the effects are more appropriately considered to be fixed. However, when the inferences are made about a population of effects from which those in the sample are made about a population of effects from which those in the data are considered to be a random sample, then the effects should be considered to be random *(Washington, et al., 2003)*.
Therefore, for implementing the LME model it is required that the data will be grouped according to one or more classification factors that have repetition in the variables that are used in the model (e.g., the group years as presented in **Equation 36**).
For a single level of grouping the classical LMM is formed as follows (**Equation 37**):

$$\boldsymbol{y_i = X_i\beta + Z_i b_i + \varepsilon_i} \tag{37}$$

where $\boldsymbol{y_i}, \boldsymbol{X_i}, \boldsymbol{\beta}$ and $\boldsymbol{\varepsilon_i}$are the vector of continuous responses, the design matrix, and the vector of residual errors for group i, while $\boldsymbol{Z_i}$ and $\boldsymbol{b_i}$ are the matrix covariates and the corresponding vector of random effects *(Gałecki & Burzykowski, 2013)*.

Moreover, the incorporation of the spatial dependence and the temporal component in the classical LME model leads to the creation of the extension of the model to a Spatio-Temporal Linear Mixed Effect model (STLME).

Based on the spatial component formation (**Equation 36**) it is added in the random effect model and the temporal component by including the time information inside the variables' observation (**Equation 37**). For instance, the STLME will have the following form (**Equation 38**):

$$\boldsymbol{y_{ij} = \beta_0 + X_{ij}\beta_n + b_1 + Spatial\ Depedence_{ij} b_{ij} + \varepsilon_{ij}} \tag{38}$$

Where b_1 is the constant for the random effect model, b_i, b_{ij} the coefficients for the random effect model, ε_{ij} the error term, β_0 the constant for the factor effect model, β_n the coefficients for the factor effect model, *n* denotes the number of inputs, i denote the number of objects based on the classification factor and j denotes the observations of each group.
The spatial dependence component that is incorporated in **Equation 38** is based on the spatial autocorrelation terms of the SAR model (**Equation 36**).

Therefore, replacing the spatial dependence of **Equation 38** with the spatial autocorrelation term $\boldsymbol{Wy}$ creates the following **Equation 39**:

$$\boldsymbol{y_{ij} = \beta_0 + X_{ij}\beta_n + b_1 + (Wy)_{ij}b_{ij} + \varepsilon_{ij}} \tag{39}$$

Overall, the characteristics of the LME model are that they applied to data where the observations are grouped according to one or more levels of DMUs and that they incorporate both fixed-effect and random-effect terms. A fixed-effect term in the model describes the behaviour of the entire population or of those units associated with repeatable levels of experimental factors. A random-effects term describes the distribution within the population of a coefficient. The "effects" in a random-effect term associated with the DMUs from the population *(Pinheiro & Bates, 2000)*. This extended form of the LME model, the Spatio-Temporal Linear Mixed Effect model (STLME), is motivated to be used when dealing with a repetition of data and when we want to combine dimensional information such as temporal and spatial information.

3.2.7. Benchmarking Analysis

Measuring the effects of different factors on different transportation phenomena can provide significant findings that are required for understanding the aspects of the transportation phenomena. Furthermore, for obtaining an overall picture of the different transportation phenomena DMUs should and must be evaluated through ranking approaches such as benchmarking analysis. Benchmarking analysis can be served through various techniques. One of the most popular benchmarking techniques is Data Envelopment Analysis (DEA). Therefore, for evaluating the performance of different DMUs on different transportation phenomena DEA method was implemented. Additionally, there are some extensions of the DEA method that can study different aspects of output wither maximization or minimization or they can also provide a different comparison criterion. For instance, DEA-Cross Efficiency (DEA-CE) measures the efficiency of the DMUs based on different comparison strategies.

Overall, the DEA method besides the efficiency scores it can also be used as a tool for setting targets for under-performing DMUs based on best-performing DMUs' performance and also as a criterion for measuring the effects of different factors on the DMUs' performance on different aspects of transportation.

3.2.7.1. Data Envelopment Analysis

DEA is a linear programming methodology and it was first reported by *(Charnes, et al., 1978)*. DEA compares the service units considering all resources used and services provided and identifies the best practice units and the under-practice units in which real efficiency improvements are possible.

The measure of the efficiency of any DMU is obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity *(Charnes, et al., 1978)*. This is one of the two common forms of basic DEA (**Equation 40**).

$$\max h_o^t = \frac{\sum_{r=1}^{s} u_r^t \, y_{ro}^t}{\sum_{i=1}^{m} v_i^t \, x_{io}^t} \qquad \textbf{(40)}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r^t y_{rj}^t}{\sum_{i=1}^{m} v_i^t x_{ij}^t} \leq 1; j = 1, \dots, n$$

$$\mathrm{u_r^t, v_i^t \geq 0; r = 1, \dots, s; i = 1, \dots, m}$$

Where, y_{rj}^t, x_{ij}^t (all positive) represent the outputs and inputs of the j^{th} DMU and the $u_r^t, v_i^t \geq 0$ are the variable weights to be determined by the solution of this problem (e.g., by the data on all of the DMU's which are being used as a reference set. The efficiency of one member of this reference set of $j = 1, \dots, n$ DMU's is to be rated relative to the others *(Charnes, et al., 1978)*. The parameter here is introduced for the indication of the different inputs and outputs over the years and thus the calculation of the different weights and efficiency scores.

Furthermore, for using DEA in favour of a transportation phenomenon that requires the outputs to be as low as possible (minimized) then the efficient DMUs, are those with minimum output level, given that of the inputs.

The suitable adapted to this framework DEA equation is formed as follows (**Equation 41**):

$$min \ \theta_o^t \qquad \textbf{(41)}$$

subject to:

$$\sum_{j=1}^{s} x_i^t \, \lambda_j^t \geq x_{io}^t; i = 1, \dots, m$$

$$\sum_{j=1}^{m} y_{ij}^{t}\,\lambda_j^{t} \le \theta_o^{t} y_{ro}^{t}; r = 1, \dots, s$$

$$\lambda_j^{t} \ge 0; j = 1, \dots, n$$

Where θ_0^t is the uniform proportion reduction in the DMU_0's and λ_j^t with $j = 1,\dots,n$ is the dual weight given to the jth DMU's inputs and outputs.

3.2.7.2. Data Envelopment Analysis-Cross Efficiency

The DEA-CE model was developed as a DEA extension, for ranking the DMUs concerning different transportation phenomena. The main idea for using DEA is to do peer evaluation, rather than a self-evaluation of the DMU performance.

For example, suppose there is a set of n DMUs and each DMU_j has s different outputs and m different inputs. The i^{th} input and r^{th} output of DMU_j with $j = 1,\dots,n$ are denoted as x_{ij}^t with $i = 1,\dots,m$ and y_{rj}^t with $r = 1,\dots,s$, respectively. DEA-CE is generally presented as a two-phase process. Specifically, phase 1 is the self-evaluation phase where DEA scores are calculated using the constant returns-to-scale model *(Charnes, et al., 1978)*. In the second phase, the multipliers arising from phase 1 are applied to all peer DMUs to arrive at the cross-evaluation score for each of the DMUs *(Cook & Zhu, 2015)*. Once again, the t parameter here is introduced for the indication of the different inputs and outputs over the different time instances. Below are presented the DEA-CE equations for Phase 1 (**Equation 42**) and Phase 2 (**Equation 43** and **Equation 44**):

- Phase 1:

$$\max E_{dd}^{t} = \sum_{i=1}^{m} v_i^{t}\, x_{id}^{t} \qquad \textbf{(42)}$$

subject to:

$$\sum_{r=1}^{s} u_r^{t}\, y_{rd}^{t} = 1$$

$$\sum_{i=1}^{m} v_i^{t}\, x_{ij}^{t} - \sum_{r=1}^{s} u_r^{t}\, y_{rj}^{t} \le 0; j = 1, \dots, n$$

$$u_r^{t}, v_i^{t} \ge 0; r = 1, \dots, s; i = 1, \dots, m$$

Where, v_i^t and u_r^t represent the i^{th} input and the r^{th} output weights.

- Phase 2:

$$E_{dj}^{t} = \frac{\sum_{i=1}^{m} v_i^{*t} x_{ij}^{t}}{\sum_{r=1}^{s} u_r^{*t} y_{rj}^{t}} \tag{43}$$

Where, "*" denotes optimal values. For DMU_j the cross-efficiency score occurs from **Equation 44**:

$$\overline{E_{dJ}^{t}} = \frac{1}{n}\sum\nolimits_{d=1}^{n} E_{dj}^{t}\,; j = 1, \dots, n \tag{44}$$

3.2.8. Tobit Model

Identifying the performance of DMUs on different transportation phenomena through evaluation procedures (e.g., DEA) is the first stage of an explanatory analysis. Measuring the effect that different factors have on the performance is considered as a follow-up procedure on a decision-making approach. Therefore, for this case, the performance of DMUs with their efficiency scores are handled as dependent variables. However, the nature of the dependent variable can be characterized as censored, due to the variations between 0 and 1.

When encountering censored data, there is at least three reasons for not simply conducting an analysis on all nonzero observations *(Washington, et al., 2003)*:

1. It is apparent that by focusing solely on the nonzero observations some potentially useful information is ignored
2. Ignoring some sample elements would affect the degrees of freedom and the *t*- and *F*-statistics; and
3. A simple procedure for obtaining efficient and/or asymptotically consistent estimators by confining the analysis to the positive subsample is lacking.

Therefore, the reason for introducing Tobit and not a classic regression model was due to the capability of Tobit of analyzing censored data and thus Tobit is also known as the censored regression model. The mathematical formation of Tobit model is based on *(Tobin, 1958)* work and can be seen in **Equation 45**:

$$y_t = X_t\beta + u_t \quad if \;\; X_t\beta + u_t \; > 0$$
$$= 0 \qquad\qquad if \;\; X_t\beta + u_t \; \leq 0 \qquad \textbf{(45)}$$
$$t = 1,2, \ldots, N.$$

Where $\boldsymbol{N}$ is the number of observations, $\boldsymbol{y_t}$ is the dependent variable (efficiency scores obtained from DEA), $\boldsymbol{X_t}$ is a vector of independent variables, $\boldsymbol{\beta}$ is a vector of unknown coefficients, and $\boldsymbol{u_t}$ is an independently distributed error term assumed to be normal with zero mean and constant variance σ^2.

Overall, Tobit model is suitable for measuring the effects of different factors on different transportation phenomena especially when the dependent variable is censored data likewise the efficiency scores obtained from DEA method. However, this approach takes account of the effects of factors for both under and best-performing DMUs.

3.2.9. Heckman's Standard Sample Selection Model

The suitable model for analyzing and measuring the effects of different factors on the efficiency level of sample selected DMUs is the Heckman's standard sample selection model or called Heckit model.

The Heckit model assuming error normality has been the dominant selection model in the literature. Additionally, the Heckit model was originally developed by (Heckman, 1976) for the case of using a non-randomly selected sample, which occurred with concepts of bias in the results due to a missing data problem. The sample selection bias may arise due to the self-selection of observations on the dependent variable by the researchers. Therefore, estimating this model (sample selection model) by OLS gives in general biased results.
Heckman's standard sample selection model consists of the following structural process (**Equation 46** and **Equation 47**):

$$y_i^{S*} = \beta^{S\prime} x_i^S + \varepsilon_i^S \qquad \textbf{(46)}$$

$$y_i^{O*} = \beta^{O\prime} x_i^O + \varepsilon_i^O \qquad \textbf{(47)}$$

Where y_i^{S*} is the realization of the latent value of the selection "tendency" for the individual i and y_i^{O*} is the latent outcome. x_i^S and x_i^O are explanatory variables for the selection and outcome equation, respectively. x^S and x^O may or may not be equal. We observe (**Equation 48** and **Equation 49**):

$$y_i^S = \begin{cases} 0 & if\ y_i^{S*} < 0 \\ 1 & otherwise \end{cases} \quad \textbf{(48)}$$

$$y_i^O = \begin{cases} 0 & if\ y_i^{S*} = 0 \\ y_i^{O*} & otherwise \end{cases} \quad \textbf{(49)}$$

Overall, Heckit model provided the ability of sample selecting under-performing DMUs for measuring the effects that their characteristics (factors) are affecting their level of performance concerning the under-study transportation phenomenon. This technique was introduced as a valid and solid approach from preventing any bias of using a classic regression model instead of the Heckit model.

3.2.9. Target Setting

The aim of setting targets is not a straightforward issue. These targets should be effective on different transportation phenomena and realistic/suitable for each DMU. The DMUs with nonzero λ weights are the DMUs who need improvement on the transportation phenomenon considered and thus the weights are indicating the value that the under-performing DMUs need to be improved based on best-performing DMUs (benchmark DMUs). Thus, the target (improvement of transportation phenomenon) of the DMUs can be obtained according to the λ weights that the benchmarking DMUs were provided. The transportation targets of the under-performing DMUs can be calculated by using **Equation 50**.

$$A_j^t = \sum_{k=1}^{K} \lambda_k^t D_k^t; j = 1, \ldots, n \quad \textbf{(50)}$$

where,

A_j^t: Aim (target) for j^{th} DMU at year *t*.

K : Number of benchmark DMUs (reference sets that belong in the set of best-performing DMUs).

D_k: Value of the dependent variable in the k^{th} benchmarking DMU.

λ_k: Lambda weights.

t : Year that the targets are referring to.

Overall, the target setting procedure adds the final piece in the decision-making approach. By this implementation, transport authorities can be supported by observing what are the potentials of different DMUs.

3.3. Explanatory Analysis

Decision-making procedures are essential when studying different transportation phenomena. These procedures can also be called explanatory analysis which is based on the outcomes of exploratory analysis. In detail, explanatory analysis is a series policymaking interpretations of the obtained results of the presented methodological approaches for supporting or even the performance of different DMUs on different transportation phenomena.

The explanatory analysis will be well presented in the following chapter with the interpretation of the results.

3.4. Summary

The methodological approaches that have been implemented so far, for analysing different macro-level transportation phenomena are varied creating a chaotic audience questioning which methodologies are more appropriate for analysis. Based on the literature there is a variety of methodologies for analysing the different macro-level transportation phenomena. This chapter introduced a robust and novel methodological framework that is appropriate for analysing different aspects of different macro-level transportation phenomena and creating an integrated “picture” of each different phenomenon starting from the point of data collection and reaching to the point of decision-making.

CHAPTER 4: APPLICATION AND RESULTS

The more transportation is becoming more and more integral to developed and developing societies, so in persons and goods mobility, the more it creates the need of understanding transportation from investigations. National, regional, and global economies rely on the efficient functioning of transportation due to the influence transportation has on economic, demographic and social aspects. Therefore, there is an essential need for understanding the mechanisms behind the evolutions of transport problems and challenges. This Thesis developed a solid and robust methodological framework for analysing different macro-level transportation phenomena.

However, for validating the methodological framework's efficiency on analysing and capturing different transportation phenomena two proofs of concept were undertaken analysing both personal and goods mobility in a macro-level scale. These proofs of concept concern:

- Road Traffic Fatalities (human mobility)
- Multimodal Freight Transportation (goods mobility)

The analytical applications of the proposed methodological framework developed in Chapter 3 are summarized in **Table 1**. The table lists the implementations of both transportation phenomena (Road Traffic Fatalities & Multimodal Freight Transportation). This chapter presents the results obtained from the applications of the suggested methodological framework developed in Chapter 4 for both proofs of concept.

Table 1 Methodological applications for both transportation phenomena (Road Traffic Fatalities & Multimodal Freight Transportation).

Approaches	Road Traffic Fatalities		European Multimodal Freight Transportation			
	European	Global	Waterborne	Road	Rail	Airborne
Descriptive Analysis	☒	☒	☒	☒	☒	☒
Exploratory Analysis	☒		☒			
Linear Regression Analysis	☒	☒	☐	☒	☒	☒
Identification of Latent Structures	☐	☒	☐	☐	☐	☐
Structural Equation modelling	☐	☒	☐	☐	☐	☐
Spatial Analysis (SAR)	☒	☐	☐	☒	☒	☒
Data Envelopment Analysis	☒	☐	☒	☒	☒	☒
Tobit model	☒	☐	☐	☐	☐	☐
Heckit model	☐	☐	☐	☒	☒	☒
Target Setting	☒	☐	☒	☐	☐	☐
Spatio-Temporal LMM	☐	☐	☐	☒	☒	☒
Explanatory Analysis	☒	☒	☒	☒	☒	☒

4.1. Proof of Concept: Road Traffic Fatalities

As mentioned above, the implementations of the proposed methodology considered the coverage of both humans and goods mobility. The following sections provide proofs of concept taken in the methodology for the analysis of the phenomenon of road traffic fatalities in a regional (European) and global scale.

The importance of investigating road traffic fatalities can be denoted from the fact that the number of traffic deaths continues to climb, reaching 1.35 million in 2016 *(World Health Organization, 2018)*. However, the study of global phenomena, like the epidemics of road traffic fatalities, calls for explanatory analysis. A suitable framework for such analysis is provided using macro-level information

4.1.1. Data Collection and Results of Descriptive Analysis

Analyzing a transportation phenomenon (likewise road traffic fatalities) outcomes several questions such as: Which factors affect road traffic fatalities? Which are the sources that provide these factors? Which DMUs should be concerned and what is the scale of investigation?

From now on when the DMUs will be referring to either European countries or UN countries when the analysis is on a regional and global scale, respectively. Moreover, analyzing phenomena with limited access and availability of information of disaggregate data, forces the data collection process to turn for aggregated data, i.e., total numbers of fatalities. Based on the literature review when analyzing phenomena such as road traffic fatalities is important collecting macro-level information that can capture, adequately, the phenomenon. This macro-level information is recognized as the, social, economic, demographic etc., context of the countries. This macro-level information can be collected from several sources/organizations. The most popular sources for collecting macro-level information related to road traffic fatalities are World Bank, Eurostat, World Health Organization, etc. However, the availability of information is an issue of concern.

Table 2 presents the macro-level information collected for capturing the phenomenon of Road Traffic Fatalities. This macro-level information was collected from the databases of World Bank, Eurostat and World Health Organization and was divided into different categories based on the meaning of the variables. In detail, these factors concern the Economic, Enforcement, Demographic/Geographic and Network Infrastructure context of countries on a regional (Europe) and global level.

The main issue that was raised during the data collection procedure was the missing information of some countries. In detail there were two cases of missing information. The first one was the missing information for most of the observations (countries), where in this case the variable was omitted from the sample and the second case was when information was not filled for some countries, where in this case the countries were omitted from the sample. The scale of analysis of this phenomenon was on a regional (16 European countries) and global (121 United Nation member countries) scale. Additionally, for incorporating the temporal component in the analysis, the information was concerning time periods or time instances. In overall, the data collection approach followed a repetition of collecting and omitting either variables or countries until the final data sample was created. The following sections will present the results of the descriptive analysis in both scales (regional and global).

Table 2. Collected macro-level information.

Sector	Var. No	Abbreviation	Variable	Type
Economy	1	Income	Income level (*WHO, 2013; WHO, 2015*)	Categorical [a]
	2	GNI	Gross National Income per capita (US $) (*WHO, 2013; WHO, 2015*)	Continuous
	3	GDP	Gross Domestic Product per capita (US $) (World Bank[1], 2019)	Continuous
	4	Food_prod	Food production index (World Bank[2], 2019)	Continuous
	5	Tax	Total tax rate (% of commercial profits) (World Bank[3], 2019)	Continuous
	6	Unemp	% Unemployment of total labor force (World Bank[4], 2019)	Continuous
	7	Diesel_price	Pump price for diesel fuel (US$ per liter) (World Bank[5], 2019)	Continuous
	8	Gasol_price	Pump price for gasoline (US$ per liter) (World Bank[6], 2019)	Continuous
	9	Int_users	Internet users (per 100 people) (World Bank[7], 2019)	Continuous
	10	Num_reg_veh	Number of registered vehicles (per 100,000 vehicles) (*WHO, 2013; WHO, 2015*)	Continuous
	11	Ind_value	Industry value added, is expressed as a percentage of GDP (World Bank[8], 2019)	Continuous
	12	Ener_con	Energy consumption of transport relative to GDP Index (World Bank[9], 2019)	Continuous
Net- work	13	Tot_nodes_net	Total Nodes (OpenStreetMap, 2019)	Continuous
	14	Tot_length_net	Total Network's Length (Km) (OpenStreetMap, 2019)	Continuous
Demographic/Geographic	15	Con	Continents	Categorical [b]
	16	Popul	Population (per 1,000,000 people) (World Bank[10], 2019)	Continuous
	17	Area	Land area (Km2) (World Bank[11], 2019)	Continuous
	18	Popul_growth	Annual % population growth (World Bank[12], 2019)	Continuous
	19	Birth_rate	Birth rate, crude per 1,000 people (World Bank[13], 2019)	Continuous
	20	Death_rate	Death rate, crude per 1,000 people (World Bank[14], 2019)	Continuous
	21	Popul_15_64	Population aged 15-64 (World Bank[15], 2019)	Continuous
	22	Mob_cell	Mobile cellular subscriptions, is expressed per 100 people (World Bank[16], 2019)	Continuous
	23	Reg_Pas_Car	Registered Passenger Cars (thousand) (Eurostat[1], 2019)	Continuous
Enforcement	24	Nat_speed_lim_law	National speed limit law (*WHO, 2013; WHO, 2015*)	Categorical [c]
	25	Nat_drink_law	National drink–driving law (*WHO, 2013; WHO, 2015*)	Categorical [c]
	26	Nat_helmet_law	National motorcycle helmet law (*WHO, 2013; WHO, 2015*)	Categorical [c]
	27	Nat_seat_belt_law	National seat-belt law (*WHO, 2013; WHO, 2015*)	Categorical [c]
	28	Nat_child_rest_law	National child restraint law (*WHO, 2013; WHO, 2015*)	Categorical [c]
	29	Nat_mob_use_law	National law on mobile phone use while driving (*WHO, 2013; WHO, 2015*)	Categorical [c]

Notes:

a *0: Low, 1: Middle, 2: High*

b *0: Asia, 1: Europe, 2: Africa, 3: North America, 4: South America, 5: Oceania*

c *0: Yes, 1: No*

4.1.1.1. European Approach

As described in the methodological framework, for understanding the data and for recognizing any possible data inflations or homogeneities in the data sample a qualitative and quantitative analysis were implemented. The visualization and the statistical analysis were undertaken in an open-source software namely RStudio. The comparative analysis of road traffic fatalities between a set of countries requires the use of the correct index that can reflect a realistic picture of the countries' standings in terms of road safety. The most popular exposure indices of road fatalities are *mortality rate* (fatalities expressed per million inhabitants) and *fatality risk* (fatalities expressed per 100,000 registered vehicles).

Concerning the qualitative analysis, several visual can be used for depicting the transportation phenomenon of road traffic fatalities. One of the visual representations is the spatial distribution of road traffic fatalities with relation to some of the macro-level information collected. **Figure 3** presents the phenomenon of road traffic fatalities from 2012 to 2016, expressed through the index of mortality rate (number of fatalities per 1,000,000 inhabitants) for each time instance. As can be seen, neighbouring countries appear with almost the same exposure rate, a fact that calls for possible spatial autocorrelation. Additionally, it can be seen from the figure that the countries that record high percentage of mortality rates through the period, compared to the rest of the European countries, are Greece, Lithuania, Bulgaria, Romania and Poland. The code for obtaining the visualization in **Figure 3** is provided in **Appendix A-R2a**.

Figure 4 presents the indicators fatality risk and mortality rate regarding the EU-23 countries concerning the period 2004-2013. According the fatality risk indicator it seems that Cyprus, Latvia, Romania and Poland had a serious problem, but as the years passed, they improved their road safety performance. This can be justified to several reasons, either to the financial crisis in 2008 likewise (*Antoniou, et al., 2016*) noticed that the drop of the GDP in Greece helped the road safety performance of the country by decreasing the number of mobiles or to a possible improvement of the policy strategy of the countries or to other reasons. Additionally, in 2013 almost all the EU-23 countries, except Romania, Hungary, Czech Republic, Poland and Latvia, were classified as well performing countries. From this point of view the particular fatality indicator provides a more optimistic perspective view of the road traffic fatalities' decrement. From the other point of view, the mortality rate appears to have a more pessimistic 'image' of the situation. In 2004 most of the EU-23 countries appeared to be in a bad situation. It seems that Iceland in 2006 worsen its road safety performance and again improved it in 2006. In 2013 many of the countries improved their road safety performance according this indicator leading to the same conclusion as the other indicator (fatality risk) that the countries improved steadily their road safety performance. The current figure can be used as a testament to why these two indicators, i.e. the fatality risk and the mortality rate, should not be unilaterally used especially when these kinds of studies are conducted towards policy and decision making. The visual of **Figure 4** is obtained from the use of the RStudio code in **Appendix A-R2.b**.

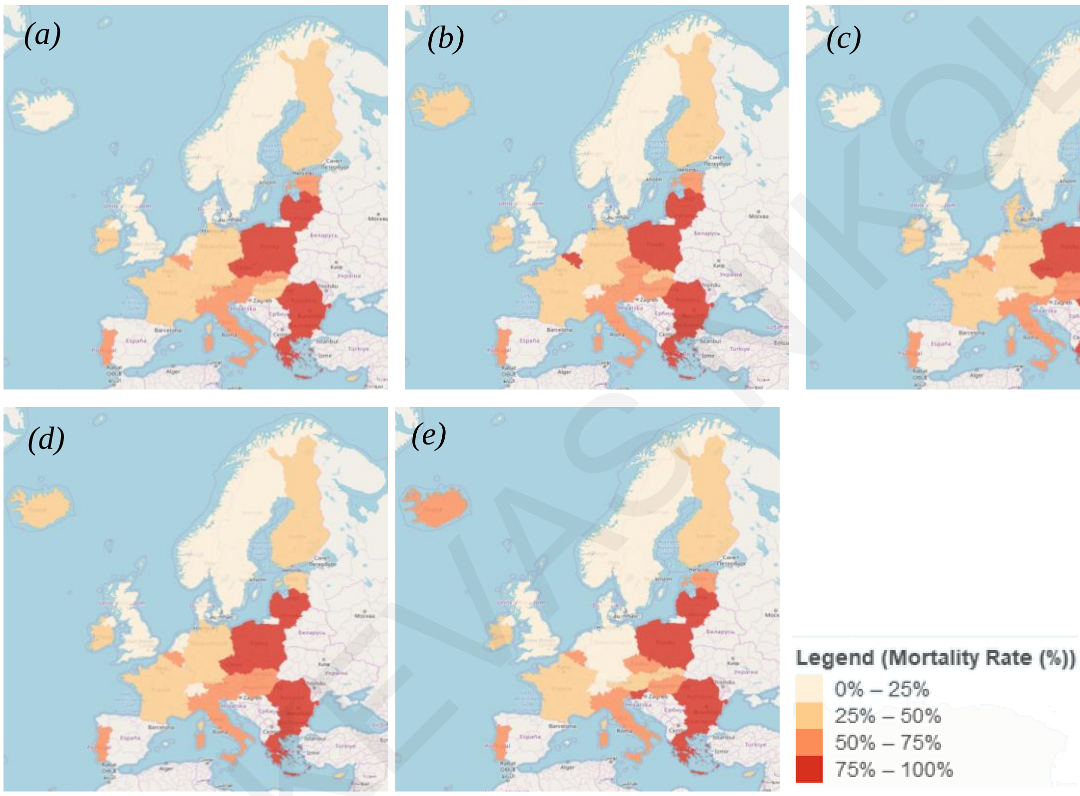


Figure 3. Spatial distribution of mortality rate for the period: a) 2012; b) 2013; c) 2014; d) 2015; and e) 2016.

Figure 4. Fatality risk and mortality rates in the period 2004-2013.

A more detailed picture of the European countries' road safety status can be seen from **Figure 5**, where now the mortality rate of 30 EU countries can be seen from 2007 to 2017. The visual of fatality risk indicator was not able to be obtained due to missing information of the number of registered vehicles. The visual of the below figure is obtained from the use of the RStudio code in **Appendix A-R2.b**.

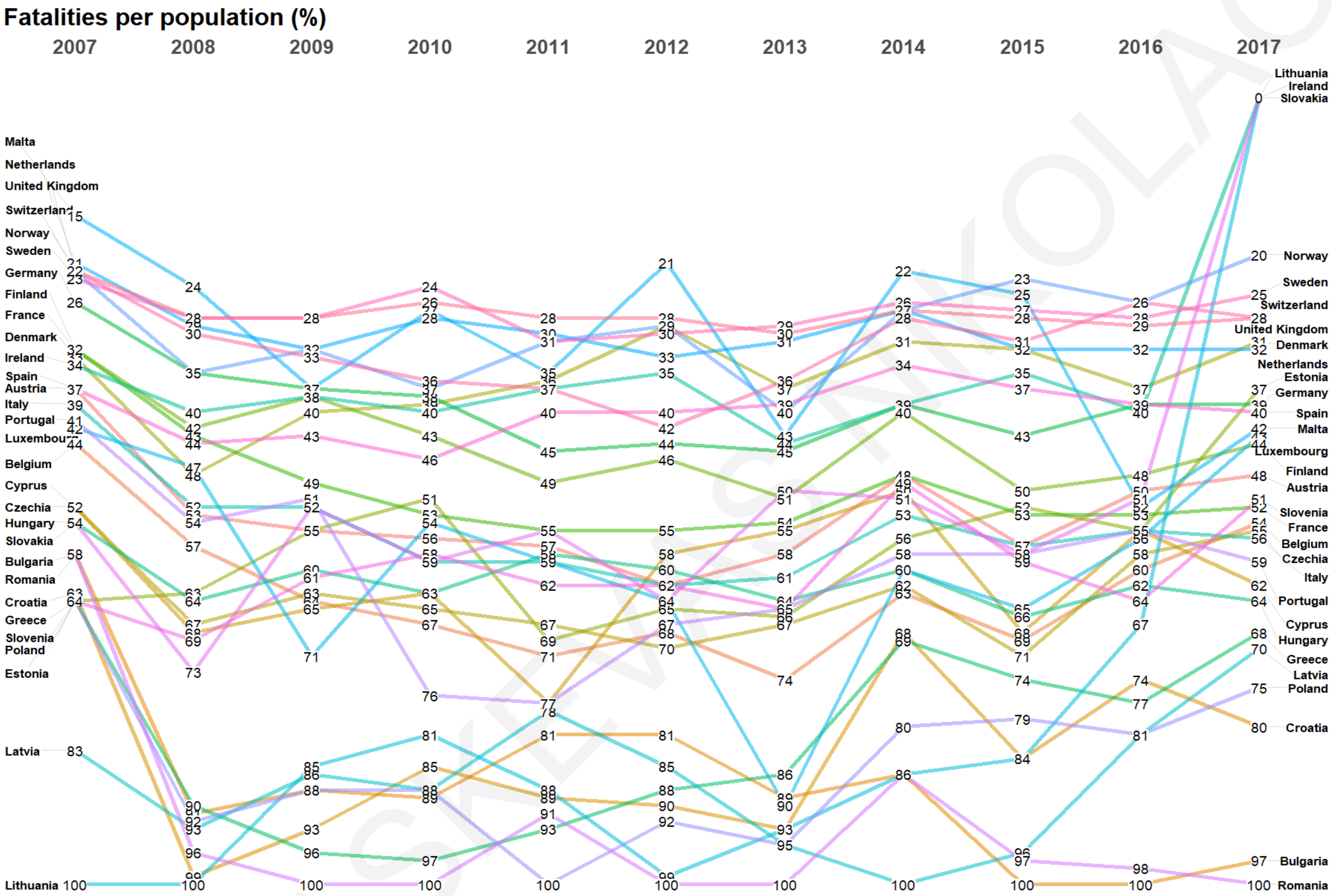


Figure 5. Mortality rate concerning 30 EU countries during the time period 2007-2017.

From the figure above we can see that Lithuania had the highest percentage of mortality rate in 2007 and 2008, where in 2009 and 2010 turned to be Romania. In 2011, Greece Slovenia and Poland had the highest percentage and in 2012 and 2013 Romania returned to the worst place where in 2014 was again Lithuania at that place. In 2015 and 2016 Bulgaria had the worst position on mortality rate and finally, in 2017 Romani was once more in the last place. Additionally, it must be mentioned that in 2017 Lithuania, Ireland and Slovenia had missing information of their mortality rate status.

Another visual representation of road traffic fatalities was a detailed representation of fatalities per mode. **Figure 6** shows five different treemaps for the mortality rate for each transport mode, concerning the overall period 2007-2016 (aggregate numbers of mortality rate). Concerning the car occupant fatalities, Bulgaria is in the top place recording the highest number of fatalities and Malta is in the last place. As for the PTW fatalities, Greece and Cyprus are in the "leading" positions. Moving to the HGV related mortality rates, Portugal, Latvia, Poland, and Croatia record the highest numbers. Additionally, the highest pedestrian mortality rates have been recorded in Romania, Latvia, Poland, and Lithuania, while the highest cyclist mortality rates appear in the Netherlands, Romania, Poland, and Hungary recorded the highest number of mortality rates in the overall time period. The visual of **Figure 6** is obtained from the use of the RStudio code in **Appendix A-R2.c**.

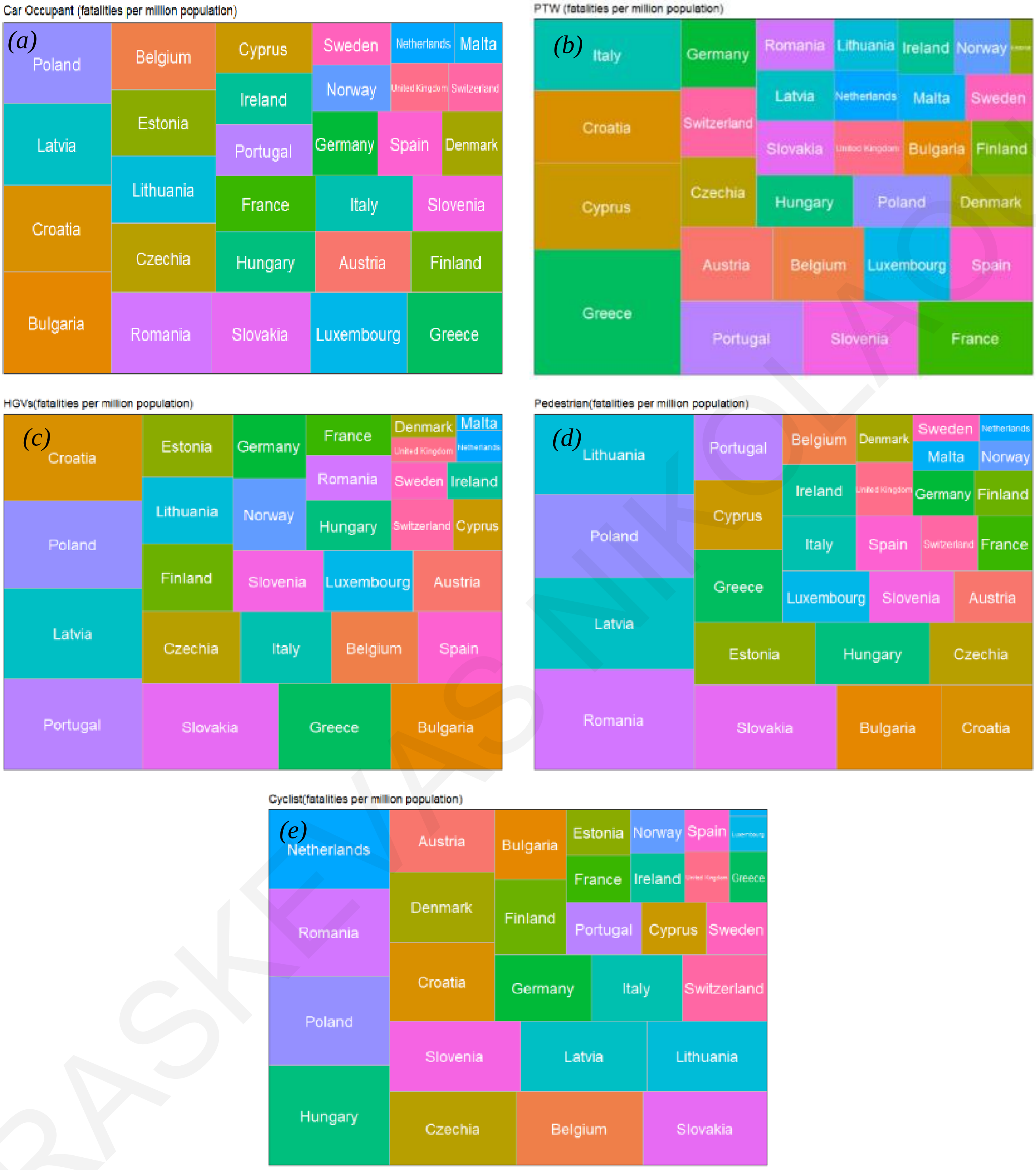


Figure 6. Mortality rate expressed for each different mode of road users: (a) Car occupants; (b) PTW; (c) HGV; (d) pedestrians; (e) cyclists.

After observing the visual representation of road traffic fatalities, the data visualization process continued with the visualization of the independent variables which are “Population”, “GDP”, “Diesel price” and “Land area”. However, due to the fact population and land area of the countries do not change over time at least drastically for the population there were no visualization for those two variables. **Figure 7** and **Figure 8** present the variations of some of the collected variables (e.g., “GDP” and “Diesel price”) for each country, over time.

As can be seen from **Figure 7** in 2012 the economic context of the countries reflected in GDP was well below the average limit depicting the negative growth of GDP due to the financial crisis of Europe. This condition was overcome in 2013 and 2014 when it was again dropped down significantly in 2015and took a recovery slope in 2016. Therefore, this figure show the financial fluctuations of the EU countries and it is considered important collecting this information and estimating the effects that this information reflect on road traffic fatalities.

Figure 8 shows the variations of the diesel price over the period 2012-2016. As can be seen from the figure the diesel price recorded negative slopes inside the time period for all the countries. In particular, it seems that between 2012 and 2014 the drop of the diesel price was smoother compared to the respective drop of 2014 and 2016. Again, this information is considered important for incorporating it in the analysis of road traffic fatalities. The RStudio code for creating these two figures (**Figure 7** and **Figure 8**) is provided in the **Appendix A-R2.b**.

In overall, visual representation of the phenomenon of road traffic fatalities revealed several aspects of how EU countries “behave” over the time and space. For instance, from the figures above it is revealed that Greece, Lithuania, Bulgaria, Romania have serious concerning the mortality rate index. Also, it appeared that spatially connected countries have similarities between their performance, likewise Greece Bulgaria and Romania from **Figure 3**.

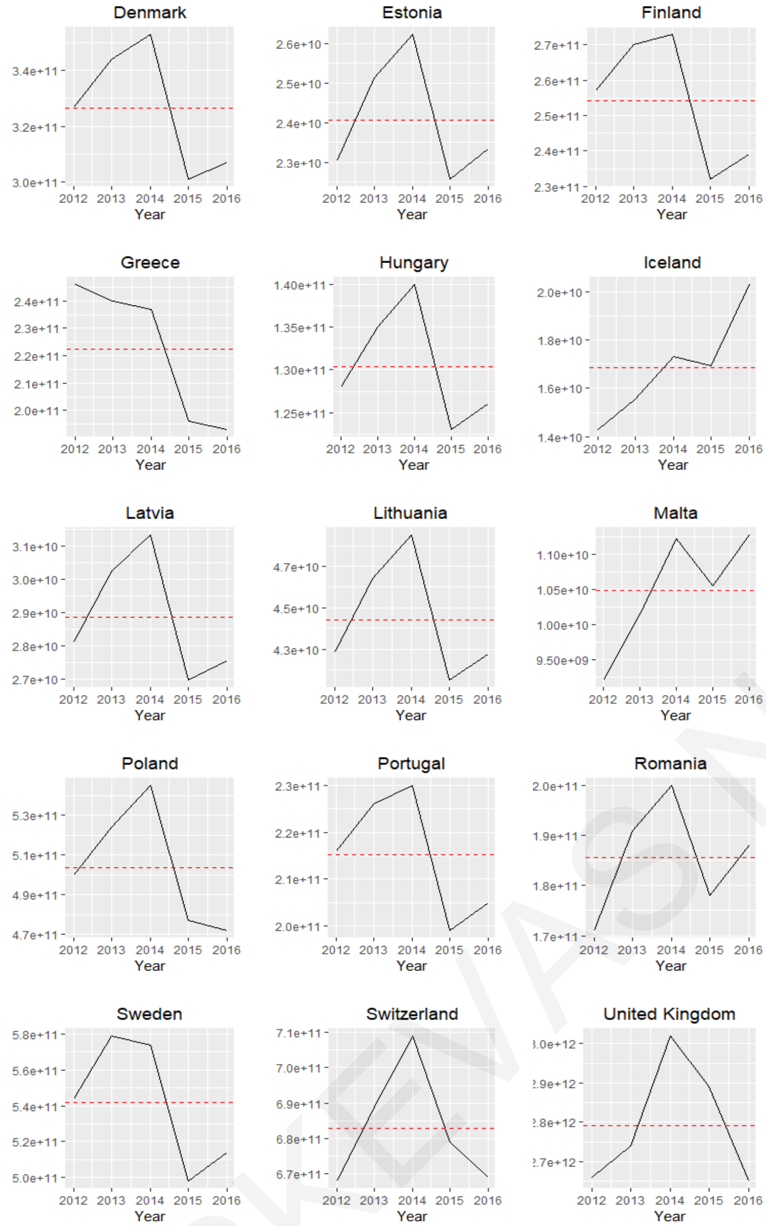


Figure 7. Recorded values of GDP over the years (black continuous lines) and average number of GDP (red dotted line) depicted for 28 EU countries.

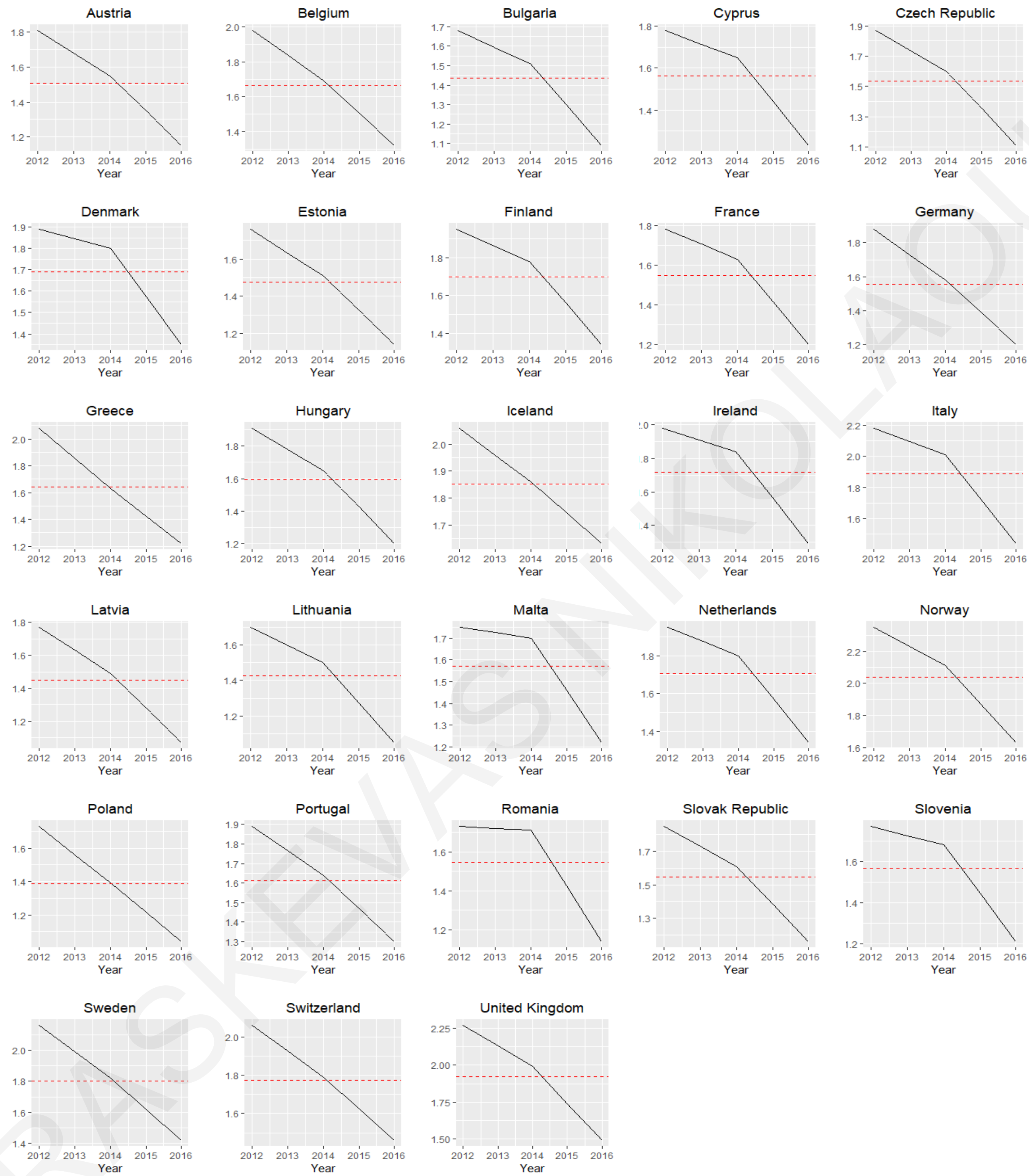


Figure 8. Recorded values of diesel price over the years (black continuous lines) and the average number of diesel price (red dotted line) depicted for 28 EU countries.

However, for identifying possible data inflations (e.g. collinearity) inside the data sample and homogeneities between the countries, correlation and cluster analysis were developed, respectively. The correlation analysis is presented in **Figure 9**. As can be seen from the figure the correlation between the variables is not changing over time fact that shows that the variables are stationary. The information that the correlation analysis provides is the identification of collinear variables, which are the pairs with high correlation (> 0.7).

In this sample only one collinear pair exists, which is the pair of the variables "Population" and "GDP". This mean that in the models' development procedure one variable of the pair should be omitted. The criterion for choosing which of the variables will be omitted is either by observing their relationship with the dependent variable (road traffic fatalities) or by the significance of the variables' meaning. As concerning the relationship of the independent variables with road traffic fatalities it seems that the variables "Population" has the most significant correlation with the dependent variable ($r \approx 0.92$) followed by "GDP" ($r \approx 0.78$), "Area" ($r \approx 0.68$), and "Diesel price" ($r \approx -0.02$). As it seems if we consider the correlation of the independent variables with the dependent the variable "GDP" should be omitted from the sample as collinear. However, due to the significance of "GDP" with road traffic fatalities and to the importance of incorporating the economic factor in the analysis of road fatalities' variation especially during the period of economic crisis (2012-2013) the variable "GDP" was considered as more important in the analysis and therefore the problem of collinearity was resolved by omitting the variable "Population". The RStudio code for creating **Figure 9** is provided in **Appendix A-R2.e**.

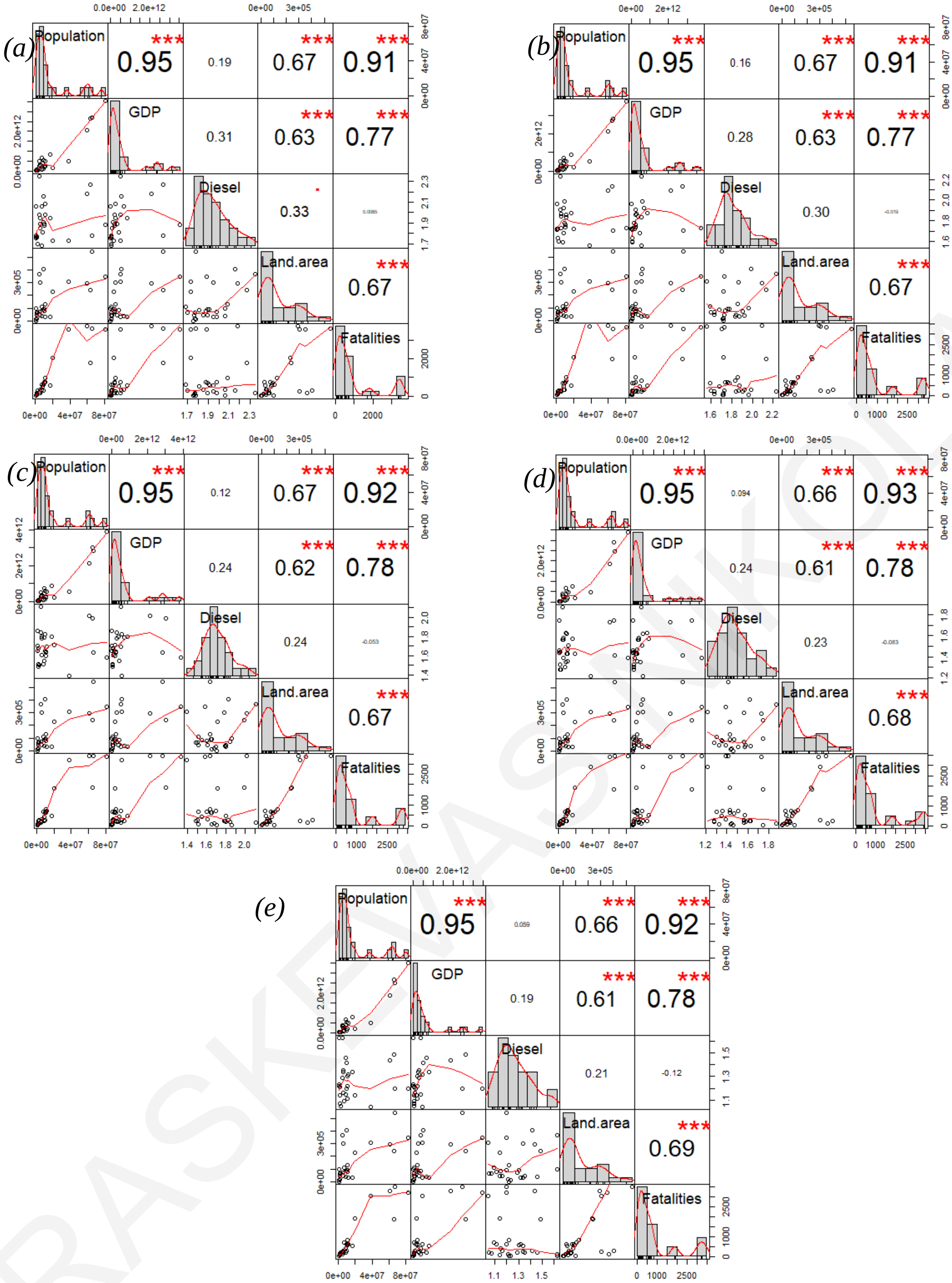


Figure 9. Correlation analysis of the sample for each time instance: a) 2012; b) 2013; c) 2014; d) 2015; and e) 2016.

As was appeared from the data visualization implementations the homogeneity between the countries, concerning the macro-level variables, is obvious. **Figure 10** presents the cluster obtained for the EU countries considering the countries' socio-economic and demographic context. From this figure can be concluded that countries in the same clusters depict a spatial relationship fact that will be incorporated in the following steps of the proposed methodology.

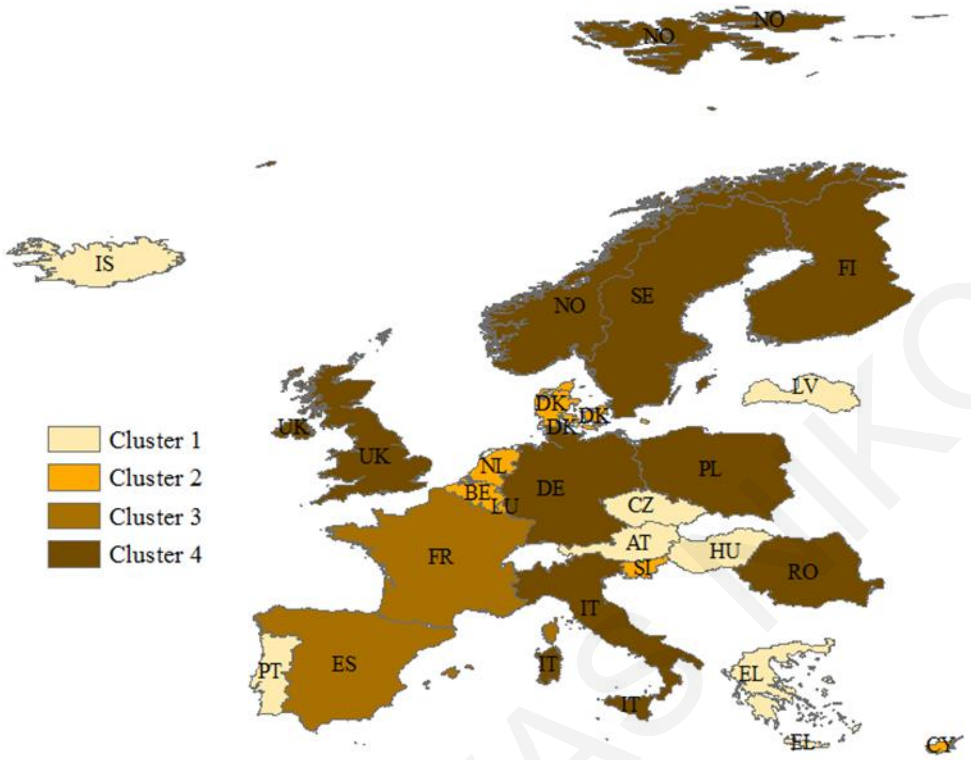


Figure 10. Clusters of EU countries based on their socio-economic and demographic characteristics.

4.1.1.2. Descriptive Analysis: Global Approach

The descriptive analysis was also deployed in the data collected for analyzing the phenomenon of road traffic fatalities in a global scale (121 UN countries). The years that the data are referring to are 2010 and 2013. **Figure 11** presents the relation of both road traffic fatalities with population and with registered vehicles in 2010 and 2013. As can be expected large countries, in terms of population, record high numbers of road fatalities. The same stands for the countries with high numbers of registered vehicles. Moreover, it seems that as the time pass the number of road fatalities remain steady or even increase, highlighting the sensitivity and importance of investigating this transportation phenomenon and providing supports to decision-making procedures. Additionally, the figure below shows the countries that were not included in the analysis due to lack of data issues. **Figure 11** was provided by using the open source QGIS software.

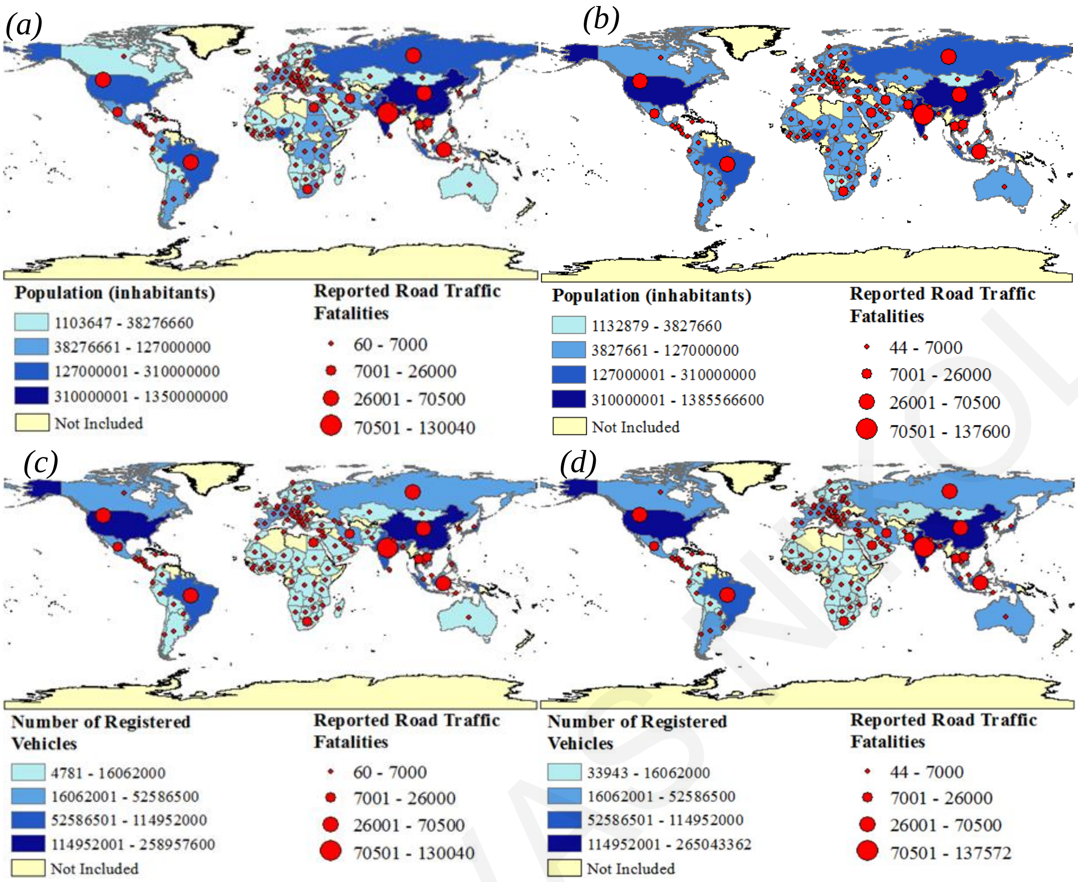


Figure 11. Comparison of road traffic fatalities with population: a) in 2010; b) in 2013; and with and the number of registered vehicles: c) in 2010; d) in 2013.

As described in the methodological framework the descriptive analysis also includes the quantitative analysis of the data sample. In this scale of analysis, the macro-level information that was used was different, in contrast with the regional analysis. The following implementation of the descriptive analysis was the identification of possible collinearities and thus a correlation analysis was implemented. **Figure 12** and **Figure 13** present the correlation matrices for the 2010 and 2013 datasets, respectively. From the correlation matrices it can be observed that the dependent variable is highly correlated, with the variables: number of registered vehicles and population. Additionally, as can be assumed the collinear pairs of variables are: GNI-GDP, Income-GNI, Income-GDP, Income-Internet users, Income-Birth rate, GNI-Internet users, GDP-Internet users, Diesel price-Gasoline price, Internet users-Birth rate, Number of registered vehicles-Total number of nodes, Number of registered vehicles-Total length network, Number of registered vehicles-Population, Total number of nodes- Total length network, Total number of nodes-Land area, Total length network-Land area, Birth rate-Population aged between 15-64, National helmet law-National seat belt law. At this point the collinear variable was chosen based on the theory developed also in the European approach of descriptive analysis and thus in the different time instant datasets (2010 and 2013) the collinear variables omitted from the sample may be different. The RStudio code for providing the below figures is provided in **Appendix A-R2.e**.

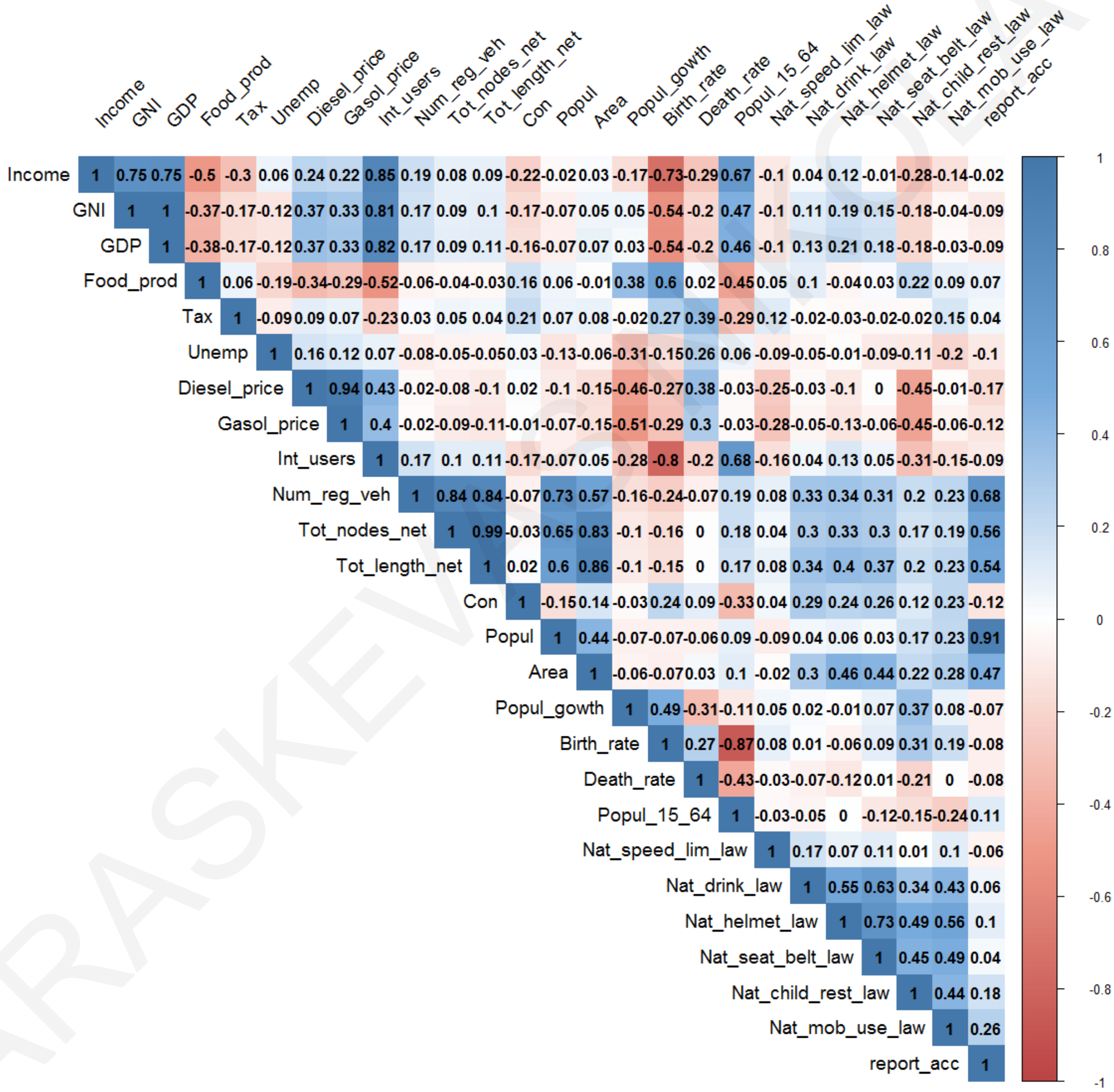


Figure 12. Correlation graphs for the 2010 dataset.

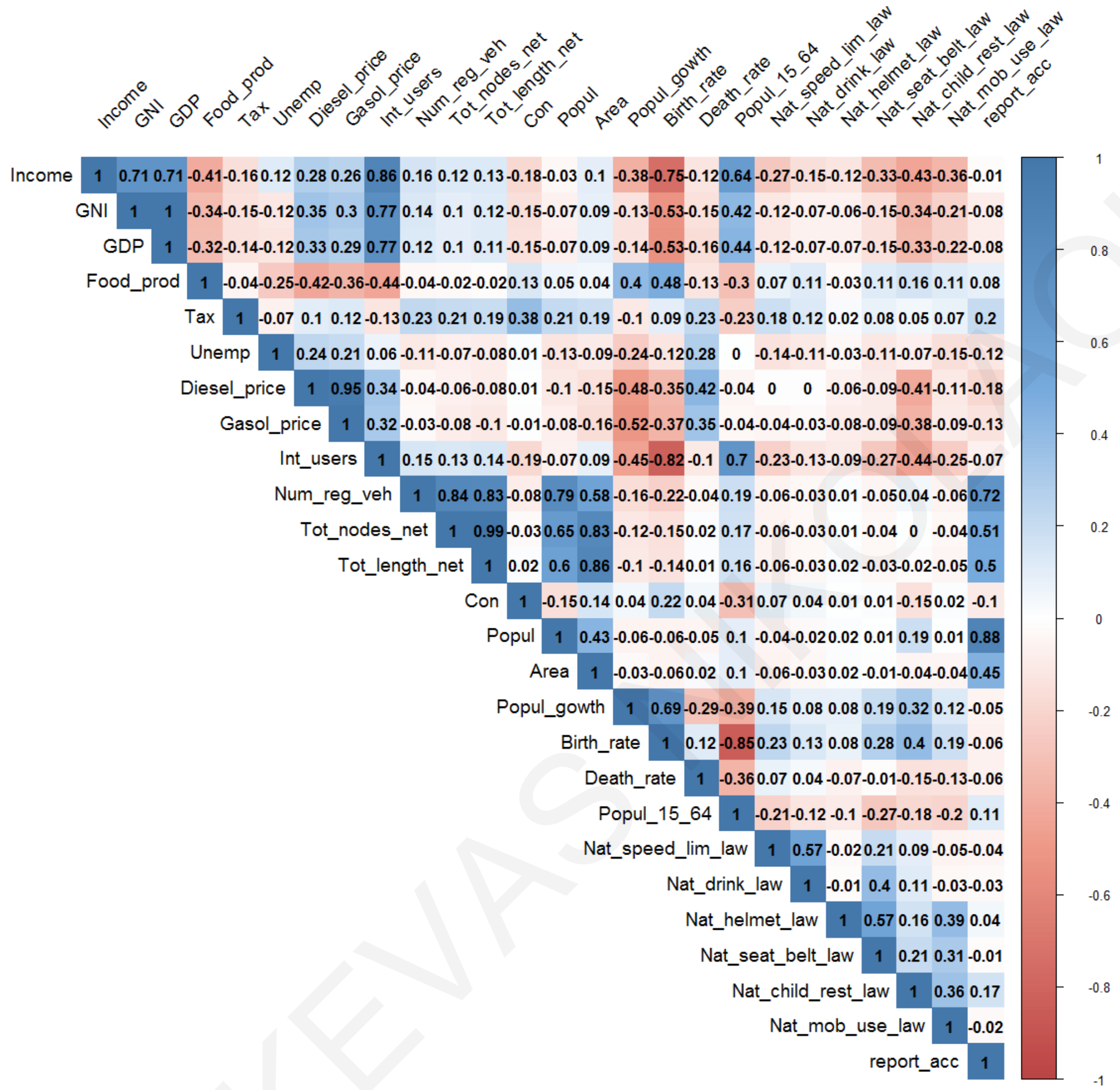


Figure 13. Correlation graphs for the 2013 dataset.

Furthermore, it must be mentioned that road traffic fatalities were collected also for the year 2016. However, the availability of information was limited so in the independent variables but also in the dependent variable. In detail, for the year 2016 only 105 UN countries were included, which are depicted in **Figure 14**. For this set of countries and for this time year of study different variables were elaborated so in descriptive and in exploratory analysis. **Figure 15** presents the correlation matrix of the 2016 collected dataset. The collinear pairs in this dataset are: Birth rate-Internet users, Birth rate-Income, GNI-Internet users, GNI-Income, Internet users-Income and Total registered vehicles-Population. As in the previous implementations so in this case the collinear variables were omitted from the dataset.

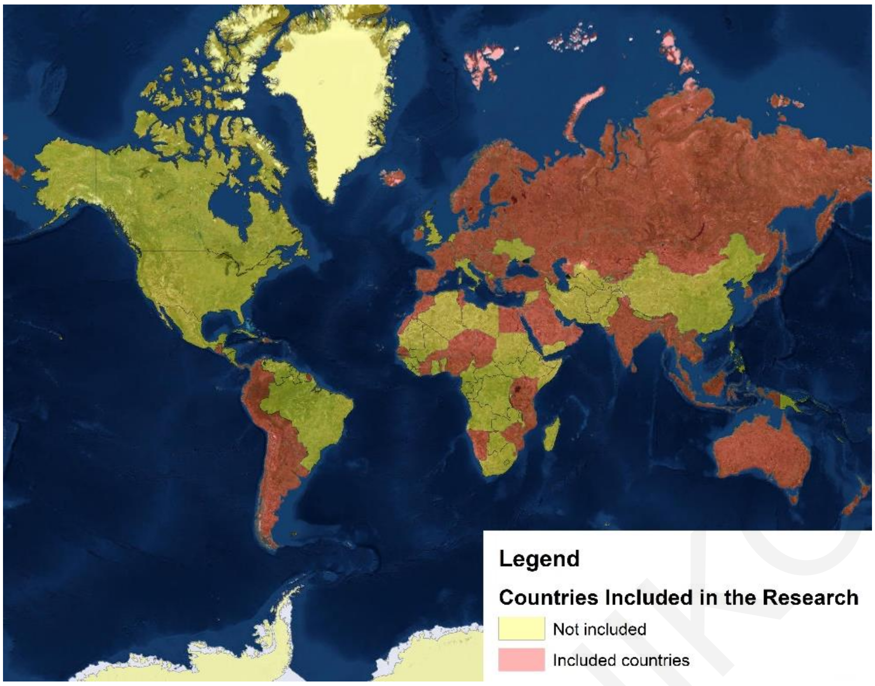


Figure 14. Countries included in the 2016 analysis.

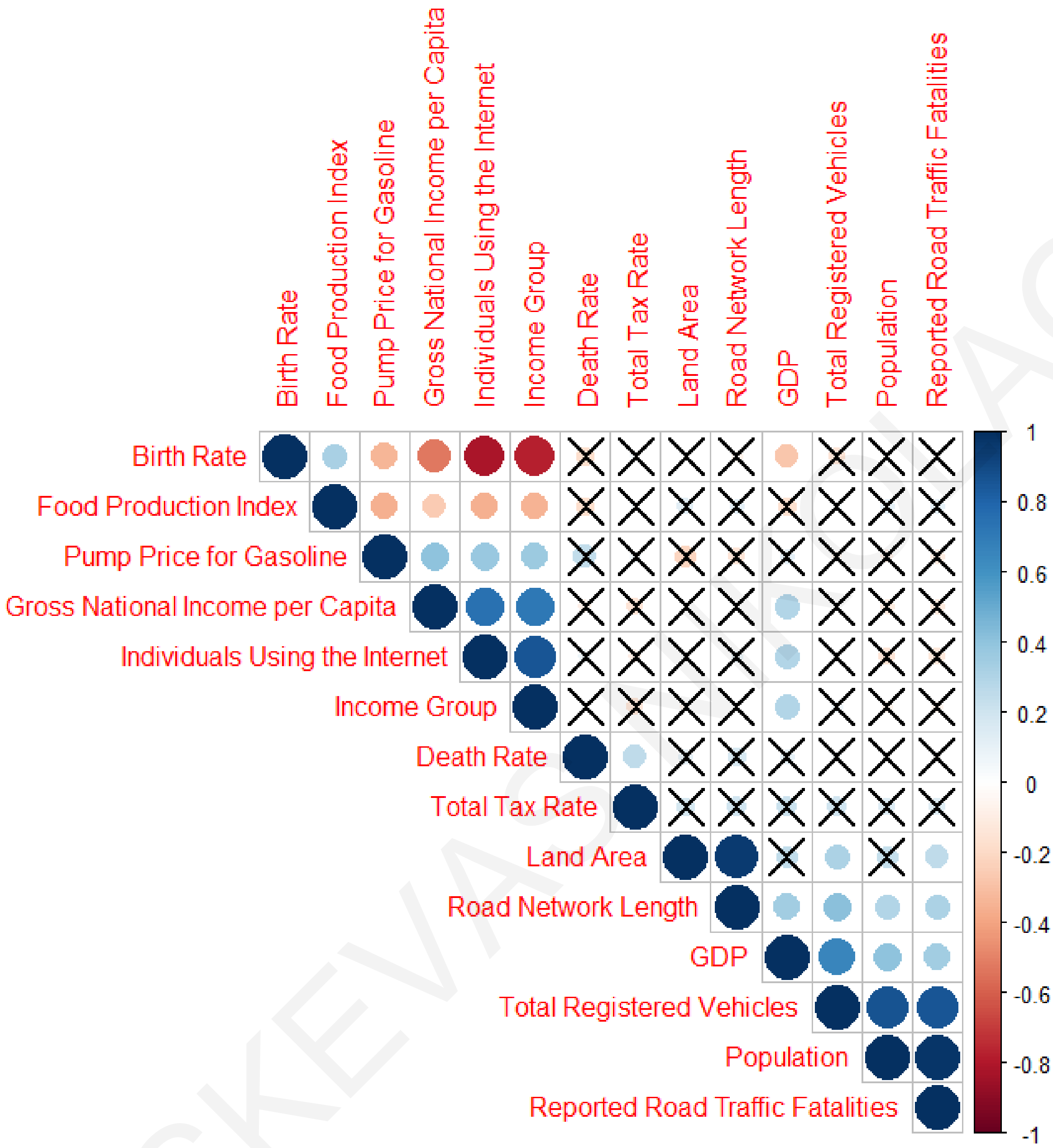


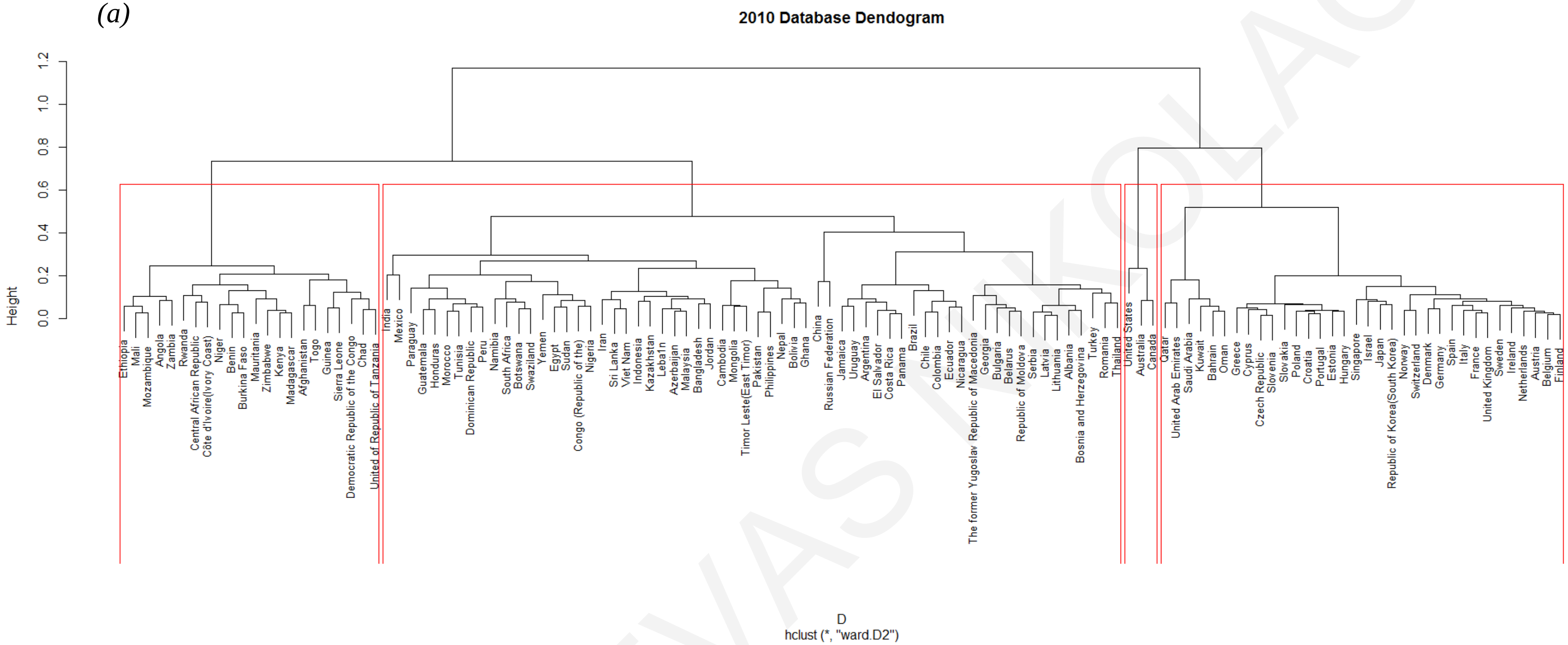
Figure 15. Correlation analysis of the 2016 collected dataset.

In the 2010, 2013 and 2016 datasets the countries that were collected are endogenous and therefore cluster analysis was considered important for obtaining the grouping information that this approach will provide prior any implementation of the exploratory analysis. **Figure 16** presents the outcome of the cluster analysis depicted in a dendrogram for both 2010 and 2013 as the set of countries and variables was the same. The number of clusters was chosen to be four based on the factors collected (Demographic, Economic, Infrastructure and Enforcement). Therefore, the four clusters were the experimental number for observing the clustering of the countries will follow the character of the above factors, i.e., if the countries will be grouped based on this information.

The resulted clusters of the different in years variables show that the countries have a significant heterogeneity on their socio-economic, demographic, enforcement, and infrastructure context. For instance, in the dendrogram of 2010 the UN-121 countries divided into 4 clusters, which includes 22, 62, 3 and 34 countries, respectively. The dissimilarity value of the first cluster seems to be the smaller one than the other three clusters. This might be due the fact that most of the countries included in the cluster are African (except from Afghanistan), which have almost the same socio-economic conditions. The third cluster includes only three countries (United States, Australia, and Canada), who seem that they approximately had the same socio-economic context in 2010.

The second dendrogram of the UN-121 countries regarding the 2013 data shows also four cluster which include 24, 30, 30 and 37 countries, respectively. Looking at the assignment of the countries within the clusters, one can assess that the right most cluster includes the more advanced countries (from a road safety point of view), including most of the Western European countries (as well as several Arab countries). Moving towards the left of the figure, the road safety level seems to decrease. Naturally, this is not a straightforward and simple process and some observations are not clearly aligned. For example, the US is clustered in the second cluster, along with Russia, China, and India. This cluster also includes Eastern European, as well as Central and South American countries. The third cluster includes primarily countries from Asia and North Africa, while the fourth one comprises countries from the rest of Africa and some less developed parts of Asia. The RStudio code for creating **Figure 16** is provided in **Appendix A-R2-d**.

(a)



(b)

Figure 16. The Hierarchical Clustering of the UN-121 countries according their socio-economic characteristics (a) in 2010 and; (b) in 2013.

After observing the cluster analysis of 2010 and 2013's datasets the next implementation of cluster analysis was for the 2016's dataset, which included a different number of countries and variables. However, before the implementation of the following clustering, the question raised was that this time the optimal number of clusters should be determined. To do so the method that was considered was the Elbow Method. As can be seen in **Figure 17**, the optimal number of clusters is 5 as it appears to be the bend of the knee (or elbow in the figure). The RStudio code for creating the Elbow graph is provided in **Appendix A-R2.d**.

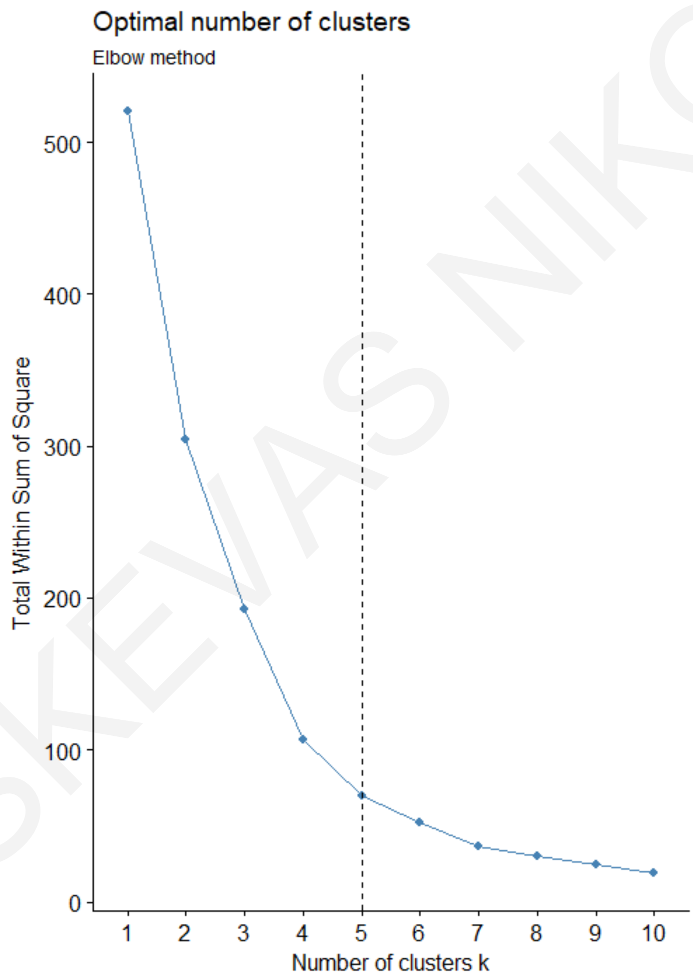


Figure 17. Elbow method for identifying the optimal number of clusters for the 2016 dataset.

After obtaining the optimum number of clusters the next implementation was based on hierarchical cluster analysis and in particular on Agglomerative Clustering (AC) and on Divisive Clustering (DC). **Figure 18** and **Figure 19** present the 5 clusters for both hierarchical cluster analyses, AC and DC, respectively, in the form of dendrograms. The height of the fusion (vertical axis) indicates the dissimilarity between the two observations. However, the implementation of AC and DC was used to identify the best performing clustering method. To do so, we checked the agglomerative and divisive coefficients, which measure the amount of clustering structure found (values closer to 1 suggest a strong clustering structure). Results showed that the agglomerative coefficient was greater than the divisive coefficient with a value of 0.989.

Overall, the resulted clusters from both methods showed the homogeneity of the countries based on their socio-economic and demographic context. As can be seen from the clusters obtained from the AC hierarchical clustering, France Germany and Japan showed to be homogeneous based on their socio-economic and demographic context and clustered in the same cluster (Cluster 3). As for India and Russia, both countries were in different clusters showing that they are heterogeneous from the other countries' socio-economic and demographic contexts. Additionally, it must be noted that if the optimal number of clusters drops down to 2 clusters then it appears that the set of countries included in the homogeneous clusters will be increased, creating a cluster with all the countries except India and Russia which will be in a different cluster. If we look at the DC clustering method then we can observe that there is a large group of homogeneous countries, a cluster with Germany, Japan, and France and then 3 separately clusters with Indonesia, Russian and India.

In overall, the global scale approach revealed also significant findings that will be taken in mind for the exploratory analysis. These findings are the spatial dependence of the countries based on the transportation phenomenon, the data inflations (e.g., collinearities) the groups of homogeneous sets of countries, etc.

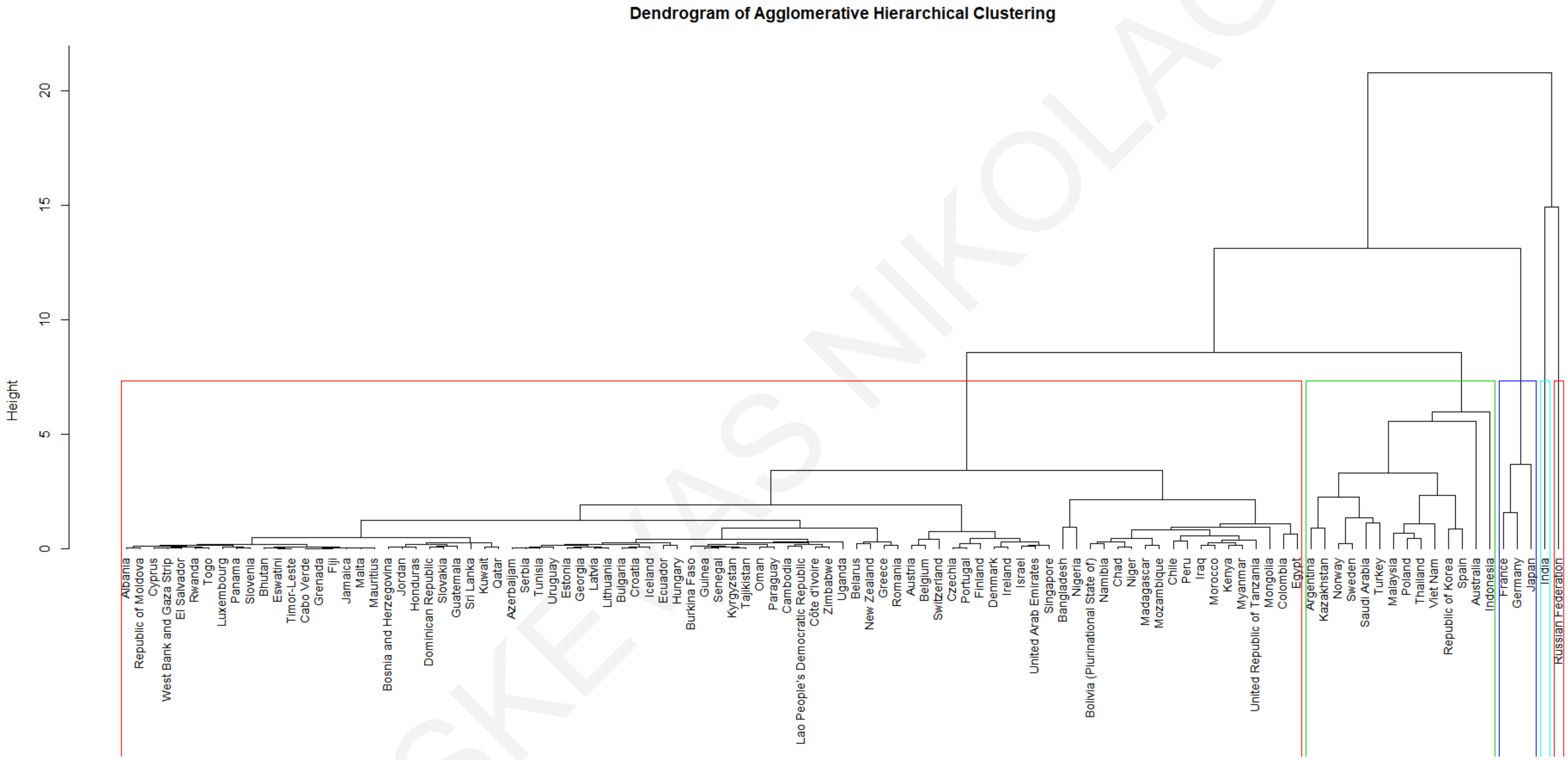


Figure 18. Dendrogram of agglomerative hierarchical clustering for the 2016 dataset.

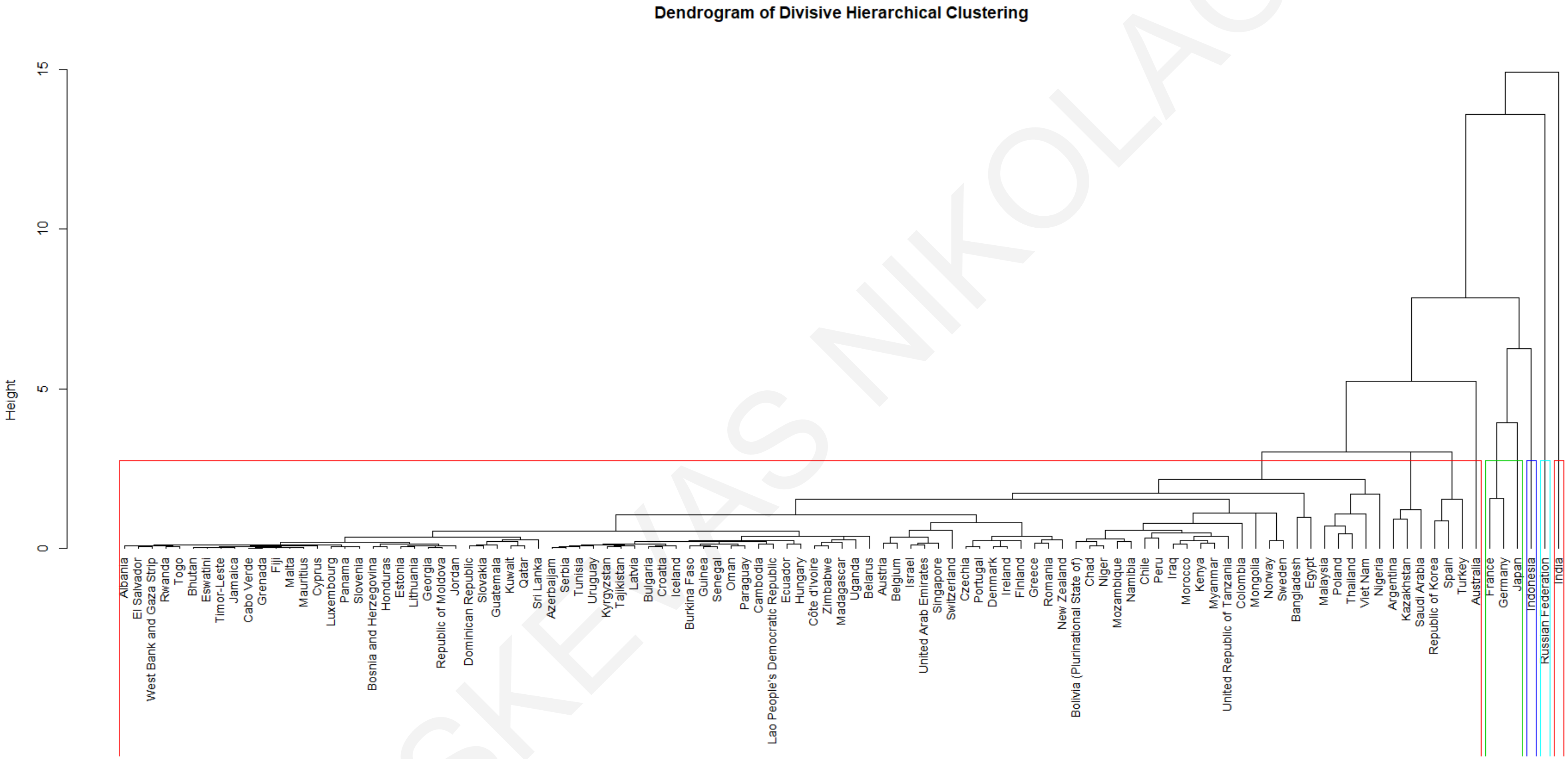


Figure 19. Dendrogram of divisive hierarchical clustering for the 2016 dataset.

4.1.2. Results from Exploratory Analysis

One of the most important steps in data analysis process, Exploratory Analysis, makes sense of the data in hand thinks like providing all aspects of data (observed and unobserved), formulating the correct questions of how to manipulate the data and use the correct methods or techniques for obtaining the required answers, and other. This section provides the findings obtained from the exploratory analysis, proposed in Chapter 3, for the proof of concept transportation phenomena (i.e., Road Traffic Fatalities and Multimodal Freight Transportation).

4.1.2.1. Exploratory Analysis: European Approach

The exploratory analysis of the European road traffic fatalities is developed based on the proposed methodology for providing a "picture" of the phenomenon. In the European approach the transportation phenomenon was investigated by analyzing the effects of socio-economic and demographic context of the countries on road traffic fatalities. In order to do that Ordinary Least Square (OLS) models were initially developed in a time dependence matter. Based on the descriptive analysis road traffic fatalities appeared to be spatially related between the EU countries, due to the homogeneity of the countries in this region. Therefore, this phenomenon was investigated for possible spatial dependence and the dimension of time was incorporated for observing how the spatial connections of the countries affect road fatalities.

Furthermore, a dimensional analysis of road fatalities was implemented by developing a novel approach based on the Linear Mixed Model extension to both time and space (Spatio-Temporal Linear Mixed Model).

Finally, an evaluation procedure of the EU countries was followed based on their road safety performance. In detail, DEA-CE, Tobit, and Target setting approaches were followed for identifying best and under-performing EU countries, for measuring the effect of macro-level factors on their performance and for setting short and long-term targets to the countries that under-perform.

4.1.2.1.1. Measuring Direct Effects of Macro-Level Factors: An Ordinary Least Square Approach

Ordinary Least Square (OLS) was developed for measuring the direct effects of socio-economic and demographic factors on road traffic fatalities. The years that the OLS models were referring were from 2012 and 2016. This section provides the outcomes from the implementation of the methodological framework described above. **Table 3** presents the results of the OLS models. In the developed OLS models the variable "Population" was omitted due to collinearity reasons (as was revealed in the descriptive analysis). Furthermore, the variable "Diesel price" was omitted from all the models and "GDP" from the 2013 model through the Backward Stepwise Regression analysis using a GOF index, which was the AIC. The RStudio code for implementing the OLS models and the Backward Stepwise Regression is provided in **Appendix A-R3.a**.

The results of the models show that GDP and the land area of the EU countries are the factors that seem to affect their road fatality records and also in a constant matter, i.e., the coefficient of the variables remain almost the same during the period 2012-2016. Additionally, the variables remained in the model are statistically significant indicating the robustness of the resulted models. However, the models were not able to capture the effects of the EU countries' economic fluctuations, over the period, on their road traffic fatality records. In contrast, the models showed that the size of EU countries have a relation with the number of road fatalities.

In overall, the obtained robust OLS models showed the direct effects of socio-economic and demographic factors on road traffic fatalities. Furthermore, the land area factor showed that the spatial context of the EU countries has significant effect on road fatalities' fluctuation. In addition, to the findings of the descriptive analysis (data visualization) of **Figure 3** there is a speculation of data dependence between the EU countries concerning the phenomenon of road traffic fatalities.

In the analysis of road traffic fatalities, the dataset collected so in observations (number of countries) and in factors (independent variables) was too small fact that cannot raise speculations of unobserved information. Thus, the analysis of latent structures cannot be taken under consideration is such small datasets and the analysis continued to the next step of the methodology which is the analysis of possible spatial dependence between the EU countries for the phenomenon of road traffic fatalities.

Table 3. Results of the OLS models.

	OLS 2012	OLS 2013	OLS 2014	OLS 2015	OLS 2016
Intercept	1.04e+02	95.16	9.05e+01	8.508e+01	6.78e+01
	(2.07e+02)	(231.62)	(1.84e+02)	(1.83e+02)	(1.79e+02)
Land area	2.57e+03.	5177.43***	2.39e+03*	2.493e+03*	2.55e+03*
	(1.30e+03)	(1121.02)	(1.14e+03)	(1.11e+03)	(1.09e+03)
Diesel price	-	-	-	-	-
GDP	7.486e-04**		6.43e-04***	7.18e-10***	6.98e-04***
	(2.02e-04)	-	(1.62e-04)	(1.79e-10)	(1.77e-04)
Population	r*	r*	r*	r*	r*
AIC	455	461	449	449	447

Note: *Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Parenthesis denotes the standard errors

r: Variable omitted due to collinearity*

-: Omitted variables due to statistical significance

4.1.2.1.2. Identifying and Incorporating Spatial Inflations of Road Traffic Fatalities Within European Countries

As it appeared from the descriptive analysis and from the OLS models, there is a speculation of spatial correlation between the EU countries that may have an effect on road traffic fatalities. For validating this spatial correlation is important to implement some tests, such as Moran's I Test. However, in order to implement the Moran's I Test it is required to estimate the linear relationship between the independent variables (socio-economic and demographic factors) and the dependent variable, which was obtained from the OLS models.

Additionally, this test requires to create a spatial weight matrix that shows the connection between the EU countries. There, are several criteria for creating this weight matrix. Some of the criteria are based on neighboring conditions (Rooks and Queen spatial weight matrices) where the EU countries are neighboring; and distant located connected EU countries (Distance-based weight matrix) where the EU countries are connected with not only with neighboring but also distant located countries.

The assumption that was taken for creating the spatial weight matrix was that the connections between the EU countries do not change over time. **Figure 20** presents the spatial weight matrix-based criteria. As can be observed from the figure the Queen and Rook criterion resulted the same weight matrix. The problem issued in these criteria was that isolated EU countries (islands), e.g., Cyprus, United Kingdom and other had no connections between the other EU countries. In the distance-based weight matrix this issue was resolved by setting that every EU country has connections with at least three nearest-countries and thus in this case the problem of the detached countries was addressed, and this criterion was selected for creating the weight matrix of the EU countries taken under study.

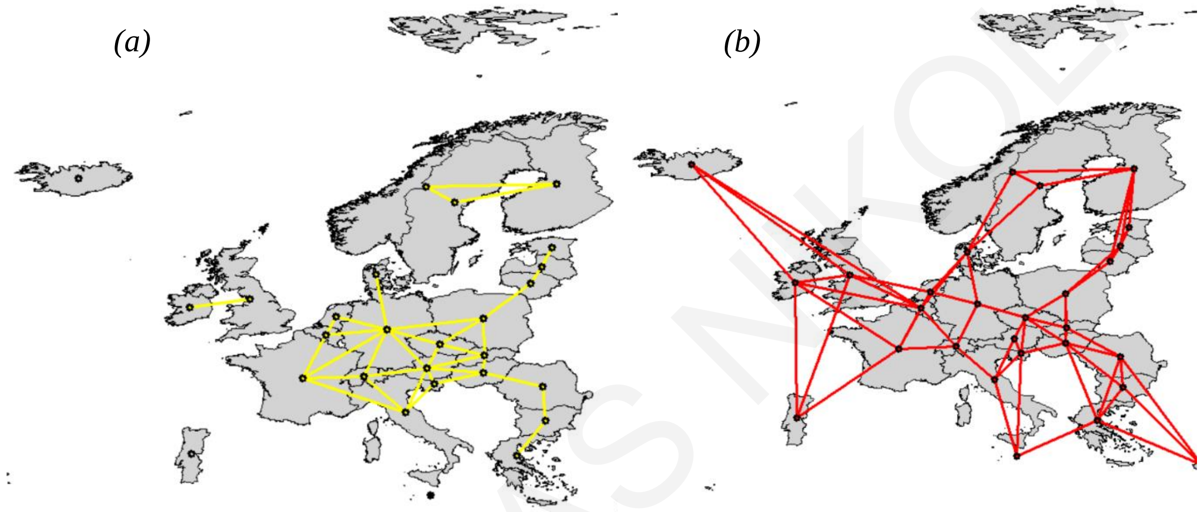


Figure 20. Spatial weight matrix-based criteria: a) Rook and Queen criterion; and b) Distance-based criterion.

Therefore, having the information of the linear relationship between the socio-economic and demographic factors with road fatalities and the spatial weight matrix, the Moran's I Test was implemented for every year. **Table 4** shows the resulted Moran's I Test, which implies that a spatial dependence exists between the countries concerning the phenomenon of road traffic fatalities. In detail the null hypothesis is rejected (p-value is statistically significant).

Table 4. Results of the Moran's I test.

	Moran's I (OLS 2012)	Moran's I (OLS 2013)	Moran's I (OLS 2014)	Moran's I (OLS 2015)	Moran's I (OLS 2016)
Statistic standard deviate	1.55	2.15	1.88	2.01	2.05
p-value	0.05	0.03	0.05	0.04	0.04
Observed Moran I	0.18	0.24	0.18	0.19	0.20
Expectation	-0.05	-0.03	-0.04	-0.05	-0.05
Variance	0.01	0.02	0.01	0.01	0..1

As spatial dependence is approved to exist between the EU countries the next step of the methodology was the implementation of a state-of-the-art method can incorporate this spatial dependence. This method is namely Spatial Autoregressive (SAR) analysis.

Table 5 presents the outcomes of the SAR models which appeared to be statistically significant and also with a significant meaning. For instance, "Diesel price" showed to have an affection on road traffic fatalities, indicating that as diesel price increases road traffic fatalities decrease, which is important to be under consideration in the decision-making processes for dropping down the numbers of road fatalities. In addition, "GDP", which indicates the economic status of the countries, shows that it increases the number of road fatalities as "Land area" does. The resulted estimates of these two variables are confirmed also in the OLS models. However, in these models the spatial component was incorporated and showed the effects of these variables with this spatial component.

Referring to the GOF index of the SAR models (AIC) showed that between the similar SAR models (those with the same included variables), the best performing model was the one estimating for 2016. Therefore, this model can be further used in the explanatory analysis.

Table 5. Results of the SAR models.

	SAR 2012	SAR 2013	SAR 2014	SAR 2015	SAR 2016
Intercept	4.15e+03**	3.80e+03**	3.33e+03**	2539.61	2.72e+03***
	(1.40e+03)	(1.26e+03)	(1.12e+03)	(1385.97)	(8.10e+02)
Land area	2.85e+03.	2.51e+03.	2.55e+03.	5994.40***	2.93e+03***
	(1.33e+03)	(1.21e+03)	(1.16e+03)	(1259.71)	(1.05e+03)
Diesel price	-2.12e+03**	-2.03e+03**	-1.91e+03**	-1805.02.	-2.17e+03***
	(7.27e+02)	(6.96e+02)	(6.61e+02)	(943.59)	(6.42e+02)
GDP	8.28e-04***	7.23e-04***	6.94e-04***		7.37e-04***
	(1.71e-04)	(1.48e-04)	(1.37e-04)	-	(1.43e-04)
Population	r*	r*	r*	r*	r*
AIC	452	447	446	461	440

Note: *Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*
Parenthesis denotes the standard errors
r: Variable omitted due to collinearity*
-: Omitted variables due to statistical significance

The investigation of the spatial component was further investigated by examining in more detail the characteristics of the SAR model, which can provide also important evidence by observing the reaction of the different values of λ (coefficient of the spatial component in the SAR model). **Figure 21** shows the correlation between the countries in relation to the values of λ. Larger values of λ leads to higher correlation between the countries, λ=0 implies no correlation, and the sign of λ implies the sigh of correlation. The figure shows the correlation between each country with all the other 27 EU countries. For example, the first plot of the figure (**Figure 21a**) shows the correlation of Austria with all the other countries, the second plot (**Figure 21b**) shows the correlation of Belgium with the rest 27 countries, etc.

The changes of λ indicates changes of the correlation between the countries. For instance, in the first plot of the figure (**Figure 21a**) when the λ is between -0.4 to 0.4 the most of the countries appear to have zero correlation with Austria except from three countries; Czech Republic, Italy, and Slovenia which are the countries connected with. Additionally, it seems as the λ continues to drops, some of the correlations became negative and some become positive. In overall, from this figure, we can note which countries have the highest interactions with the other 27 EU countries during the changes of the λ values. All the figures included in this section were obtained in by using the RStudio code depicted in **Appendix A-R3.c**.

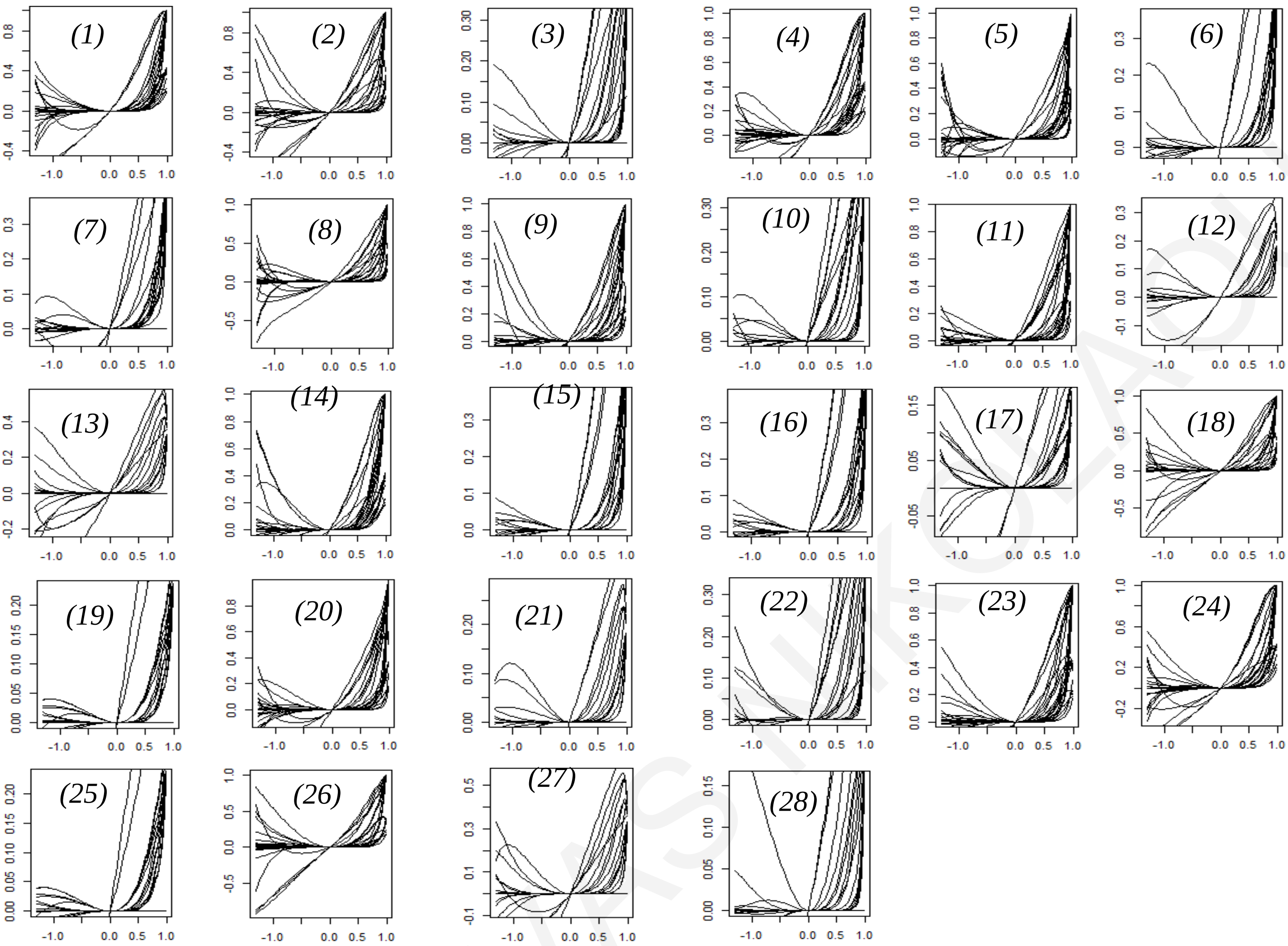


Figure 21. Relation of fluctuated λ value with correlated countries: 1) Austria; 2) Belgium; 3)Bulgaria; 4) Cyprus; 5) Czech Republic; 6) Denmark; 7) Estonia; 8) Finland; 9) France; 10) Germany; 11) Greece; 12) Hungary; 13) Iceland; 14) Ireland; 15) Italy; 16) Lithuania; 17) Malta; 18) Netherlands; 19) Norway; 20) Poland; 21) Portugal; 22) Romania; 23) Slovakia; 24) Slovenia; 25) Sweden; 26) Switzerland; 28) United Kingdom, with the rest 27 countries.

4.1.2.1.3. Evaluation Procedures Based on the EU Countries' Road Safety Performance

The understanding of the road safety performance of the EU countries can support the development of suitable policy changes towards the desired goal. Consequently, the identification of best-performing countries (in terms of road safety) can be a helpful tool to the strategic road safety planning for under-performing countries (in the same terms) by considering them as benchmark cases.

A technically sound method and a powerful benchmarking technique that handles multi-inputs and multi-outputs as introduced in the methodology is Data Envelopment Analysis (DEA). Therefore, suitably adapted to road safety framework, DEA and DEA-Cross Efficiency Model (DEA-CEM) were introduced and applied for the EU countries' road safety evaluation over 2004-2013. However, the possible reflection of EU's economy (e.g. the financial crisis of 2008-2009 and 2012-2013) on countries' road safety performance cannot be captured when the evaluation is considering for the whole decade. Thus, an intra-period evaluation was undertaken which eventually showed that EU's financial situation in 2008, 2009, 2012 and 2013 had effects on each country's road safety performance. The proposed intra-period analysis has useful practical and methodological implications, since it can expose the evolution of road safety levels among the countries, besides a static overall picture.

Evaluating the EU-23 countries' road safety performance, provides the ranking of countries in terms of the previously selected risk exposure indicators. As so, under-performing countries may identify the introduce policies and strategies from the best-performing countries, and in particular from those with the most similar characteristics. For instance, a 'poor' country (in terms of GDP) might not be able to adopt the same strategies that a 'wealthy' (in the same terms) best-performing country is following. Therefore, the DEA and DEA-CEM scores will be classified into the four clusters depicted in **Figure 10** for providing the knowledge of best-performing and under-performing countries in each cluster, which shows the countries with the same socio-economic and demographic context.

The first implementation of the evaluation analysis was considered the road safety performance of EU-23 countries over a decade (2004-2013), based on averaged socio-economic and demographic data. The road safety scores from both models used here (DEA and DEA-CEM) classified into the four clusters in **Figure 10**.

Table 6 shows the road safety scores of each country. The ranking of the countries in each cluster is based on DEA-CEM scores, which are considered to be more realistic than the DEA scores, due to the cross-country evaluation DEA-CEM model is taken into consideration.

From **Table 6** it can be assumed that the best-performing countries from clusters 1, 2, 3 and 4 are Iceland, Netherland, Spain and Sweden, respectively. Therefore, under-performing countries from each cluster should study and possibly adopt/introduce some of the strategies of the best performing countries that belong to the same cluster. In addition, this table presents the calculated standard deviation regarding the DEA-CEM scores.

From the values of standard deviation, it can be concluded that a portion of countries obtained high values, i.e., Iceland, Netherland, Spain, Denmark, Luxemburg, Norway, Cyprus, etc., which means that the set of road safety scores varies the most from DEA-CEM score. This indicates the high uncertainty of the countries' road safety score and possibly the uncertainty involved in their road safety policies. This outcome was partly anticipated since the high financial changes occurred inside the EU region over the time period 2004-2013, especially during the financial crisis of 2008-2009. In order, to verify the road safety score of each country, intra-period benchmarking analysis was implemented.

Table 6. Road safety efficiency scores concerning the period 2004-2013.

Country Code	**Clusters**	**DEA Scores**	**DEA-CEM Scores**	**Standard Deviation**
IS (8th)	Cluster 1	1	0.62588	0.205816
AT (13th)		0.597194	0.394583	0.14099
PT (14th)		0.563068	0.393369	0.150652
CZ (16th)		0.492113	0.329918	0.130998
HU (17th)		0.487531	0.329224	0.147471
EL (20th)		0.496436	0.314782	0.13407
LV (22nd)		0.377654	0.236768	0.115767
NL (7th)	Cluster 2	1	0.697449	0.265534
DK (10th)		0.775021	0.568168	0.194117
LU (12th)		0.732441	0.402914	0.198528
BE (15th)		0.464205	0.361916	0.126235
CY (18th)		0.544751	0.327854	0.158174
SI (19th)		0.43757	0.319415	0.12161
ES (5th)	Cluster 3	1	0.705296	0.259872
FR (9th)		0.837748	0.59568	0.111563
SE (1st)	Cluster 4	1	0.999001	0.004684
UK (2nd)		1	0.838605	0.13052
NO (3rd)		1	0.816786	0.179443
DE (4th)		0.782206	0.712411	0.063417
FI (6th)		0.81118	0.698413	0.08532
IT (11th)		0.646709	0.516304	0.097562
PL (21st)		0.455284	0.29958	0.126224
RO (23rd)		0.331962	0.22205	0.100477

The intra-period benchmarking analysis is founded on the assumption that there is an uncertainty on the road safety score of the EU-23 countries when using average 2004-2013 data. The outcome of the intra-period DEA and DEA-CEM models provided information on the relevance between specific financial conditions (e.g., financial crisis) and the road safety performance of 23 EU countries, for each time instance.

Table 7 shows the overall road safety performance of 23 EU countries on each year. For instance, Czech Republic, Denmark, France, Italy, Netherlands, Finland and Norway appeared to have a steady fluctuation on their road safety performance between 2004 and 2013. Furthermore, Germany, Luxembourg and Poland followed a downhill course, fact that is highlighted for further research. In contrast, Hungary, Spain and United Kingdom appeared with a significant improvement on their road safety performance. Sweden, is presented as the best-performing country for the decade, a fact that should raise the interest to the policymakers for introducing strategies applied in that country. From the intra-period evaluation of the countries it can be observed how their performance was affected due the financial crisis. As it seems, in 2008-2009 some countries were affected on their performance positively (e.g., UK), negatively (e.g. Poland) and some others didn't show any effect on them. Taking these road safety evaluations as an example, significant improvements can be achieved in favour of the under-performing countries. **Appendix A-R3.e** provides the RStudio code used for implementing DEA.

Table 7. Road safety performance rankings of the EU countries for each time instance.

Country	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Austria	15th	13th	13th	13th	15th	12th	13th	13th	13th	13th
Belgium	13th	14th	16th	15th	14th	18th	18th	17th	20th	19th
Cyprus	22nd	19th	18th	16th	17th	19th	16th	19th	12th	12th
Czech Republic	16th	16th	15th	17th	18th	17th	17th	16th	19th	16th
Denmark	8th	8th	8th	12th	13th	10th	9th	7th	6th	7th
Finland	4th	6th	5th	8th	8th	4th	7th	8th	7th	8th
France	7th	7th	7th	5th	9th	9th	10th	10th	10th	9th
Germany	2nd	3rd	3rd	2nd	3rd	5th	8th	9th	9th	6th
Greece	18th	21st	21st	20th	20th	22nd	22nd	21st	18th	17th
Hungary	21st	18th	19th	19th	16th	15th	14th	15th	15th	18th
Iceland	11th	9th	14th	7th	4th	8th	2nd	5th	4th	10th
Italy	10th	11th	11th	10th	11th	11th	12th	11th	11th	11th
Latvia	23rd	23rd	23rd	23rd	22nd	20th	20th	20th	22nd	22nd
Luxembourg	14th	15th	10th	14th	10th	14th	11th	12th	17th	20th
Netherlands	5th	4th	6th	6th	7th	6th	5th	6th	8th	5th
Norway	3rd	2nd	2nd	3rd	6th	2nd	4th	2nd	2nd	4th
Poland	12th	12th	17th	18th	21st	21st	21st	22nd	21st	21st
Portugal	17th	17th	12th	11th	12th	13th	19th	18th	16th	15th
Romania	19th	22nd	22nd	21st	23rd	23rd	23rd	23rd	23rd	23rd
Slovenia	20th	20th	20th	22nd	19th	16th	15th	14th	14th	14th
Spain	9th	10th	9th	9th	5th	7th	6th	4th	5th	3rd
Sweden	1st	1st	1st	1st	1st	1st	1st	1st	1st	1st
United Kingdom	6th	5th	4th	4th	2nd	3rd	3rd	3rd	3rd	2nd

4.1.2.1.4. Measuring the Effects of Socio-Economic and Demographic Factors on EU Countries' Road Safety Performance: A Tobit Approach

The next approach from in the evaluation process of the EU countries' road safety performance was developed based on the outputs obtained from the DEA method, i.e. the efficiency scores of the countries' road safety performance. In detail, the efficiency scores were used as outputs in the Tobit regression models. The Tobit regression models that were developed revealed the extent of affection of these variables to the efficiency scores of the EU countries' road safety performance.

Table 8 presents the outcomes from the Tobit models. As can be seen from the table, diesel price has a significant effect on the countries' road safety performance, indicating that as the diesel price of a country increases the performance of the country also increases. This can be justified as the increase of fuel prices leads to lower use of private motorized vehicles and thus, less exposure to fatality risk. The number of registered vehicles has also a positive relationship with the efficiency levels of the countries, which is in line with previous literature findings indicating that while a positive relationship among the vehicle ownership and fatality risk exists, after a specific motorization rate this relationship is reversed *(Yannis, et al., 2011)*.

Finally, the relationship of GDP and efficiency levels of the countries shows that economic prosperity plays a beneficial role in the road safety performance of the countries, which is potentially achieved through road infrastructure improvements, vehicle fleet renewal, or associated and cultural changes. However, it should be noted that these results are not consistent during the overall examined period, with some of these indicators not being found statistically significant in all models, which underlines the need for further exploration of this phenomenon. **Appendix A-R3.e** provides the RStudio code used for implementing Tobit.

Table 8. Results from the Tobit regression models.

Variables/Year	2007	2008	2009	2010	2011	2012	2013
Intercept	0.22 (0.37)	-7.26e-03 (0.33)	0.82*** (0.05)	0.47*** (0.09)	0.75*** (0.06)	0.62*** (0.10)	0.06 (0.34)
GDP per capita	-	-	-	8.71e-06** (3.19e-06)	-	6.10e-06. (3.15e-06)	-
Total length of road network	-	-	-	-	-	-	-
Pump price for diesel fuel	0.47. (0.26)	0.55* (0.23)	5.16e-06. (2.73e-06)	-	-	-	0.36* (0.18)
Registered Passenger Cars (thousand)	-	5.27e-06. (2.85e-06)	-	8.24e-06** (2.59e-06)	6.49e-06* (3.07e-06)	5.02e-06. (2.73e-06)	7.79e-06** (2.60e-06)
Log-Lik.	5.926	8.873	8.310	9.128	5.719	7.845	8.524
AIC	-5.852	-9.745	-10.620	-10.256	-5.437	-7.691	-9.048

Note: *Parenthesis denotes the standard error of the variables*

-: denotes the non-statistically variables that were omitted from the model

4.1.2.1.5. Target Setting for the EU Countries

The current section sets quantitative long-term and short-term road safety targets regarding two different outputs (mortality rate and fatality risk). A fundamental assumption for doing so is that the countries were considered as successive on their road safety targets if they achieve mortality rate and fatality risk goals. Setting road safety targets, enables policymakers to identify which under-performing countries should put more effort on strategic road safety policy plans. The target setting approach was developed based on DEA method as described in the methodology.

A reasonable timeframe for setting targets and getting the desired road safety results is considered here to be ten years. In doing so, the socio-economic and demographic context of the 23 EU countries in 2004 was considered for setting road safety targets (regarding both mortality rate and fatality risk) to be achieved after a decade, i.e. 2013.

Figure 22 presents the mortality rate and the fatality risk indicators in 2004 and 2013 and the targets that were set concerning both indicators. As it can be observed, Austria, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Iceland, Italy, Netherland, Norway, Poland, Spain, Sweden and United Kingdom succeeded their targets according the mortality rate indicator. Furthermore, Denmark, Finland, France, Germany, Iceland, Netherland, Norway, Spain, Sweden and United Kingdom seem that they achieved their long-term targets concerning the fatality risk indicator. Meanwhile, the 23 EU countries who achieved mortality rate and fatality risk targets are considered as the countries with an overall successive road safety strategy. These countries are Denmark, Finland, France, Germany, Iceland, Netherland, Norway, Spain, Sweden and United Kingdom. The remaining countries that did not manage to succeed their targets need to be addressed through strategic road safety changes and improvements.

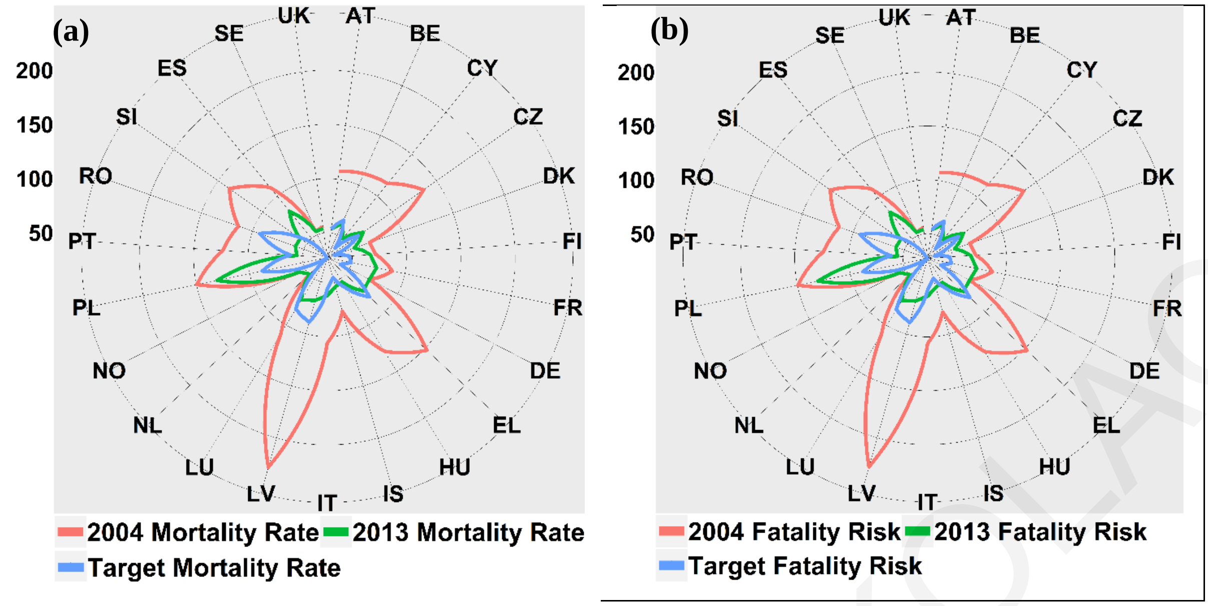


Figure 22. Setting targets concerning (a) mortality rate and (b) fatality risk indicators.

Furthermore, an additional target setting procedure was implemented, in which short-term targets were set for the 23 EU countries. More precisely, each year from 2005 to 2013 was targeted based on previous year's socio-economic and demographic data. For instance, the 2005 road safety targets, were set based on the socio-economic and demographic context of the 23 EU countries in 2004.

Figure 23 and **Figure 24** present the annual mortality rate and fatality risk targets, respectively. The countries that achieved the mortality rate targets in 2005 are Germany, Netherlands, Norway and Sweden. Germany and Netherlands also achieved their mortality rate targets in 2006, 2007 and 2008. In 2007, Iceland and Norway were also fulfilling the particular target. Sweden, France and United Kingdom were also succeeded their mortality rate target in 2008. Moreover, in 2009 Norway, Spain, Sweden and United Kingdom fulfil their target.

The succeeded countries in 2010 are Iceland, Netherlands, Norway, Spain, Sweden and United Kingdom. In 2011, are only Norway and Spain. In 2012, are Denmark, Finland, Iceland, Norway, Spain, Sweden and United Kingdom. Finally, in 2013 Netherland, Sweden, Spain and United Kingdom were succeeded. It seems that Norway has achieved the particular target every year except 2006 and Spain was also successful from 2009 to 2013.

Moreover, it was mentioned that the countries who succeeded both targets were considered as those with efficient road safety strategies. As it can be observed from the figures, these countries are Germany, Netherland, Norway and Sweden in 2005; Germany and Netherlands in 2006; Germany, Iceland, Netherlands and Norway in 2007; France, Germany, Iceland, Netherlands, Sweden and United Kingdom in 2008; Norway, Spain and Sweden in 2009; Iceland, Netherlands, Norway, Spain, Sweden and United Kingdom in 2010; Norway and Spain in 2011; Denmark, Finland, Iceland, Norway, Spain, Sweden and United Kingdom in 2012 and Spain, Sweden and United Kingdom in 2013.

In overall, this scale of analysis touched a transportation phenomenon inside a region that is characterized as homogeneous (based on the socio-economic and demographic context of the countries) and spatially related.

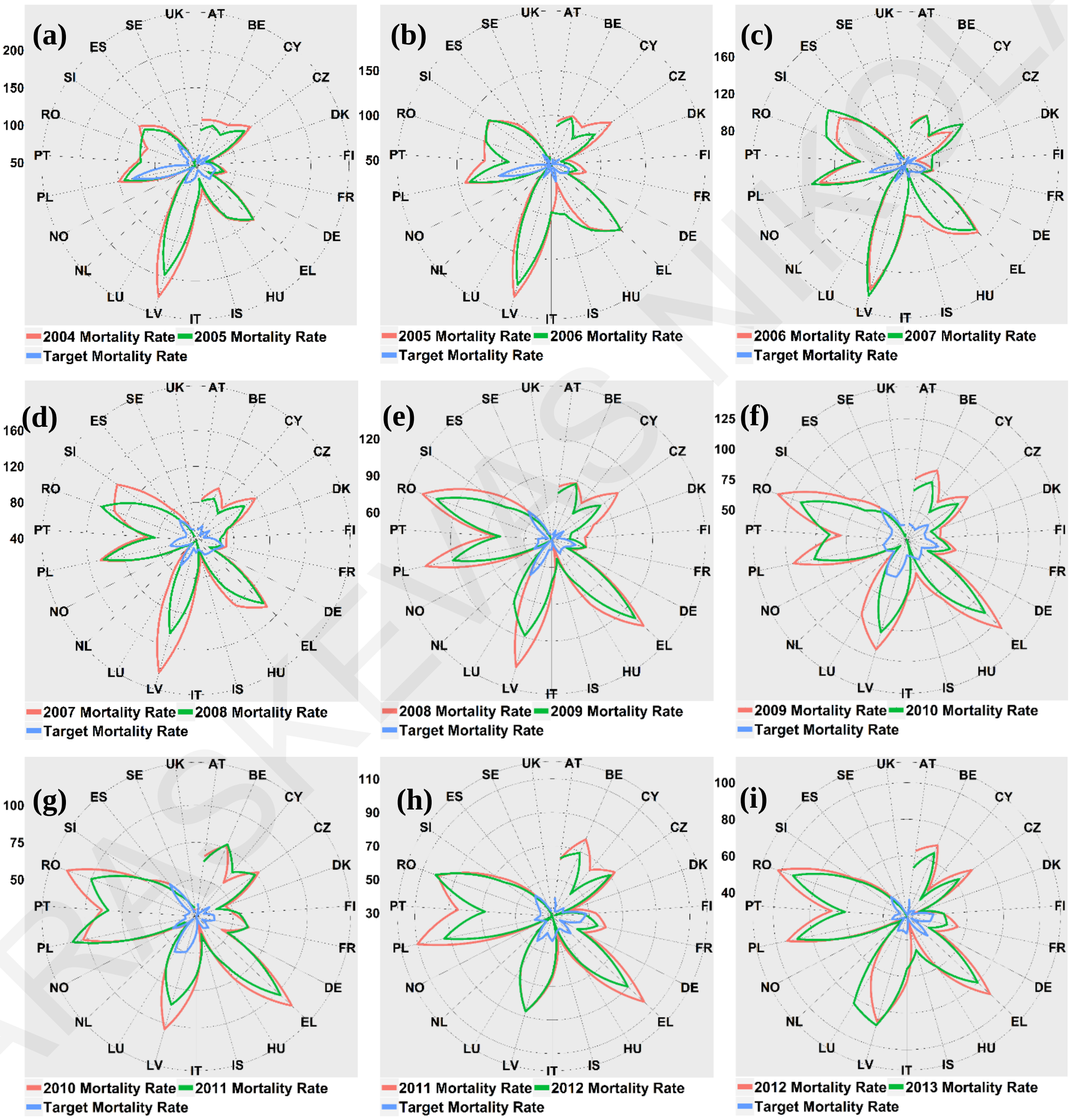


Figure 23. Annual mortality rate targets concerning the years (a) 2005; (b) 2006; (c) 2007; (d) 2008; (e) 2009; (f) 2010; (g) 2011; (h) 2012; (i) 2013.

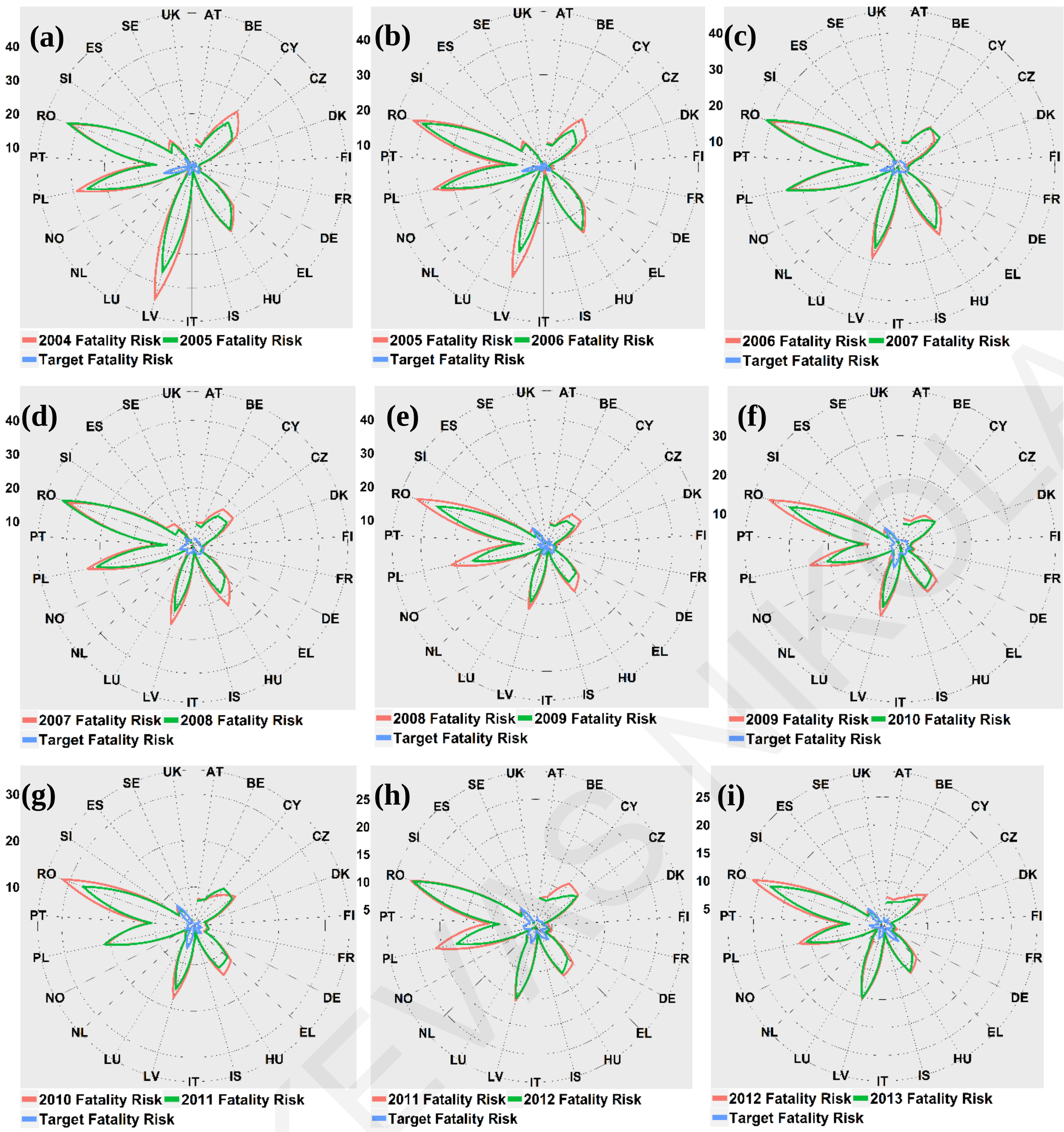


Figure 24. Annual fatality risk targets concerning the years (a) 2005; (b) 2006; (c) 2007; (d) 2008; (e) 2009; (f) 2010; (g) 2011; (h) 2012; (i) 2013.

4.1.2.2. Exploratory Analysis: Global Approach

The Global scale approach was developed for analyzing the transportation phenomenon of road traffic fatalities in countries members of the United Nation (UN). The dataset collected for this analysis consistent of several factors depicted in **Table 2**, and an extensive number of observations (UN countries). Based on the methodological framework developed in Chapter 3, the analysis of a complex transportation phenomenon, like road traffic fatalities, is important first capturing the picture of the phenomenon and the direct effects that different factors have on the phenomenon. In the European scale an Ordinary Least Square is developed for analyzing this direct linear relationship. However, in the global scale analysis a different linear regression model was developed, namely Negative Binomial (NB) regression analysis. NB regression is tested in this case due to its ability of controlling dependent variables that are non-negative or cannot be negative, likewise the phenomenon of road traffic fatalities.

The analysis of the global road fatalities continued with identifying and analyzing possible latent structures inside this extensive dataset by implementing Principal Component Analysis (PCA) and Factor Analysis (FA). The identified latent structures were analyzed by using Structural Equation Modeling.

4.1.2.2.1. Implementation of Negative Binomial Regression Analysis

For estimating the direct effects of macro-level information on the road traffic fatalities of 121 UN countries in 2013 NB regression model was considered. It must be noted that in the global scale analysis the availability of exposure data (road fatalities) was limited for the similar time duration considered in the European analysis of the phenomenon.

Table 9 and **Table 10** show the coefficients of the direct relationship between the macroscopic information with Road Traffic Fatalities. The symbol "r*" in the tables indicates the omitted collinear variables, the symbol "-" for the omitted non-statistically significance variables. All the concluded variables in the models has a significance level (p-value < 0.05). The NB models developed had an additive form, which included all the macro-level variables.

As can be seen from the NB regression results of the mortality rate index, economic factors such as taxation and diesel price have a negative effect on road traffic fatalities fact that must be under consideration. Furthermore, it seems that in the continents of North and South America the mortality rate increases, fact should be also considered to improve the road safety "picture" of the countries in these continents. As it concerns the legislations the countries that do not apply a legislation for a front rear, they record higher numbers of mortality rate.

Continuing, to the NB results of fatality risk it seems that most of the variables appeared to be non-statistically significant. However, for the variables that remained in the models, taxation is reducing fatality risk as gasoline price does, and as concerned the legislation strategies that the countries are following, countries without a rear end legislation have higher numbers of fatality risk.

Table 9. Results of NB for mortality rate index.

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	5.125	3.144	2.993	2.003	1.736
Income (High)	0.051	-	-	-	0.280
Income (Middle)	0.390	-	-	-	0.230
GNI (US $)	r*	r*	r*	r*	r*
GDP (US $)	r*	r*	r*	r*	r*
Food_prod	-	-	-	-	-
Tax (%)	-0.004	-0.006	-0.006	-0.005	-0.005
Unemp (%)	-	0.012	0.013	-	-
Diesel_price (US $ per litre)	-0.528	-0.531	-0.537	-0.361	-0.232
Gasol_price (US $ per litre)	r*	r*	r*	r*	r*
Int_users (per 100 people)	-	-0.005	-0.004	-	-
Con (Africa)		-0.182	-0.218	-0.138	-0.127
Con (Europe)		-0.251	-0.331	-0.110	-0.212
Con (N.America)		0.344	0.366	0.430	0.433
Con (Oceania)		-0.082	-0.108	0.027	0.066
Con (S.America)		0.516	0.514	0.403	0.366
Area/Popul (Km^2*10^{-1}/ No. people)		-	-	5.304	-
Popul_growth (%)		-	-	-0.050	-0.0623
Birth_rate (Birth rate per 1000 people)		r*	r*	r*	r*
Death_rate (Death rate per 1000 people)		0.061	0.069	0.054	0.061
Popul_15_64 (No. people)		0.029	0.031	0.033	0.032
Tot_length_net ($Km*10^{-6}$)			-1.463	-1.577	-1.784
Tot_nodes_net (No. nodes$*10^{-5}$)			r*	r*	r*
Est_road_traf (Road traffic rate per 100 000 people)				0.042	0.051
Num_reg_veh/Popul (No. cars$*10^{6}$/ No. people)				r*	r*
Leg_front_rear (No)					0.132
Leg_airbags (No)					-0.291
Leg_anti_lock (No)					-
AIC	1445.6	1435	1435	1378	1301.6

Table 10. Results of NB for fatality risk index.

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	5.819	3.096	2.996	2.529	2.437
Income (High)	r*	r*	r*	r*	r*
Income (Middle)	r*	r*	r*	r*	r*
GNI (US $)	r*	r*	r*	r*	r*
GDP (US $)	r*	r*	r*	r*	r*
Food_prod	0.006	0.007	0.008	0.007	0.007
Tax (%)	0.006	-0.005	-0.005	-0.005	-0.005
Unemp (%)	-	-	0.006	-	-
Diesel_price (US $ per litre)	r*	r*	r*	r*	r*
Gasol_price (US $ per litre)	-0.515	-0.943	-0.941	-0.722	-0.635
Int_users (per 100 people)	-0.046	r*	r*	r*	r*
Con (Africa)		-	-	-	-
Con (Europe)		-	-	-	-
Con (N.America)		-	-	-	-
Con (Oceania)		-	-	-	-
Con (S.America)		-	-	-	-
Popul/Num_reg_veh (No. people*10^{-3}/ No. cars)		6.073	6.104	6.409	5.870
Area/Num_reg_veh (Km^2/ No. cars)		r*	r*	r*	r*
Popul_growth (%)		-0.181	-0.174	-0.159	-0.195
Birth_rate (Birth rate per 1000 people)		0.087	0.087	0.075	0.075
Death_rate rate (Death rate per 1000 people)		-	-	-	-
Popul_15_64 (No. people)		r*	r*	r*	r*
Tot_length_net/Num_reg_veh (Km/ No. cars)			r*	r*	r*
Tot_nodes_net/Num_reg_veh (No. nodes/ No. cars)			r*	r*	r*
Est_road_traf (Road traffic rate per 100 000 people)				0.032	0.043
Leg_front_rear (No)					0.268
Leg_airbags (No)					-
Leg_anti_lock (No)					-0.200
AIC	1532.5	1447.7	1449.3	1439.7	1362.9

Appendix A-R3.a provides the RStudio code for developing the NB regression models.

4.1.2.2.2. Identifying Latent Structures Inside Extensive Datasets

The inclusion of an extensive dataset in an analysis it may contain information that is not directly observed but have an affection on the phenomenon's estimation and interpretation. The first attempt for identifying possible latent structures in a dataset is Principal Component Analysis.

Figure 25 visualizes the two PCAs for the 121 UN countries, regarding the 2010 and 2013 datasets. The eight first Principal Components (PC), cumulatively, explain more than 80% of the variance in the data. While the two first components seem to be very consistent across the two considered time-periods, validating the significance of the two first PCs. In the first PC the variables that appear to big significant (estimation value > 0.25) are: gasoline price, GDP, GNI, internet users and population aged between 15 and 64. In the second PC the variables that appear to be significant, in the same term, are: national law on mobile use while driving, land area, population, unemployment rate and total length of road network. The significance of these variables is also validated in the 2013's resulted PCA.

However, in the other PCs of both PCAs do not show a similarity, fact that makes difficult the interpretation of PCA for identifying any latent structures inside the datasets of 2010 and 2013 and thus Factor Analysis (FA) was developed.

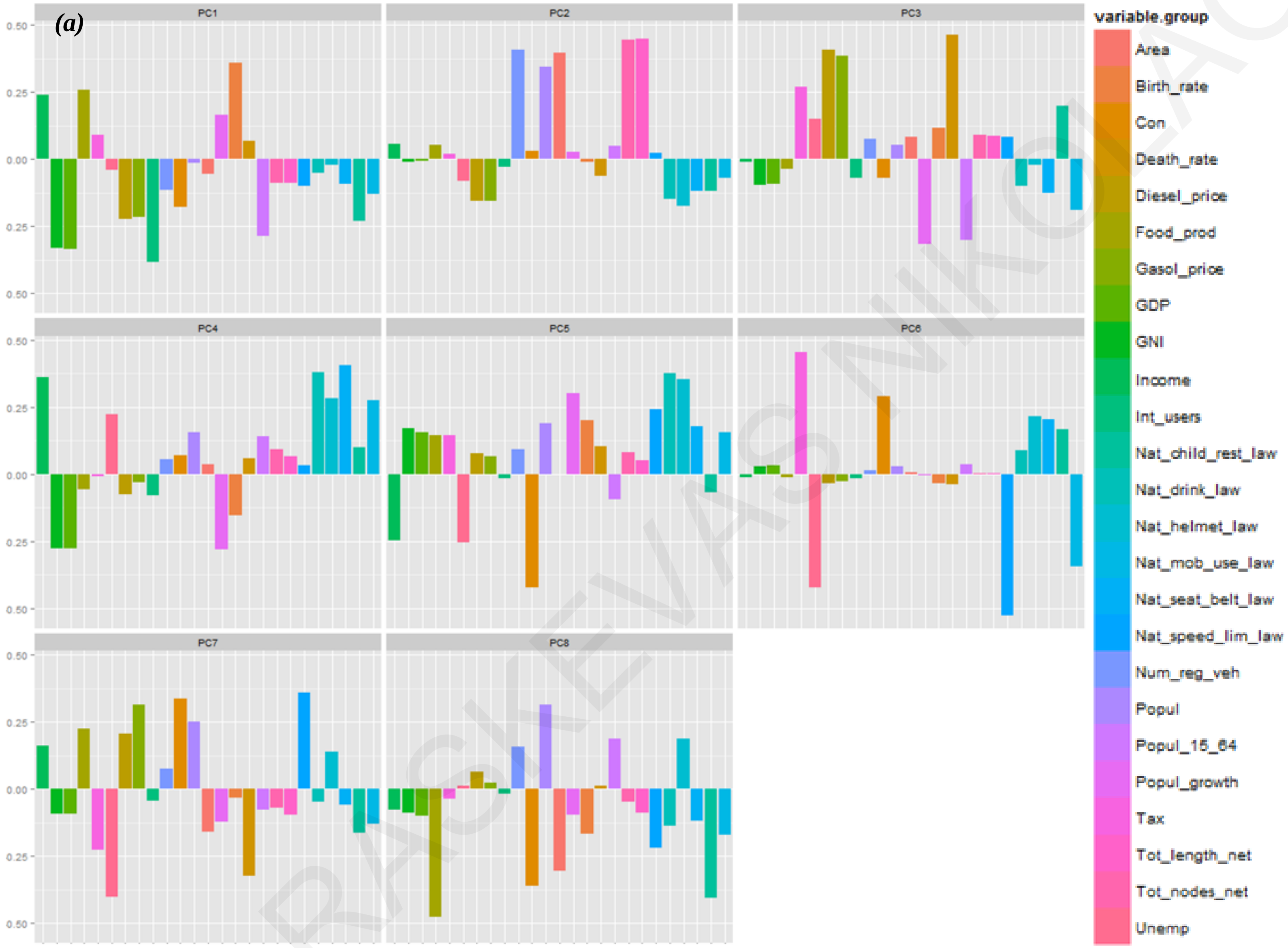

(a)
PC1
PC2
PC3
PC4
PC5
PC6
PC7
PC8
0.50
0.25
0.00
0.25
0.50
variable.group
Area
Birth_rate
Con
Death_rate
Diesel_price
Food_prod
Gasol_price
GDP
GNI
Income
Int_users
Nat_child_rest_law
Nat_drink_law
Nat_helmet_law
Nat_mob_use_law
Nat_seat_belt_law
Nat_speed_lim_law
Num_reg_veh
Popul
Popul_15_64
Popul_growth
Tax
Tot_length_net
Tot_nodes_net
Unemp

Figure 25. Principal Component Analysis for the global scale macro-level information for: a) 2010 and; b) 2013.

The factors' extraction method that was followed in FA was the Maximum-Likelihood method, which produces parameter estimates. FA has the ability of identifying and omitting any data inflations (e.g., collinearity) or statistically insignificant variables from the dataset and thus, 9 of the 15 variables were omitted.

The development of the FA requires the check of adequacy, validity and reliability of the variables-factors and therefore some statistical tests were set. The first statistical tests for FA were the Kaiser-Meyer-Olkin (KMO) of sampling adequacy and the Bartlett's test of sphericity. The criterion for KMO test is more than 0.5 and the criterion for Bartlett's test is less than 0.05. As it can be observed from **Table 11**, both test values meet both tests' criterion.

Table 11. KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.679
	Approx. Chi-Square	445.611
Bartlett's Test of Sphericity	**df**	15
	Sig.	.000

The next step of FA was the identification of the number of factors (latent variables) that are included in the dataset. The number of factors is calculated based on the eigenvalue of the factor. Thus, the criteria for choosing the number of factors were the factors with eigenvalues greater than one and the cumulative percentage of variance explained to be greater than 60%. Furthermore, regarding **Table 12** only two factors were suggested to be used in the following CB-SEM and PLS-SEM models.

Table 12. Total variance explained.

Factor	**Initial Eigenvalues**		
	Total	**% of Variance**	**Cumulative %**
1	2.660	44.3	44.4
2	2.148	35.8	80.1
3	.591	9.8	90
4	.304	5.1	95.0
5	.168	2.8	97.84
6	.129	2.2	100

Choosing the rotation method, in this case Promax with Kaiser Normalization it appeared that all the loadings are greater than 0.5. Moreover, the two factors (latent variables) that were extracted and used in CB-SEM and PLS-SEM, are namely “Socio-Economy” and “Demographic”. Moreover, the variables ‘income’, ‘GDP’ and ‘internet users’ will be used to measure the “Socio-Economic” factor. Additionally, the variables ‘number of registered vehicles’, ‘population’ and ‘land area’ will be used to measure the “Demographic” factor. **Table 13**, shows the resulted factors and the weights of their included variables.

Table 13. Structure matrix.

	Factor	
	1	**2**
Income	.892	
GDP	.798	
Internet users	.965	
Number of registered vehicles		.997
Population		.806
Land area		.573

4.1.2.2.3. Incorporating Latent Structures Using Structural Equation Modeling: A Covariance-Based and Partial Least Square SEM Models

The latent factors identified in the FA were incorporated and measured of their effects on road traffic fatalities. This section presents the development of Structural Equation Modeling (SEM) for measuring the direct and indirect effects of the variables incorporating also the two latent factors. The SEM models developed were: the Covariance-Based and Partial Least Square SEM models concerning the observed and unobserved data of 2013 and the 121 observations (121 UN countries).

In the CB-SEM model, several modification actions were carried out in order to improve the fit of the model. These actions are the creation of a correlation between the sixth (e6) and the fourth (e4) residual, the creation of a correlation between the two latent variables “Socio-Economic” and “Demographic” and the creation of a causal effect between the latent variable “Socio-Economic” and the measured variable “Number of registered vehicles”. **Figure 26** presents the CB-SEM path as it is concluded and also presents the Standardized Regression weights between the latent and observed variables. The significant level of all weights is below the 5%.

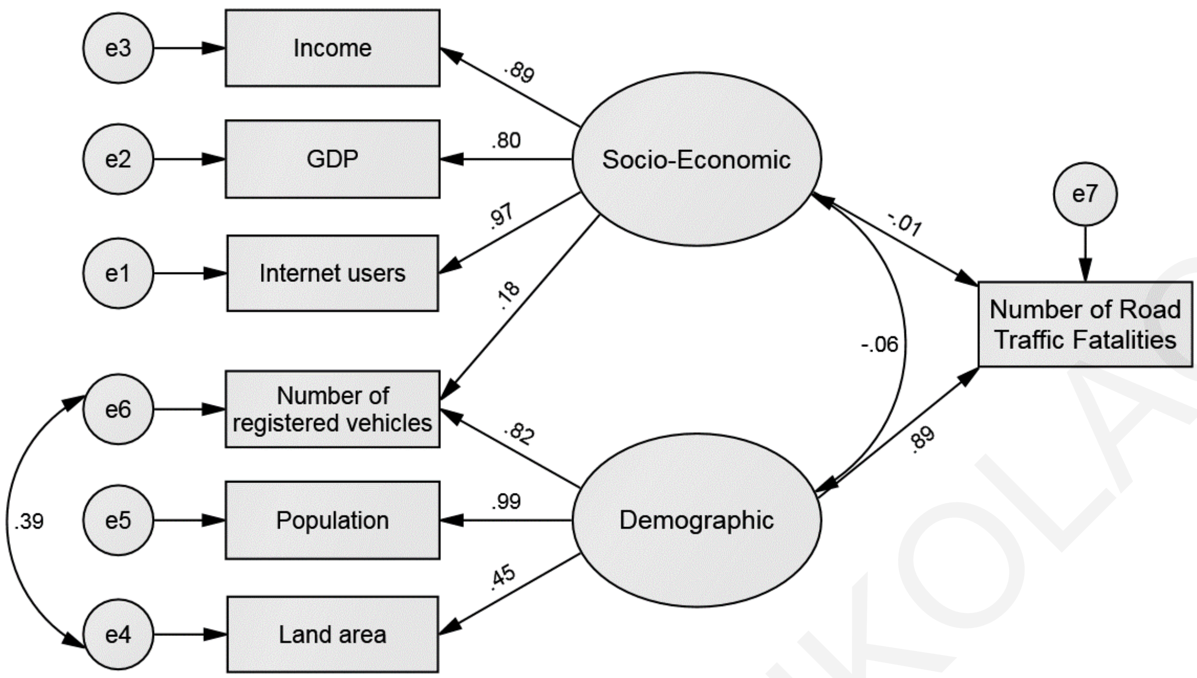


Figure 26. Covariance-Based SEM diagram.

Table 14 shows the fit indices and the limits of acceptance for the model. As it can be observed, the CB-SEM model maintains all the limits of acceptance regarding these particular fit measures and thus it can be said that this is a robust model and appropriate for estimating the road traffic fatalities of the UN-121 countries in 2013.

Table 14. CB-SEM model's fit indices and limits of acceptance.

Fit Indice	Value	Limits of Acceptance
χ2	7.823	χ2/ Df<3
Df	10	
GFI	.982	≥0.95
AGFI	.950	≥0.90
RMSEA	.000	≤0.08
CFI	.000	≥0.95

According to *(Hair, et al., 2011)* and *(Astrachan, et al., 2014)* PLS-SEM model is more suitable than a CB-SEM model when the sample size is relatively small (less than 400 observations). The type of measurement model used in this research for PLS-SEM is the reflective. The reflective model shows the relationship that observed variables reflect on their respective latent variable.

The first investigation of the model was the check of the values of loadings and communalities. Referring to *(Sanchez, 2013)*, acceptable values for the loadings are values greater than 0.7 and for communality greater than 0.5. **Table 15** presents the outer weights, loadings and communalities. As it can be observed, all the variables have loading values greater than 0.7 and communality values greater than 0.5, except from the variable land area ("Area"). Thus, the particular variable was omitted from the model.

It is essential in the reflective model to check the internal consistency due to that each block is assumed to be homogeneous and unidimensional *(Vinzi, et al., 2010)*. Thus, the particular reflective blocks (Socio-Economic and Demographic) should be homogeneous and unidimensional. In order to check the homogeneity and unidimensionality in each block, two indices were used; Gronbach's alpha and; Dillo-Goldstein's rho. **Table 16** presents the values of both indices for each block. Furthermore, both blocks are diagnosed as homogeneous since both indices have values greater than 0.7.

Table 15. Measurement's model weights, loadings and communalities.

Variables	Weights	Loadings	Communality
	Socio-Economic		
Income	0.0834	0.854	0.729
GDP	0.5386	0.944	0.891
Int_users	0.4493	0.936	0.876
	Demographic		
Num_reg_veh	0.4003	0.935	0.873
Popul	0.4908	0.918	0.843
Area	0.2520	0.696	0.484

Table 16. Indices for checking the blocks' homogeneity and dimensionality.

Blocks	Gronbach's alpha	Dillo-Goldstein's rho
Socio-Economic	0.915	0.946
Demographic	0.885	0.946

Thereinafter, the investigation continued with the inspection of the cross-loadings, i.e. the correlation of the observed variables with all latent variables. **Table 17** presents the cross-loading values. The criterion for identifying and discarding a variable from the model is the loading value of an observed variable with its corresponding latent variable to be smaller than the loading value of the same observed variable with the rest latent variable. As it can be seen from the table, all variables approved to be good.

Table 17. Cross-loadings of the measurement model.

Observed Variable	Latent Variable (block)	Socio-Economic	Demographic
Income	**Socio-Economic**	0.85	0.05
GDP	**Socio-Economic**	0.94	0.01
Int_users	**Socio-Economic**	0.94	0.03
Num_reg_veh	**Demographic**	0.14	0.94
Popul	**Demographic**	-0.07	0.96

The overall PLS-SEM model was evaluated using GoF indices. Referring to *(Sanchez, 2013)*, a GoF value greater than 0.7 is considered as very good. The GoF value of the current PLS-SEM model is 0.793, which indicates that the overall PLS-SEM model is robust and thus it can be trusted from the decision makers for taking measures that will lead to the road traffic fatalities reduction or even elimination. Figure 2 shows the final structure of the PLS-SEM model and the loadings of the inner and outer models.

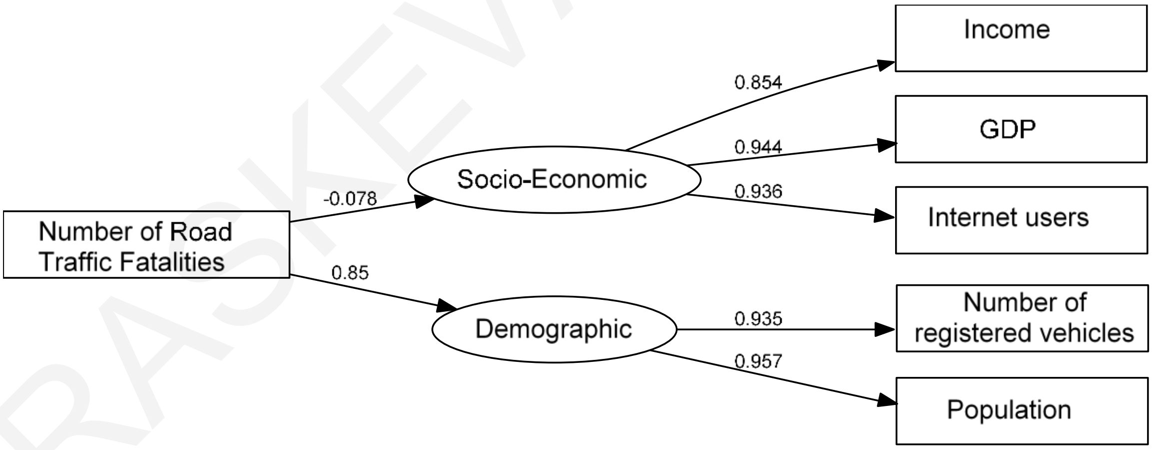


Figure 27. PLS-SEM diagram.

4.1.3. Explanatory analysis: Supporting Road Safety Decision-Making Procedures

Investigating the phenomenon of road traffic fatalities revealed several issues on the data, on the number of observations, and on the methodological approaches. In the descriptive analysis it appeared that the phenomenon of road traffic fatalities is spatially related on the European scale but not in the global scale. Additionally, it appeared that economic factors that were considered for the analysis of this transportation phenomenon have a significant meaning. In addition, it appeared that the economic context of the countries was shaken especially due to the economic crisis. The quantitative analysis of the European and Global datasets showed that the European countries can be characterized as homogeneous based on their socio-economic and demographic context, something that cannot be said for the global set of countries. Additionally, the correlation analysis identified the collinear variables that were omitted prior the exploratory analysis of the phenomenon.

The exploratory analysis of road traffic fatalities both at the European and Global level revealed several matters concerning the data collected, the affect of the socio-economic and demographic macro-level information on road fatalities and the road safety performance of the countries.

In the European analysis of the phenomenon the linear relationship of the macro-level factors with road traffic fatalities was tested using Ordinary Least Square, which revealed that economic factors (GDP) have an important relationship with road fatalities' increment. Additionally, land area shows that plays a role on the number of fatalities and also showed that the spatial dimension of the of the countries is important. In the Global analysis the applications started by implementing also a linear regression model with the particularity that the dependent variables are not or cannot be negative (Negative Binomial Regression Analysis). The results from the NB regression showed that economic factors are important on the analysis of road traffic fatalities. For instance, is important taking under consideration that economic factors such as "diesel price" can affect the number of road traffic fatalities by reducing them. In addition, in the global dataset legislation/enforcement variables were included which showed in the NB regression models that some legislations are indeed working and for the countries who do not enforce some legislations have increments of road fatalities.

At this point it must be noted that the European dataset included approximately 10 variables were some of them were collinear and were omitted from the dataset. In addition, due to the availability of information the European analysis was conducted between 2004 and 2013 and between 2012 and 2016. Due the different time variations the number of EU countries was different. For the period 2004-2013 the availability of data considered 28 EU countries and for the period 2012-2016 the availability of data considered 23 EU countries. As for the Global analysis the analysis included 25 variables for 121 United Nation countries. However, in this scale of analysis the availability of data was restrict and therefore the data concerned only the years 2010, 2013 and 2016. However, the global sample for 2016 was only concerned in the descriptive analysis and not in the exploratory analysis due to the lack of information for a large proportion of the 121 UN countries.

Furthermore, the next step of the exploratory analysis was the identification of possible latent structures that have an unobserved effect on road traffic fatalities. In the European level of analysis the sample included less than four variables and thus latent factors cannot be identified by less than four measured/observed variables *(Thompson, 2004)*. Therefore, the European dataset (concerning all the time durations) was not investigated for latent structures. However, the Global sample due its extensive dimension, both at variables and at observations, was exanimated for identifying latent structures. The methods for identifying latent structures are Principal Component Analysis and Factor Analysis. The PCA was developed for both years' datasets (2010 and 2013). The dissimilarity between the two PCAs was not able to obtain the information of latent factors and therefore the FA was conducted. FA revealed two latent factors in the dataset which were named as "Socio-Economy" and "Demography" based on the observed variables that each latent factor is related.

These two latent factors were analyses in for the effect on road traffic fatalities by using Covariance-Based and Partial Least Square Structural Equation Modeling. The results of both PLS and CB-SEM that "Socio-Economy" has an overall, negative effect on road fatalities, in contrast with "Demography" which appeared that it increases the road traffic fatalities. The respective measured variables of both latent factors showed to have an indirect relationship with road fatalities with the same sign as the latent factors.

The next step of the methodology, as denoted in Chapter 3, was the investigation of spatial autocorrelation between the countries based on the phenomenon and the incorporation of this component in the analysis. The European set as was revealed in the descriptive analysis and particular in the cluster analysis the countries appeared to be homogeneous fact that indicated a possible spatial autocorrelation. In order to verify this a Moran's I Test was implemented, which indeed showed that a spatial autocorrelation exists. As for the Global set it appeared in the cluster analysis that the 121 UN countries were not homogeneous and therefore the Moran's I Test was not considered for this sample. Therefore, the spatial dependence of the European countries was incorporated in the Spatial Autoregressive models. The resulted SAR models revealed once again the importance of the economic factors on road traffic fatalities.

Finally, the exploratory analysis considered the evaluations of the EU countries' road safety performance. In detail, Data Envelopment Analysis and DEA-Cross Efficiency methods (both suitably adapted to the road safety framework) were applied and identified the efficiency level of the countries based on their road safety performance. In this approach, under and best-performing countries were identified. The next implementation in the evaluation procedure, was the undertaken of the efficiency scores as dependent variables and the measurement of the effect of the socio-economic and demographic variables on the countries' performance. The final implementation was the set of long and short-term targets based on the efficiency scores. In this approach the under-performing countries (in terms of road safety) were advised to follow the strategies of best-performing countries (in the same terms) in the same socio-economic and demographic context (clusters).

Overall, the methodology proposed in this Thesis appeared to be adequate for capturing all the aspects that a macro-level transportation phenomenon may have. However, for validating this speculation the next proof of concept was developed based on the transportation phenomenon of Multimodal Freight Transportation.

4.2. Proof of Concept: Multimodal Freight Transportation

The methodology of this Thesis was validated for its robustness by developing the methods suggested in the transportation phenomenon of Multimodal Freight Transportation (waterborne, airborne, rail and road). This section presents the applications that were developed for analyzing this transportation phenomenon. It must be noted that in this transportation phenomenon the methodological applications of the exploratory analysis started from the evaluation analysis for waterborne freight transportation while it was considered more important capturing the performance of the container port terminals in Europe.

As for the other modes of freight transportation, the exploratory analysis started from a spatial analysis and tested the connection between the European countries concerning these three modes and continued with an evaluation analysis. Finally, a novel dimensional analysis was implemented, as introduced in the methodological framework, which is the Spatio-Temporal Linear Mixed Model.

4.2.1. Waterborne Freight Transportation

The growing competition among container terminals enhances the pressure for optimizing their performance. However, comparing container terminals and thus observing their performance is a complicated task due to the variety of port types, scale and service configuration. No doubt, container terminals' infrastructure plays the most significant role in their performance. This section analyses the waterborne freight transportation and in particular the performance of European container port terminals.

The role of the waterborne sector in the European region is recognized as of paramount importance. Indicatively, 74% of goods are entering or leaving Europe by the sea *(European Commission, 2020)*, a fact highlighting the importance of the maritime system, especially that of containerized cargo, in economic development. Accordingly, container port terminals, corresponds to a critical part of the European supply chain since acts as gateways from/to the system of the international trade.

The current period, important developments are taking place in the ownership, management, organization and technological development of container terminals, where vast effort (and capital) is invested throughout the European market of cargo handling and especially in container terminals, fostering competition among them in attracting cargo. These investments concern all elements that effect on port performance, such as terminals organization structure, equipment, and infrastructure. To analyze the performance of the invested efforts, an appraisal mechanism should be used, able to provide evidence on the port performance, especially with respect to the competitors and taking into account their operational characteristics.

To support the investigation of container port terminals' performance, the proposed methodological framework was developed.

4.2.1.1. Data Collection and Results from the Descriptive Analysis

The ports that were included in this application correspond to Antwerp, Zeebrugge, Ghent, Limassol, Aarhus, Port Said, Helsinki, Le Havre, Marseille, Dunkirk, Rouen, Bordeaux, Hamburg, Bremerhaven, Piraeus, Thessaloniki, Genoa, La Spezia, Trieste, Venice, Ravenna, Riga, Klaipeda, Rotterdam, Amsterdam, Oslo, Gdansk, Gdynia, Sines, Leixoes, Lisbon, Constantza, Algeciras, Valencia, Barcelona, Bilbao, Tarragona, Gothenburg, Belfast, Gioia Tauro, Tanger, as depicted in **Figure 28**.

Figure 28. Container port terminals servicing the European continent.

For capturing the performance of the European container port terminals, seven inputs and one output were collected. Four out of the nine inputs were referring to the countries' socio-economic and demographic context, geo-location of the container terminals and the rest of the inputs were referring to ports’ characteristics (infrastructure/equipment). The output variable concerns the productivity of the ports, which in this case is expressed through the number of TEUs. **Table 18**, presents the variables collected.

Table 18. Variables included in the data sample.

#	Variable	#	Variable
1	T.E.U.	5	Total terminal's area (m²)
2	G.D.P. (US$)	6	Number of cranes
3	Exports of goods and services (current US$)	7	Population (per 1,000,000 people)
4	Unemployment, total (% of total labor force)	8	Length of the quay wall (m)

For identifying the possible existence of collinear variables, a correlation analysis was implemented. **Figure 29** presents the correlation matrix of the dataset and as it can be seen the high contributing variables to ports’ productivity are namely: Exports of goods and services; Length of the quay wall; Number of cranes and Total terminal’s area. The collinear pair was appeared to be Population-GDP were again the variable “Population” was omitted from the dataset.

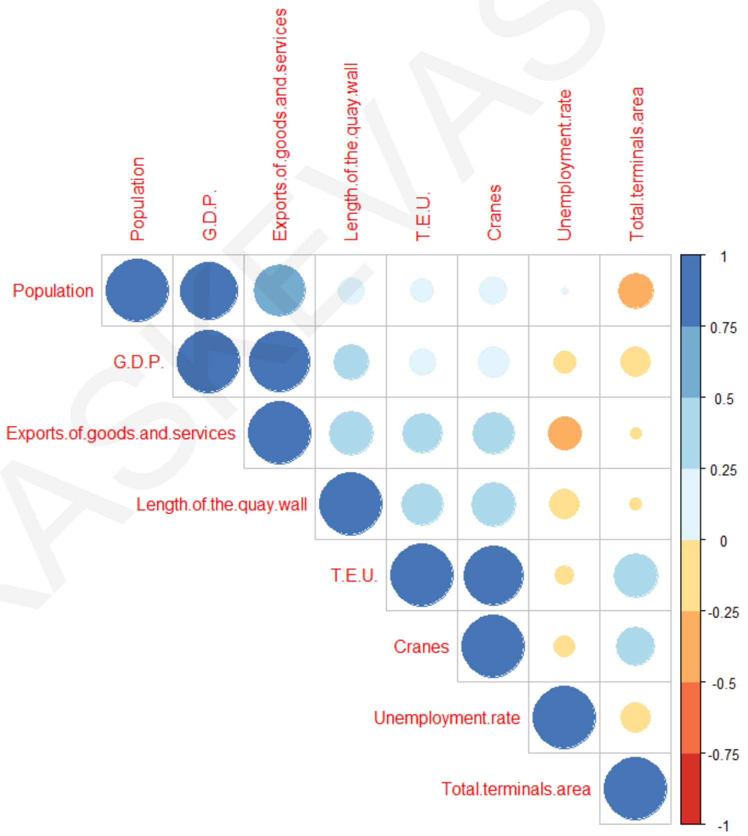


Figure 29. Dataset’s correlation matrix.

Evaluating the 41 ports' performance will provide the ranking of the ports in terms of their productivity. However, under-performing ports cannot follow or adapt the strategies that all best-performing ports are following. Thus, the question that arises is; which best-performing port/s an under-performing port should follow? In order to answer this question, and also for investigating possible homogeneities between the container port terminals a cluster analysis was developed. In detail, the clustering was developed based on the data sample (inputs and output). Before, identifying these groups it was necessary to identify the optimum number of clusters by implementing the Elbow Method, which showed that the optimal number of clusters is 3 where it seems to be the location of a bend (knee) in **Figure 30**, which is the indicator of the optimal number of clusters.

Therefore, the resulted clusters which were occurred from the cluster analysis are depicted in **Figure 31**. As can be seen, most of the ports appeared to have approximately the same characteristics/equipment. One of the clusters, depicted by the red color, includes Hamburg, Antwerp, and Rotterdam ports. Regarding the literature review and specifically *Iaphworldports*, these three ports are ranked in the world's top 20 ports list for, 2007-2016. Thus, the outcome of the hierarchical analysis appeared to be valid for further analysis.

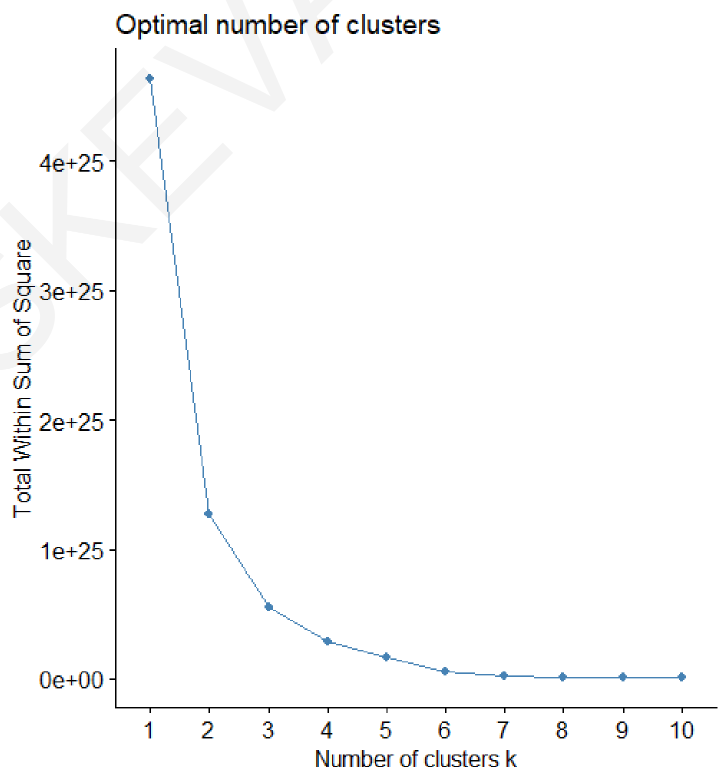


Figure 30. Elbow Method for identifying the optimal number of clusters.

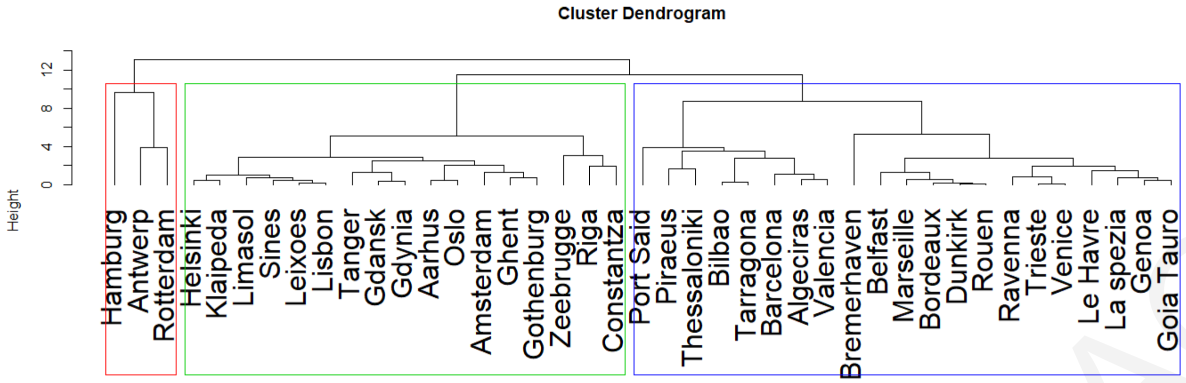


Figure 31. Hierarchical clustering based on the container port terminals' characteristics.

4.2.1.2. Exploratory Analysis and Results for the European Waterborne Freight Transportation

This section presents the results from the evaluation procedure of the container port terminals and the target setting approaches for addressing the under-performing container port terminals by following the strategies of the best-performing container port terminals.

4.2.1.2.1. Evaluation of Container Port Terminals

Container terminals' performance is a complex business which requires much effort from policymakers in order to provide effective strategies to the ports, which will assist best-performing container terminals to maintain their performance and under-performing container terminals to outperform and thus to be included in the top ranking ports' list. In this study, 41 container terminals servicing the European continent were evaluated and thus efficiency scores were estimated by using an output-oriented, technically sound DEA-CCR model.

The efficiency scores provided in the current application showed which ports are best-performing and which are under-performing, in terms of productivity expressed through TEUs service. However, as it was pointed in the previous section, under-performing container terminals cannot follow all best-performing container terminals.

Table 19 shows which best-performing container terminals the under-performing container terminals should follow based on the cluster analysis. The rankings in each cluster are ordered according to the values of efficiency (from 1 –efficient- to higher than 1 –inefficient-). We can verify that the DEA-CCR index is lower than 1 for most of the ports with the exception of 13 container terminals. From the first cluster, it seems that all container terminals operate efficiently. In the second cluster, only 4 container terminals from the 17 appeared to best-perform. Finally, from the third cluster 7 out of the 21 container terminals operate efficiently. This table provides an address to the policymakers of the under-performing container terminals by showing which best-performing container terminal should follow, i.e., from the same cluster.

Table 19. DEA-CCR efficiency scores for the 41 ports, 2016.

Container Port Terminals	Efficiency
Cluster1	
Antwerp	1.00
Hamburg	1.00
Rotterdam	1.00
Cluster 2	
Zeebrugge	1.00
Sines	1.00
Gothenburg	1.00
Tanger	1.00
Limassol	1.14
Riga	1.52
Gdansk	1.58
Helsinki	1.79
Leixoes	2.01
Klaipeda	2.04
Lisbon	2.41
Aarhus	2.62
Gdynia	2.68
Constantza	4.30
Oslo	4.35
Amsterdam	32.83
Ghent	107.19
Cluster 3	
Port Said	1.00
Le Havre	1.00
Marseille	1.00
Bremerhaven	1.00
Piraeus	1.00
Algeciras	1.00
Belfast	1.00
Valencia	1.12
Gioia Tauro	1.77
Barcelona	2.15
Genoa	2.36
Thessaloniki	2.40
Trieste	2.51
La Spezia	2.97
Bilbao	4.08
Venice	5.10
Tarragona	5.62
Dunkirk	5.80
Ravenna	11.99
Rouen	17.91
Bordeaux	42.71

4.2.1.2.2. Target Setting for Under-Performing Container Port Terminals

Beyond the findings of the container terminals' efficiency level this study aims the improvement of the 41 ports by setting targets to the under-performing ports that can be taken by exploiting more efficiently their existing infrastructure/equipment and increasing their production in TEUs. Therefore, using the efficiency scores obtained from the DEA-CCR method, the targeted values of TEUs was obtained for the under-performing countries. **Table 20** presents the recorded values of TEUs for the under-performing container terminals and their targeted values. The overall outcome of this research is an ace in the sleeve of policymakers for creating targeted strategies to increase the productivity of the container port terminals.

Table 20. Under-performing ports recorded and targeted values of TEUs.

Under-Performing Container Port Terminals	Recorded TEUs	Targeted TEUs
Ghent	12210	1308839
Limassol	344949	393484
Aarhus	456652	1197447
Helsinki	426721	764447
Riga	387975	589729
Klaipeda	441665	898673
Amsterdam	51475	1689737
Oslo	206533	899044
Gdansk	1559169	2459474
Gdynia	656740	1758326
Leixoes	602543	1212085
Lisbon	392625	945862
Constantza	706157	3033756
Dunkirk	334455	1940246
Rouen	78403	1404155
Bordeaux	56219	2400936
Thessaloniki	598206	1433369
Genoa	2356487	5568479
La Spezia	1605365	4759478
Trieste	579084	1454844
Venice	393703	2009455
Ravenna	221878	2661043
Valencia	4692986	5272126
Barcelona	2224862	4779179
Bilbao	598077	2438962
Tarragona	83700	470442
Gioia Tauro	2797070	4943379

4.2.2. Road Rail and Airborne Freight Transportation

World trade can play a major role in national development, in terms of economic growth. Therefore, it is important identifying the factors that mostly effect on freight demand. As referred to *(World Trade Statistical, 2019)* in 2017 Asia recorded the highest increase in freight volume with the growth of 8.1% and Europe recorder the second smallest increase in volume, with the growth of 3%, while Middle East region recorded a -2.2% decrease in volume growth. However, the European Union (EU) remains a significant 'player' in the global freight system, accounting for a third of world exports in 2017.

Generally, European region appears to have a leading role in the world's merchandise trade, however, the questions that arise are: What's the trade flow performance within the European region and more precisely which countries are under performing and what are the economic factors that are highly related to their under-performance? How space and time affect multimodal freight transportation and how these dimensions can be incorporated in the same model?

Generally, for improving the freight flow performance of countries or regions, it is important investigating the multimodal freight demand over at least the three important surface modes, i.e., road, rail and airborne, facilitating a holistic treatment in policymaking. The multimodal freight demand approach will provide an overall "picture" of how the countries are performing, in terms of their freight cargo that are generating and service. Therefore, the study of freight transportation is significant in the matter of efficiently operating.

4.2.2.1. Data Collection and Results from the Descriptive Analysis

The data collection procedure focused on the collection of economic factors that are expected to mostly affect the multimodal freight transportation performance of under-performing countries within the European region over a 5-year period (2012-2016). In detail, the transport modes that were taken under consideration are roadway, railway, and airway and the information for the three modes was collected from Eurostat (roadway freight transportation: *Eurostat*[2]*, (2019);* railway freight transportation: *Eurostat*[3]*, (2019)* and airway freight transportation: *Eurostat*[4]*, (2019)*). The countries that are taken into consideration correspond to Austria, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom. The countries, Iceland, Cyprus, Malta, Belgium, and Croatia were excluded from the dataset due to missing values on the dependent variables. **Figure 32**, presents the EU countries that were included in the analysis and the multimodal transportation that was concerned for the purposes of the study.

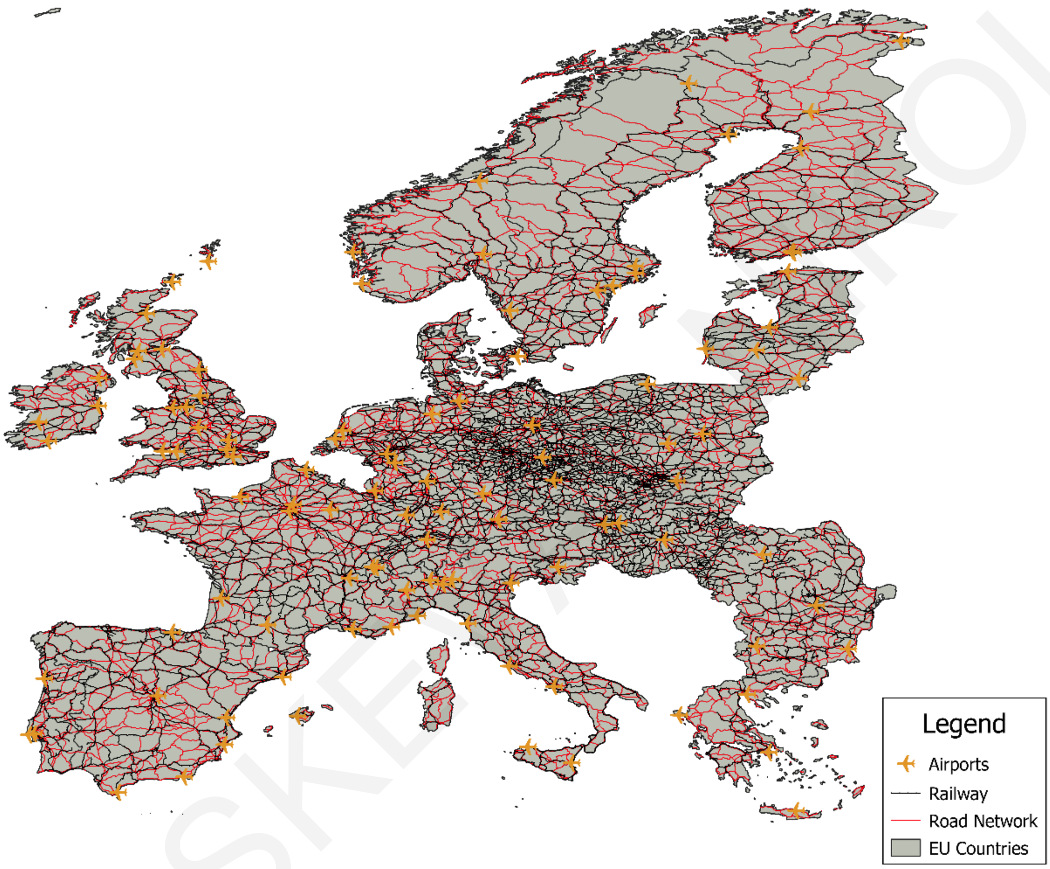


Figure 32. Rail, Road and Airborne freight transportation in the EU region.

The dependent variables that concerned the freight flow modes were namely: goods transport by road million tonne-kilometer (TKM); goods transport by rail million tonne-kilometer (TKM); and air transport of goods (Tonnes). The variables that were collected and investigated for their relation with the dependent variables are: population; unemployment rate; GDP; diesel fuel price; land area; total motorway length; total length of railway lines (km); number of commercial airports; exports of goods and services in GDP; and imports of goods and services in GDP. The reason for collecting mainly economic nature's variables for the study of the multimodal freight transportation can be validated from the qualitative analysis (visualizations) of the economic variables in the analysis of Road Traffic Fatalities. Additionally, all the collected data were collected from the dataset of Euroastat.

The collected data were divided into three datasets concerning each different freight mode. In detail, the three datasets included the same economic variables but the respective variables of the mode, i.e., the network length of the rail and road models or the number of airports of the airway and the variables that concerned the different transport of goods for each mode.

Figure 33, **Figure 34**, and **Figure 35** present the three different dependent variables for each year. As it can be observed from the figure, central European countries appear to be homogeneous on the dependent variables, highlighting the possibility of spatial influence existence.

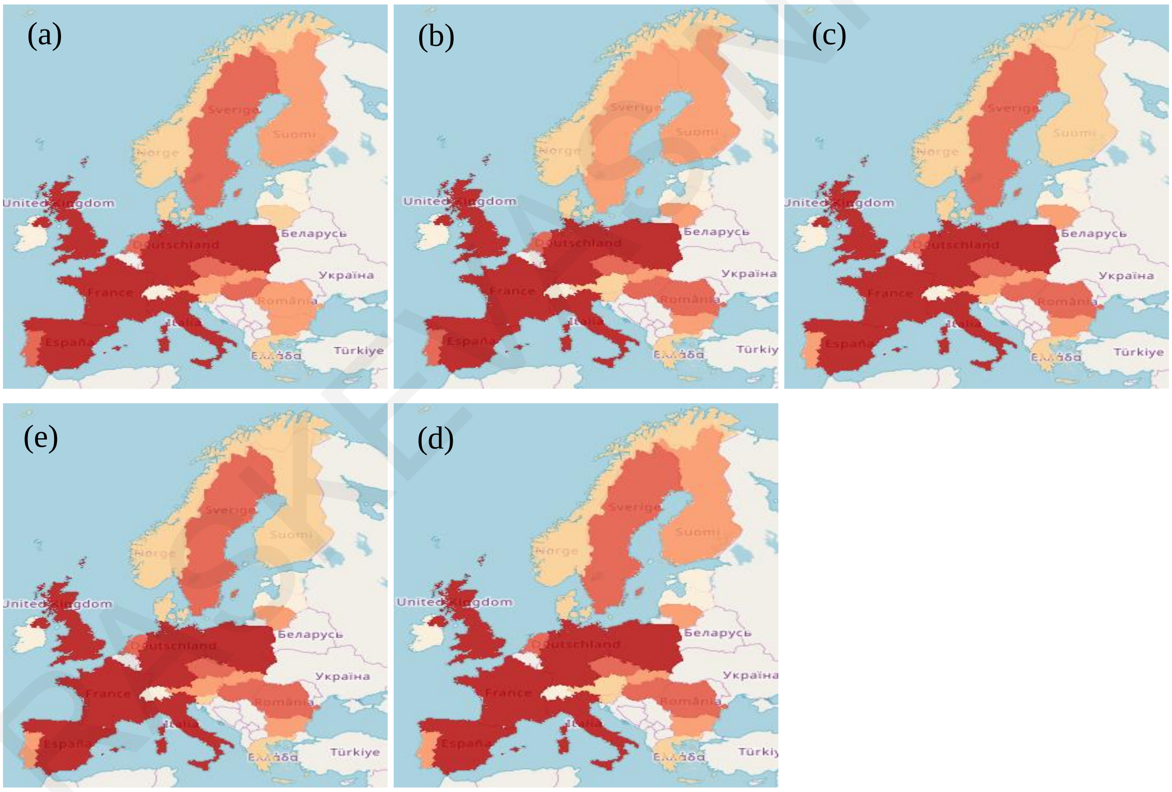


Figure 33. Freight transport by road million tonne-kilometre (TKM) in the EU region for the years: a) 2012; b) 2013; c) 2014; d) 2015 and e)-2016.

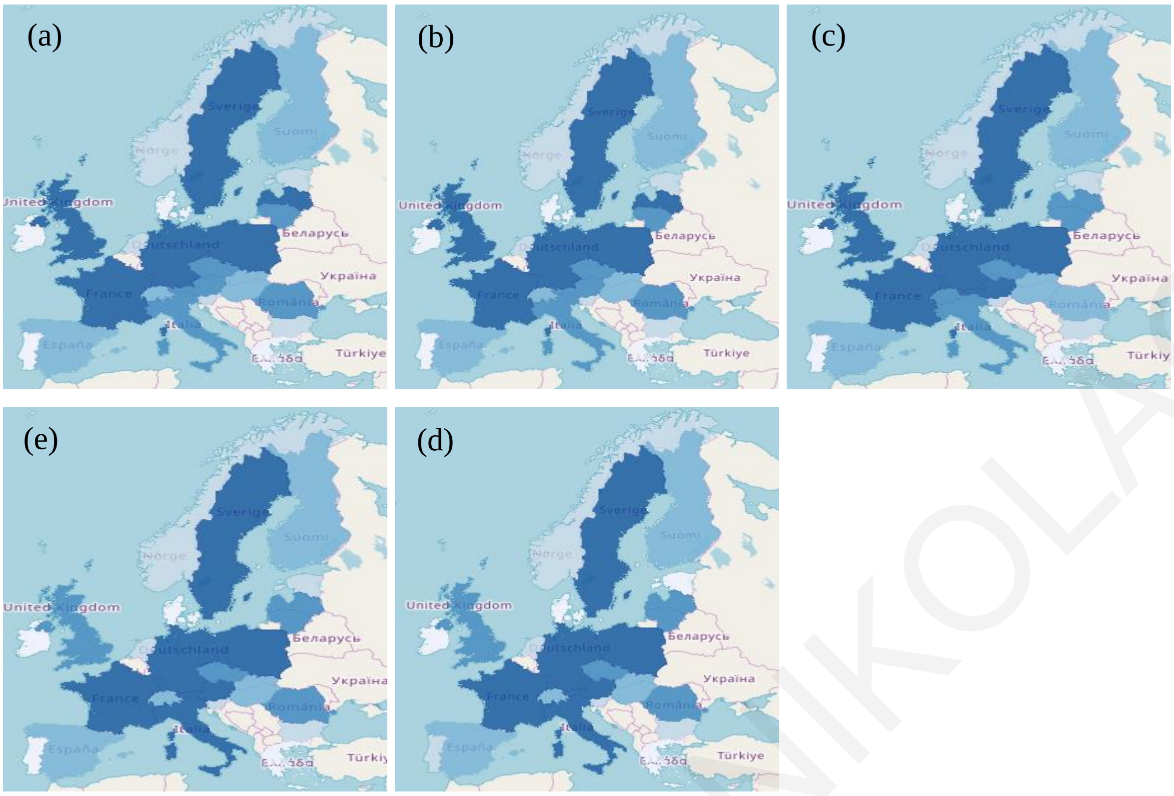


Figure 34. Freight transport by rail million tonne-kilometre (TKM) in the EU region for the years: a) 2012; b) 2013; c) 2014; d) 2015 and e)-2016.

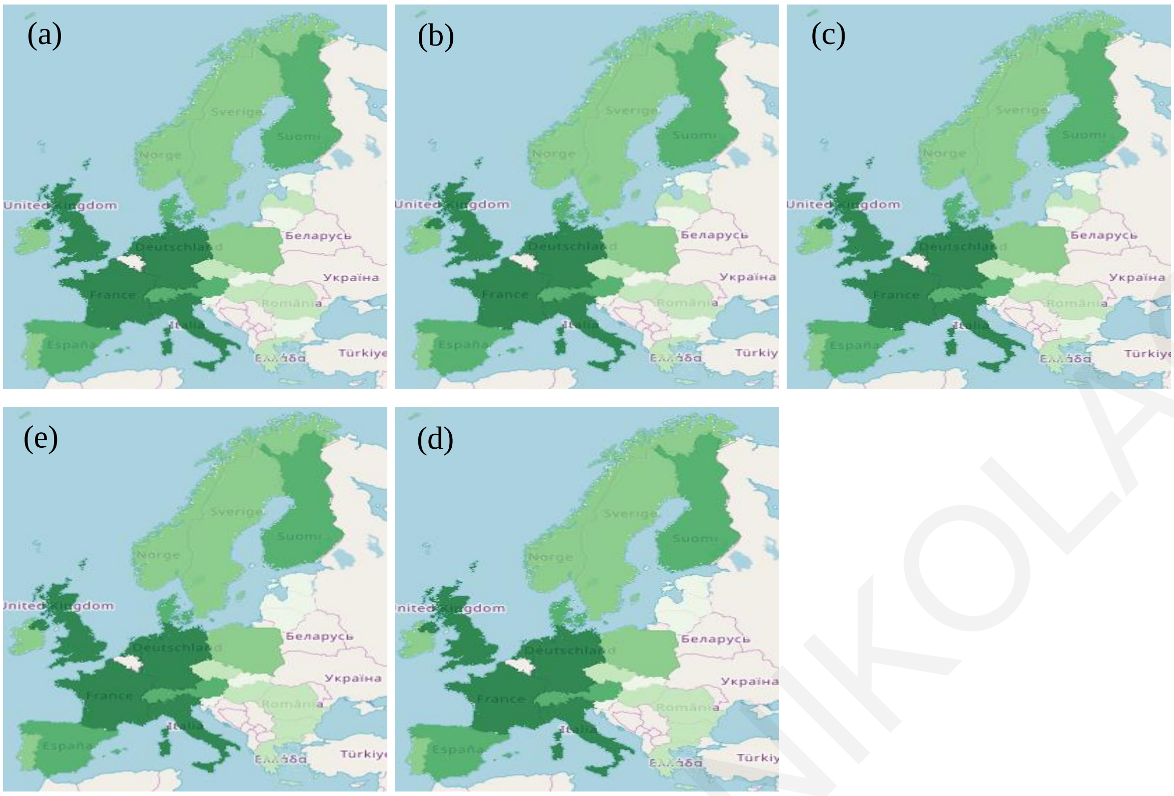


Figure 35. Freight transport by air tonnes (T) in the EU region for the years: a) 2012; b) 2013; c) 2014; d) 2015 and e)-2016.

The collected independent variables are presented in **Figure 36**. As concerned the “air transport of goods” it seems that the leading countries are Germany, the United Kingdom, and France, with Germany to be way above the other two. Continuing with the “goods transport by rail”, again Germany is in the leading position and as for the last dependent variable “goods transport by road million” Germany is in the first place. In the unemployment rate Spain, Greece, and Portugal are in the first three places with the highest unemployment rate. Observing the GDP of the countries it seems that Germany, France, and the United Kingdom are leading again in the European Union over the period 2012-2016.

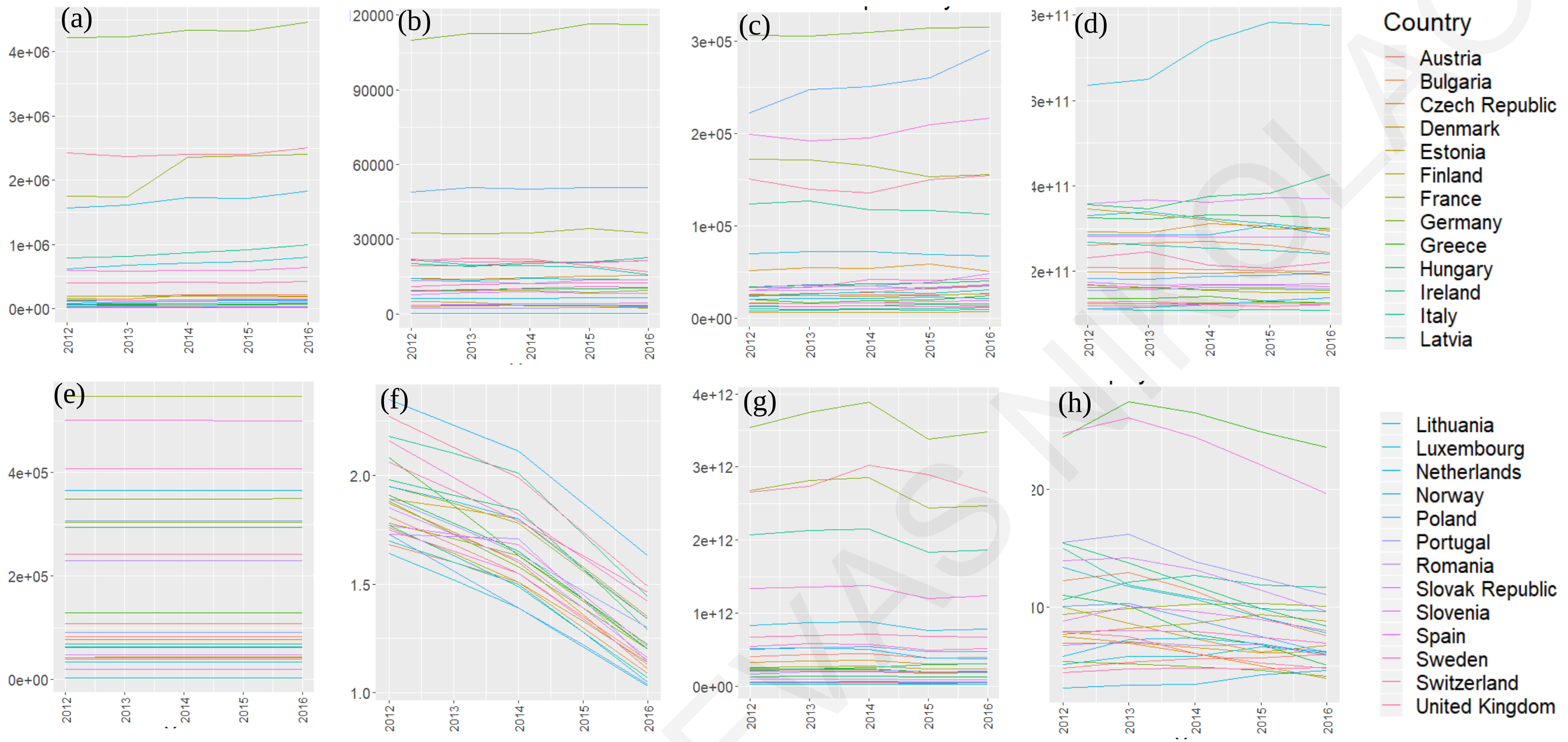


Figure 36. Data visualization of the concluded variables: (a) air transport of goods (Tonnes); (b) goods transport by rail million tonne-kilometer (TKM); (c) goods transport by road million tonne-kilometer (TKM); (d) imports of goods and services in GDP; (e) land area; (f) diesel fuel; (g) GDP; and (h) unemployment rate.

The following of the qualitative analysis was the quantitative analysis of the dataset and particular the correlation analysis. **Figure 37**, **Figure 38** and **Figure 39** present the correlation diagrams for each different in time instance dataset. Consequently, by the observation of the correlation diagrams, two remarks can arise: the collinear variables (that are necessary to be omitted from the datasets); and the highly correlated explanatory variables with the dependent variables. As it can be observed the collinear variables that have to be omitted from all datasets are "population" and "exports" and additionally from dataset 1 the "total motorway length", from dataset 2 the "total length of railway lines (km)" and from dataset 3 the "number of commercial airports".

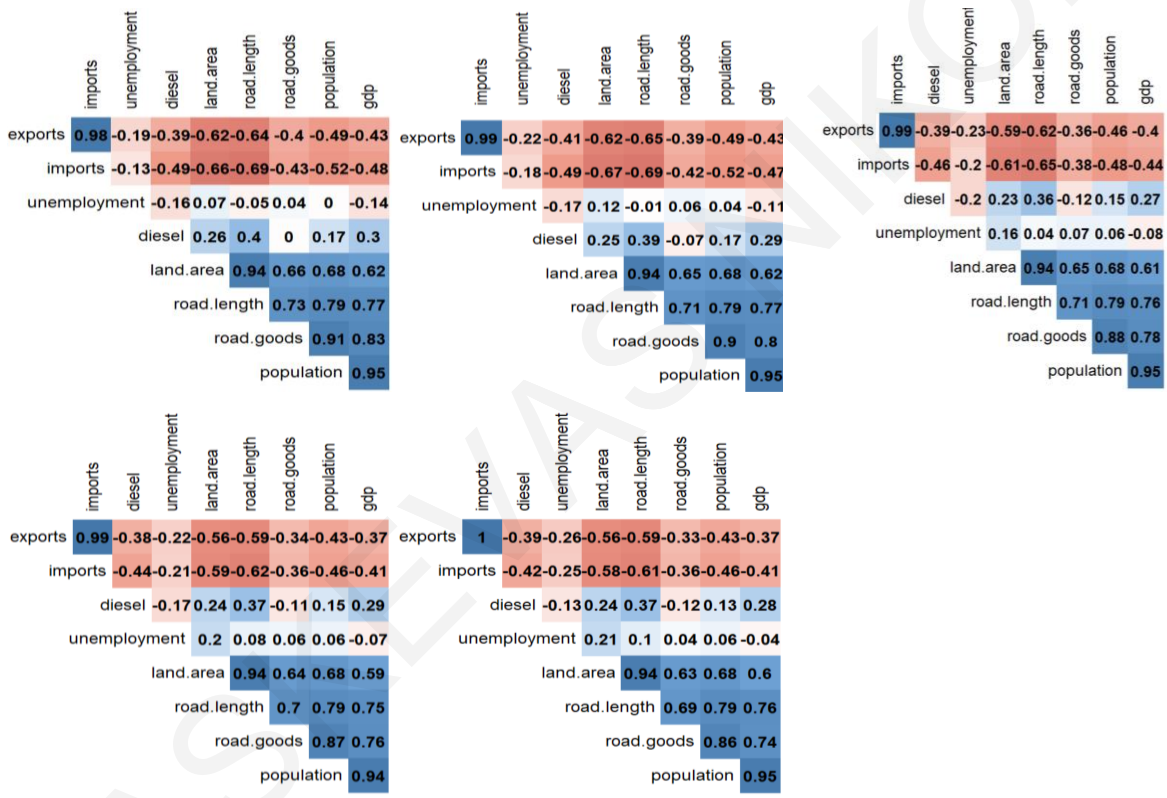


Figure 37. Correlation diagrams of the dataset concerning roadway freight transport from: a) 2012; b) 2013; c) 2014; d) 2015 and e) 2016.

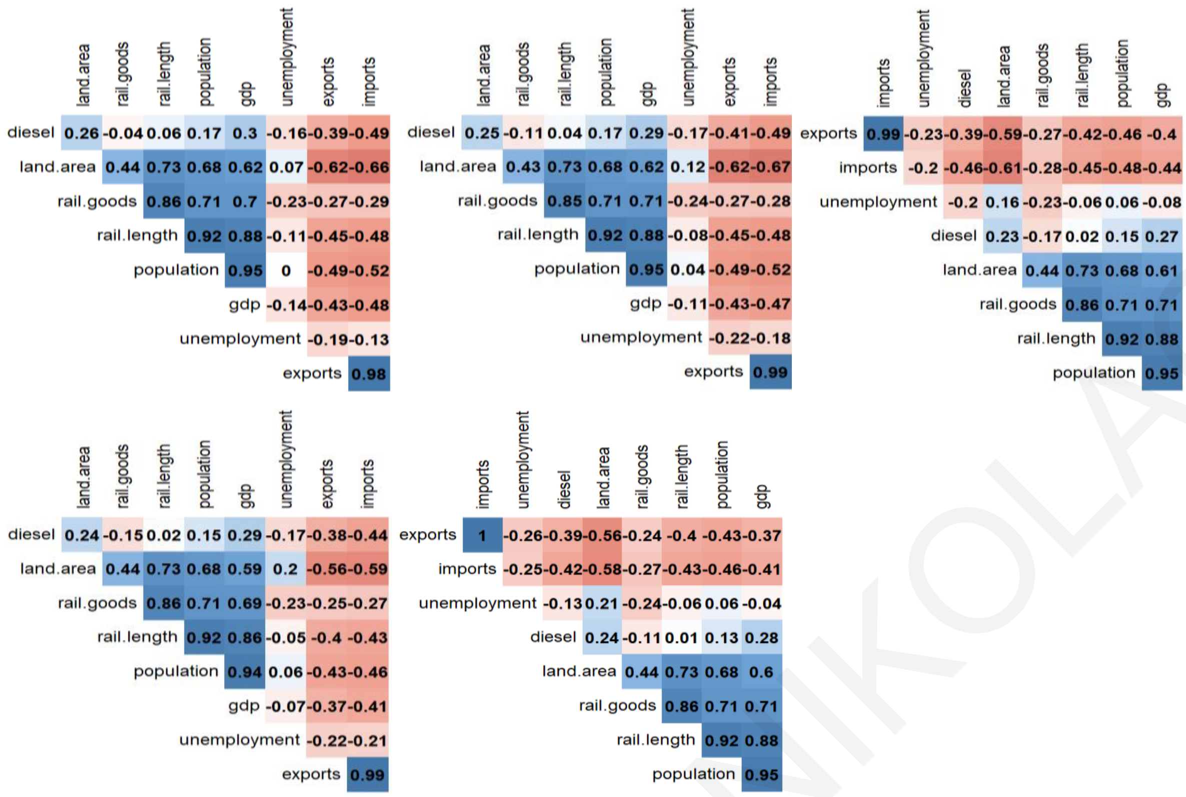


Figure 38. Correlation diagrams of the dataset concerning railway freight transport from: a) 2012; b) 2013; c) 2014; d) 2015 and e) 2016.

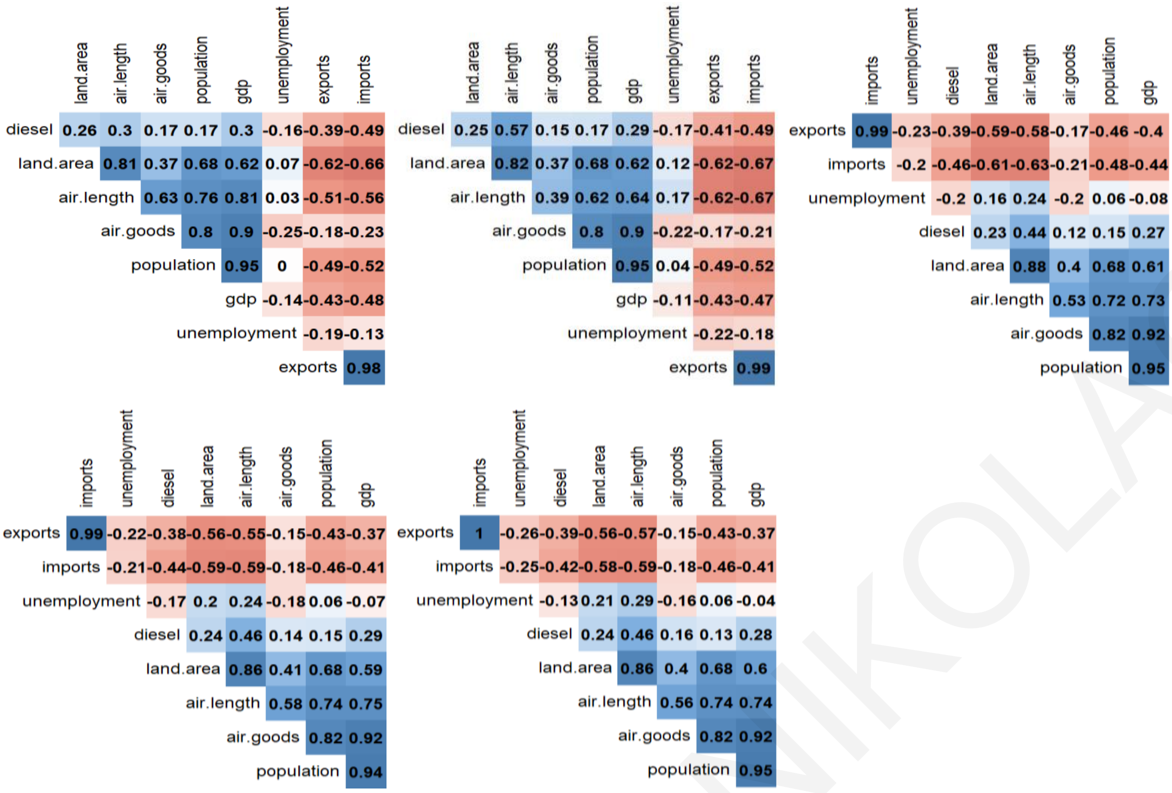


Figure 39. Correlation diagrams of the dataset concerning airway freight transport from: a) 2012; b) 2013; c) 2014; d) 2015 and e) 2016.

Overall, the implementation of the descriptive analysis revealed significant information of the dataset collected for investigating the phenomenon of multimodal freight transportation on road, rail and airborne modes. Additionally, the speculations left from the visualization of the dependent variables raise the speculation for spatial dependence of the phenomenon in the European region and therefore the exploratory analysis provided an in depth investigation following the methodological framework developed for this Thesis.

4.2.2.2. Exploratory Analysis of Multimodal Freight Transportation (Road, Rail and Airborne)

The exploratory analysis of the transportation phenomenon of multimodal freight transportation (road, rail and airborne) is based on the proposed methodology of this Thesis. The analysis started from the implementation of linear regression analysis (OLS) for estimating the direct relationship of observed independent variables with the dependent variables. These relationships with were integrated in the investigation of spatial existence (Moran's I Test) in the phenomenon for the set of the EU countries.

Furthermore, the investigation of latent information, as in the European analysis of road traffic fatalities, was not implemented due to the small in range dataset (both on variables' number and on the size of observations). Thus, the investigation continued directly to the spatial analysis and to the evaluation processes.

Finally, the last implementation of this section is the novel dimensional analysis that this Thesis' methodology is suggested for incorporating both time and space in an extended from of Linear Mixed Model.

4.2.2.2.1. Spatial Autoregressive Analysis of Road, Rail and Airborne Freight Transportation

For assessing the potential spatial autocorrelation within the EU region in regard to the multimodal freight transportation, the global Moran's I Test was applied. Prior the development of the SAR models and for implementing the Moran's I Test the spatial weight matrix was created. The spatial weight matrix was based on the two criteria: of neighbouring countries (Rook and Queen criterion) and of distant-located countries (nearest countries based on distance). The selection of the spatial weight matrix criterion was based on the mode of freight transportation. For instance, the connection of road and rail freight transportations is more logical to be based on the criterion of connected/neighbouring countries (Rooks/Queen criterion) as depicted from **Figure 32**. As for the spatial weight matrix criterion for the airborne freight transportation was based on distant-located countries (nearest neighbours). The number of nearest neighbours selected for the airborne freight transportation was 8, due to the number of classified countries presented in **Figure 35**.

Figure 40 presents the criteria used for connecting neighbouring countries for the multimodal freight transportation within the EU region. As it can be seen Queen Criterion connected all neighbouring countries together which is logic as the rail and road network of the countries are indeed connected with their neighbours. The disadvantage of Queen/Rook Criterion was that it could not recognize the road and rail connectivity of the UK with France due to the fact that they are not connected polygons.

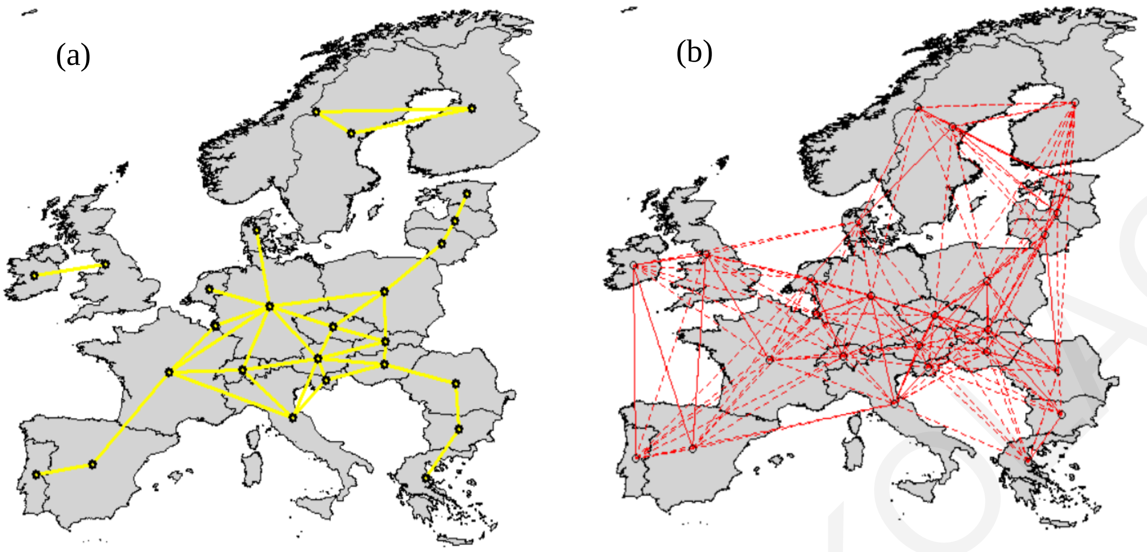


Figure 40. Spatial Influence based on the criteria: (a) Queen/Rook's criterion for railway and roadway; and (b) Distance-based (8-nearest neighbors) criterion for airborne.

After obtaining the spatial weight matrix the Moran's I Test was able to be implemented. **Table 21** presents the results of the Moran's I Test for each case (different time instance in different datasets). As it appeared from the table there exist a spatial autocorrelation between the countries (p-value < 0.05) that have to be estimated in order to observe how this spatial information might add a new pin on the "map" of multimodal freight flows' analyses.

Table 21. Results of the Moran's I Test, regarding the three different outputs and the different time instances.

	Roadway Freight Transportation				
	2012	**2013**	**2014**	**2015**	**2016**
Statistic standard deviate	2.18	1.94	2.05	1.95	1.97
p-value	0.01	0.03	0.02	0.02	0.02
Observed Moran I	0.26	0.22	0.24	0.23	0.24
Expectation	-0.11	-0.11	-0.10	-0.10	-0.10
Variance	0.03	0.03	0.03	0.03	0.03
	Railway Freight Transportation				
	2012	**2013**	**2014**	**2015**	**2016**
Statistic standard deviate	1.80	2.45	2.46	2.58	1.80
p-value	0.04	0.01	0.01	0.01	0.04
Observed Moran I	0.20	0.33	0.34	0.36	0.21
Expectation	-0.11	-0.09	-0.09	-0.09	-0.10
Variance	0.03	0.03	0.03	0.03	0.03
	Airway Freight Transportation				
	2012	**2013**	**2014**	**2015**	**2016**
Statistic standard deviate	3.85	3.42	3.58	3.19	2.66
p-value	5.885e-5	0.00	0.00	0.00	0.00
Observed Moran I	0.16	0.13	0.13	0.11	0.08
Expectation	-0.06	-0.06	-0.06	-0.06	-0.06
Variance	0.00	0.00	0.00	0.00	0.00

Having all the information required (inputs, outputs, and spatial weights matrices), SAR models were developed for analyzing and estimating the spatial dependence and how this dependence reflects on the multimodal freight transportation in the EU region. The variables included in the SAR model are those which estimated from the descriptive data analysis.

However, the final form of the SAR models was differentiated from its initial form. **Table 22** presents the outcome of the SAR models' development. From the results of the SAR models, it can be claimed that economic factors have a stationary effect on multimodal freight transportation. In general, it seems that spatial econometric models such as the SAR model can provide meaningful results that are essential to be used in policy-making. The current SAR models showed that GDP is increasing the freight flows of each country, which is a reasonable evidence. Additionally, it appeared that fuel pricing can be a strong tool in the hands of policymakers due to the increment of sustainable freight transportation. The other thing that is interesting to see is the negative sign of land area in the airway freight transportation, which can be interpreted as the bigger the country is, the less frequently they use their airway as a mean for freight transportation but they seem to prefer more the railway and then the roadway due to economic reasons, since the cost of the railway is much less than roadway freight transportation.

As for the fit of the models, the fit-index Akaike Information Criterion-AIC was used for observing how the models might change (statistically speaking) over time. In overall, the SAR models are robust and can be close-eye trusted for policy-making for the enforcement of EU's region multimodal freight transportation.

Table 22. Results of the SAR model regarding the three datasets.

Roadway Freight Transportation					
	SAR 2012	**SAR 2013**	**SAR 2014**	**SAR 2015**	**SAR 2016**
Intercept	-3.31	-3.15	-3.29	-2.89	-3.22
GDP	0.69	0.63	0.57	0.56	0.57
Unemployment rate	0.01	0.00	-0.00	-0.01	-0.02
Diesel fuel price	-2.59	-2.83	-2.59	-3.10	-3.54
Land area	0.17	0.25	0.29	0.32	0.33
Imports of goods and services in GDP	-	-	-	-	-
AIC	48.69	51.69	50.99	50.72	47.10
Railway Freight Transportation					
	SAR 2012	**SAR 2013**	**SAR 2014**	**SAR 2015**	**SAR 2016**
Intercept	4.06	2.80	0.54	-0.84	-2.75
GDP	0.11	0.22	0.25	0.27	0.28
Unemployment rate	-0.14	-0.15	-0.15	-0.17	-0.18
Diesel fuel price	-3.54	-4.24	-3.99	-4.26	-3.86
Land area	0.91	0.88	0.87	0.88	0.85
Imports of goods and services in GDP	-	-	-	-	-
AIC	90.76	87.00	87.40	87.75	89.57
Airway Freight Transportation					
	SAR 2012	**SAR 2013**	**SAR 2014**	**SAR 2015**	**SAR 2016**
Intercept	-15.29	-14.73	-16.10	-16.62	-17.41
GDP	1.22	1.16	1.19	1.25	1.31
Unemployment rate	-0.01	-0.01	-0.03	-0.02	-0.01
Diesel fuel price	-0.82	-1.10	-1.29	-1.15	-0.93
Land area	-0.47	-0.40	-0.36	-0.42	-0.48
Imports of goods and services in GDP	-	-	-	-	-
AIC	66.92	67.58	62.29	61.02	61.15

Note:

-: Non-statistically significant variables

4.2.2.2.2. Benchmarking Analysis of Road, Rail and Airborne Freight Transportation

Benchmarking analysis is a well-known method for evaluating different DMUs and providing a realistic ranking of the units referring to their performance in multimodal freight flows. DEA was implemented in three datasets that concern the same economic factors as explanatory variables and different outputs reflecting the trade in three different modes of transports: roadways (dataset 1); railways (dataset 2); and airways (dataset 3).

Table 23, **Table 24**, and **Table 25** presents the overall efficiency scores of the EU countries for each different modes of freight transportation for each instant year. Best-performing countries scored with 1 as efficiency score and those who are under-performing scored with values above 1. As it can be seen from the table the countries that are best-performing over the 5-years analysis as concerned their goods transported by road are: Germany; Lithuania; Luxembourg; Netherlands and Spain. The rest of the 26 EU countries seem to under-perform.

In the rail freight transportation (**Table 24**) Germany, Latvia, and Poland ranked as the best-performing countries. As for the airborne freight transportation (**Table 25**), it appeared that only three countries were best-performing which are: Germany; Luxembourg; and the Netherlands. In overall, Germany was the only country that scored with 1 (best-performing) for every freight transportation mode, meaning that policymakers from different underperforming countries should consider Germany as an ideal example for adapting the strategies that are following.

Table 23. Efficiency score of the EU countries concerning road freight transportation.

Country	Road Freight Transportation				
	2012	**2013**	**2014**	**2015**	**2016**
Austria	2.93	3.43	3.33	3.34	3.51
Bulgaria	1.12	1.09	1.11	1	1.03
Czech Republic	1.21	1.24	1.27	1.2	1.56
Denmark	2.77	3.08	3.09	3.2	3.25
Estonia	2.18	2.38	2.4	2.31	2.52
Finland	4.52	5.26	5.42	5.23	5.52
France	1.36	1.36	1.45	1.6	1.6
Germany	1	1	1	1	1
Greece	4.6	6.37	5.54	5.44	4.86
Hungary	1.73	1.82	1.77	1.78	1.97
Ireland	5.82	6.93	6.72	7.11	6.63
Italy	1.64	1.55	1.68	1.75	1.83
Latvia	1.26	1.34	1.33	1.18	1.4
Lithuania	1	1	1	1	1
Luxembourg	1	1	1	1	1
Netherlands	1	1	1	1	1
Norway	4.43	4.7	5.14	6.7	9.8
Poland	1	1	1	1	1
Portugal	2.15	2.14	2.27	2.56	2.6
Romania	2.6	2.69	2.67	2.54	2.44
Slovak Republic	1.23	1.35	1.32	1.27	1.32
Slovenia	1.02	1.12	1.12	1.04	1.12
Spain	1	1	1	1	1
Sweden	5.51	6.02	5.35	5.59	5.78
Switzerland	4.77	4.68	4.63	4.86	5.3
United Kingdom	1.43	1.54	1.6	1.46	1.43

Table 24. Efficiency score of the EU countries concerning rail freight transportation.

	Rail Freight Transportation				
Country	**2012**	**2013**	**2014**	**2015**	**2016**
Austria	1.08	1.15	1.1	1.15	1.06
Bulgaria	6.89	6.42	6.18	5.35	4.45
Czech Republic	1.3	1.37	1.27	1.19	1.05
Denmark	6.3	5.5	5.48	5.26	4.99
Estonia	2.87	2.89	4.11	3.95	4.76
Finland	3.07	3.22	3.05	3.37	3.02
France	2.57	2.64	2.6	2.54	2.63
Germany	1	1	1	1	1
Greece	87.07	103.62	78.12	80.15	89.39
Hungary	2.42	2.31	2.01	2.02	1.66
Ireland	264.11	220.31	217.52	227.09	196.17
Italy	3.36	3.56	3.3	3.28	2.95
Latvia	1	1	1	1	1
Lithuania	1.44	1.47	1.37	1.31	1.07
Luxembourg	3.7	3.6	3.77	3.92	4.02
Netherlands	1.87	1.79	1.76	1.72	1.69
Norway	6.95	7.57	7.41	9.19	11.01
Poland	1	1	1	1	1
Portugal	8.97	9.32	8.8	7.99	7.19
Romania	1.57	1.81	1.96	1.87	1.84
Slovak Republic	2.23	1.79	1.71	1.76	1.53
Slovenia	2.04	1.67	1.54	1.49	1.25
Spain	5.68	5.8	5.19	5.02	5.19
Sweden	1.93	2.09	2.17	2.24	2.11
Switzerland	1.18	1.08	1.04	1.06	1.06
United Kingdom	3.57	3.49	3.53	4.18	4.72

Table 25. Efficiency score of the EU countries concerning airborne freight transportation.

	Airborne Freight Transportation				
Country	**2012**	**2013**	**2014**	**2015**	**2016**
Austria	4.19	4.39	4.21	4.16	4.35
Bulgaria	16.32	16.58	13.61	9.71	9.78
Czech Republic	9.75	10.11	10.38	10.38	8.43
Denmark	4.14	4.81	3.63	3.52	3.97
Estonia	10.53	13.14	14.39	17.64	22.47
Finland	2.81	2.96	3.1	3.13	3.32
France	1.82	1.83	1.36	1.33	1.34
Germany	1	1	1	1	1
Greece	7.01	7.42	8.58	7.73	7.2
Hungary	7.65	7.77	8.17	7.63	7
Ireland	5.17	5.37	5.36	5.83	6.84
Italy	3.17	3.01	2.8	2.63	2.49
Latvia	8.48	5.34	8.23	14.92	14.93
Lithuania	23.82	23.59	25.94	22.08	24.47
Luxembourg	1	1	1	1	1
Netherlands	1	1	1	1	1
Norway	10.4	7.81	7.4	6.28	6.86
Poland	12.73	12.74	12.8	11.51	10.51
Portugal	4.03	3.92	3.87	3.86	4.08
Romania	14.63	14.68	15.34	14.37	14.25
Slovak Republic	21.33	23.36	25.05	21.96	22.07
Slovenia	40.52	41.04	36.25	34.48	37.63
Spain	2.92	2.91	2.93	2.9	2.84
Sweden	6.95	7.71	7.54	7.03	7.69
Switzerland	3.09	2.95	3.08	3.3	3.5
United Kingdom	1.23	1.27	1.27	1.26	1.26

4.2.2.2.3. Investigation of Under-Performing Countries: A Heckit Model Approach

Estimating the performance of the countries was able to provide a group of under and best-performing countries, based on the different modes of freight transportation. Therefore, a sub-sample was selected for each different mode, including observations (inputs and outputs) that are referring only to the under-performing countries. However, manually selecting the a part of the sample that is referring to the under-performing countries raises speculations of bias in the results due to a missing data problem or due to mismatch of the observations and the performance condition of the countries.

Therefore, the use of classic regression models such as Ordinary Least Square (OLS) may lead to biased results that will further lead to the wrong direction of policymaking. A technically sound and suitable model that incorporates and overcomes the selected sample problem is the Heckman's Two-Step Estimation (Heckit model).

In this implementation, the Heckit model was developed for each dataset referring to each separate year and mode and concerning only the under-performing countries. The performance condition of each country and every mode was obtained from the Benchmarking analysis (DEA).

The scope of this implementation is to identify which of the economic factors play the most significant role in this set of countries and therefore to emerge by changing or in general affecting these factors through the direction of policymaking**.** **Table 26**, **Table 27** and **Table 28** presents the results of the Heckit models. As it can be seen from the tables the under-performing countries for each different mode of freight transportation have a high relation with the diesel fuel pricing and with the unemployment rate, which is causing the main problem on their performance. Therefore, it is essential the policymakers to seriously consider how overcoming the problem of high pricing on diesel fuel prices and also how to decrease the unemployment rate.

Table 26. Results of the Heckit model concerning the road freight transportation.

	Roadway Freight Transportation				
	Heckman 2012	**Heckman 2013**	**Heckman 2014**	**Heckman 2015**	**Heckman 2016**
Intercept	114,660.10	122,510.40	106,219.10	96,990.40	96,894.40
GDP	0.06	0.05	0.05	0.05	0.05
Unemployment rate	-	-	-	-	-
Diesel fuel price	-45,152.18	-53,227.69	-52,594.53	-61,097.33	-53,227.69
Land area	129.36	192.906	442.80	524.10	192.91
Imports of goods and services in GDP	-	-	-	-	-
Log Likelihood	-236.82	-236.110	-231.590	-220.44	-226.79

Note:

-: a variable that was not statistically significant and therefore was omitted from the model

Table 27. Results of the Heckit model concerning the rail freight transportation.

	Railway Freight Transportation				
	Heckman 2012	**Heckman 2013**	**Heckman 2014**	**Heckman 2015**	**Heckman 2016**
Intercept	27,169.99	35,529.48	38,898.41	39,499.72	31,547.61
GDP	0.01	0.01	0.04	0.01	0.01
Unemployment rate	-469.67	-367.42	-361.23	-390.25	-392.72
Diesel fuel price	-10,172.66	-17,388.00	-21,065.05	-24,585.29	-22,600.96
Land area	181.824	177.240	200.268	233.879	230.02
Imports of goods and services in GDP	-	-	-	-	-
Log Likelihood	-234.145	-240.950	-243.460	-242.696	-243.11

Note:

-: a variable that was not statistically significant and therefore was omitted from the model

Table 28. Results of the Heckit model concerning the airborne freight transportation.

	Airway Freight Transportation				
	Heckman 2012	**Heckman 2013**	**Heckman 2014**	**Heckman 2015**	**Heckman 2016**
Intercept	27,169.99	35,529.48	38,898.41	39,499.72	31,547.61
GDP	0.01	0.01	0.01	0.01	0.01
Unemployment rate	-469.67	-367.42	-361.23	-390.25	-392.72
Diesel fuel price	-10,172.66	-17,388.00	-21,065.05	-24,585.29	-22,600.96
Land area	181.82	177.24	200.27	233.88	230.02
Imports of goods and services in GDP	-	-	-	-	-
Log Likelihood	-234.15	-240.95	-243.46	-242.70	-243.11

Note:

-: a variable that was not statistically significant and therefore was omitted from the model

4.2.2.2.4. Spatio-Temporal Analysis of Multimodal Freight Transportation.

This section presents the analysis of the transportation phenomenon of multimodal freight transportation integrating in a model the dimensional effects of this and all macro-level transportation phenomena. The dimensions are time and space which will be incorporated in one model that can handle fixed effects and random effects of the variables.

Therefore, this application suggests a novel dimensional extension of the classic Linear Mixed Model to a Spatio-Temporal Linear Mixed Model (STLMM). The applications of this model were based on the grouped factor scenarios “Countries” and “Year”. In detail, the first implementation of the STLMM was based on the grouping factor “Countries” and the results appear in **Table 29**, **Table 30** and **Table 31**.

In this implementation, each group of countries (26 groups) had 5 observations for each year. The fixed-effect variables were GDP, unemployment rate, diesel price, land area, and year and the random-effect variable was the spatial component. This model has been developed for all three modes of freight transport (road, rail, and air). The results indicate that road freight transport has an increase in transported goods over the years as a consequence of the GDP increase and unemployment rate decrease. Additionally, it seems that the size of the country plays a role on the countries’ road freight performance. Based on the random effects it seems that the variability of road freight transport (dependent variable) is high enough (0.629 standard deviation) when using on the random effect countries. As far as the spatial component with countries the grouping factor it seems that the variability of road freight transport is very low.

As for the “residual” which stands for the variability that is not due either the grouping factor or the random effect, i.e., this is the “ε” error. In this case, this value is very low. Moving to the results of the rail mode, it seems that only the land area appears to affect the transport of goods with rail mode. As for the outputs of the random effect, it seems that the residual of the model is low enough although higher than the model of road freight transport. The findings from the air freight transport GDP favour the use of air mode for freight transports and it seems that as the years pass the use also is increasing. The residual of the random effect in this model is also low but higher than the respective model of road freight transport. As for the spatial component, it appeared that in every model that it was used the dependent variable had a very small variability due to this component.

Table 29. STLMM Results Based on “Country” grouping factor concerning road freight transportation.

Fixed Effect		**Random Effect**		
	Estimate		**Variance**	**Standard Deviation**
Intercept	38.240** (11.584)	Intercept	0.395	0.629
Year	0.019*** (0.005)	Spatial Component	6.742e-05	0.008211
GDP	0.178* (0.077)	Residual	0.004	0.066
Land Area	0.489*** (0.132)			
Unemployment rate	-0.019*** (0.005)			
Diesel price	-			
AIC: -131.833 | BIC: -106.025				

Note: *Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*
Parenthesis denotes the standard errors
-: Omitted variables due to statistical significance

Table 30. STLMM Results Based on "Country" grouping factor concerning rail freight transportation.

Fixed Effect		Random Effect		
	Estimate		**Variance**	**Standard Deviation**
Intercept	0.800 (2.561)	Intercept	2.530	1.591
Year	-	Spatial Component	0.0003	0.017
GDP	-	Residual	0.008	0.088
Land Area	0.691** (0.220)			
Unemployment rate	-			
Diesel price	-			
AIC: -64.729 | BIC: -47.521				
Note:	*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*			
	Parenthesis denotes the standard errors			
	-: Omitted variables due to statistical significance			

Table 31. STLMM Results Based on "Country" grouping factor concerning airborne freight transportation.

Fixed Effect		Random Effect		
	Estimate		**Variance**	**Standard Deviation**
Intercept	-88.049*** (19.869)	Intercept	0.900	0.949
Year	0.040*** (0.009)	Spatial Component	1.639e-05	0.004
GDP	0.707 *** (0.117)	Residual	0.022	0.148
Land Area	-			
Unemployment rate	-			
Diesel price	-			
AIC: 36.220 | BIC: 56.292				
Note:	*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*			
	Parenthesis denotes the standard errors			
	-: Omitted variables due to statistical significance			

The next implementation of the STLMM was based on the grouping factor "Year" for observing the variability of the dependent variables and the estimated fixed effects. As can be seen from **Table 32** road mode is positively affected by GDP and land area. Rail mode (**Table 33**) is also positively affected by GDP, land area, and negatively affected by unemployment and diesel price. Furthermore, air mode (**Table 34**) is affected GDP (positively), land area (negatively), and diesel price (negatively). Concerning the residuals produced from the random effect, the rail mode model produced the highest residual followed by the air mode model and the road mode model. As for the variability of the spatial component of the models with the dependent variables, it seems that the results of these models show higher variability form the respective models of **Table 29**, **Table 30** and **Table 31**.

Table 32. STLMM Results Based on "Year" grouping factor concerning road freight transportation.

Fixed Effect		**Random Effect**		
	Estimate		**Variance**	**Standard Deviation**
Intercept	-3.528*** (0.861)	Intercept	6.644	2.578
GDP	0.559*** (0.042)	Spatial Component	0.025	0.157
Land Area	0.321*** (0.046)	Residual	0.248	0.498
Unemployment rate	-			
Diesel price	-2.705*** (0.283)			
AIC: 229.752 | BIC: 252.692				

Note: *Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Parenthesis denotes the standard errors

-: Omitted variables due to statistical significance

Table 33. STLMM Results Based on "Year" grouping factor concerning rail freight transportation.

Fixed Effect		Random Effect		
	Estimate		**Variance**	**Standard Deviation**
Intercept	0.490 (1.821)	Intercept	2.530	1.591
GDP	0.197* (0.197)	Spatial Component	0.0003	0.017
Land Area	0.897*** (0.102)	Residual	1.092	1.045
Unemployment rate	-0.151*** (0.019)			
Diesel price	-3.646*** (0.595)			
AIC: 299.560 | BIC: 325.367				

Note: *Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*
Parenthesis denotes the standard errors
-: Omitted variables due to statistical significance

Table 34. STLMM Results Based on "Year" grouping factor concerning airborne freight transportation.

Fixed Effect		Random Effect		
	Estimate		**Variance**	**Standard Deviation**
Intercept	-16.277*** (1.115)	Intercept	8.844	2.974
GDP	1.360*** (0.054)	Spatial Component	0.041	0.203
Land Area	-0.591 (0.062)	Residual	0.436	0.660
Unemployment rate	-			
Diesel price	-0.527* (0.210)			
AIC: 289.425 | BIC: 312.365				

Note: *Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*
Parenthesis denotes the standard errors
-: Omitted variables due to statistical significance

Finally, the next implementation presents the results of the STLMM model concerning two grouping factors “Countries” and “Year” (**Table 35**, **Table 36** and **Table 37**). Road mode model appeared to be again positively affected by GDP and land area and negatively affected by unemployment rate and diesel price. Rail mode model is positively affected by land area and the air mode model is positively affected by GDP and negatively affected by land area and unemployment. The residuals of these models in the random effect seem to be low enough but not lower than the respective model when only “Country” was the grouping factor. As for the variability of the dependent variables, it seems that in this case where two grouping factors were used is very low.

Table 35. STLMM Results Based on “Year” and “Country” grouping factors concerning road freight transportation.

Fixed Effect		**Random Effect Based on Countries**		
	Estimate		**Variance**	**Standard Deviation**
Intercept	-0.367 (1.924)	Intercept	0.383	0.619
GDP	0.230** (0.079)	Spatial Component	4.123e-05	6.421e-03
Land Area	0.451** (0.128)			
Unemployment rate	-0.016** (0.005)	**Random Effect Based on Year**		
Diesel price	-0.136*** (0.034)		**Variance**	**Standard Deviation**
		Intercept	3.006e-08	1.734e-04
		Spatial Component	1.949e-10	1.396e-05
		Residual	0.004	0.066
AIC: -132.423 | BIC: -98.012				

Note: *Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*
Parenthesis denotes the standard errors
-: Omitted variables due to statistical significance

Table 36. STLMM Results Based on "Year" and "Country" grouping factors concerning rail freight transportation.

Fixed Effect		**Random Effect Based on Countries**		
	Estimate		**Variance**	**Standard Deviation**
Intercept	8.643** (3.006)	Intercept	1.645	1.283
GDP	-	Spatial Component	0.001	0.037
Land Area	0.289** (0.258)			
Unemployment rate	-	**Random Effect Based on Year**		
Diesel price	-		**Variance**	**Standard Deviation**
		Intercept	0.051	0.227
		Spatial Component	0.0003	0.017
		Residual	0.019	0.138
AIC: 48.102 | BIC: 73.910				

Note: *Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*
Parenthesis denotes the standard errors
-: Omitted variables due to statistical significance

Table 37. STLMM Results Based on "Year" and "Country" grouping factors concerning airborne freight transportation.

Fixed Effect		Random Effect Based on Countries		
	Estimate		**Variance**	**Standard Deviation**
Intercept	-11.452*** (2.578)	Intercept	0.686	0.828
GDP	1.079*** (0.119)	Spatial Component	2.456e-05	0.005
Land Area	-0.408* (0.150)			
Unemployment rate	-	**Random Effect Based on Year**		
Diesel price	-0.238* (0.075)		**Variance**	**Standard Deviation**
		Intercept	0.450	0.671
		Spatial Component	0.002	0.043
		Residual	0.023	0.152
AIC: 36.763 | BIC: 68.306				
Note:	*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1* *Parenthesis denotes the standard errors* *-: Omitted variables due to statistical significance*			

Notwithstanding the significance in meaning of the results, only the Good-Of-Fit (GOF) models were chosen based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). For the case of the road mode models, the GOF model was chosen to be the one with the two grouping factors. Based on the rail mode model the GOFs of the models the one STLMM models that best performed was the model with the grouping factor ("Country"). For the air mode model, it seems that based on the GOF of the STLMM the preferred model was the one with the grouping factor ("Country") and was preferred for supporting decision-making policies.

From the overall results from the three approaches (based on the grouping criteria), it can be said that as concerning the road mode model of freight transport it is generally positively affected with GDP and land area, rail mode model of freight transport is positively affected from the land area and finally for the air mode model of freight transport there is a constant relationship with GDP in every grouping case scenario. As for the random effects high standard deviation shows high variability in the dependent variable due to the spatial component or to the grouping factor. Additionally, the inclusion of the spatial component in the model, provides significant information on how much affection do spatial component may provide on dependent variables of freight flows.

4.2.2.2.5. Explanatory Analysis: Multimodal Freight Transportation

The above sections provided the results from the implementations of the proposed methodology for analyzing the transportation phenomenon of multimodal freight transportation. The descriptive analysis of the data collected for studying the 41 EU container port terminals revealed the collinear variables that were omitted from the dataset and the homogeneous clusters of the container port terminals.

In the exploratory analysis the evaluation of the container port terminals was conducted and under and best-performing container port terminals were identified. For supporting the decision-making procedures of policymakers, it suggested that under-performing container port terminals should follow the strategies of the best-performing container port terminals from the same socio-economic and infrastructure/equipment context. **Table 19** presents the results of the under and best-performing container port terminals based on the cluster they are grouped.

The next implementation considered the multimodal freight transportation (road, rail and airborne) of the EU countries. In the descriptive analysis of this dataset, spatial relationship between the countries was identified. In addition, the correlation analysis revealed the collinear models that were excluded from the exploratory analysis.

In the exploratory analysis of the multimodal freight transportation (road, rail and airborne) began with the investigation of the direct linear relationships between the collected variables with the phenomenon. In this exploratory analysis the investigation of latent structures was skipped due to the small in size dataset (as proved in the analysis of road traffic fatalities in the EU region). Therefore, the applications continued with the development of the Moran's I Test for identifying the possible existence of spatial dependence. As it was appeared the EU countries are spatially related based on the phenomenon of road traffic fatalities. This spatial dependence was incorporated using the SAR model. The outcomes of the SAR models revealed that diesel fuel is affecting the freight transportation of road, rail and airborne. Additionally, the size of the countries reflects on the preference of the mode for the freight transportation. The economic background of the countries which is reflected through GDP is also an important positive effect on multimodal freight transportation. Finally, unemployment rate should be a consideration of local authorities if they want to improve their performance in each of the three modes of freight transportation.

The applications followed the evaluation of the countries based on each different mode (road, rail and airborne) of freight transportation using DEA. From this implementation it was observed that the European countries that best-perform on every mode of freight transportation is Germany. Therefore, policymakers should turn their attention on the strategies that this country is following.

The next implementation was the measurement of the economic factors that are affect the performance of the under-performing countries, identified in DEA. The method applied was the Heckit model which verified that the under-performing countries for each different mode of freight transportation have a high relation with the diesel fuel pricing and with the unemployment rate, which is causing the main problem on their performance. Thus, it is important considering how overcoming the problem of high pricing on diesel fuel prices and how to decrease the unemployment rate.

The final application of the exploratory analysis was based on a dimensional approach of the phenomenon of multimodal freight transportation. Therefore, a novel model was developed combining both spatial and temporal dimension for analyzing the effects of these components on each different mode of freight transportation. The applied model was named as Spatio-Temporal Linear Mixed Model. The application of this model followed a grouping scenario of repeated observations based on the formation that the data had. The results indicated that road and rail modes of freight transportation on their variations of time and space have a constant effect with GDP and land area. As for the airborne freight transportation showed that it does have a constant relationship with the economic background of the countries (GDP). The outcomes of the STLMM model can be used for capturing the "picture" of how the phenomenon of multimodal freight transportation fluctuates over time and between the countries. With this model the policymakers will be able to study the dimensional concepts of any macro-level transportation incorporating macro-level information.

4.3. Summary

Based on **Table 1** the descriptive analysis of road traffic fatalities in the European scale revealed that the countries are homogeneous considering their socio-economic and demographic context, something that does not stand for the global scale of analysis. Additionally, in the descriptive analysis for both scales of analysis (regional and global) the collinear variables were identified and omitted from the data samples.

In the exploratory analysis of the phenomenon, linear regression models were developed and in particular Ordinary Least Square and Negative Binomial regression models, which revealed the direct relationship between the explanatory factors with the phenomenon. Furthermore, following the regression analysis an identification procedure was followed for identifying any possible latent structures in the datasets. However, based on the literature when the samples are small (concerning the number of observations and the number of explanatory variables), the identification techniques of latent structures (such as Factor Analysis and Principal Component Analysis) will not reveal anything. Therefore, the identification procedures of latent structures were followed only for the Global scale, where the dataset collected was extensive. The identified latent constructs were measured using a suitable method namely, Structural Equation Modeling, which revealed significant information for the latent factors and their relationship with the phenomenon.

As revealed in the descriptive analysis the European countries were spatially related, concerning the phenomenon, and therefore the spatial component was incorporated in Spatial Autocorrelation models. This spatial dependence was not obvious for the global set of countries in the descriptive analysis.

The analysis of the phenomenon followed the evaluation of the European countries and the under and best-performing (in terms of road safety) countries were identified. Then the following sept of the evaluation was the measurement of the factors that affect the performance of the under and best-performing countries. Finally, a target setting procedure was implemented for supporting the under-performing countries by pointing the targets they should have been acceded for becoming best-performers, in road safety terms.

The next implementation and validation of the robustness of the methodology was the analysis of the transportation phenomenon of Multimodal Freight Transportation. In these applications the European region was considered to its homogeneous formations between the countries and the spatial dependence of the countries. In this analysis all the modes of freight transportation were investigated. First an evaluation procedure was followed for identifying the best and under-performing container port terminals of Europe and finally targets are suggested for the under-performing container port terminals to improve their performance.

For the other three modes of transportation a spatial analysis of the phenomenon was conducted and indeed revealed a spatial dependence which was incorporated and measured it’s overall effects on the three modes (road, rail and airborne) of freight transportation. Continuously, the evaluation procedure was conducted and identified the performance of each country on the three different modes of freight transportation.

Then a sample-selection procedure was followed for analysing and measuring the effects of the factors that have a relationship with the under-performing countries’ performance, using the Heckit model.

The final implementation of the methodology concerning this phenomenon was the incorporation of both time and space in a model that can adequately produce the effects that these dimensions have on the phenomenon. Therefore, the Spatio-Temporal Linear Mixed Model was introduced and strongly suggested for analyses of different macro-level transportation phenomena such as Road Traffic Fatalities and Multimodal Freight Transportation.

CHAPTER 5: CONCLUSIONS AND FUTURE WORK

This Thesis aimed to identify effective methodological frameworks for integrating spatio-temporal macro-level information on the investigation of different macro-level transportation phenomena. The methodological framework that this Thesis is proposing when analyzing any macro-level transportation phenomenon is tested by using two entirely different macro-level transportation phenomena. The first transportation phenomenon concerned this Thesis is based on human mobility and is namely, Road Traffic Fatalities. As for the second transportation phenomenon that proof the concepts of this Thesis, is based on the goods mobility, namely, Multimodal Freight Transportation.

5.1. Methodological Applications and Results

The Methodology of this Thesis has been developed based on the findings form the literature review and for analysing from scratch different transportation phenomena, i.e., from the data collection to the support of policymaking. The proposed methodological framework has been applied to two different transportation phenomena, namely, Road Traffic Fatalities and Multimodal Freight Transportation providing proof to the robustness and novelty of this methodology for analysing different macro-level transportation phenomena using socio-economic and demographic contexts. The collection of information for both phenomena included the temporal variations of the socio-economic and demographic variables. The analysis of the temporal component in the model was based on a repetition of the models reflecting each different year of study. Furthermore, the collection of the data was from global organizations' databases (e.g. World Bank, World Health Organization and Eurostat).

The results from the descriptive analysis revealed that in the European region it is obvious the countries are homogeneous based on their socio-economic and demographic context something that is not expected for the global set of countries (121 United Nation member countries). Additionally, from this analysis a spatial dependence was also obvious for the European countries and not for the global set of countries. As for the correlation analysis collinear variables were identified and omitted from the samples. As a conclusion from this analysis was that the spatial dependence and the homogeneity is more obvious when analyzing almost similar DMUs likewise countries members in the EU.

In the exploratory analysis, the direct relationship of the socio-economic and demographic factors with the different transportation phenomena was observed and revealed that the economic instability had also an effect on the phenomena. As for the road traffic fatalities it appeared that for decreasing the number of fatalities someone should look at the effects of diesel price.

The following implementation was the identification of the latent factors in the samples. However, when analysing small data sample (in terms of number of observations and of explanatory factors) this latent information does not exist. Therefore, identification techniques of latent structures were used, namely, Principal Component Analysis and Factor Analysis. As was appeared the PCA method was not entirely able to recognize the latent structures in the sample of the 121 UN countries, but provided an important information of the significant variables are between the economic factors (e.g. GDP). The Factor Analysis provided the information of the latent variables, which were two that were named as "Socio-Economic" and "Demographic" based on the meaning of the variables that were explaining these latent factors. For incorporating these latent factors and estimating their effect on the transportation phenomenon of road traffic fatalities, the Structural Equation Modeling method was applied. The findings from this implementation revealed that economic factors such as GDP are decreasing road fatalities in contrast with the effects of demographic factors which are increasing fatalities, likewise the number of registered vehicles which shows a positive correlation with road fatalities' increment.

The next implementation as introduced in the literature review was the incorporation of the space component in the analysis of the phenomena. However, as it was revealed in the descriptive analysis and in particular in the cluster analysis, the global set of countries showed no homogeneity between the countries fact that was considered and therefore the global set of countries was excluded from this procedure. Besides this preliminary conclusion on spatial existence the European sets of countries were analyzed for spatial existence based on both transportation phenomena, and as was appeared indeed there is a spatial dependence between the countries considering these macro-level phenomena. In this step, it is also important mentioning that the analysis of the spatial component requires the creation of a spatial weight matric depicting the connection between the DMUs. The connections are variant and are based on the nature of the transportation phenomenon. For instance, when studying the multimodal freight transportation and particular the rail connections between countries, then the spatial weight matrix should and must include the connections of neighbouring countries where the rail network of a country continues. Therefore, having created the spatial weight matrix the spatial component was incorporated in the Spatial Autoregressive model. The results of this model, as concerned the road traffic fatalities, showed again that economic factors as GDP and diesel price have an important meaning in the phenomenon. As for the multimodal freight transportation, Spatial Autoregressive model also revealed that economic factors such as GDP is increasing the freight transportation in roadway, railway and airborne.

The next implementation of this Thesis' methodological framework was the incorporation of both time and space in a single model. However, the method that could handle this dimensional analysis was the extensive form, to the macro-level transportation phenomena, Linear Mixed Model which was named as Spatio-Temporal Linear Mixed Model. The results from this approach it appeared that as the years pass the roadway and airborne freight transportation show a prosperity something that cannot be said for railway freight transportation. Additionally, once again economic factors have a significant meaning in the entire procedure.

The final implementation of this methodology was the evaluation of the DMUs based on their performance on terms of road safety and on multimodal freight transportation. For this purpose, the Data Envelopment Analysis method was applied. This method revealed the best and under-performing DMUs. Considering the phenomenon of road traffic fatalities, the results of the Data Envelopment Analysis were further analysed by incorporating them as dependent variables in a Tobit model and measuring the effects of the socio-economic and demographic context on the performance of both under and best-performing DMUs. Once again, the economic factors are improving the performance of DMUs and therefore must be taken under consideration in the future decision-making strategies. For the same phenomenon, a target setting approach was developed considering the results from DEA. From the target setting procedure it was able to observe which best-performing DMUs should an under-performing DMU follow. In addition, to that this procedure also identified the DMUs that are not achieving their goals, in terms of road safety, and thus they should be seriously consider this on the enforcements they are applying. As concerned the multimodal freight transportation the evaluation method of DEA also revealed best-and under-performers highlighting the country of Germany as the only best-performing country for the three modes of freight transportation (roadway, railway and airborne). In addition, to this observation a method was added for measuring the effects that socio-economic and demographic factors have only on the under-performing DMUs and economic factors were added to this equation.

Overall, the entire methodological framework provides a compound of applications that individual are not novel to the field of transportation but this compound is novel and therefore is important following the steps presented for having a complete investigation of any macro-level transportation phenomenon and for incorporating the spatio-temporal components in the analysis.

5.2. Future Work

In future work it will be possible to analyse more extended samples with methodologies that can handle this information and provide more robust estimations of the models, like Markov Chain-Monte Carlo (MCMC).

Additionally, our future research interest will include the analysis of transportation phenomena, for example mobility patterns between areas based on Origin-Destination matrices, migration dynamics, epidemic spreading and other.

Appendix A. RStudio Software Codes

The methodologies introduced in Chapter 3 and applied in Chapter 4 required some programming that was developed in the RStudio software. For reference, this Appendix presents a brief R code fragments of possible implementations. Any implementation in the RStudio requires the installation and call of the packages that are necessary in order to make a function to work. The necessary libraries are:

- library(rgdal)
- library(maptools)
- library(GISTools)
- library(sp)
- library("latticeExtra")
- library(dplyr)
- library(leaflet)
- library(spdep)
- library(lmtest)
- library("olsrr")
- library(MASS)
- library(RColorBrewer)
- library(treemap)
- library(d3treeR)
- library(ggplot2)
- library(ape)
- library(sparcl)
- library(ggdendro)
- library(pvclust)
- library(corrplot)
- library(reshape2)
- library(MASS)
- library(tidyverse)
- library(caret)
- library(leaps)

Appendix A-R1: Uploading Data

This section presents some instructions on how to upload data into the RStudio software.

Upload a csv file:

- Data=read.csv("C:/*direction of csv file*")

Upload a shapefile which include the data in its attribute table:

- shapefile<-readOGR("C:/*direction of shapefile*","*name of shapefile*")

Appendix A-R2: Data Visualizations and Data Analysis

RStudio packages offer a variety of data visualizations.

R2.a-Leaflet maps:

The leaflet map provides a visualization of the data distributed on the map.

- leaflet(***name of shapefile uploaded in RStudio***)

In case we want to add to the leaflet a classification of a particular variable with a smoothness:

- m=leaflet(***name of shapefile uploaded in RStudio***)
- m %>% addPolygons(stroke = FALSE, fillOpacity = 0.5, smoothFactor = 0.5) %>%
- addTiles()
- q<-colorQuantile("OrRd", (***shapefile@data included in the shapefile***), n= ***# of classifications***)
- leaflet(***shapefile***) %>% addPolygons(stroke = FALSE, fillOpacity = .8, smoothFactor = 0.2, color = ~q %>% addTiles()%>% addLegend("bottomright", pal = q, values = ~***variables***, title = "Legend",opacity = 1)

R2.b-Time Series Data

For visualizing time series data, the ggplot function is the most appropriate. The time series data most of the time are presented as line paths. Therefore, the code of this visualization if provided below:

- ggplot(data="")+ geom_line(aes(x= "", y= ""))+facet_wrap(~ ***set the variable which includes the countries***)

In the aesthetic ("aes") we can also add the parameter or data in case we want our line to be coloured or shaped or weighted based on the variations of this parameter. For instance, if we have a variable with three classifications and set this as the colour classification then all colours will be coloured by group based on the classifications included in this variable.

R2.c-Treemap

The below code concerns the creation of treemaps:

- p <- treemap(data, index=c("***group***","***subgroup***"), vSize="***value***", type="index", palette = "Set2", bg.labels=c("white"), align.labels=list(c("center", "center"), c("right", "bottom")))

R2.d-Cluster Analysis Visualizations

This code will present first the implementation of k-means clustering with the elbow method, which is suitable for recognizing the optimum number of clusters.

- wss <- function(k) {kmeans(df, k, nstart = 10)$tot.withinss}

Compute and plot wss for k = 1 to k = 15

- k.values <- 1:15
- wss_values <- map_dbl(k.values, wss)
- plot(k.values, wss_values,type="b", pch = 19, frame = FALSE,xlab="Number of clusters K",ylab="Total within-clusters sum of squares")

Based on the results of the Elbow Method plot the dendrogram with the identified optimum number of clusters.

- result <- pvclust(data, method.dist="cor",method.hclust="average", nboot=10)
- plot(result)

R2.e-Correlation Analysis

The code below offers the obtain of the relationships between the variables and the figure for visualizing the correlations of the sample.

- Correlation= cor(***data***)
- corrplot(Correlation, type="upper",order="hclust",col=brewer.pal(n=8, name="RdYlBu"))

Appendix A-R3: Exploratory Analysis

This section presents the RStudio codes that were used for obtaining the results in Chapter 4.

R3.a-Negative Binomial and Ordinary Least Square

The code for obtaining the results of the Negative Binomial Regression Analysis is:

- summary(m1 <- glm.nb(***dependent variable*** ~ ***independent variable 1*** + ***independent variable 2+…***, data = ***data***))

For obtaining the results from the Ordinary Least Square the following code was used:

- summary(chi.ols<-lm(***dependent variable*** ~ ***independent variable 1*** + ***independent variable 2+…***, data= ***data***))

For creating robust models, in terms of Good-Of-Fit a Backward Stepwise regression analysis was analyzed in RStudio by using the following code:

- step.model <- stepAIC(**m1**, direction = "both",trace = FALSE)
- summary(step.model)

R3.b-Principal Component Analysis

The below codes provide the execution and visualization of Principal Component Analysis:

- pca <- prcomp(***data***, scale=T)
- melted <- cbind(***variable.group***, melt(pca$rotation[,1:9]))

- barplot <- ggplot(data=melted) + geom_bar(aes(x=***variable***, y= ***variable***, fill=***variable.group***), stat="identity") + facet_wrap(~***Variable***)

R3.c-Spatial Analysis

The spatial analysis of a transportation phenomenon requires the development a spatial weight matrix based on the different connection criteria which are: Queens, Rooks and Distance-based. Below are the codes for obtaining the weight matrix based on all the criteria:

Extract a 'queen's case' adjacency object and print it out

- col.queen.nb <- poly2nb(EU,queen=TRUE)
- col.queen.nb

Extract a 'rooks's case' djacency object and print it out

- col.rook.nb <- poly2nb(EU,queen=FALSE)
- col.rook.nb

Extract a 'distance-based' djacency object and print it out

- coords<-coordinates(EU)
- k3 <- knn2nb(knearneigh(coords, k=3, RANN=FALSE))
- W2<-nb2listw(k3, style="W", zero.policy=TRUE)

#Plot all the adjacensy matrices

- plot(EU,col='lightgrey')
- plot(col.queen.nb,coords=coordinates(EU),add=T,col='blue',lwd=3)
- plot(W2,coords=coordinates(EU),add=T,col='red',lwd=3)
- plot(col.rook.nb,coords=coordinates(EU),add=T,col='yellow',lwd=3)
- box(which='outer',lwd=2)

#Implement the Moran’s I Test for checking whether or not a spatial dependence exists.

- moran.I<-lm.morantest(chi.ols, W2, alternative="two.sided")
- print(moran.I)
- moran.I$p.value

#Spatial Autoregressive Analysis

summary(sar.EU.ols8<-lagsarlm(***dependent variable*** ~ ***independent variable 1*** + ***independent variable 2+…***, data=***data***, W2))

#Observing the characteristics of the Autoregressive Regression Model.

- covmat <- function(lambda,adj) {solve(tcrossprod(diag(length(adj)) - lambda* listw2mat(nb2listw(adj))))}
- cormat <- function(lambda,adj) {cov2cor(covmat(lambda,adj))}

Create a range of valid lambda values

- lambda.range <- seq(-1.3,0.99,l=101)

Create an array to store the corresponding correlations

- cor.41.47 <- lambda.range*0

... store them

- for (i in 1:101) cor.41.47[i] <- cormat(lambda.range[i],col.rook.nb)[41,47]

... plot the relationship

- plot(lambda.range,cor.41.47,type='l')

R3.d-Dimensional Analysis

The dimensional analysis of the transportation phenomena was developed through the construct of the Linear Mixed Model. The code below showed the extended Linear Mixed Model form:

- model1=lmer(***dependent variable*** ~ ***independent variable 1*** + ***independent variable 2+…+***(**Spatial Component of dependent variable** | Year)+(**Spatial Component of dependent variable** | Country_code),data=***data***)

R3.e-Evaluation Procedures

The evaluation implementations start with the development of the Data Envelopment Analysis method. The code for DEA is provided below and shows an input-oriented variable return to scale model:

- DEA(x, y, rts="vrs", orientation="input")

Based on the results of DEA, Tobit and Heckit models were implemented. The code for Tobit model is:

summary(m <- vglm(***dependent variable*** ~ ***independent variable 1*** + ***independent variable 2+…***, tobit(Upper = 800), data = ***data***))

and the code for the Heckit model is:

Heckit<- heckit(***dependent variable*** ~ ***independent variable 1*** + ***independent variable 2+…***, data=***data***)

Appendix B. Publications

B1-Published Journals Related to this Thesis

1. Dimitriou, L., Nikolaou, P. and Antoniou, C. (2019). Exploring the temporal stability of global road safety statistics. Accident Analysis & Prevention, 130, pp.38-53.
2. Dimitriou, L., Nikolaou, P. and Antoniou, C. (2017). Policy-Driven Investigation of Sectoral Latent Information Regarding Global Road Fatalities. Transportation Research Procedia, 22, pp.685-694.
3. Nikolaou, P. and Dimitriou, L. (2018). Evaluation of road safety policies performance across Europe: Results from benchmark analysis for a decade. Transportation Research Part A: Policy and Practice, 116, pp.232-246.
4. Dimitriou, L. and Nikolaou, P. (2017). Data envelopment analysis for investigating optimal road safety policies utilising global epidemiological, risk exposure and socio-economic statistics. International Journal of Decision Support Systems, 2(4), p.278.
5. Maas, S., Nikolaou, P., Attard, M. and Dimitriou, L., 2020. Examining spatio-temporal trip patterns of bicycle sharing systems in Southern European island cities. Research in Transportation Economics, p.100992.

B2-Papers Under Review Related to this Thesis

1. Nikolaou, P., and Dimitriou, L. Road Traffic Fatalities on a Global Scale: A Structural Equations Modelling of Macro-Level Information. *Case Studies on Transport Policy*, 2020.
2. Nikolaou, P., and Dimitriou, L. Spatial Correlation in Temporal Dynamics of Road Fatalities: A European Regional Analysis. *Transport Policy, 2020*.
3. Folla, K., Nikolaou, P., Dimitriou, L., and Yannis, G. Explanatory Analysis of Road Safety Performance in Selected European Regions: A Tobit Regression over Data Envelopment Analysis. *Transport Policy, 2020.*
4. Nikolaou, P., and Dimitriou, L. Analyzing European Countries' Performance with Respect to Multimodal Freight Transport Production: A DEA-Heckit Approach. Transportation Business & Management, 2020.

5. Maas, S., Nikolaou, P., Attard, M. and Dimitriou, L., 2020. Spatial and temporal analysis of shared bicycle use in Limassol, Cyprus. *Journal of Transport Geography, 2020*.

B3- Conferences Related to this Thesis

1. Dimitriou, L. and Nikolaou, P. (2016). Identifying and addressing multi-source database inconsistences: Evidences from global road safety information. 11th European Conference on Product and Process Modelling, eWork and eBusiness in Architecture, Engineering and Construction.
2. Nikolaou, P. and Dimitriou, L. (2018). Comparative Evaluation of European Container Port Terminals Productivity Based on their Operational Characteristics. 98th Transportation Research Board Annual 47 Meeting, 2019, Washington D.C., U.S.A.
3. Nikolaou, P., Dimitriou, L., and Constantinou, A. (2018). Global Road Traffic Fatalities: Explanatory Analysis Based On Alternative Structural Equations Modeling Approaches. 98th Transportation Research Board Annual 47 Meeting, 2019, Washington D.C., U.S.A.
4. Nikolaou, P. and Dimitriou, L. (2019). A European Multimodal Freight Model accounting for Under-Performing Countries. 99th Transportation Research Board Annual 47 Meeting, 2019, Washington D.C., U.S.A.
5. Nikolaou, P. and Dimitriou, L. Incorporating Spatial Dependence in Analyzing European Road Traffic Fatalities. 9TH International Congress on Transportation Research, 2019, Athens, Greece.
6. Nikolaou, P., Dimitriou, L., and Antoniou, C. A Comprehensive Multinational Analysis of Road Traffic Fatalities: Aspects for Policy-Making. mobil.TUM 2019 - International Scientific Conference on Mobility and Transport Conference Management System, Technical University of Munich.
7. Folla, K., Nikolaou, P., Dimitriou, L., and Yannis, G. Benchmarking Analysis of Road Safety Levels for an Extensive and Representative Dataset of European Cities. 5th Conference on Sustainable Urban Mobility, 2020, Greece.
8. Nikolaou, P., Folla, K., Dimitriou, L., and Yannis, G. European Countries’ Road Safety Evaluation by Taking Into Account Multiple Classes of Fatalities. 23rd EURO

Working Group on Transportation Meeting, EWGT 2020, 16-18 September 2020, Paphos, Cyprus.

B4. Publications and Conferences beyond the scope of this Thesis

1. Dimitriou, L., Kousta, O. and Nikolaou, P. (2016). A Discrete-Time Nonlinear Optimal Control Mechanism for Monitoring Dynamic Signalized Urban Traffic Networks. IFAC-PapersOnLine, 49(3), pp.19-24.
2. Dimitriou, L., & Nikolaou, P. (2017). Dynamic partitioning of urban road networks based on their topological and operational characteristics. In 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2017 - Proceedings (pp. 457–462).
3. Nikolaou, P. and Dimitriou, L. (2019). Investigation of the European Airport System Robustness against Infectious Deseases Spreading through the Airline Network: Results from Extensive Stress-tests. 99th Transportation Research Board Annual 47 Meeting, 2019, Washington D.C., U.S.A.
4. Nikolaou, P. and Dimitriou, L., 2020. Identification of critical airports for controlling global infectious disease outbreaks: Stress-tests focusing in Europe. Journal of Air Transport Management, 85, p.101819.
5. Nikolaou, P., Basbas, S., Politis, I. and Borg, G., 2020. Trip and Personal Characteristics towards the Intention to Cycle in Larnaca, Cyprus: An EFA-SEM Approach. Sustainability, 12(10), p.4250.
6. Nikolaou, P., and Dimitriou, L. Investigating and Identifying Critical Airports for Controlling Infectious Diseases Outbreaks. 23rd EURO Working Group on Transportation Meeting, EWGT 2020, 16-18 September 2020, Paphos, Cyprus.
7. Maas, S., Nikolaou, P., Attard, M., and Dimitriou, L. Classifying bicycle sharing system use in Southern European island cities: cycling for transport or leisure? 23rd EURO Working Group on Transportation Meeting, EWGT 2020, 16-18 September 2020, Paphos, Cyprus.

B5. Awards

Awarded presentation:

Co-Author of the awarded presentation with the title "Data Envelopment Analysis for Investigating Optimal Road Safety Policies Utilizing Global Epidemiological, Risk Exposure and Socio-Economic Statistics" in the 1st International Transport Conference - Special Conferences of HELORS (Alexandroupoli, Greece, 15-16 October 2015).

Awarded paper:

First place award of the competition TRA Vision 2020 Young Researcher in the category of cross modality. Title of the study: “Controlling the possible spread of infectious diseases through the air transportation network: a dynamic network approach”.

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