DETECTING AND MEASURING CORRUPTION AND INEFFICIENCY IN INFRASTRUCTURE PROJECTS USING MACHINE LEARNING AND DATA ANALYTICS

by

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Dedicated to peacemakers, veterans, and martyrdoms who have fought corruption and injustices

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LIST OF ABBREVIATIONS

AADT	Annual Average Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
APEC	Asia-Pacific Economic Cooperation
ARIMA	Autoregressive Integrated Moving Average
ARIMAX	Autoregressive Integrated Moving Average with Exogenous Input
AI	Artificial Intelligence
ASCE	American Society of Civil Engineers
AV	Autonomous Vehicle
BEEPS	Business Environment and Enterprise Performance Survey
BIC	Bayesian Information Criterion
BPTT	Back Propagation Through Time
BU	Bottom-Up
COVID-19	Coronavirus Disease of 2019
CPI	Corruption Perceptions Index
CRS	Congressional Research Service
CV	Connected Vehicle
DEA	Data Envelopment Analysis
EGI	Electronic-Governance Index
FEVD	Forecast Error Variance Decomposition
FHSA	Federal Hazardous Substances Act
FHWA	Federal Highway Administration
FLJ	Frontier-Located Jurisdictions
GAO	U.S. Government Accountability Office
GCI	Global Competitiveness Index
GDP	Gross Domestic Product
GFI	Global Financial Integrity

GIACC	Global Infrastructure Anti-Corruption Centre
GMM	Generalized Method of Moments
GIS	Geographic Information System
GNI	Gross National Income
GNP	Gross National Product
GPR	Ground Penetration Radar
GPRA	Government Performance and Review Act
GPS	Global Positioning System
GSDRC	Government and Social Development resource Centre
HDI	Human Development Index
ICT	Information and Communications Technology
IFGICT	International federation of global & green information communication technology
IMF	International Monetary Fund
IRF	International Road Federation
KSA	Kingdom of Saudi Arabia
LiDAR	Light Detection and Ranging
MAE	Mean Absolute Error
MAP	The Moving Ahead for Progress Act
ML	Machine Learning
MSE	Mean Squared Error
NARX	Nonlinear Autoregressive Exogenous Model
NBI	National Bridge Inventory
NCDC	National Climatic Data Center
NCEES	National Council of Examiners for Engineering and Surveying
NCHRP	National Cooperative Highway Research Program
NGO	Non-Governmental Organization
NN	Neural Network
NPMAC	National Performance management Advisory Commission
NPR	National Performance Review
NSPE	National Society of Professional Engineers
NSTPRSC	National Surface Transportation Policy and Revenue Study Commission

OECD	Organization for Economic Co-operation and Development
PACI	Partnering Against Corruption Initiative
PCA	Principal Component Analysis
PVAR	Panel Vector Autoregression
QIC	Quasi Information Criterion
Radar	Radio Detection and Ranging
RFA	Random Forest Analysis
RMLP	Risk Management Leadership Program
RMSE	Root Mean Square Error
SARIMA	Seasonal Autoregressive Integrated Moving Average
SVM	Support-Vector Machines
TD	Top-Down
TI	Transparency International
TRB	Transportation Research Board
UAE	United Arab Emirates
UK	United Kingdom
UN	United Nations
UNDESA	United Nations Department of Economic and Social Affairs
UNDP	United Nations Development Programme
UNODC	United Nations Office on Drugs and Crime
USA	United States of America
USAID	U.S. Agency for International Development
USDOT	U.S. Department of Transportation
VAR	Vector Autoregression
VMT	Vehicle-Miles of Travel
WBG	World Bank Group
WEF	World Economic Forum
WFEO	World Federation of Engineering Organizations
WHO	World Health Organization

ABSTRACT

Corruption is a social evil that resonates far and deep in societies, eroding trust in governance, weakening the rule of law, impairing economic development, and exacerbating poverty, social tension, and inequality. It is a multidimensional and complex societal malady that occurs in various forms and contexts. As such, any effort to combat corruption must be accompanied by a thorough examination of the attributes that might play a key role in exacerbating or mitigating corrupt environments. This dissertation identifies a number of attributes that influence corruption, using machine learning techniques, neural network analysis, and time series causal relationship analysis and aggregated data from 113 countries from 2007 to 2017. The results suggest that improvements in technological readiness, human development index, and e-governance index have the most profound impacts on corruption reduction. This dissertation discusses corruption at each phase of infrastructure systems development and engineering ethics that serve as a foundation for corruption mitigation. The dissertation then applies novel analytical efficiency measurement methods to measure infrastructure inefficiencies, and to rank infrastructure administrative jurisdictions at the state level. An efficiency frontier is developed using optimization and the highest performing jurisdictions are identified. The dissertation's framework could serve as a starting point for governmental and non-governmental oversight agencies to study forms and contexts of corruption and inefficiencies, and to propose influential methods for reducing the instances. Moreover, the framework can help oversight agencies to promote the overall accountability of infrastructure agencies by establishing a clearer connection between infrastructure investment and performance, and by carrying out comparative assessments of infrastructure performance across the jurisdictions under their oversight or supervision.

CHAPTER 1. INTRODUCTION

1.1 Background

1.1.1 Corruption

A review of literature published over the past fifty-five years shows the vast range of ways in which corruption has been defined. The etymology of the word is rooted in Latin: *Com*, means "with, together," and *rumpere* means "to break." Therefore, a corrupt act by an individual means a break with the trust that others place in that person. In the context of willful human behavior, corruption can be termed as any self-serving behavior at the expense of societal good. In the literature, researchers have offered several corruption definitions, but there exist common taxonomical threads across the definitions: willful, fraudulent, or illicit acts; selfish intent; personal gain; reduced public funds due to misdirection to inappropriate destinations; overlooking anti-social behavior of others; and loss of public trust.

More than 5% of the world GDP is lost due to corruption practices every year (Irisova, 2014), and a vast majority of countries grapple regularly with corruption. Many of these countries are in due need of development loans, however, when they receive such funds, the money is not only deviated from development purposes in a few cases, but actually used in crimes related to drugs and human trafficking (Integrity Vice Presidency, 2016). This can be considered a serious issue realizing that 1.2 billion people live on $1.25 or less per day, and the extra money lost to corruption amounts to billions of dollars per year.

On the other hand, ways to devise fraud, collusion, or corruption are found to be similar, no matter where in the world it happens. Therefore, formulating common ways of involvement in those malfeasances on a global basis to classify the allegations of such misconducts is significantly crucial in fighting against corruption (Integrity Vice Presidency, 2009), which is discussed and analyzed in this dissertation by performing an extensive machine learning, time series analysis, causal relationship analysis, and ethics and policy assessment at a global-level scale and at a project-level scale.

1.1.2 Inefficiency

Inefficiency can be generally defined as a state where the maximum productivity is not achieved; for example, where goals are reached at unduly high cost. In the construction industry, where time and cost are two critical project outcomes, inefficiency can be interpreted in two ways (Paraskevopoulou & Boutsis, 2020) (Le-Hoai et al., 2008). First, inefficiency can result from several different issues that arise from the society (e.g. culture and tradition), or from the lack of an expert workforce (Al-Hazim et al., 2017; Barbosa et al., 2017). Inefficiency can also be a sign of lack of effective management of assets at any phases of project development. Projects are often not run in their most possible efficient way (Changali et al., 2015b). In some cases, inefficiencies may be traced back to corruption, lack of knowledge and technology, project complexity and uncertainty, lack of organizational team structure, weak strategic plan, etc. (Kenny, 2012).

Figure 1.1. illustrates the scale of cost overruns (actual compared with estimated costs) for some major projects − an indication of immense inefficiencies in those projects. Given the fact that the infrastructure investment will be doubled in the next 15 years (Changali et al., 2015a), monetary consequences of inefficiencies are expected to increase, accordingly. For example, for every $1 billion spent on a capital project, $135 million is at risk (PMI, 2013). 65% of all projects over $1 billion and 35% of all projects under $500 million are significantly over budget or late (Klaver, 2012). Moreover, $122 million is wasted for every $1 billion invested due to poor project performance. 40% of projects in the oil and gas industry are subject to budget and schedule overruns (McKenna et al., 2006). For twenty-seven recent infrastructure projects in Italy, 179% overbudget on average was reported (Locatelli et al., 2017).

The assessment of spending and outcomes for infrastructure projects can be performed in various ways, from a broad perspective of implementing network-level data assessment to a narrower perspective of implementing project-level data assessment, which is discussed and analyzed in the second part of this dissertation by performing data envelopment and frontier analysis at a state-level scale.

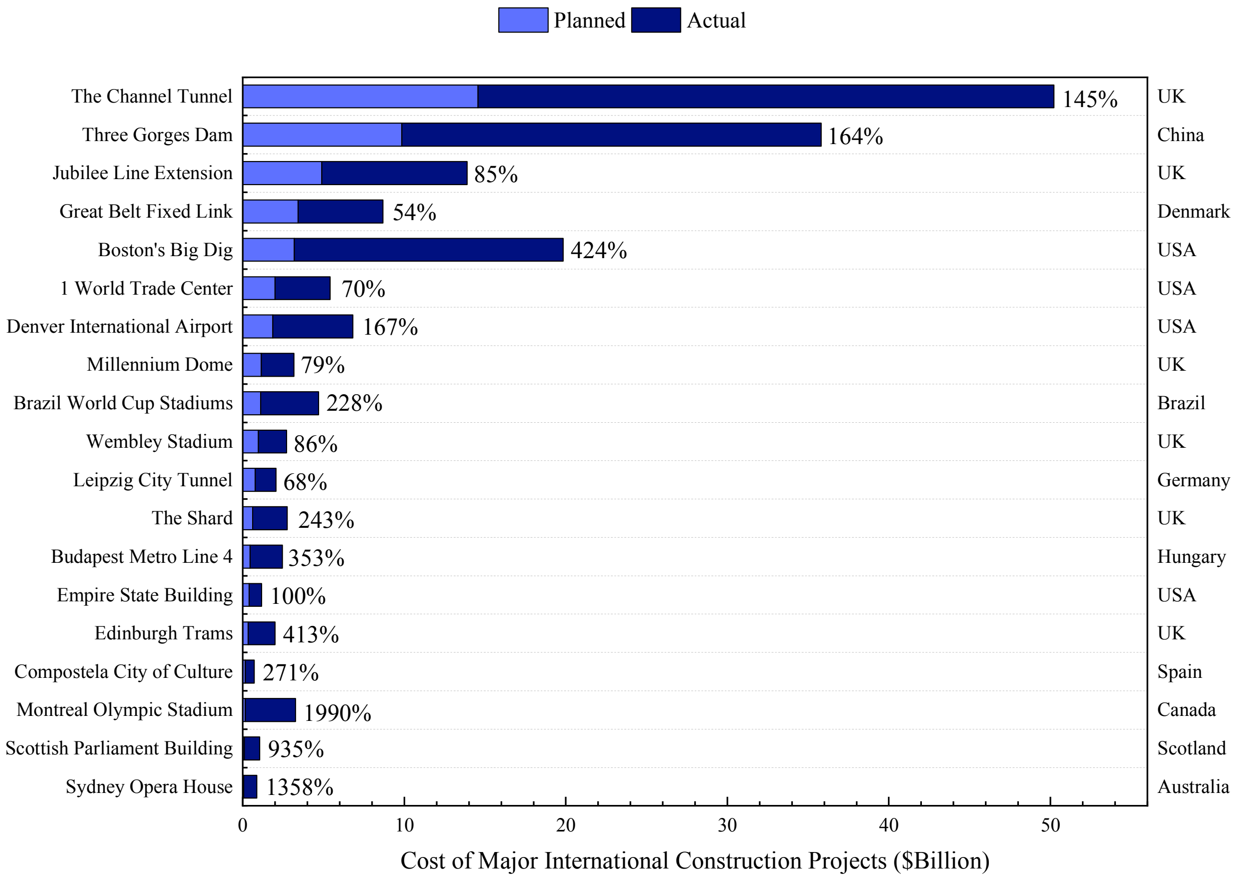


Figure 1.1. Topmost Inefficient International Infrastructure Projects (McCarthy, 2018)

1.2 Problem Statements and Research Objectives

1.2.1 Corruption

Corruption remains a global scourge that causes massive losses to governments that already struggle to deliver essential services to their citizens. The effects of corruption are certainly not felt equitably, as the low-income groups are most affected. Evidence from the literature suggest that in developing countries, such as Paraguay and Sierra Leona, higher income groups pay a lower proportion of their income to bribes compared to lower income groups (World Bank, 2018).

The World Bank maintains that corruption mitigation is an urgent task if the organization is to achieve its goals of "ending extreme poverty by 2030" and "boosting shared prosperity for the poorest 40 percent of people in developing countries" (World Bank, 2018). For the United

Nations, lowering corruption is at the core of the organization's Sustainable Development Goals, and is key to attaining the impressive objectives set for Financing for Development (UN, 2020; UNDP, 2017). In addition, corruption wears down faith in governments, weakens social agreements, and increases disparities and disgruntlement that leads to vulnerability of societies to strife (Menkhaus, 2010).

Corruption is a convoluted topic, and it happens at both micro and macro scales. Hence, analyzing corruption requires a comprehensive consideration of the attributes that play key roles in either mitigating or exacerbating corruption. This dissertation investigates the following objectives as described below.

Objective 1: Corruption is a multi-dimensional concept and it may not be feasible to eliminate all causes of corruption, and as noted above, several attributes can contribute to corruption levels in countries. Government officials, politicians, and NGOs, as well as oversight agencies, might be better equipped to curb corrupt activities if they possess knowledge of the main aggregate causes or inhibitors of corruption in a country. The first objective of the corruption part of this dissertation is to determine the attributes that have a significant influence on the corruption levels in countries. For this purpose, this dissertation investigates the aggregate causes using data from 113 countries based on thirteen aggregate attributes and four approaches: principal component analysis (PCA), hierarchical structure cluster analysis, regression tree analysis, and random forest (RF) machine learning (ML) technique.

Objective 2: It is essential for policymakers to have knowledge of corruption trends, so that they can identify types and timings of corruption mitigation strategies. Therefore, the second objective of the corruption part of the dissertation is to implement an artificial neural network (ANN) to forecast corruption levels in countries. Specifically, the research seeks to apply nonlinear autoregressive recurrent neural network methods with exogenous inputs (NARX) technique to forecast corruption levels considering Corruption Perceptions Index (CPI) as a function of influential attributes in each cluster.

Objective 3: The third objective of the corruption part of the dissertation is to identify the association between transparency and corruption levels in countries by investigating the causal relationship between e-governance index and corruption perceptions index using a panel vector autoregression (PVAR) time series analysis (including Orthogonalized Impulse-Response Functions (IRF), Granger-causal, and variance decomposition analysis).

Objective 4: The fourth objective of the first part of this dissertation is to use conceptual analysis to determine corruption propensity at each phase of infrastructure development. The goal is to discuss possible sources of corruption at each phase, and therefore, to identify opportunities for mitigations that are rooted in engineering ethics.

Figure 1.2. shows the connection between the first three objectives of the treatment of corruption in this dissertation.

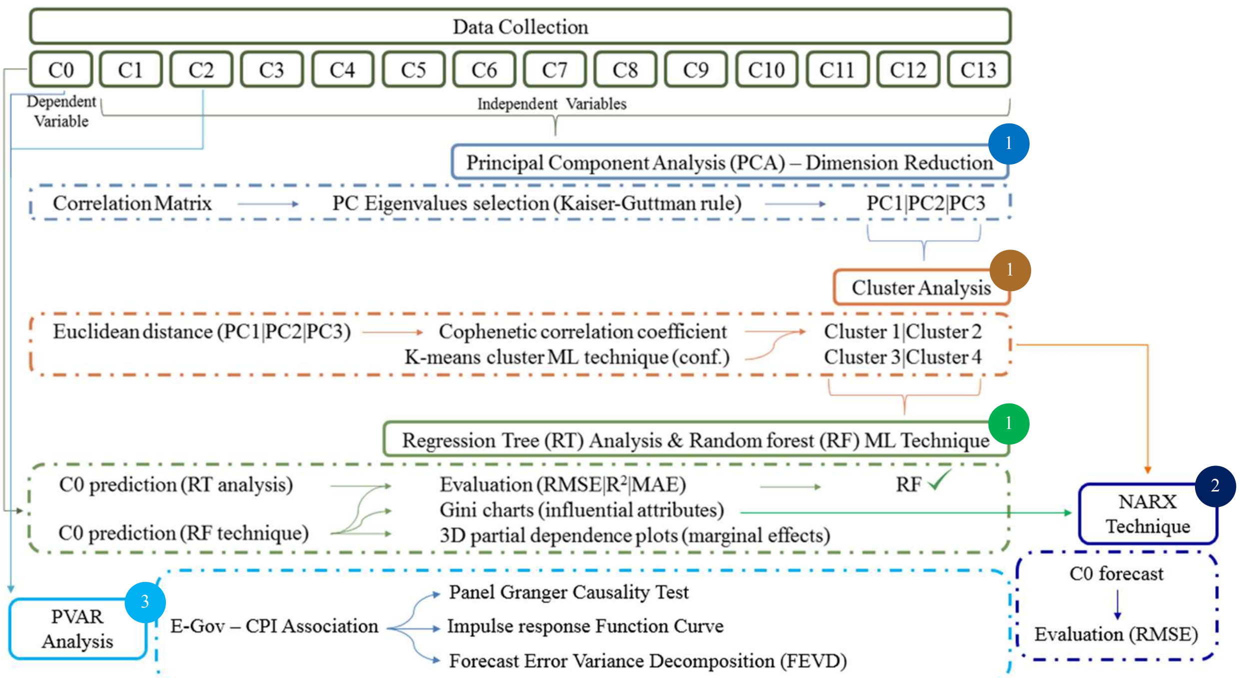


Figure 1.2. Connection between three objectives of the corruption part of the dissertation

1.2.2 Inefficiency

In the U.S., transportation and infrastructure spending accounted for over $85 billion in mandatory and discretionary funds allocated to transportation and infrastructure in 2015 (GPO, 2015). Of this amount, over $48 billion was allocated to the U.S. Department of Transportation (USDOT) and related agencies to invest in all aspects of the nation's infrastructure, with the following breakdown: $27.5 billion for highway infrastructure investment, $8.4 billion for mass transit, $8 billion for high-speed intercity rail, $1.5 billion for surface transportation infrastructure, $1.3 billion for Amtrak, $1.3 billion for the Federal Aviation Administration, and $100 million for maritime administration. The sheer volume of taxpayer-funded expenditures on transportation infrastructure makes it imperative to establish a reliable and continuous way of monitoring the outcomes of such expenditures, not only at the project or program level but also at the jurisdiction (agency) level.

In any country, there exist oversight bodies responsible for monitoring the levels of these expenditures and their overall performance outcomes in terms of mobility, safety, infrastructure condition or longevity, or the specific purpose of the investment. This tracking has been performed not only on an individual project or program basis but also for all combined project expenditures in a jurisdiction. Depending on the oversight organization, the agency in question may be at the level of a city, state, province, region, or even the entire country: oversight organizations for city and county agencies include state and provincial governments; oversight organizations for state and provincial agencies include federal/national bodies such as the Federal Highway Administration (FHWA), the USDOT, and the Government Accountability Office (GAO); and oversight organizations for countries, at least for a limited time period, may include international bodies such as multilateral donor institutions including the World Bank, the International Monetary Fund (IMF), the African Development Bank, the Organization for Economic Cooperation and Development (OECD), the Inter-American Development Bank (IADB), and the Asian Development Bank.

Objective 1: As evidenced by past practice in the area of performance management, there is a need for a general methodology that characterizes the relationship between infrastructure expenditures in a specific area of infrastructure management (for example, preservation, safety, or mobility) and the resulting performance in terms of enhanced infrastructure condition or longevity, crash reductions, reduced travel delay and improved travel time reliability, and so on.

Moreover, it is useful to ensure that such a methodology is robust in the sense that it duly accounts for both the relevant factors in the expenditure-performance relationship as well as extenuating conditions that could more completely explain the link between expenditure and performance at a given agency. Part 2 of this dissertation, presents and demonstrates a methodology to address part of this research need, namely, infrastructure condition impacts of preservation expenditures. Hence, the first objective of the second part of this dissertation is to characterize the expenditure-performance relationship, develop a methodology to account for this, and use data from highway interstate bridges in the USA to demonstrate the methodology.

A key benefit of such a methodology is the ability for individual agencies to assess their own performance in a way that is duly normalized by their inventory size and corresponding level of investment and other extenuating factors. With this knowledge, agencies can be better positioned to track their progress toward national goals and targeted outcomes in comparison to their peer agencies and thereby enhance the accountability of their spending. In addition, oversight organizations at any level of government can use such a methodology to compare the relative performance of agencies that fall under their administrative purview.

Objective 2: The second objective of the second part of this dissertation is to compare the investment efficiency at agencies using a linear programming based nonparametric efficiency approach. The methodology involves the development of an efficiency frontier using optimization, identification of frontier-located jurisdictions (FLJs), removal of the FLJs and re-development of the next frontier, and continuation of this cycle until all jurisdictions have been removed. To demonstrate the methodology, this dissertation uses state highway agencies as the jurisdiction level and interstate highway bridges as the asset of interest. To mitigate bias, the dissertation adjusts duly to account for the different inventory sizes, levels of traffic loading, and climate severity across the states, and presents an overall ranking of the US states with regard to the efficiency of their bridge investments.

Overall, the second objective of the inefficiency studies in this dissertation is to provide a method that oversight agencies can use to monitor the overall accountability of individual jurisdictions with respect to their expenditures and performance outcomes and to rank the jurisdictions based on efficiency. Moreover, the individual jurisdictions can apply the methodology to learn from each other and estimate the expected benefits they could earn if they move up to the efficiency frontier.

1.3 Organization of the Dissertation

This dissertation follows the "multiple publications" format, and therefore, it is divided into two major parts and seven chapters (excluding the introduction and concluding remarks chapters). The first 4 chapters address corruption, the three remaining chapters address inefficiency, and the last chapter presents concluding remarks, study limitations, and suggestions for future work. Each chapter has its sections for introduction, review of literature, methodology, data analysis and discussion, and conclusion. Considerable portions of the chapters have been published or submitted for review and publication in peer-reviewed journals and/or conferences.

The dissertation proceeds as follows. Chapter 2, the first chapter of the research studies related to corruption, investigates thirteen attributes that influence corruption levels among 113 countries. This chapter identifies the attributes that are most influential to corruption, using principal component analysis (PCA) as a dimension reduction technique, and K-means and hierarchical structure cluster analysis to identify groups of countries that share similar levels of development-related attributes. Also, using a machine learning technique (random forest algorithm), and decision tree analysis, this chapter estimates corruption perceptions index (CPI) for each cluster based on the development-related attributes.

Chapter 3 forecasts corruption levels of countries using an artificial neural network time series analysis. The analysis includes data from 2007 to 2017 for 113 countries, at two different levels: the world level (where all countries are considered as one group), and cluster level (where countries are studied in four clusters based on their development-related similarities). Using an artificial neural network technique - the nonlinear autoregressive recurrent neural network with exogenous inputs (NARX) – this chapter forecasts corruption levels in each cluster based on the attributes that directly affect those levels.

Chapter 4 investigates the association between the efficiency of electronic governance and the level of corruption in countries. The chapter uses data from 133 countries from 2007 to 2017, and performs panel vector autoregression (PVAR) analysis to identify the causal relationship and shock effects between the relevant variables at the world level (where all countries are considered as one group), and income level (where the countries are clustered based on their gross national income per capita).

Chapter 5 provides conceptual discussions of corruption and offers guidance to assist in mitigation efforts. The chapter discusses corruption at each phase of infrastructure development, and reviews engineering ethics that serve as a background to support efforts to fight corruption. By setting the discussion of corruption in this context, the chapter connects the propensity for corruption in each phase of infrastructure development to strategic, tactical, and operational mitigation actions supported by examples in practice.

Chapter 6, the first chapter of the research studies related to inefficiency, discusses the analytical efficiency methods, including data envelopment analysis, that have been applied in various fields, such as human resource management, transit, public administration, human resource management, management control system, and health care system. Also, this chapter identifies the limitations associated with the studied methods.

Chapter 7 presents a methodology for examining the expenditure-performance nexus among infrastructure preservation spending and physical condition of the infrastructure in a bid to promote the overall accountability of infrastructure agencies in each of multiple jurisdictions. The chapter examines whether the integrity of the expenditure-performance relationship is jeopardized by situational and measurement biases associated performance-related attributes. The methodology is demonstrated using aggregate repair expenditures and performance data for interstate highway bridges in the USA.

Chapter 8 presents a nonparametric efficiency for ranking infrastructure agencies using a linear programming-based approach. The chapter duly adjusts for inventory size and measurement bias, and the effect of different average age, climate severity, and traffic across the jurisdictions. The methodology develops an efficiency frontier using optimization, identifies frontier-located jurisdictions (FLJs), removing the FLJs and re-develops the next frontier, and so on until all jurisdictions have been removed. The chapter presents an overall efficiency ranking of the US states, with regard to the efficiency of their bridge investment.

Chapter 9 presents the overview of the dissertation and a summary for each part. This section of the dissertation further proposes the overall strategic practical implications of the research presented in this dissertation. This followed by the contribution of the dissertation, the study limitations, and suggested future work.

CHAPTER 2. CORRUPTION - CLUSTER ANALYSIS OF GLOBAL TRENDS USING PRINCIPAL COMPONENT ANALYSIS AND MACHINE LEARNING METHODS

2.1 Introduction

Over the decades, corruption has been defined in several ways: "… behavior that deviates from the formal duties of a public role (elective or appointive) because of private-regarding (personal, close family, private clique) wealth or status gains" (Nye, 1967), "… behavior that deviates from the formal rules of conduct governing the actions of someone in a position of public authority because of private-regarding motives such as wealth, power, or status" (Khan, 1996), "... the misuse of public office for private gain" (Treisman, 2000), and "the abuse of public power for private benefit (or profit)" (Transparency International, 2017; WBG, 2020). Irrespective of the way it is defined, corruption continues to be a pervasive multidimensional and complex societal malady that occurs in various forms and contexts. For this reason, it is essential that efforts to combat corruption are preceded, or at least accompanied, by a thorough examination of the attributes that might play role in either exacerbating or inhibiting corrupt environments. It can be hypothesized that these attributes, and the magnitude and severity of their impacts on corruption, exhibit significant variation across countries and continents. Specifically, it can be hypothesized that if countries can be clustered into families each having similar development-related attributes, some insights may be acquired to help build the basic blocks not only for investigating the causes and forms of corruption within each cluster, but also to identify appropriate corruption mitigation methods based on lessons learned in specific countries.

In order to address this research objective, there is a need to investigate country-specific development-related attributes that hypothetically influence corruption levels in various countries, and to identify the attributes that significantly influence the levels of corruption. Such analysis includes identification of the groups of countries based on the attribute levels and development of the clusters. Identifying clusters that require attention from a corruption control viewpoint and estimating the corruption perceptions index (CPI) within each cluster are also needed. Against this background, the objectives of this chapter of the dissertation are to identify groups of countries based on the levels of development attribute levels and estimate the CPI for countries in each cluster using different techniques and identify the most reliable technique. The first objective is intended to help identify attributes that are most relevant to assessing corruption levels in each cluster, and to identify clusters that require attention from a corruption control viewpoint. In the clustering process, some attributes may be correlated with each other, and therefore, this chapter seeks to use an appropriate statistical technique reduce the dimensionality and thereby address such possible correlations.

In the next section of the chapter, the literature related to corruption attributes and measurement are reviewed, and the analytical tools implemented in this assessment are discussed. The next section discusses data collection and the research methodology. Then the analysis results are discussed, suggestions are made for corruption mitigation based on the results. The chapter's final section presents the study conclusions and recommended directions for future work in this research area.

2.2 Literature Review

2.2.1 Development-Related Attributes and Corruption

In recognition of the multi-dimensional nature of corruption, this chapter's review of existing literature adopted a cross-disciplinary search approach to identify the relevant literature on the relationships between development-related attributes and corruption. The search was conducted through the Scopus, Science Direct, Web of Science, and Engineering Village databases, and was limited to the years 1970–2021. As a secondary process, the study scope is categorized into separate areas to refine the search. Literature on six corruption-related topical areas were investigated: (a) impact of corrupt behaviors on the governance of commons; (b) corruption at various hierarchies – individual, organizational, project, and society; (c) institutional elements – regulations, normative elements, and cognitive elements; (d) geographic location – East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia, and sub-Saharan Africa; (e) research methods; and (f) types of corruption – bid-rigging, bribery, collusion, embezzlement, facilitation of payments, fronting, gerrymandering, rent-seeking, and theft. The literature review helped identify the development-related attributes that might be influencing (or at least, associated with) the level of corruption in countries. Appendix A presents a list of the research papers associated with each category.

Past research has shown that there exist several development-related attributes that influence the level of corruption in a country. Shleifer (1997) found that in post-communist countries, the emergence of open-market economies has been overshadowed by corruption. Treisman (2007) and Saha and Sen (Saha & Sen, 2021) also found that lower levels of corruption are found in developed nations that tend to trade openly with other nations, and have long-established democracies, a free press, and high female participation rates in their development. Treisman (2000), Shabanova and Ismagilova (2014), and Stoliova and Patonov (2020) determined that the levels of social and economic development, and government investment are strongly correlated with the level of corruption in a country. Adomako et al. (2021) found that corruption is positively related to institutional networking and that this relationship is amplified when levels of financial slack are greater. Auti and Skitmore (2008), and Akbar and Vujić (2014) argued that the level of education and culture can influence the level of corruption in a country. This position is supported by Rose-Ackerman (1996b) who used this premise as a basis to suggest corruption mitigation through cultural transformation, rewarding honesty, and improving monitoring and detection of corruption. In addition, recent studies have investigated the labor market as a development related factor in corruption: Hao et al. (2020) found that labor market efficiency is strongly and inversely related to corruption. This motivated the selection of variables related to transport infrastructure quality, labor market efficiency, and security for investigation in the present study, regarding their possible impacts on corruption.

The effectiveness of government function and political participation have been determined to profoundly influence corruption in a country. Rose-Ackerman (1996b) and Abreu and Gomes (2021) carried out quantitative regression on multivariate panel data and determined that the maturity of democratic institutions is strongly associated with corruption levels. This finding corroborated Johnston (1998)'s assertion that low engagement of the civil society in governance weakens the capacity for law enforcement, and suggests that indices related to human development, information that are currently available for all countries, could help throw light on current efforts to identify the potential factors of corruption in a country. Also, of relevance is the practice of electronic governance (e-governance), which is growing rapidly, catalyzed by advancements in information and computer technology, and more recently, the COVID-19 pandemic. Ghahari et al. (2021b) performed an artificial neural network analysis − a non-linear autoregressive network with exogenous inputs method − and carried out panel vector autoregression analysis using data spanning the 2007–2017 period, from 113 countries, and determined that there is a strong association between this emerging practice and corruption. Other researchers that have studied the relationship between e-governance and corruption include Andersen (2009), Garcia-Murillo & Ortega (2010), Mauro (1995), and Mistry (2012). Their findings suggest that the e-governance index and technological readiness, data items that are currently available in global datasets, could serve as potential explanatory variables in a corruption factor attribution model.

The infrastructure construction industry has the dubious honor of being the most corrupt business sector (Kottasova, 2014; Mertzanis et al., 2020; Mokeresete & Esiefarienrhe, 2020; Taghizadeh-Hesary et al., 2021). Corruption in this sector causes not only significant reduction in quality but also reduced safety, and in many cases, the combined value of quality and safety reduction exceeds the infrastructure construction contract cost (Kenny, 2007a; Lyman et al., 1978; OECD, 2016). For these reasons, government's regulatory and oversight roles in the infrastructure industry can be a significant contributor to corruption inhibition. Lee & Larnemark (2007) indicated South Korea's road authorities instituted initiatives that explicitly sought to reduce corruption in the road construction sector. Unfortunately, it seems that not all countries possess the political will to establish these corruption mitigation policies and regulations. From a general perspective of all sectors, the Global Infrastructure Anti-Corruption Centre (GIACC) (2011) identified some general conditions and practices that foster or inhibit corruption, and offers insights into the choice of quantitative variables that could represent these factors. Government corruption could be represented by data on public sector performance, and corporate corruption could be measured using business sophistication. The level of corruption pressure could be measured using data on security/undue influence. The inadequacy of corporate controls could be measured through the e-governance index and technological readiness. Inadequacy of employee salaries could possibly (but not perfectly) be measured using the income per capita and the gross national income, goods market efficiency, market size, and the financial market development. The human development index could help assess the awareness of citizens regarding corruption (Ghahari et al., 2018c).

2.2.2 Statistical and Machine Learning Methods

As stated earlier in this document, corruption is a multi-faceted phenomenon, and many variables affect corruption, and more importantly, correlations exist between these variables. In dealing with numerous variables such as those identified in this study, dimension reduction techniques are used to account for potential collinearity among the variables. Principal component analysis (PCA) is one such dimension reduction tool. In this study, clustering is used with PCA to group similar observations. This is particularly needed in problem contexts (such as this study) where there is merit not only in developing clusters based on some attribute such as continent location, for example, but more importantly, for identifying palliatives that are based partially on the nature of the developed clusters.

In the agriculture sector, Safeer et al. (2020) recently used PCA to estimate diversity among fifty species of a crop. Based on the developed clusters, they detected significant variations for certain traits, characterized the diversity, and identified the most impactful variables that determine the crop characters. In the energy sector, Kantar & Keskin (2013) studied patterns of electricity consumption and GDP in Asian countries, identified clusters of countries according to their geographical location and economic growth, and developed a roadmap for policymakers for efficient energy and environmental strategies. In the tourism industry, Brida et al. (2020) investigated the interaction between tourism and economic growth using data from 80 countries over the period 1995–2016, and applied clustering techniques to identify appropriate tourism policies for governments of countries in each cluster.

It is also vital for the analyst to identify the most influential characteristics of a given outcome variable. Where there exists a large sample size and complex relationships between the attributes under investigation, the application of a wide range of techniques, not only linear or non-linear regression, could help throw more light on the issue. In this chapter of the dissertation, analyzing corruption in over one hundred countries over ten years using data on thirteen attributes or more, is performed by means of machine learning (ML) techniques. In a recent study, Hu et al. (2020) developed artificial intelligence methodologies for performance prediction of organic solvent nanofiltration membranes. They applied the random forest (RF) ML technique using 38,430 data points with 18 dimensions. With a 98% model prediction accuracy, they also identified five of the most important explanatory variables (Hu et al., 2020). In another study, Yoon (2020) used RFA to forecast the real GDP growth of Japan using data spanning 2001 to 2018. They found that the forecasts produced by the RF machine learning technique were more reliable compared to those in the literature. In general, the reliability of predictions using the RF technique has been corroborated by several researchers (Boateng et al., 2020; Liang et al., 2020; Wang et al., 2020).

2.3 Data

Data on the attributes that are pertinent to this dissertation's chapter research objectives were obtained from five databases from the following organizations: the World Bank Group (WBG) (WBG, 2017), the United Nations Department of Economic and Social Affairs (UNDESA) (UNDESA, 2017), the United Nations Development Programme (UNDP) (UNDP, 2017), the World Economic Forum (WEF) (WEF, 2018), and Transparency International (TI) (Transparency International, 2017). Table 2.1. summarizes the data used in the preliminary analysis including the source, the name of the database and a code used to reference the data.

Table 2.1. Corruption-related attributes from all databases considered, Year 2017

Organization	Database		Code
TI	Corruption Perceptions Index		C0
WBG	GNI per Capita		C1
UNDESA	E-Governance Index		C2
UNDP	Human Development Index		C3
WEF	Global Competitiveness Index	Undue Influence	C4
		Public-Sector Performance	C5
		Security	C6
		Transport Infrastructure	C7
		Goods Market Efficiency	C8
		Labor Market Efficiency	C9
		Financial Market Development	C10
		Technological Readiness	C11
		Market Size	C12
		Business Sophistication	C13

Corruption Perceptions Index (CPI), developed by Transparency International (a pioneer in global corruption evaluation), measures the prevailing levels of public-sector corruption in each country as perceived by experts and businesspersons on a scale of 0–100, where 0 is highly corrupt and 100 is very "clean" (European Commission, 2019). It is based on thousands of surveys administered annually to gage the perceived degree of corruption in governments (GFI, 2020). In 2017, two-thirds of the countries around the globe had a CPI rating below 50. It is noteworthy that CPI currently does not include "legalized" corruption, such as excessively high salaries and benefits that lawmakers legislate for themselves, corporate lobbying of legislators, and so on. Although, the subjectivity of the survey responses has been brought into question, CPI is still considered a good approximation of the extent and severity of corruption that prevails in a country, and the CPI remains the favored metric of corruption (Lambsdorff, 1999).

Data on the gross national income (GNI) per capita were obtained from the World Bank's National Accounts Data (World Bank, 2017a). Data on e-governance index (on a 1 to 0 scale), which were obtained from the United Nations Department of Economic and Social Affairs (UNDESA, 2017), represent the degree of digital interaction between a governments and its citizens, and the consistency of governmental supervision at all scales and government levels (Nathan Associates, 2016). Data on the Human Development Index (HDI) were obtained from the United Nations Development Programme (UNDP). This index recognizes that not only economic growth should be used to assess a country's development, and therefore measures the capabilities of people in a country (UNDP, 2017).

The Global Competitiveness Index (GCI), published by the World Economic Forum (WEF), measures the competitiveness landscape of economies and provides unique insights into the drivers of the productivity and prosperity of people in a country. For each country, WEF splits the productivity characteristics into twelve pillars – "The Twelve Pillars of Competitiveness." The computation of the GCI is based on the successive aggregation of indicators within each pillar and then scores from each pillar (WEF, 2018). In this chapter of the dissertation, the following indexes from specific pillars are selected: the 1st pillar (Institutions), the 2nd pillar (Infrastructure), the 6th pillar (Goods Market Efficiency), the 7th pillar (Labor Market Efficiency), the 8th pillar (Financial Market Development), the 9th pillar (Technological Readiness), the 10th pillar (Market Size), and the 11th pillar (Business Sophistication). Table 2.2. presents the detailed breakdown of the GCI data used in this chapter study by pillar and then subsection.

Table 2.2. Selected Global Competitiveness Indices from WEF (2018)

Database	Pillar	Sub Sections
Undue Influence	1st Pillar: Institutions	▪ Judicial independence ▪ Favoritism in decisions of government officials
Public-Sector Performance	1st Pillar: Institutions	▪ Wastefulness of government spending ▪ Burden if government regulation ▪ Efficiency of legal framework in setting disputes ▪ Efficiency of legal framework in challenging regulations ▪ Transparency of government policymaking
Security	1st Pillar: Institutions	▪ Business costs of terrorism ▪ Business costs of crime and violence ▪ Organized crime ▪ Reliability of police services
Transport Infrastructure	2nd Pillar: Infrastructure	▪ Quality of overall infrastructure ▪ Quality of roads ▪ Quality of railroad infrastructure ▪ Quality of port infrastructure ▪ Quality of air transport infrastructure ▪ Available airline seat kilometers
Goods Market Efficiency (GME)	6th Pillar: GME	▪ Competition ▪ Quality of demand conditions
Labor Market Efficiency (LME)	7th Pillar: LME	▪ Flexibility ▪ Efficient use of talent
Financial Market Development (FMD)	8th Pillar: FMD	▪ Efficiency ▪ Trustworthiness and confidence
Technological Readiness (TI)	9th Pillar: TI	▪ Technological adoption ▪ ICT use
Market Size (MS)	10th Pillar: MS	▪ Domestic market size ▪ Foreign market size
Business Sophistication (BS)	11th Pillar: BS	▪ Local supplier quantity ▪ Local supplier quality ▪ State of cluster development ▪ Nature of competitive advantage ▪ Value chain breadth ▪ Control of international distribution ▪ Production process sophistication ▪ Extent of marketing ▪ Willingness to delegate authority ▪ Reliance on professional management

2.4 Methodology

Several techniques were used to determine the attributes that have a significant influence on corruption in a country: principal component analysis (PCA), hierarchical structure cluster analysis, and regression tree analysis and random forest (RF) machine learning (ML) technique. The principal component analysis (PCA), a well-known dimension reduction technique, was carried out to address possible collinearity among the 13 corruption-related attributes (C1-C13). Accordingly, the countries that share similar development-related characteristics are clustered, so that within each cluster, the attributes that influence corruption can be identified. Finally, regression tree analysis are performed and random forest technique is implemented to pinpoint the most important and influential attributes for each cluster using Gini charts.

The overall methodology and approaches used in this chapter of the dissertation is summarized in Figure 2.1., which consists of data collection, correlation analysis, principal component analysis, cluster analysis, confirmation of the cluster analysis with cophenetic correlation coefficients and K-means cluster machine learning technique, regression tree analysis and the random forest (RF) machine learning, evaluation of the RF results, Gini charts, and marginal effects analysis. All these steps are discussed in the following subsections.

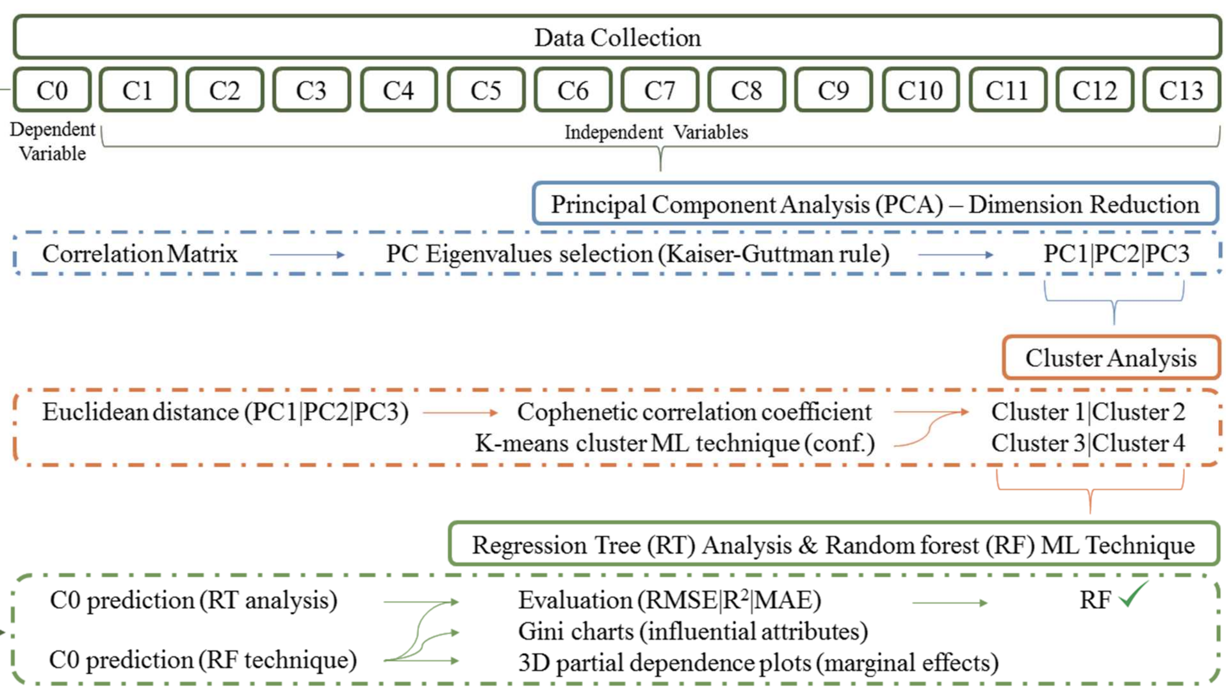


Figure 2.1. The methodology and approaches used in the study of corruption

2.4.1 Machine Learning Techniques

Machine learning (ML) is a technique for data analysis that automates systematic model development. ML is a division of artificial intelligence on the basis of the premise that systems are capable of learning from the available data, recognize patterns, and perform rapid decision making with negligible human interference. Machine learning methods can be divided into two main branches: supervised learning, in which both input and output are given to the model, and unsupervised learning, in which only input is given to the machine with no output variable.

For example, supervised learning methods for continuous variables include: linear or polynomial regression, decision tree and random forest techniques, and for categorical variables include: logistic regression, K-nearest neighbor algorithms, and support vector machine. Examples for unsupervised learning methods for continuous variables are: principal component analysis, K-means clustering algorithm, singular value decomposition, and for categorical variables include: association analysis and hidden Markov model. Below, I discuss the machine learning methods that are used in the data analysis of this chapter of the dissertation.

2.4.2 Principal Component Analysis (PCA)

The correlation between variables in datasets containing a large number of variables can impede efforts to discern relationships in the data. PCA offers an opportunity to address this issue by condensing the original variables into their principal components (in other words, linear combinations of the variables) with a minimum potential loss of data information (Heckler, 2005; Joliffe & Morgan, 1992). In this chapter, principal components were developed, using the following steps. The principal component variable, *Pi* is given by:

$$P_{\mathrm{i}} = \alpha_{\mathrm{i1}} V_1 + \alpha_{\mathrm{i2}} V_2 + \ldots + \alpha_{\mathrm{im}} V_{\mathrm{m}} \qquad \text{Eq. 2.1.}$$

where, V_{i} (i = 1, 2, …, m) are m original variables, P_{i} (i = 1, 2, …, m) are the m principal component variables, each of which is a linear combination the initial variables, and α_{ij} (i, j = 1, 2, …, m) are the associated coefficients. The eigenvector of the correlation matrix in this equation is the vector (α_{i}) from α_{i1} to α_{ik}, known as the normed solutions of the following system of equations:

$$(\Sigma_z - \lambda_i I)\alpha_i = 0 \qquad \text{Eq. 2.2.}$$

where, Σ_Z is the covariance matrix of the initial variables, I is the unit matrix, and λ_i is obtained via the following equation:

$$|\Sigma_Z - \lambda I| = 0 \qquad \text{Eq. 2.3.}$$

Eq. 2.3. is the characteristic equation of the covariance matrix of the initial variables (Σ_Z), and its solutions are the eigenvalues.

P_1 (the first principal component) explains the maximum variance of the initial values; P_2 accounts for the second-highest variance of the initial values, and so on, with P_1 to P_m showing no correlations. In this chapter, the Kaiser-Guttman rule is used to determine the optimum number of principal components. The Kaiser-Guttman rule considers the eigenvalues higher than 1 to be in the acceptable threshold (Joliffe & Morgan, 1992).

2.4.3 Cluster Analysis

In dealing with large sets of observations with a large number of attributes or characteristics, it is often useful to group (cluster) observation units that are homogenous (Everitt et al., 2011). This can be done using hierarchical or non-hierarchical methods, and the results illustrated using a dendrogram (Hartigan, 1975). In the hierarchical method, the most similar observation units form individual clusters. Similar clusters form individual groups. This is achieved via measuring the degrees of resemblance often referred to as "distance." Gauging the "distance" between the observation units and clustering them into separate groups can be done using one of the following methods: median, Ward's method, nearest neighbor, and average linkage. The present chapter of this dissertation selects the average linkage method of clustering, which calculates the Euclidean distance using Eq. 2.4.:

$$d_{ij} = \sqrt{\sum_{i=1}^{m}(\gamma_{im} - \gamma_{jm})^2} \qquad \text{Eq. 2.4.}$$

where, γ_{im} and γ_{jm} are the coordinates of the m^{th} variable for the i^{th} and the j^{th} observation units, respectively.

After developing the matrix for all the distances between each pair of observation units, the clustering process begins. The first clustering event identifies the two observations with minimum distance (this leads to the formation of the first cluster). This process continues until all the observations are placed in one of the formed clusters. Cophenetic correlation coefficients (CCCs) are then calculated to verify the clustering results and choose the optimum clustering method based on the largest CCC. CCC, which measures the accuracy of a dendrogram based on the distances between the original data points and the modeled data points in the dendrogram, is calculated as follows (Eq. 2.5.):

$$c = \frac{\sum_{i<j}(d_{i,j}-\bar{d})(\tau_{i,j}-\bar{\tau})}{\sqrt{\left|\sum_{i<j}(d_{i,j}-\bar{d})^2\right|\left[\sum_{i<j}(\tau_{i,j}-\bar{\tau})^2\right]}} \qquad \text{Eq. 2.5.}$$

where, $d_{i,j}$ is the ordinary Euclidean distance between the i^{th} and the j^{th} data points in the original dataset ($|\, d_i - d_j \,|$), and τ_{ij} is the distance between the i^{th} and the j^{th} points in the dendrogram. This distance is the height of the node at which these two points are initially linked.

2.4.4 K-means Clustering Algorithm

The accuracy of the number of clusters (obtained in the cluster analysis section) is verified using K-means clustering method - one of the well-known machine learning techniques for clustering (Ren et al., 2020; Žiberna, 2020). Any machine learning technique needs a starting set to approach a solid solution. In this algorithm, the main goal is to minimize intra-cluster variances while maximizing the distances between the clusters. K-means clustering process is initiated by capturing k points from the dataset as the "central cluster," then, the other clusters are formed by calculating the Euclidean distances between other data points (objects) and the central cluster. The center of gravity for each cluster is chosen by calculating the average distance of the points in that cluster (Ren et al., 2020).

2.4.5 Decision Tree Analysis

A comprehensive regression tree analysis was carried out using the study dataset in order to develop a nonlinear predictive model. Contrary to linear or polynomial regression, decision trees partition the data space into small parts. For this, one of the most comprehensible non-parametric methods is k-nearest-neighbor (Hnizdo et al., 2008). The drawbacks to this method, however, are: (a) defining "similar" is entirely in terms of the inputs and not the response; and, (b) k is constant everywhere, whereas, some points may likely have more "very-similar" neighbors than others

(Hnizdo et al., 2008). Decision/prediction trees – known as adaptive nearest-neighbor methods – solve both problems. This tool (a) leaves space (a neighborhood) corresponding to the regions of the input, and (b) has sizes which can vary arbitrarily (Hastie & Tibshirani, 1996). A benefit of a decision tree method is that it demonstrates all potential outcomes of a decision, and traces each course to a conclusion. It produces a thorough analysis of the consequences along each branch, and pinpoints the outcomes that require additional analysis (Grana et al., 2010). Hence, decision tree algorithms are beneficial not only for classification purposes but also for regression analysis and prediction.

Regression trees or decision trees can provide a vivid picture of the underlying structure in data and associations between attributes. They are an outstanding means for data inspection and for recognizing the connections between variables (R Statistics, 2017). In the case of having a single predictor, the range of the predictor is segregated into pieces, and within each segment, the projected regression fit is given by the mean of the response in the segment (Kutner et al., 2005). This method is very powerful, yet conceptually simple, for any nonparametric regression (Loh, 2014).

In this analysis, the bootstrap technique is applied to achieve even more accurate data. Bootstrap aggregation (or, bagging) reduces the variance of the outcomes. As Figure 2.2. shows, the bootstrap technique re-samples the training dataset (often, 85% of the complete dataset) multiple times with replacement, and it re-estimates the models. This raises the likelihood of the individual trees to be independent models (Díaz-Uriarte & De Andres, 2006). Therefore, higher precision is gained by taking the average of the models (Rebai et al., 2020). Finally, it makes the final model prediction as the average of the predictions across the trees, and the model testing occurs with the test dataset (often, 15% of the complete dataset).

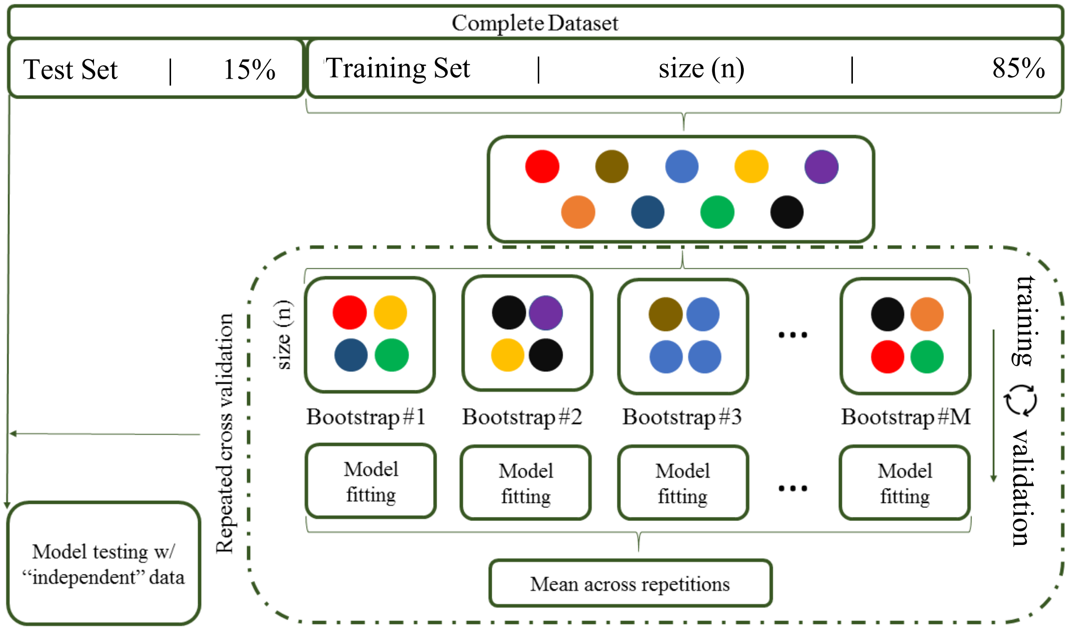


Figure 2.2. The schematic diagram for the bootstrapping technique

2.4.6 Random Forest Algorithm (RFA)

The Random Forest technique provides an improvement over the decision tree algorithm by de-correlating the trees. The RFA aggregates the predictions made by multiple decision trees of varying depth. In this machine learning (ML) technique, every decision tree is trained on a subset of the dataset called the bootstrapped dataset. Although RFA is less likely to make overfit outputs, cross-validation helps ensure that all samples will appear in the training and test sets. In this chapter, the *k*-fold cross-validation technique (Figure 2.3.) is used to yield lower-variance estimates for the models. This cross-validation method works by breaking the entire data into *k* equal-sized "folds." It repeats the process through each fold (shown in the schematic figure) treats that fold as a test dataset, trains a model on all the other *k*–1 folds, and evaluates the model's performance on the test dataset fold.

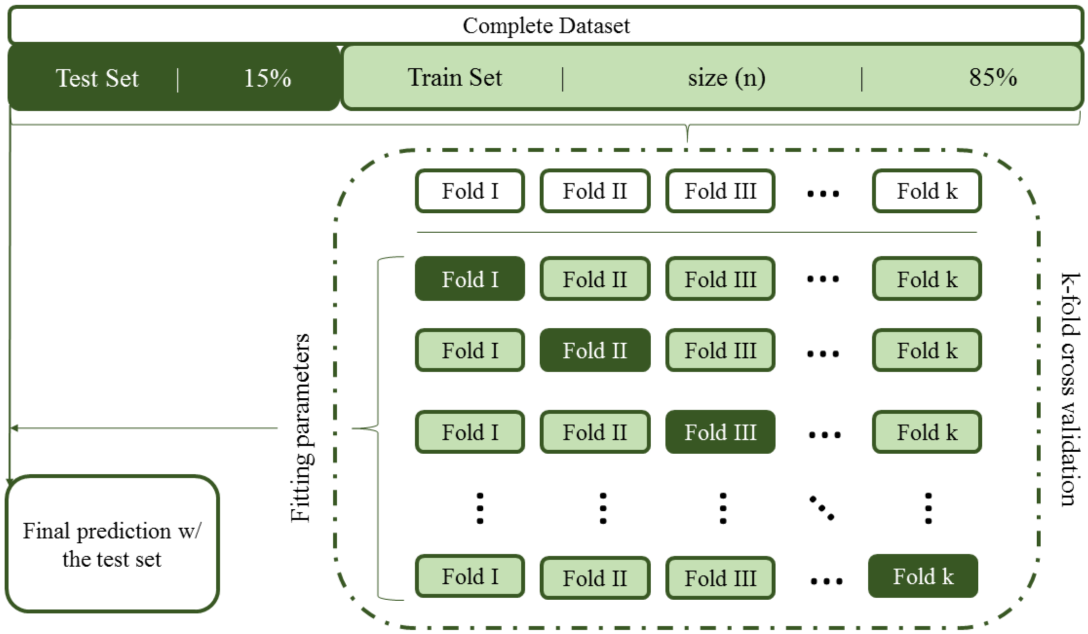


Figure 2.3. The schematic diagram for the k-fold cross-validation technique

RFA generally offers higher precision compared with other machine learning prediction methods (Bosso et al., 2019) and is a robust technique that builds on decision trees to predict models and perform analysis on the behavior of objects. RFA considers each object independently and chooses that with the maximum number of returns as the designated prediction. In this chapter, RFA is used to identify attributes that contribute most to corruption. Also, RFA is applied with bootstrap sampling as one of the powerful machine learning techniques in predicting the outcomes of our large dataset that has multiple variables. The accuracy of the random forest prediction models is assessed by comparing their values of adjusted-R^2, root mean square error (RMSE), and mean absolute error (MAE). Finally, the most influential attributes of corruption is identified using the observed mean decrease in Gini Index or Impurity, a measure of the likelihood of an incorrect classification. Gini Impurity refers to the total decrease in node impurities from splitting on the variable, averaged over all trees (Bosso et al., 2019). The impurities are measured by the residual sum of squares (Liaw, 2018). Furthermore, partial dependence plots (graphical visualizations of the marginal effect of a variable on the outcome (Colak et al., 2020) are used) to investigate the relationship between corruption-related attributes and the RF outcome.

2.5 Results and Discussion

2.5.1 Principal Component Analysis (PCA)

As discussed in the previous section, the first step in any principal component analysis is to establish a correlation matrix and determine which variables are strongly correlated, as this helps identify the need for normal regression analysis or principal component analysis. Table 2.3. presents the absolute value of the correlation coefficients for the variables considered in this chapter. This table illustrates the coefficient of correlation (r) as a key determinant of a relationship between any two variables. A 0.25 threshold is used in this table to determine the intensity of correlations: $0.75 < |r| \leq 1$ denotes strong correlations (**the bold values**), $0.50 < |r| \leq 0.75$ moderate correlation, $0.25 < |r| \leq 0.50$ weak correlation, and $|r| \leq 0.25$ no correlations.

Table 2.3. Absolute value of the correlation coefficients

Attributes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
C1	1	**0.92**	**0.97**	0.53	0.37	0.52	0.72	0.69	0.37	0.54	**0.91**	0.46	0.72
C2		1	**0.95**	0.58	0.42	0.54	**0.76**	0.73	0.45	0.58	**0.94**	0.51	**0.76**
C3			1	0.53	0.35	0.54	0.71	0.68	0.37	0.54	**0.92**	0.45	0.72
C4				1	**0.88**	0.67	0.71	**0.80**	0.71	0.66	0.67	0.31	**0.80**
C5					1	0.63	0.66	**0.78**	**0.76**	0.67	0.50	0.22	0.70
C6						1	0.53	0.64	0.54	0.40	0.62	0.06	0.52
C7							1	**0.81**	0.55	0.66	**0.78**	0.62	**0.87**
C8								1	**0.75**	**0.78**	**0.81**	0.36	**0.90**
C9									1	0.65	0.57	0.12	0.67
C10										1	0.65	0.34	**0.76**
C11											1	0.39	**0.83**
C12												1	0.51
C13													1

*Note: The **bold values** show strong correlations. C1-GNI, C2-E-governance index (EGI), C3-human development index (HDI), C4-undue influence, C5-public-sector performance, C6-security, C7-transport infrastructure, C8-goods market efficiency, C9-labor market efficiency, C10-financial market development, C11-technological readiness, C12-market size, C13-business sophistication.*

As the correlation matrix shows, GNI (C1) is highly correlated with the EGI (C2), HDI (C3), and technological readiness (C11) ($|r| > 0.90$). EGI (C2) is highly correlated with HDI (C3) and technological readiness (C11) ($|r| > 0.90$), and correlated with transport infrastructure (C7) and business sophistication (C13) ($|r| > 0.75$). HDI (C3) is highly correlated with technological readiness (C11) ($|r| > 0.90$), and moderately correlated with undue influence (C4). Undue influence (C4) is correlated with public-sector performance (C5), goods market efficiency (C8), and business sophistication (C13) ($|r| > 0.80$). Public-sector performance (C5) is correlated with goods market efficiency (C8) and labor market efficiency (C9) ($|r| > 0.75$). Transport infrastructure (C7) is correlated with goods market efficiency (C8), technological readiness (C11), and business sophistication (C1) ($|r| > 0.75$). Goods market efficiency (C8) is correlated with labor market efficiency (C9), financial market development (C10), technological readiness (C11), and business sophistication (C13) ($|r| > 0.75$). Financial market development (C10) is correlated with business sophistication (C13) ($|r| > 0.75$), and finally, technological readiness (C11) is correlated with business sophistication (C13) ($r > 0.8$). These results suggest that a large number of attributes (almost 40%) exhibit significant correlation with other attributes, and this justifies the need to carry out PCA. PCA reduces dimensionality by forming new independent variables from the original variables, and this addresses the correlation problem.

Eigenvalues associated with each principal component (PC) are shown in the scree plot (Figure 2.4.). The thick horizontal blue line represents the optimum number of PCs by setting the limit of eigenvalues to 1, according to the Kaiser-Guttman rule. Table 2.4. presents the eigenvalue variances and cumulative variances (%). The eigenvalues are 8.7, 1.7, and 1.0 for the first PC to the third PC, respectively, meaning that the first three principal component describes 87.1% of the cumulative variance of the original data; the other principal components describe 12.9% of the cumulative variance. Consistent with the Kaiser-Guttman rule, the first three principal components were identified as the optimal number of PCs.

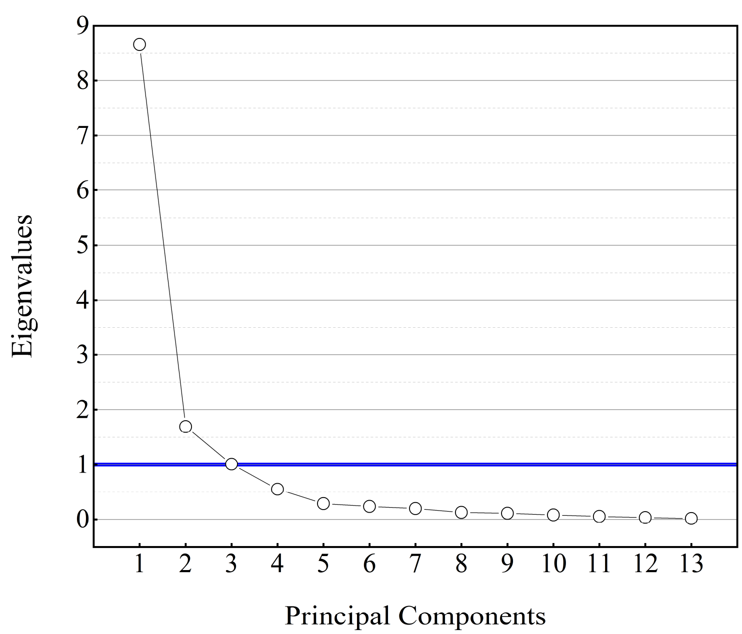


Figure 2.4. The scree plot for the principal component analysis

Table 2.4. Eigenvalues' variances and cumulative variances (%) associated with each principal component

Component	1	2	3	4	5	6	7	8	9	10	11	12	13
Eigenvalue	8.7	1.7	1.0	0.5	0.3	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0
Variance (%)	66.6	13.0	7.5	4.2	2.2	1.8	1.5	1.0	0.8	0.6	0.4	0.3	0.1
Cumulative Variance (%)	66.6	79.6	87.1	91.3	93.5	95.3	96.8	97.8	98.6	99.2	99.6	99.9	100

Table 2.5. presents the principal component eigenvector coefficients and (contributions (%)) associated with each attribute. It can be observed that C1 to C4, C7, C8, C11, and C13 are the dominant attributes (contribution percentage >7.5%) for the first principal component (PC1). It is also seen that C1 to C5, C9, and C12 have a major influence (contribution percentage >7.5%) on the second principal component (PC2), and C6 and C12 have the most influence on the third principal component (PC3), with a contribution percentage > 7.5%.

To acquire a better understanding of where our original data stands vis-à-vis the transformed coordinate system of the principal components, the first principal component (PC1) against the second principal component (PC2) are plotted (Figure 2.5.). The figure illustrates the original data points (color coded by continent) in the coordinate system of the first two principal components: PC1 with a 66.6% cumulative variance of the data on the x-axis and PC2 with a 13.0% cumulative variance of the data on the y axis. Hence, in total, 79.6% of the total variance among all attributes (C1 to C13) are explained in this plot. The plot reveals that certain countries fall into outlier categories: Rwanda and Gambia on one hand, and Switzerland and Singapore on the other hand. Also, Italy, Argentina, Libya, and Mauritania exhibit evident disparities compared with other countries. Figure 5a. also illustrates the vectors associated with all the corruption-related attributes (C1 to C13). This loading plot shows how strongly each attribute influences a principal component. Also, this plot provides a basis to discern the core attributes (characteristics) possessed by countries in each cluster. It may be noted that in the figure, the vectors are scaled to facilitate visualization. The vectors' direction and position are important in this graph, and can be interpreted as follows:

(a) *Vector length*. Longer vectors denote a higher contribution to PC1 and PC2. For example, GNI (C1), EGI (C2), human development index (C3), public-sector performance (C5), and labor market efficiency (C9) are identified in this plot as the most influential attributes.

(b) *Axis proximity of vectors*. Closer vectors to the x-axis are more influential to PC1, and those closer to the y-axis are more influential to PC2. For example, Business sophistication (C13) and Transport infrastructure (C7) Influence PC1, and Public-sector performance (C5), Labor market efficiency (C9), and Market size (C12) Influence PC2.

(c) *Vector angles*. The angles between the vectors indicate the degree of correlation between them: closer vectors (smaller angles) denote positive correlation, and when the angles get closer to 180º, it shows a negative correlation. For example, GNI (C1) and HDI (C3) are highly correlated as well as Undue influence (C4) and Security (C6). Public-sector performance (C5) and Labor market efficiency (C9), and Goods market efficiency (C8) and Financial market development (C10) are highly correlated. Also, note that C13, C10, C8, C6, C4, C9, and C5 are negatively correlated with PC2 (all attributes are positively correlated with PC1); in other words, the countries with higher PC2 values have lower values for C13, C10, C8, C6, C4, C9, and C5.

(d) *Positions of countries relative to a vector*. Countries on the same side of a given vector have a high value for that vector and those on opposite sides have a low value for that vector. For example, Germany has a considerably high value for Business sophistication (C13) and Transport infrastructure (C7), and Mauritania has a position opposite to Germany. Market size (C12) for Italy is considerably high versus Rwanda that is placed on the other side of the plot. Similarly, Rwanda's Public-sector performance (C5) and Labor market efficiency (C9) is opposite to Italy.

Table 2.5. Selected principal component eigenvector coefficients and *attribute contributions (%)*

PCs	Attributes												
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
PC1	0.28	0.30	0.29	0.29	0.26	0.23	0.30	0.32	0.24	0.27	0.31	0.17	0.32
(%)	*(8.10)*	*(8.85)*	*(8.14)*	*(8.20)*	*(6.54)*	*(5.46)*	*(9.17)*	*(9.96)*	*(5.89)*	*(7.07)*	*(9.79)*	*(2.78)*	*(10.04)*
PC2	0.35	0.30	0.36	-0.28	-0.44	-0.19	0.07	-0.14	-0.40	-0.15	0.19	0.33	-0.02
(%)	*(12.29)*	*(9.24)*	*(12.71)*	*(8.02)*	*(19.11)*	*(3.54)*	*(0.44)*	*(2.06)*	*(15.68)*	*(2.25)*	*(3.47)*	*(11.12)*	*(0.06)*
PC3	-0.21	-0.14	-0.23	0.04	0.11	-0.48	0.25	0.02	-0.02	0.22	-0.21	0.68	0.18
(%)	*(4.21)*	*(2.02)*	*(5.31)*	*(0.20)*	*(1.20)*	*(22.84)*	*(6.04)*	*(0.05)*	*(0.02)*	*(4.64)*	*(4.60)*	*(45.64)*	*(3.21)*

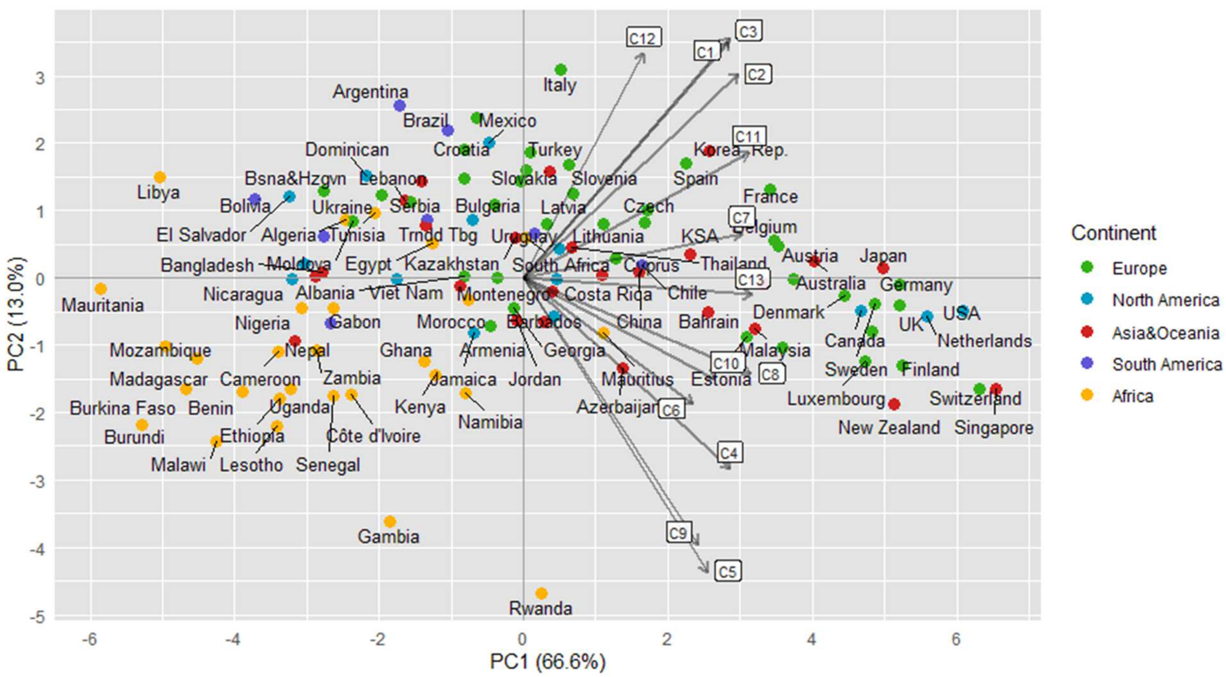


Figure 2.5. The original data in the principal components' coordinate system of the (color-coded by continent) where PC1and PC2 are the 1st and 2nd principal components, respectively

A PCA plot converts the correlations (or lack thereof) across all the countries into a 2-dimensional graph, and it is indicative of the clustering potential of the data. Also, a biplot with vectors helps to identify the common characteristics not only in each country but also in each cluster. As this study focus is related to identifying the corruption levels in countries, the countries are grouped by their CPI values with respect to PC1 and PC2. Figure 2.6. shows the same data as Figure 2.5. color coded by the level of corruption as follows: Very High Corruption (CPI ≤ 25); High Corruption (25 < CPI ≤ 50); Medium Corruption (50 < CPI ≤ 75); and Low Corruption (75 < CPI ≤ 100). As observed from the graph, countries with perceived low corruption levels are grouped on the right side of the plot, while those perceived to be highly corrupt are grouped on the left side. Most of the countries with medium corruption levels are located between the origin, and the countries with perceived low corruption levels, and most countries with perceived high corruption levels are positioned between the origin and the countries with perceived very high corruption levels. These observations seem to provide validation for the need to cluster the countries. This is because it provides policymakers with both opportunity and basis to develop unique sets of palliatives for countries within each cluster, as a one-size-fits-all policy for all countries may not be practical.

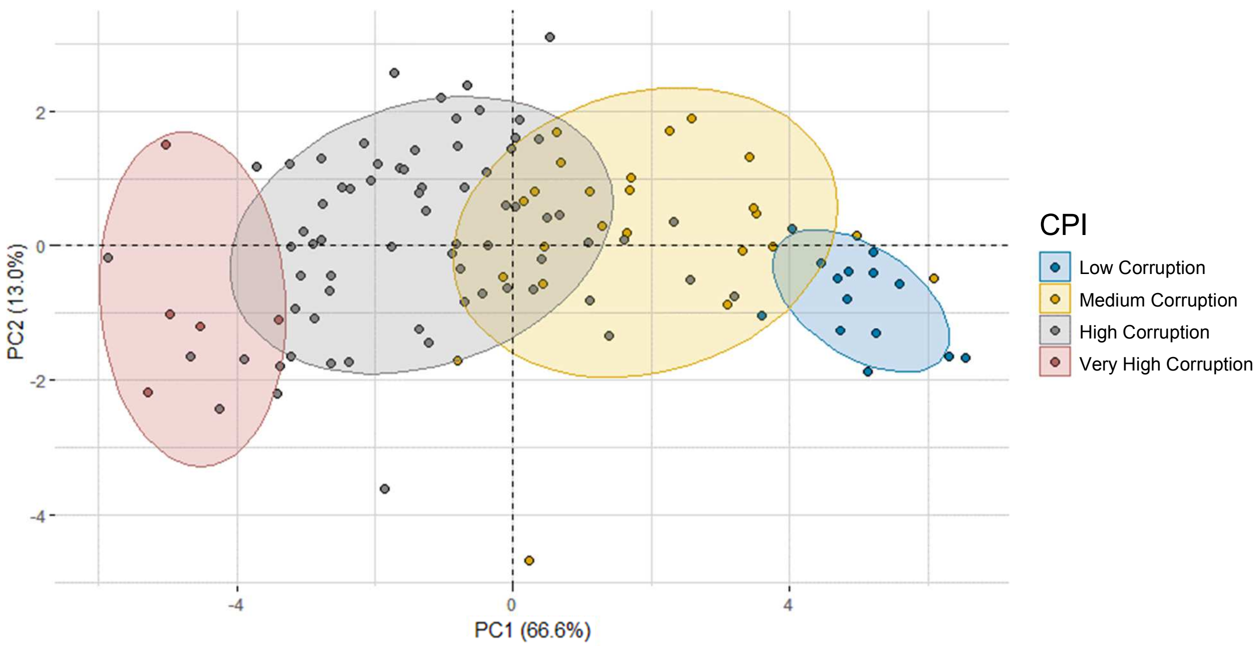


Figure 2.6. Clustering of countries based on perceived corruption using PCA dimensions

2.5.2 Cluster Analysis

The results of the cluster analysis helped address two questions: (1) What is the optimum number of clusters? (2) Which countries fall into each cluster? The hierarchical method was used for clustering the countries based on their development-related attributes represented by the three principal components (PC1, PC2, and PC3) selected in the previous section, and the measured Euclidean distance between these components. Four different distance measures were used: median clustering method, Ward's method, the nearest neighbor algorithm, and the average linkage clustering technique. The results are compared using the cophenetic correlation coefficients (CCCs) for verification and comparison purposes, and for purposes of identifying the best clustering method. CCC helped gage the extent to which the dendrogram upholds the pairwise distances between the original unmodeled data points (Shoba et al., 2019). The maximum value of the CCC helped identify the best method for the hierarchical agglomerative clustering. Table 2.6., which presents the cophenetic correlation coefficients, suggests that the average linkage method is the best clustering for clustering the data in this study. Further, the optimal number of clusters using the K-means clustering method – a machine-learning based clustering technique, was identified as four clusters (Table 2.7.).

Table 2.6. The cophenetic correlation coefficient values

Methods	Median method	Ward's method	Nearest neighbor algorithm	**Average linkage technique**
Values	0.872	0.889	0.907	**0.928**

Table 2.7. K-means clustering method results

Machine learning trials	Optimum number of clusters
4	2
3	3
8	**4**
3	7
2	10
1	12
1	15

Figure 2.7. and Table 2.8. present the cluster analysis results, including the number of countries on each continent in each cluster, and the dendrogram representation, respectively, using the average linkage technique. Figure 2.8. illustrates the position of each country in each cluster considering the corruption levels (CPI values). Table 2.8. indicates that there are 41 countries in Cluster 1, 28 countries in Cluster 2, 20 countries in Cluster 3, and 24 countries in Cluster 4.

Assuming that high CPI values are associated with higher levels of corruption control, it is observed that Estonia, France, Uruguay, Chile, and Barbados are located at the top corruption control level (higher CPI values ~70) in the first cluster. Azerbaijan, Kazakhstan, Russia, and Mexico on the other hand are positioned at the bottom of this cluster with considerably low CPI values (~30). Croatia and Greece are grouped into Cluster 2 with CPI values around 50. Nigeria, Nicaragua, and Bangladesh fall into the same cluster with significantly lower CPI values around 25. It is also observed that New Zealand, Denmark, Finland, and Norway are at the top of Cluster 3 with CPI values near 88. In the same cluster, Israel with CPI near 62 and Malaysia with CPI close to 45 are at the bottom of Cluster 3. Rwanda (CPI close to 60) and Namibia (CPI near 50) are positioned at the top of Cluster 4, and Cameroon, Mozambique, Burundi, and Libya are located at the bottom of Cluster 4 with CPI values lower than 25. All in all, these results suggest that countries in the Clusters 2 and 4 are in significant need of corruption control measures.

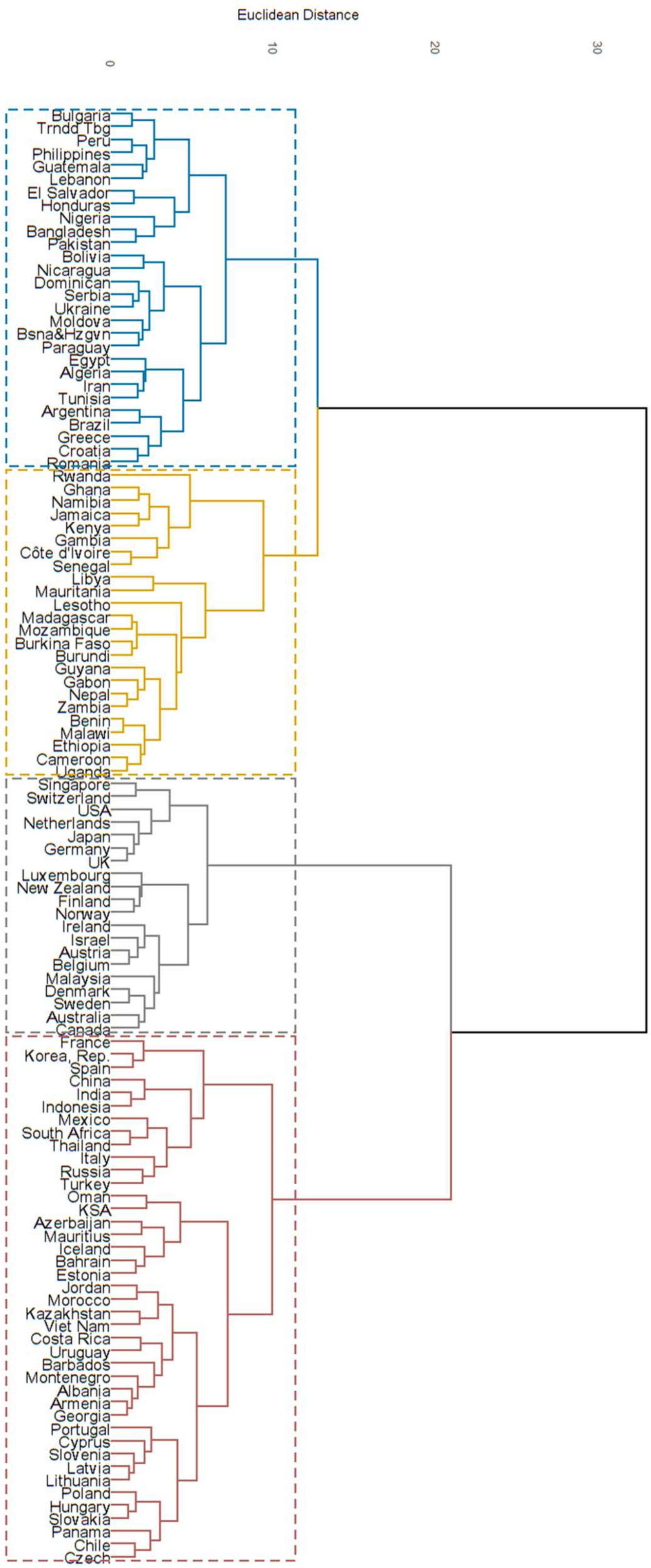


Figure 2.7. Cluster dendrogram – Cluster 1: Red, Cluster 2: Blue, Cluster 3: Grey, and Cluster 4: Yellow

Table 2.8. The cluster analysis results

Clusters	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Countries	Albania, Armenia, Azerbaijan, Bahrain, Barbados, Chile, China, Costa Rica, Cyprus, Czech, Estonia, France, Georgia, Hungary, Iceland, India, Indonesia, Italy, Jordan, Kazakhstan, Korea (Rep.), Latvia, Lithuania, Mauritius, Mexico, Montenegro, Morocco, Oman, Panama, Poland, Portugal, Russia, KSA, Slovakia, Slovenia, South Africa, Spain, Thailand, Turkey, Uruguay, Viet Nam	Algeria, Argentina, Bangladesh, Bolivia, Bosnia-Herzegovina, Brazil, Bulgaria, Croatia, Dominican, Egypt, El Salvador, Greece, Guatemala, Honduras, Iran, Lebanon, Moldova, Nicaragua, Nigeria, Pakistan, Paraguay, Peru, Philippines, Romania, Serbia, Trinidad Tobago, Tunisia, Ukraine	Australia, Austria, Belgium, Canada, Denmark, Finland, Germany, Ireland, Israel, Japan, Luxembourg, Malaysia, Netherlands, New Zealand, Norway, Singapore, Sweden, Switzerland, UK, USA	Benin, Burkina Faso, Burundi, Cameroon, Côte d'Ivoire, Ethiopia, Gabon, Gambia, Ghana, Guyana, Jamaica, Kenya, Lesotho, Libya, Madagascar, Malawi, Mauritania, Mozambique, Namibia, Nepal, Rwanda, Senegal, Uganda, Zambia
No. of Countries in Each Continent	Africa 3 Asia & Oceania 13 Europe 19 North America 4 South America 2	Africa 4 Asia & Oceania 5 Europe 8 North America 6 South America 5	Africa 0 Asia & Oceania 6 Europe 1 North America 1 South America 3	Africa 21 Asia & Oceania 1 Europe 0 North America 1 South America 1

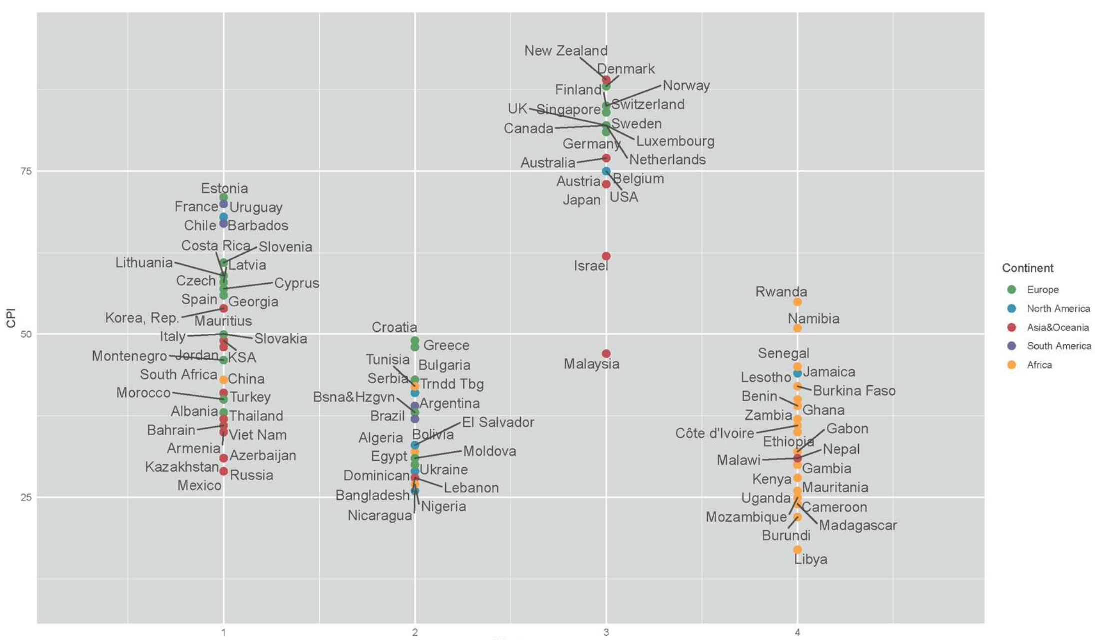


Figure 2.8. Country positions within each cluster based on perceived corruption level

2.5.3 Regression Tree Analysis & Random Forest Machine Learning Technique

The results of the regression tree (or, decision tree) analysis can provide a clear picture of the underlying structure in data and relationships between the corruption-related variables and for understanding the interactions between these variables. Figure 2.9. presents the regression tree analysis on the dataset for all countries. As discussed in the methodology section, 85% of the data were allocated to the "training" dataset and 15% of the data to the "test" dataset. Therefore, the decision tree analysis started by predicting the CPI value for 96 countries. As seen from the figure, the attribute C11 (Technological readiness) is highly influential in estimating the level of corruption in a country. The regression tree analysis begins with 96 countries and an average CPI value of 46.8 (root node #1). The root node (the topmost node in a decision tree) breaks into decision nodes. It may be recalled that in the PCA section of this dissertation, the CPI values were categorized as follows: Very High Corruption (CPI ≤ 25); High Corruption (25 < CPI ≤ 50); Medium Corruption (50 < CPI ≤75); Low Corruption (75 < CPI ≤ 100). The CPI value for root node #1 indicates that if all countries considered altogether, the CPI value for the entire world would be below 50 ("High Corruption Level").

Root node #1 is split into decision nodes #2 and #3 based on the value of C11 with the 5.17 cutoff. Decision node #2 (C11<5.17) contains 71.9% of the data (69 countries) with an average CPI value of 37.2, and decision node #3 (C11>5.17) includes the remaining countries with a mean CPI value of 71.5. Following C11, C3 (Human development index) becomes more influential for the countries with higher corruption levels (higher CPI values); decision node #3 splits into leaf node #6 (C3<0.9) and leaf node #7 (C3>0.9) for the countries with predicted CPI values of 60.2 (12 Mid Corruption countries) and 80.6 (15 Low Corruption countries), respectively. This indicates that C3 (Human development index) directly affects the corruption level performance in those certain countries where C11 is over 5.17.

On the other side of the spectrum, C11 is still the most influential attribute for decision node #2. Decision node #2 splits into decision node #4 and leaf node #5 based on the new C11 threshold of 4.7. Decision node #4 (C11<4.7) and leaf node #5 (C11>4.7) include 58 countries and 11 countries. The average CPI value for decision node #4 and the predicted CPI value for leaf node #5 are 34.8 and 49.5 (Mid-High Corruption), respectively. This indicates that C11 (Technological readiness) directly affects the corruption level where C11 is between 4.7 and 5.17.

Finally, for decision node #4, the most influential attribute is C5 (Public-sector performance) with a threshold value of 3.74. Decision node #4 breaks into two subtrees: leaf node #8 (C5<3.74) with 41 countries or 42.7% of the data and leaf node #9 (C5>3.74) with 17 countries or 17.7% of the observations. Leaf node #8 contains the countries with the highest corruption values and the predicted CPI value of 32 (High Corruption), and the predicted CPI value for leaf node #9 is 41.8 (High Corruption). This indicates that C5 (Public-sector performance) directly affects the corruption level in those certain countries where C11 is below 4.7.

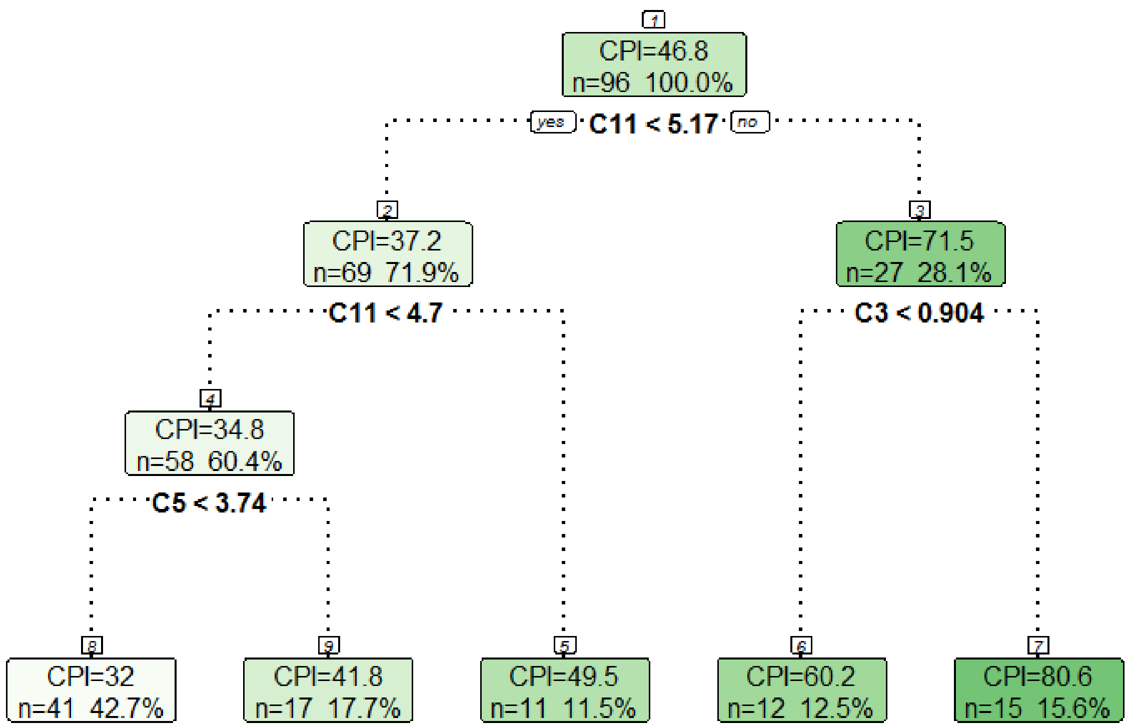


Figure 2.9. Regression tree analysis for all countries (with 85% "training" dataset)

To confirm and compare the results obtained from the decision tree analysis, a random forest analysis is performed. This technique improves predictive precision by producing a large number of bootstrapped trees (based on random samples of variables), categorizing a case using each tree in this new "forest", and determining a final projected outcome by joining the results across all of the trees (Munasinghe, 2019). The results of the random forest technique (which was applied to all countries and to each of the four clusters established in the previous section of this dissertation) helped identify the attributes that are most influential to the corruption levels within each cluster. Similar to the decision tree analysis, the Corruption Perceptions Index (CPI) was used as the dependent variable, and the predictive accuracy of the random forest prediction models were compared using the following metrics of model performance: the adjusted-R^2, root mean square error (RMSE), and mean absolute error (MAE).

Table 2.9. presents the errors for the decision tree analysis, the random forest technique errors, and the CPI mean values for the training dataset, the decision tree prediction, and the random forest prediction for all countries and each cluster. The first row indicates the statistics related to all countries. The errors for the random forest technique are observed to be slightly lower than those of the decision tree analysis, meaning that the random forest technique outcome is relatively more accurate and provides a superior fit compared with the decision tree output. The average CPI value for the test dataset for all countries is 53.62. The RF prediction for CPI values for all countries is 52.85 versus 52.19 from the decision tree analysis. For Cluster 1 through Cluster 4, the errors are slightly higher than that of all countries. The errors from the decision tree analysis are slightly higher those from the RF analysis for all clusters, similar to what observed from the first-row analysis. The average CPI value for the test dataset for Cluster 1 to Cluster 4 is 39.14, 83.67, 56.41, and 33.74, respectively. The RF prediction is closer to this value compared with that of the decision tree output. The RF prediction for Cluster 1 to Cluster 4 is 37.24, 82.31, 55.03, and 32.23, respectively, and this value from the decision tree prediction is 35.46, 78.94, 53.21, and 30.23, respectively.

Table 2.9. The decision tree and random forest prediction statistics for CPI for each cluster

	Regression Tree Errors			Random Forest Errors			CPI Values		
	RMSE	R^2	MAE	RMSE	R^2	MAE	Test Set Mean	Reg. Tree Prediction	RF Prediction
All Countries	8.6000	0.8010	6.9759	8.2640	0.8005	6.3772	53.6250	52.1944	52.8550
Cluster 1	9.7969	0.6721	8.0865	9.1410	0.6664	7.7917	39.1429	35.4626	37.2426
Cluster 2	9.6365	0.5279	7.7912	9.6106	0.5336	7.3628	83.6667	78.9412	82.3108
Cluster 3	10.4577	0.4803	9.5438	9.6794	0.5137	8.5018	56.4109	53.2105	55.0265
Cluster 4	9.4280	0.5211	7.8629	9.0186	0.5366	7.7529	33.7398	30.2353	32.2296

Partial dependence plots (graphical visualizations of the marginal effect of given variables on the outcome (Milborrow, 2020)) are used to further investigate the relationship between the predictors and the outcome in random forests. The plots are useful for acquiring deeper understanding of the trends in large datasets, and provide useful information where the random forest is governed by lower-order interactions and main effects (Martin, 2014). Since human perception is limited, the attributes are kept to three including the outcome variable (CPI) and the first two attributes that have the most impact on the RFA. For this purpose, the impact from each variable is shown in Figure 2.10.(a) through Figure 2.14.(a) as the Importance Level – also known as “the Mean Decrease in Gini charts.” In other words, each variable in the matrix is an indication of the importance of that variable in classifying the data. Figure 2.10.(b) through Figure 2.14.(b) show the partial dependence plot between the predicted variable (CPI) and the first two important predictors in each cluster – resulting in the three-dimensional partial dependence plots.

Figure 2.10.(a) and Figure 2.10.(b) illustrate the RFA results for all countries. Figure 2.10.(a) suggests that of all the attributes C1 to C13 that predict the outcome (CPI), the attributes C11, C3, and C2 have the highest influence. This indicates that overall, Technological readiness (C11), Human development index (C3), and e-governance index (C2) are most important in predicting a country’s level of corruption (CPI). In other words, these three attributes are the key elements that deserve a particular attention from oversight agencies and policymakers that seek to mitigate corruption. Clearly, improvements in technological readiness, human development index, and e-governance index would have the most profound impacts on corruption reduction. Figure 2.10.(b) presents the relationship between CPI and the contribution of C11 and C3 (the topmost influential attributes of CPI identified using the random forest technique). The plot indicates a positive relationship between CPI, and C11 or C3: an increase in the value of each of these two attributes is strongly associated with an increase in the CPI, suggesting that an improvement in C11 and C3 may lead to a significant increase in CPI (reduction in corruption). With technological readiness above 5 and human development index above 0.8, countries can expect a significant reduction in their corruption levels.

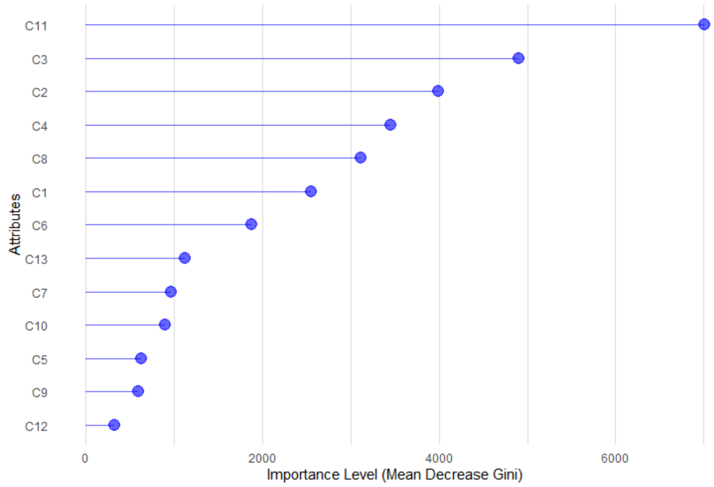
Figure 2.11.(a) and Figure 2.11.(b) present the results of the random forest analysis on Cluster 1. It shows that of all the attributes, C11, C1, and C6 have the highest impact on CPI. It indicates that for the countries in Cluster 1, technological readiness (C11), GNI (C1), and security (C6) have highest importance for predicting their corruption level (CPI). This result suggests that in their efforts to combat corruption, countries in the first cluster could pay more attention to these three characteristics). Figure 2.11.(b) presents the relationship between CPI and the contribution of C11 and C1 (the two most crucial attributes in predicting CPI, identified using the random forest algorithm). It is noticed from the contour plot that by moving GNI to exceed 10 and technological

readiness to exceed 4.5, a considerable reduction in corruption level can be experienced in the Cluster 1 countries.

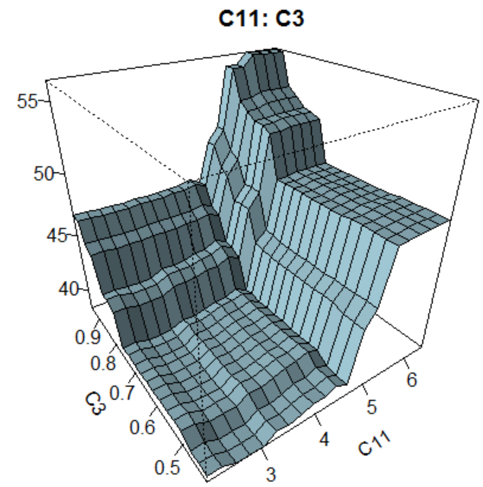
Figure 2.12.(a) and Figure 2.12.(b) present the results for the random forest analysis on Cluster 2. It is observed that, the human development index (C3), undue influence (C4), and e-governance index (C2) are among the most influential attributes in predicting the CPI values for Cluster 2, and therefore could be among focal points in efforts to address corruption in those countries. Figure 2.12.(b) presents CPI versus the contribution of C3 and C4 (the two highly critical attributes in the prediction of CPI with RFA). This contour plot suggests that increasing C3 to exceed 0.92 and a 0.5 unit increase in C4 in Cluster 2 would lead to a significant reduction in corruption (that is, increase in the CPI value).

Figure 2.13.(a) and Figure 2.13.(b) present the results for the random forest analysis on Cluster 3, and indicate that C5, C9, and C2 are the top three attributes that influence the CPI values in that cluster. It shows that for the countries in the third cluster, public-sector performance (C5), labor market efficiency (C9), and e-governance index (C2) are of highest importance in predicting their corruption level (CPI), and could serve as the points of attention in efforts towards corruption mitigation in those countries. Figure 2.13.(b) presents the CPI versus the contribution of C5 and C9 (the two most crucial attributes in predicting CPI with the random forest algorithm). From this contour plot, it is recognized that there is an optimum level in the public-sector performance value (between 3.5 – 4.0) and labor market efficiency (around 4.5).

Figure 2.14.(a) and Figure 2.14.(b) illustrate the results for the random forest analysis on Cluster 4. As can be seen from the figures, C4, C5, and C6 in Cluster 4 have the most significant effect on the outcome of the predicted CPI values. This shows that among the countries in Cluster 4, undue influence (C4), public-sector performance (C5), and security (C6) are of the highest importance in predicting the level of corruption (CPI) for Cluster 4. These three attributes are the key elements that could be given a significant attention from the policymakers of the countries in this cluster to reduce corruption. Figure 2.14.(b) demonstrates CPI versus the contribution of C4 and C5 (the topmost important attributes in predicting CPI with the random forest technique). The plot shows that improving both variables can lead to a significant increase in CPI values. With undue influence and public-sector performance above 3, the countries in this cluster can expect a significant decrease in their corruption levels.

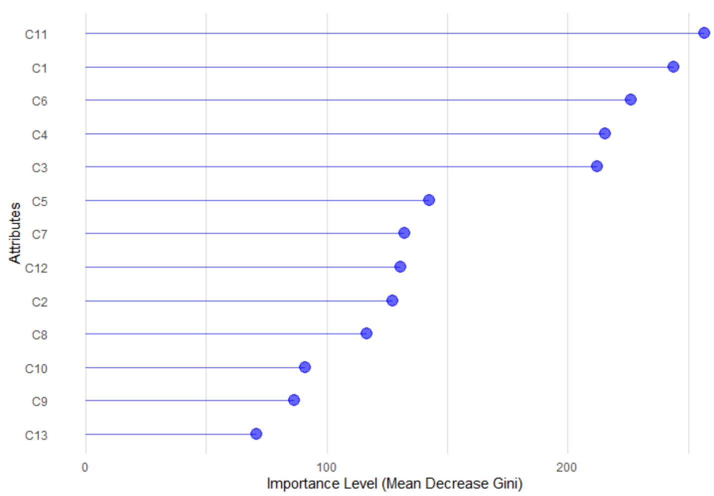


(a) Importance level
(mean decrease in Gini)

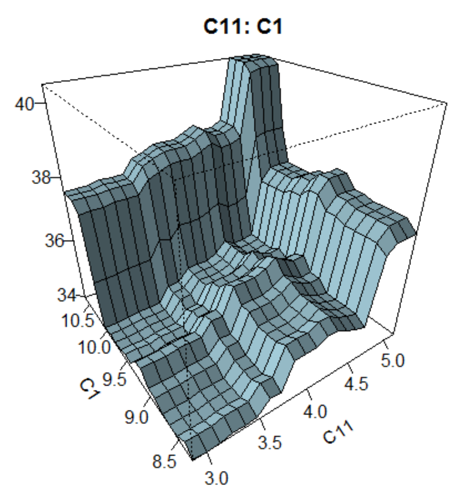


(b) Partial dependence plot
(CPI versus C11, and C3)

Figure 2.10. ML Results for All Countries

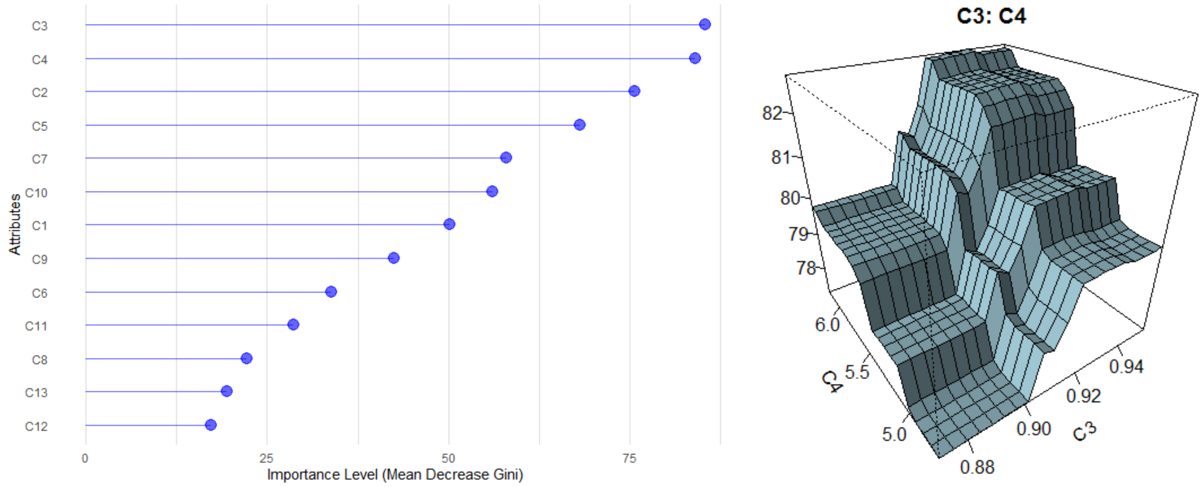


(a) Importance level
(mean decrease in Gini)



(b) Partial dependence plot
(CPI versus C11, and C1)

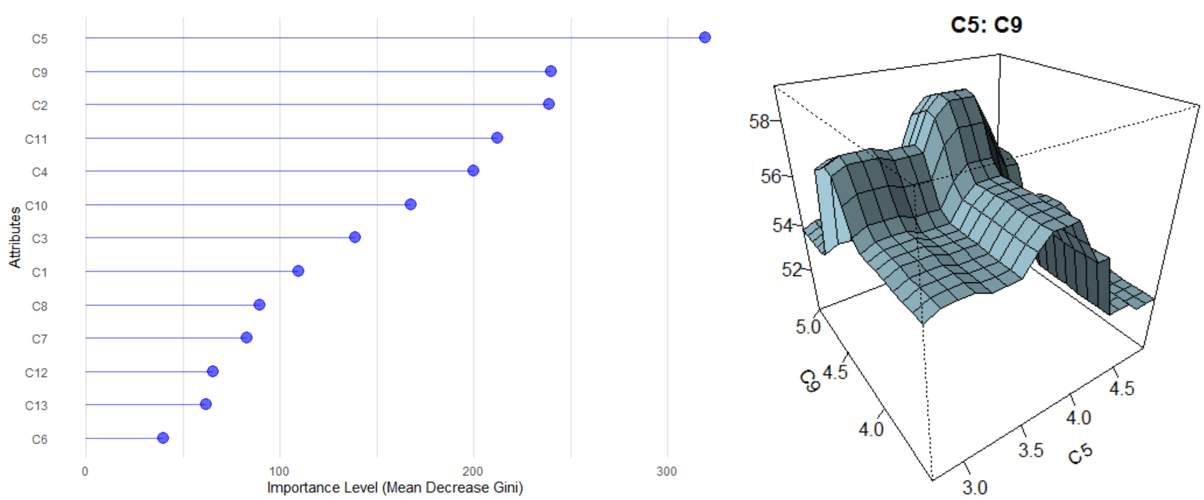
Figure 2.11. ML Results for Cluster 1 Countries



(a) Importance level
(mean decrease in Gini)

(b) Partial dependence plot
(CPI versus C3, and C4)

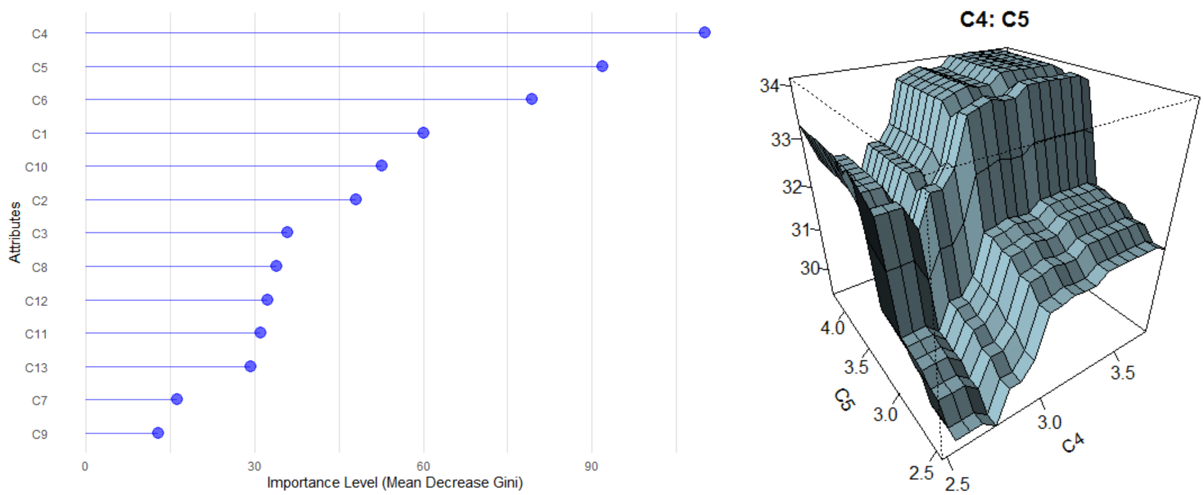
Figure 2.12. ML Results for Cluster 2 Countries



(a) Importance level
(mean decrease in Gini)

(b) Partial dependence plot
(CPI versus C5, and C9)

Figure 2.13. ML Results for Cluster 3 Countries



(a) Importance level
(mean decrease in Gini)

(b) Partial dependence plot
(CPI versus C4, and C5)

Figure 2.14. ML Results for Cluster 4 Countries

2.6 Concluding Remarks

Corruption is a multidimensional and complex societal malady that occurs in various forms and contexts. Corruption has been found to be related to inefficiency and instability, and therefore degrades the political economy of countries. As an antithesis of the values of honesty, equity, and transparency, corruption weakens the integrity and stability of governmental institutions and degrades trust and confidence in governments. Annually, more than 5% of the world GDP is lost due to collusion, corruption, and fraud (Irisova, 2014) and therefore, the need to address the problem cannot be overemphasized. It is important that any effort to fight corruption must be preceded by a forensic analysis not only of the high-level factors that promote (or are associated with) high levels of corruption but also those that inhibit the practice or are associated with relatively low levels.

As such, corruption analysis studies must be accompanied by a thorough examination of the attributes that might play role in promoting or exacerbating corrupt environments. These attributes, and the magnitude and severity of their impacts on corruption, are generally believed to exhibit significant variation across the countries and continents. In this chapter, thirteen (13) country-specific development-related attributes that hypothetically influence corruption levels were investigated at one hundred and thirteen (113) countries. The attributes that significantly influence corruption were identified. First, principal component analysis (PCA) is conducted, and

K-means and hierarchical structure cluster analysis to identify groups of countries based on the attribute levels. The results helped identify clusters that require attention from a corruption control viewpoint. Then, Corruption Perceptions Index (CPI) was estimated for each cluster using decision tree analysis and random forest algorithm (a machine learning technique), separately. The results suggest that the random forest algorithm yields relatively reliable predictions compared with decision tree analysis. The results also indicate that improvements in technological readiness, human development index, and e-governance index would have the most profound impacts on corruption reduction. The clusters identified in this chapter could serve as a starting point for governmental and non-governmental oversight agencies to study corruption forms and contexts that are common to the countries in each cluster, and to identify which mitigation techniques have worked in these countries.

In this chapter of the dissertation, the attributes that have a significant influence on the corruption levels in countries were identified. For 113 countries, 13 attributes including the GNI, e-governance index (EGI), human development index (HDI), transport infrastructure, and technological readiness were investigated. Principal component analysis (PCA) was carried out to remove any collinearity among the attributes. Also, K-means and hierarchical structure cluster analyses were conducted to establish groups of countries that share similar development-related attributes. Finally, a regression tree analysis and random forest technique were implemented to predict corruption levels for and within each cluster. Using this machine learning technique, the most important attributes for each cluster, were determined. The bootstrap technique was used to ensure the reliability of the decision tree analysis, and a k-fold cross-validation technique was applied to ascertain the accuracy of the random forest analysis.

The PCA biplot showed that the most influential attributes of corruption were a country's development-related attributes GNI (C1), EGI (C2), human development index (C3), public-sector performance (C5), and labor market efficiency (C9). From the PCA plots and country clusters based on their CPI values, the highest development-related attribute variability was observed in the countries that fall into medium and high corruption levels. This corroborated the notion that clustering the countries is an important prelude to identifying corruption mitigation measures, and that a one-size-fits all policy for all countries, may not be efficacious. The results of the K-means clustering and the cophenetic correlation coefficient for hierarchical clustering indicated that the countries can be placed into four groups (clusters) based on their development-related attributes.

The regression tree analysis for predicting and classifying CPI values based on the 13 attributes suggest that public-sector performance value (C5) directly affects the level of corruption in countries where the technological readiness value (C11) is below 4.7. On the other hand, in the countries with technological readiness (C11) exceeding 5.17, the human development index (C3) directly affects the corruption levels.

The partial dependence plots from the random forest analysis suggest that for all countries, there is a positive relationship between technological readiness (C11) and human development index (C3), and corruption levels. The Gini charts obtained from the random forest machine learning technique showed that of all the attributes investigated, technological readiness (C11), human development index (C3), and e-governance index (C2) are the most influential of corruption levels in a country. It indicated that improvements in technological readiness, human development index, and e-governance index would have the most profound impacts on corruption reduction. Furthermore, the results identified, for each cluster, the attributes that could serve as a focal point for efforts geared toward corruption mitigation, as follows: Cluster 1: technological readiness, GNI, and security; Cluster 2: human development index, undue influence, and e-governance index; Cluster 3: public-sector performance, labor market efficiency, and e-governance index; and Cluster 4: undue influence, public-sector performance, and security. Overall, the result of this study provides valuable guidance to governments, non-governmental agencies, and other stakeholders that are involved in corruption identification and measurement, and more importantly, corruption control or mitigation efforts.

The results of this study are based on the data that are available at the time of writing. With time, more data will be available as they are reported annually. With updated information from the various sources (and consequently, an expanded study dataset), it will be possible, in future research, to replicate the analysis, to draw conclusions with greater confidence. Another avenue of prospective future work is to finetune the hyperparameters of the machine learning model in order to enhance the reliability of that part of the analysis. Further, the conclusions and recommendations in this study are made for each cluster of countries and not each country. These results could serve as platform upon which further analysis could be carried out for each country, account for the relevant attributes of each country that are occluded when the analysis is carried out at a high level. Finally, while this study focused on corruption estimation and prediction, the results lay the groundwork for advancing other research s that addresses corruption mitigation and control.

CHAPTER 3. CORRUPTION - CLUSTER FORECASTING USING NONLINEAR AUTOREGRESSIVE MODEL WITH EXOGENOUS VARIABLES (NARX) – AN ARTIFICIAL NEURAL NETWORK TIME SERIES ANALYSIS

3.1 Introduction

Transparency International (2017) defines corruption as "the abuse of public power for private benefit (or profit)." Fraudulent practice, according to the World Bank (2009) guidelines, is "any act or omission, including a misrepresentation, that knowingly or recklessly misleads, or attempts to mislead, a party to obtain a financial or other benefit or to avoid an obligation"; a collusive practice is "an arrangement between two or more parties designed to achieve an improper purpose, including influencing improperly the actions of another party."; and a corrupt practice is defined as "the offering, giving, receiving or soliciting, directly or indirectly, of anything of value to influence improperly the actions of another party" (Integrity Vice Presidency, 2009).

Corruption is a multifaceted phenomenon that ranges from a minor infraction or small act of a forbidden compensation to a pervasive mass looting by public officials. Hence, it has considerable detrimental effects on sustainable development (Loosemore & Lim, 2015; Tabish & Jha, 2012a). Sustainable development is defined as "Development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (ASCE, 2010). In other words, sustainable development is conservation of resources and the minimization of waste and pollution (Brundtland, 1987).

Ten thousand years ago, during the Neolithic Revolution, human beings started changing the environment in a way that they could pursue their needs. Small villages and societies were formed quickly, and that led to unsustainable practices due to the immediate change in the environment. As a result of the Industrial Revolution, humans overcame the limitations associated with agrarian societies (Ghahari et al., 2019b; Labi, 2014).

The principles of sustainability include enhancing or maximizing the quality and quantity of natural resources through reduction of use, reuse, and recycling, which minimizes the damage to the physical environment (Brundtland, 1987). A corrupt society, however, fails to take the constructive steps toward a sustainable development, such as (a) avoiding adverse institutional effects; (b) maintaining or enhancing the current and future quality of life; (c) providing flexibility for changes in stakeholder requirements; (d) basing policy and business on values such as fairness, duty, knowledge-based solutions, and efficient production; and sharing responsibility for decision making, planning, and results. Corruption causes short-term economic inefficiency (specifically in the private market), and in the long-term, dynamic inefficiency and instability in economic growth and sustainability.

An accurate picture of how global corruption is evolving is need to develop effective policies and corruption-control measures, not only from a monitoring standpoint, but also from the perspective of being able to assess the long-term effectiveness of programs, policies, and initiatives targeted towards corruption mitigation. The main objective of this study is to forecast corruption levels globally and also in clusters of like countries using artificial neural network (ANN) techniques. The data are from 113 countries, and span the time period 2007 to 2017. The study considers two levels of analysis. The first is the global level (all countries considered together as a single group). Then to ensure model flexibility by avoiding making the same predictions for countries that are very dissimilar in terms of development-related attributes, cluster-level analysis was carried out using techniques established in the literature.

In the previous chapter (chapter 2 of this dissertation) that addresses cluster analysis of corruption in all countries using machine learning methods, the four most influential factors of corruption (measured in terms of Corruption Perceptions Index (CPI)) were identified for each cluster, and those factors are used as independent variables in the model in the current chapter of this dissertation. The model type used in this chapter is the nonlinear autoregressive recurrent neural network with exogenous inputs (NARX) technique. In the next section of this chapter, the literature on related studies in the area of corruption is reviewed. This is followed by data collection and the methodology used for the research, discussion of the results, and conclusions and recommendations for future work.

3.2 Literature Review

Many factors affect the levels of corruption in countries, some exacerbate corruption, and some inhibit corruption. Corruption is a complex phenomenon, and multiple linear regression and other similar methods inadequately model corruption. Hence, a method that can handle time series in complex systems is needed to reveal the patterns and trends in the corruption data analysis. In this chapter, the focus is made on artificial neural network (ANN) techniques due to their potential for solving problems of this nature (Khalil et al., 2019; López-Iturriaga & Sanz, 2018;

Woldemariam et al., 2016). ANNs also possess superior predictive accuracy compared to multi-linear regression, support vector machine (SVM), and multivariate adaptive regression splines (Ekonomou, 2010; Yin et al., 2018). Of the various well-known ANN approaches and reliable training algorithms, the nonlinear autoregressive recurrent neural network with exogenous inputs (NARX) forecasting method (a feed backward approach) with the Bayesian regularization training algorithm has been proven to be efficacious in various applications and disciplines (Al-Sbou & Alawasa, 2017; Cicceri et al., 2020; Kayri, 2016; Khan et al., 2014; Yu et al., 2019).

In addition, NARX has been found to be a particularly effective tool for time series analysis (Chen et al., 1990) and in non-linear time series projection, because NARX can utilize its "memory" capability to recollect the preceding values of the predicted time series. It has also been claimed that NARX provides more accurate results compared with other neural network techniques and time series models, such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) (Yu et al., 2019).

The NARX neural network method has been used in various research studies, for example, forecasting heating and cooling electrical loads (Buitrago & Asfour, 2017; Powell et al., 2014), network traffic flows (Alfred, 2015), rainfall (Benevides et al., 2019; Peña et al., 2020), and crop yield and price (Khamis & Abdullah, 2014; Paul & Sinha, 2016). Peña et al. (2020) found that NARX provides significantly more accurate results for rainfall predictions compared with nonlinear regression models and the SVM techniques, and Paul and Sinha (2016) determined that NARX outperforms ARIMA time series models in forecasting crop yield.

NARX has also been applied in macroeconomic modeling. For example, recognizing the episodic and non-linear nature of the gross domestic product (GDP) of a country, researchers have espoused the use of machine learning (ML) techniques such as NARX to improve forecast accuracy of that variable. An example is Cicceri et al. (2020) who showed that the great recession in Italy in 2008-2009 could have been forecasted by NARX neural network methods (Cicceri et al., 2020). Tang (2020) assessed the feasibility of applying NARX for macroeconomic forecasting, national goal setting, and global competitiveness assessment, and carried out case studies using data from countries including China, U.S., and Russia and demonstrated the capability of NARX in forecasting macroeconomic indicators. Khan et al. (2014) performed a performance evaluation of NARX in the foreign exchange market (Khan et al., 2014).

With regard to corruption forecasting, which is considered a complex phenomenon that occurs at different scales and is influenced by numerous factors that change over time, the NARX technique seems to be a promising tool for such predictions. To the best of our knowledge, no study has implemented artificial neural networks, particularly a nonlinear autoregressive recurrent neural network with exogenous inputs (NARX), in predicting CPI in countries.

In this chapter of the dissertation, insights to this critical need in forecasting corruption is provided. For this purpose, data from 113 countries, from 2007 to 2017 is used. The main goal of this chapter is to forecast the Corruption Perceptions Index (CPI) values of countries at the world level and at the cluster level. Building upon the previous chapter, the forecast within the clusters is performed to analyze the countries that have similar development-related levels with each other. The objective function in our NARX models is CPI, and the exogenous variables are chosen based on the previous research outcomes − the top four influential variables on the level of corruption within each cluster as the corresponding exogenous variables for the models. Finally, to fine-tune the neural network hyperparameters, NARX models are generated with different numbers of hidden layers, lags, and neurons to obtain the optimum NARX neural network model as the final model.

3.3 Data

There is rather limited data that can be used in studies of this nature. The data were from the following databases: the World Bank Group (WBG) (WBG, 2017), the United Nations Department of Economic and Social Affairs (UNDESA) (UNDESA, 2017), the United Nations Development Program (UNDP) (UNDP, 2017), the World Economic Forum (WEF) (WEF, 2017), and Transparency International (TI) (TI, 2017) (see Table 3.1.).

The Gross National Income (GNI) is the dollar value of a country's annual income and data on GNI are from the World Bank national accounts database (World Bank, 2017a). UNDESA publishes the E-Governance Index (EGI) data, which indicates the consistency of being able to supervise all scales and levels of government authority, and digital interaction of governments and citizens (UNDESA, 2017). According to UNDP, people and their capabilities is the fundamental benchmark to evaluate the development of a country (HDI), and not its economic growth alone (UNDP, 2017)." In this study, the Human Development Index (HDI) is taken from the UNDP database (UNDP, 2017). The Global Competitiveness Index (GCI) shows the competitiveness landscape of economies, offering exceptional vision into the contributors to the productivity and prosperity of countries (WEF, 2018). In this study, the following attributes from GCI are used: undue influence, public sector performance, security, transport infrastructure, goods market efficiency, labor market efficiency, financial market development, technological readiness, market size, and business sophistication. Finally, Corruption Perceptions Index (CPI) from TI is a ranking indicator that indicates the perceived levels of public sector corruption (TI, 2017); the CPI is the dependent variable in this study.

Table 3.1. Data used for the study and sources

	Database				
	WBG	UNDESA	UNDP	WEF	TI
Variables	Gross National Income per Capita (GNI)	E-Governance Index (EGI)	Human Development Index (HDI)	Global Competitiveness Index (GCI): undue influence; public-sector performance; security; transport infrastructure; goods market efficiency; labor market efficiency; financial market development; technological readiness; market size; business sophistication	Corruption Perceptions Index (CPI)
Code	C1	C2	C3	C4-C13	C0

More discussion on the reasoning behind choosing these attributes can be found in the second chapter of this dissertation on the cluster analysis of corruption level in continents using principal component analysis and machine learning techniques. In the second chapter of this dissertation, a principal component analysis (PCA), cluster analysis, and a random forest technique to determining CPI values for countries were performed. By performing PCA, the potential correlations between the thirteen attributes (C1 to C13 shown in Table 3.1.) were dealt with, and the original potentially correlated attributes were condensed into principal components – with a minimum potential loss of data information. Then, the top three selected principal components (PC1, PC2, and PC3) were used to measure the Euclidean distance between the components for each of the 113 countries to form the clusters. The optimum number of clusters was verified using the K-means machine learning technique, and categorized the countries into four clusters. Table 3.2. shows the list of the countries within their corresponding clusters.

Further, using a random forest algorithm, the marginal effects of the given variables on the outcome were analyzed, and the most important attributes in determining the CPI values using Gini charts were identified and ranked. In the time series analysis that is presented in this dissertation, the top four important attributes corresponding to each cluster were used to predict the CPI values. These attributes are shown in Table 3.3. in descending order of importance/influence.

Table 3.2. The cluster analysis results

Clusters	Countries	No. of Countries in Each Continent	
1	Albania, Armenia, Azerbaijan, Bahrain, Barbados, Chile, China, Costa Rica, Cyprus, Czech, Estonia, France, Georgia, Hungary, Iceland, India, Indonesia, Italy, Jordan, Kazakhstan, Korea (Rep.), Latvia, Lithuania, Mauritius, Mexico, Montenegro, Morocco, Oman, Panama, Poland, Portugal, Russia, KSA, Slovakia, Slovenia, South Africa, Spain, Thailand, Turkey, Uruguay, Viet Nam	Africa Asia & Oceania Europe North America South America	3 13 19 4 2
2	Algeria, Argentina, Bangladesh, Bolivia, Bosnia-Herzegovina, Brazil, Bulgaria, Croatia, Dominican, Egypt, El Salvador, Greece, Guatemala, Honduras, Iran, Lebanon, Moldova, Nicaragua, Nigeria, Pakistan, Paraguay, Peru, Philippines, Romania, Serbia, Trinidad Tobago, Tunisia, Ukraine	Africa Asia & Oceania Europe North America South America	4 5 8 6 5
3	Australia, Austria, Belgium, Canada, Denmark, Finland, Germany, Ireland, Israel, Japan, Luxembourg, Malaysia, Netherlands, New Zealand , Norway, Singapore, Sweden, Switzerland, UK, USA	Africa Asia & Oceania Europe North America South America	0 6 11 3 0
4	Benin, Burkina Faso, Burundi, Cameroon, Côte d'Ivoire, Ethiopia, Gabon, Gambia, Ghana, Guyana, Jamaica, Kenya, Lesotho, Libya, Madagascar, Malawi, Mauritania, Mozambique, Namibia, Nepal, Rwanda, Senegal, Uganda, Zambia	Africa Asia & Oceania Europe North America South America	21 1 0 1 1

Table 3.3. Attributes corresponding to the world level and cluster level, 2007 to 2017

Level	Top four influential attributes
World	C11 - technological readiness, C3 - Human Development Index, C2 - E-Governance Index, C4 - undue influence
Cluster1	C11 - technological readiness, C1 - Gross National Income, C6 - security, and C4 - undue influence
Cluster 2	C3 - Human Development Iindex, C4 - undue influence, C2 - E-Governance Index, C5 - public sector performance
Cluster 3	C5 - public sector performance, C9, C2 - E-Governance Index, C11- technological readiness
Cluster 4	C4 - undue influence, C5 - public sector performance, C6 - security, C1 - Gross National Income

3.4 Methodology

3.4.1 Artificial Neural Network Techniques

Artificial neural network (ANN) are biologically inspired computational networks which simulate the way the human brain investigates and processes information (Park & Lek, 2016). Modeling of complex phenomena requires a comprehensive knowledge of the available data, different modeling approaches, and the outcome of each approach. The approaches for modeling complex systems can be categorized as: Bottom-up (BU) and Top-Down (TD). Each approach requires different levels of details of the data required, and tend to yield different outputs (Swan & Ugursal, 2009). The BU approach follows a hierarchical structure where higher level results are calculated using the accumulation of the lower-level results. However, this approach requires detailed data from the lower levels. Moreover, BU models simply become black boxes when the connection between higher-level data and lower-level (detailed) data is inseparable.

In this chapter, the available data does not meet the criteria required of data for BU. In other words, the attributes for forecasting CPI are not fully separated, and the interconnections between the attributes make the BU approach unfeasible (Brandt et al., 2013). Therefore, the BU approach was eschewed in this study. The TD approach, in the literature, has been considered applicable where economic analysis is being carried out at a national or regional level. This approach avoids outliers and does not need up-to-the-minute data to forecast results (Ozturk et al., 2004). Hence, TD approaches have been implemented in analyzing macro-economic indicators including population (Bianco et al., 2009), environmental factors (Shabani & Shahnazi, 2019), GDP (Ozturk et al., 2004), etc. Due to the nature of the available data in the present chapter, the TD approach is used.

Artificial neural networks (ANNs) with TD approach are significantly beneficial for modeling complex nonlinear functions (Murat & Ceylan, 2006). An ANN model has an input layer, hidden layers, and an output layer, uses neurons to find a pattern within a dataset and expands the pattern to the other or future events. The model is established on a nonlinear relationship between the input layers and the output layers (Muyeen et al., 2014). The ANN accuracy varies with the network structure. Therefore, different training/learning algorithms, and changes in the number of hidden layers, neurons, lags, hyperparameters, etc. can change the output (Beyca et al., 2019).

ANN techniques can be categorized as follows: feed-forward and feed-backward. As shown in Figure 3.1., each category consists of different training algorithms (Poznyak et al., 2018). Feed-forward NN training algorithms include: single-layer perceptron, multi-layer perceptron, and radial-based function network. On the other hand, recurrent or feed-backward NN algorithms include: Bayesian regularization NNs, Hopfield networks, competitive networks, art models, and Kohonen's self-organizing map. One well-known ANN approach and reliable training algorithm for nonlinear complex time series analysis is the nonlinear autoregressive with exogenous variables (NARX). This is an NN time series forecasting method (a feed-backward approach) with the *Bayesian regularization training algorithm* (highlighted in Figure 3.1.) (Al-Sbou & Alawasa, 2017; Cicceri et al., 2020; Kayri, 2016; Khan et al., 2014; Murat & Ceylan, 2006; Yu et al., 2019). This topic is further discussed in the next section.

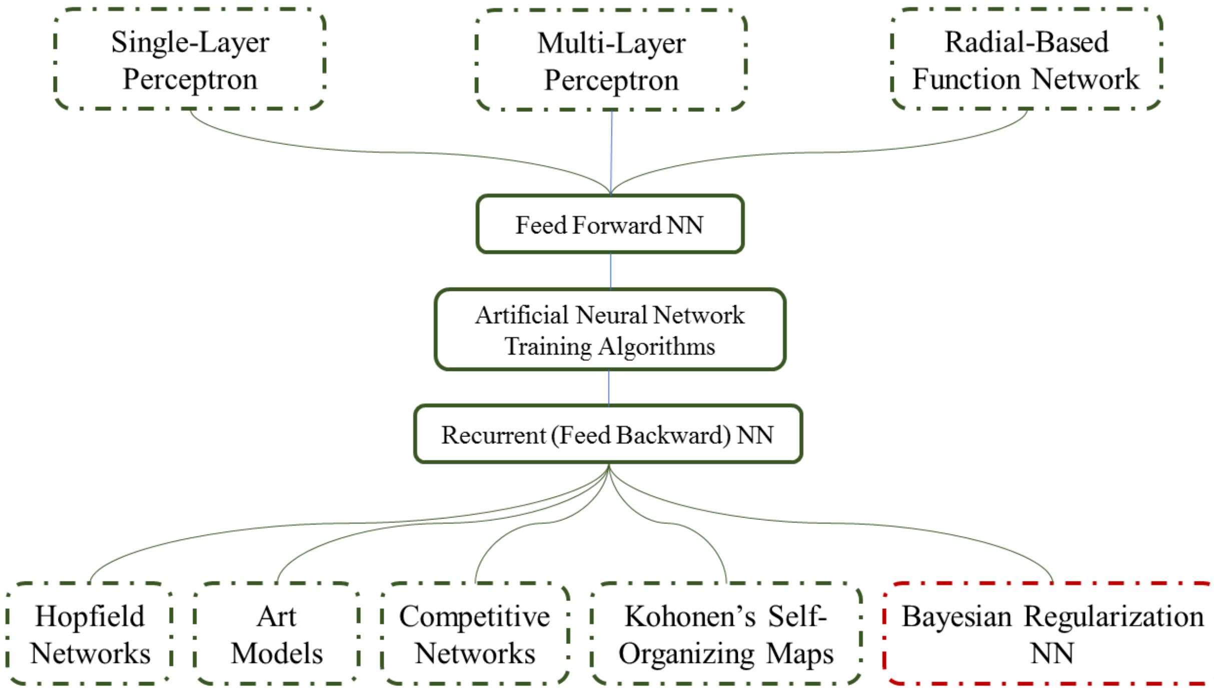


Figure 3.1. Training algorithm classification for artificial neural networks

3.4.2 Nonlinear Autoregressive Recurrent Neural Network with Exogenous Inputs (NARX) Models

The nonlinear autoregressive recurrent neural network with exogenous inputs (NARX) technique is a time series modeling technique that relates the current value of a time series to both past values of the time series and the current and past values of the exogenous inputs time series (Taqvi et al., 2020). In fact, this characteristic of NARX, which accepts dynamic variables from different time series sets, makes it superior over other feed-forward backpropagation through-time algorithm (BPTT) neural networks (Diaconescu, 2008; Jaeger, 2002).

The recurrent NNs, including NARX, are cyclic in nature. Time lag connections, which transfer values between successive activations, form the cycles that include exogenous inputs and endogenous inputs (Paul & Sinha, 2016). NARX NN performs this procedure via autonomous learning (Yu et al., 2019). The NARX technique builds complex interconnections amongst the exogenous variables and ultimately creates a function, and this renders NARX as a reliable approach for time series forecast analysis (Boussaada et al., 2018; Ruiz et al., 2016). Figure 3.2. presents the architecture of the NARX neural network methodology which was applied to the world-level corruption data. In this architecture, the output is forecasted from the past values of

CPI as well as the past and present values of the exogenous variables. The NARX technique is defined according to Eq. 3.1.:

$$y(t+n) = f\big(y(t+1), \dots, y(t+n-1), x(t-l+1), \dots, x(t-l+n-1)\big) + \varepsilon \qquad \text{Eq. 3.1.}$$

where, n is the discrete time step, $y(t+n)$ is the predicted value of CPI, $f(.)$ is the neural network mapping function, $y(t+1), \dots, y(t+n-1)$ are the past predicted values for CPI, n is the number of lags, $x(t-l+1), \dots, x(t-l+n-1)$ are the past values for the exogenous variables (including l number of lags), and ε is the error term. The variable $y(t)$ (Figure 2) is defined as follows:

$$y(t) = \sum_i \alpha_i \emptyset \left(\sum_{j=1}^{k} \left(\beta_{ji} x_{t-j} + \gamma_{ji} y_{t-1}\right)\right) \qquad \text{Eq. 3.2.}$$

where, $\emptyset$ is the hidden layer activation function, β_{ji} and γ_{ji} are the hidden layer input weights at the neuron j, α_i is the hidden layer output weights, and k is the number of input nodes.

In the NARX technique, a recurrent multi-layer perceptron (RMLP) is utilized to estimate the mapping function of $f(.)$, which consists of input layers, hidden layers, and output layers. RMLP also includes neurons, activation functions, and weights. Within the hidden layer, neural network functions are operated through the interior neurons (Tang, 2020; Yu et al., 2019). The neurons multiply the previous layers' input vectors by the weight vectors, and they provide the scalar output. The connection weights are tuned using the Bayesian regularization algorithm. Afterward, the activation function maps each output layer to generate the neuron output to be forwarded to the next layer. In other words, to compute the output, the weighted sum of the inputs is being applied to the activation function (Diaconescu, 2008). When the generalization improvement (in the training period) ends, and the changes in the mean square error values (MSE) become stable, the training process automatically stops. MSE is a crucial performance evaluation criterion that assists with determining the optimum initial hyperparameters for the neural network. MSE can be obtained according to Eq. 3.3.:

$$MSE = SSE/df \qquad \text{Eq. 3.3.}$$

where, SSE is the sum of square errors, and df is the degree of freedom. Consequently, the lowest MSE value for the neural network models lead to the optimum model (Hagan et al., 1997). After the first model is fitted through the series-parallel architecture, more time steps ahead can be forecast in a closed-loop parallel architecture, where each predicted output (in the previous step) is fed into the model to predict a future output.

In NARX, the number of hidden layers, lags, and neurons, as the main hyperparameters, influence the accuracy of the results. Hence, several different numbers of hidden layers, lags, and neurons is investigated to identify the optimum model. The variation of the number of hidden layers, lags, and the number of neurons selected in this study were 1 to 7 for the number of hidden layers, 1 to 3 for the number of lags, and 1 to 20 for the number of neurons, respectively. The precision of the models is investigated by comparing the mean square error values (MSE).

Our exogenous variables (inputs), as shown in Table 3.3., include GNI, E-governance index (EGI), human development index (HDI), undue influence, public-sector performance, security, labor market efficiency, and technological readiness. CPI is used as the dependent variable (output). Data from 2007 to 2017 for 113 countries are assembled for all variables with 70% of the data used for training the model, 15% for validation, and 15% of the data to test the model. In the next section, the results of the NARX neural network analysis outcome are presented.

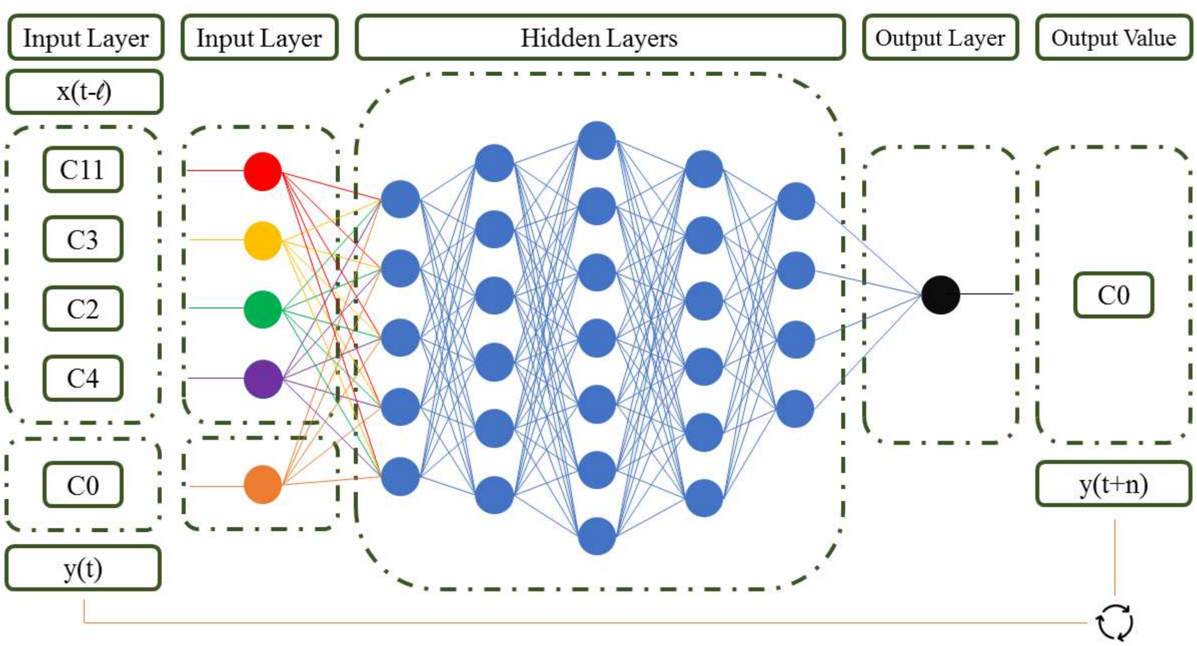


Figure 3.2. The architecture of NARX neural network applied to the world-level data

3.5 Results and Discussion

Hyperparameters play a critical role in the accuracy of the NARX analysis or any neural network analysis. (Al-Sbou & Alawasa, 2017). The hyperparameters, which need to be tuned to give models with higher accuracies, in the NARX analysis are the number of hidden layers, lags, neurons, and epochs and the learning rate. In many cases, a higher number of hidden layers causes overfitting in the model, and lower prediction accuracy (Kim et al., 2019; Liu & Kim, 2018). In the analysis, different numbers of hidden layers and lags are investigated to initiate the neural network analysis, and the least error associated with a hidden layer and a lag are chosen. Table 3.4. presents the errors associated with the number of lags and the number of hidden layers for the world-level data.

The data shows that 4 hidden layers with 1 lag gives the least possible error among the other number of hidden layers and lags. The training MSE is calculated 0.261, the error for the validation phase is 0.180, and the testing error is 0.243. The 4 hidden layer training MSE for lag 2 and lag 3 are 26.82% and 15.71% higher than that of the 4 hidden layer MSE for lag 1, respectively. When it comes to the testing MSE, lag 2 and lag 3 show 93.49% and 181.61% higher MSE compared to lag 1, respectively. Similarly, 4 hidden layer NN with lag 1 is 29.08% lower than that of the MSE values for the 7 hidden layer NN with lag 1. Likewise, 4 hidden layer NN with lag 1 illustrates a 50.01% lower testing MSE compared to that of 7 hidden layer NN with lag 1. This also shows that when the number of hidden layers increases, lower prediction accuracy is obtained.

To fine-tune another crucial NARX NN hyperparameter, the focus is made on the number of neurons at each hidden layer. Table 3.5. presents the errors associated with the number of hidden layers (H) and the number of neurons (N) for the world-level data. The data indicates that 4 hidden layers with 5 neurons give the least possible error among the other number of hidden layers and neurons. The training MSE for H4|N5 is calculated 0.236 and the testing error is 0.209. H3, H5, and H6 with 5 neurons show 2.48%, 4.45%, and 0.84% higher training MSE compared with H4|N5, respectively. Likewise, testing MSE for H4|N5 is 15.72%, 36.08%, and 53.76% lower than that of the H3, H5, and H6 testing MSE with 5 neurons. When the number of neurons exceeds 10 neurons, the errors significantly increase. The H4|N5 training and testing MSE values are 43.13% and 49.64% lower than that of the training and testing MSE for H4 with 10 neurons. This also confirms the importance of fine-tuning hyperparameters for the NARX NN.

Table 3.4. NARX errors associated with the number of hidden layers and the number of lags (world-level category) (neuron = 1, epochs = 100, and learning rate = 0.1)

Lag	No. of Hidden Layers	Training MSE	Validation MSE	Testing MSE
1		0.278	0.175	1.073
2	1	0.494	0.385	0.253
3		0.315	1.484	0.715
1		0.351	0.228	0.561
2	2	0.375	0.669	0.309
3		0.619	1.164	0.675
1		0.267	0.188	0.280
2	3	0.341	0.485	0.540
3		0.527	0.793	0.466
1		**0.261**	**0.180**	**0.243**
2	**4**	0.331	0.505	0.553
3		0.302	0.735	0.487
1		0.379	0.287	0.413
2	5	0.271	0.374	0.499
3		1.128	0.652	0.425
1		0.256	0.189	0.688
2	6	1.388	0.372	0.375
3		0.488	0.502	0.814
1		0.368	0.360	1.507
2	7	0.327	0.851	0.966
3		0.278	0.175	1.073

Table 3.5. Hyperparameter fine tuning for the world-level data – NARX errors associated with the number of hidden layers (H3-H6) and number of neurons (N1-N10, N15, and N 20) (lag =1, epochs = 100, and learning rate = 0.1)

	Training MSE				Testing MSE			
	H3	**H4**	H5	H6	H3	**H4**	H5	H6
N1	0.267	0.261	0.279	0.256	0.280	0.243	0.413	0.688
N2	0.257	0.253	0.271	0.251	0.265	0.235	0.399	0.612
N3	0.250	0.244	0.265	0.246	0.264	0.228	0.379	0.545
N4	0.242	0.239	0.251	0.238	0.254	0.224	0.352	0.462
N5	0.242	**0.236**	0.247	0.238	0.248	**0.209**	0.327	0.452
N6	0.252	0.249	0.254	0.240	0.264	0.233	0.340	0.480
N7	0.271	0.267	0.286	0.278	0.297	0.249	0.371	0.509
N8	0.295	0.282	0.304	0.315	0.329	0.259	0.400	0.691
N9	0.349	0.334	0.361	0.403	0.374	0.347	0.478	0.922
N10	0.431	0.415	0.435	0.615	0.460	0.401	0.563	1.085
N15	1.034	1.008	1.175	1.456	1.199	0.972	1.140	2.266
N20	1.471	1.456	1.640	2.649	1.656	1.370	1.578	3.646

The final hyperparameter tuning is related to epochs and learning rates. The epochs range from 100 to 1000 and learning rates (LRs) from 0.0001 to 0.1 are investigated to determine the optimum MSE. Table 3.6. presents the results for the training and testing MSE values associated with different ranges of epochs and LRs for the NARX NN with 4 hidden layers, 5 neurons, and lag 1. According to the results, the differences between the epochs and LRs are insignificant, demonstrating that the number of hidden layers, neurons, and lags have been selected properly. The epochs and the learning rates are kept at 100 epochs and 0.1 learning rate, as a starting point, to keep the computational expensiveness as low as possible.

Table 3.6. Hyperparameter fine tuning for the world-level data – NARX errors associated with the epochs and learning rates (LR) (lag =1, hidden layers = 4, and neurons =5)

Epoch	Learning Rate							
	Training MSE				Testing MSE			
	0.0001	0.001	0.01	0.1	0.0001	0.001	0.01	0.1
100	0.240	0.235	0.238	0.236	0.213	0.206	0.211	0.209
200	0.241	0.239	0.240	0.237	0.215	0.207	0.215	0.211
400	0.240	0.234	0.237	0.236	0.213	0.205	0.210	0.209
600	0.250	0.235	0.236	0.236	0.213	0.207	0.211	0.209
800	0.241	0.238	0.238	0.238	0.214	0.209	0.215	0.212
1000	0.241	0.239	0.240	0.240	0.215	0.210	0.216	0.215

The data at each level (world-level data and cluster level data) is distinct, therefore, different errors are likely for each cluster. This means that the number of lags, hidden layers, and neurons can vary for the NARX analysis for each cluster. The analysis of training, validation and testing MSE for ranges of the various hyperparameters for each cluster was conducted following the process described for the world-level data. The hyperparameter values resulting in optimal performance and MSEs for each the world-level and each cluster are presented in Table 3.7. According to the results, Cluster 2 and Cluster 3 have a lower MSE value compared with the MSE values for Cluster 1 and Cluster 4, which could be due to fact that the CPI variance among the countries in Cluster 2 and Cluster3 is significantly less (as shown in Figure 3.3.). Likewise, Cluster 1 and Cluster 4 exhibits higher errors of 0.254 and 0.259 at the testing phase. Considering the error values, four hidden layers are selected for Cluster 1 and Cluster 4, whereas three hidden layers is found to be optimum for Cluster 2 and Cluster 3.

Table 3.7. NARX model hyperparameters and performance values for the world-level and the cluster-level analysis

Category	Lag	No. Hidden Layer	No. Neurons	Training MSE	Validation MSE	Testing MSE
World level	1	4	5	0.236	0.161	0.209
Cluster 1		4	6	0.324	0.267	0.254
Cluster 2		3	6	0.280	0.189	0.210
Cluster 3		3	5	0.208	0.140	0.150
Cluster 4		4	6	0.350	0.294	0.259

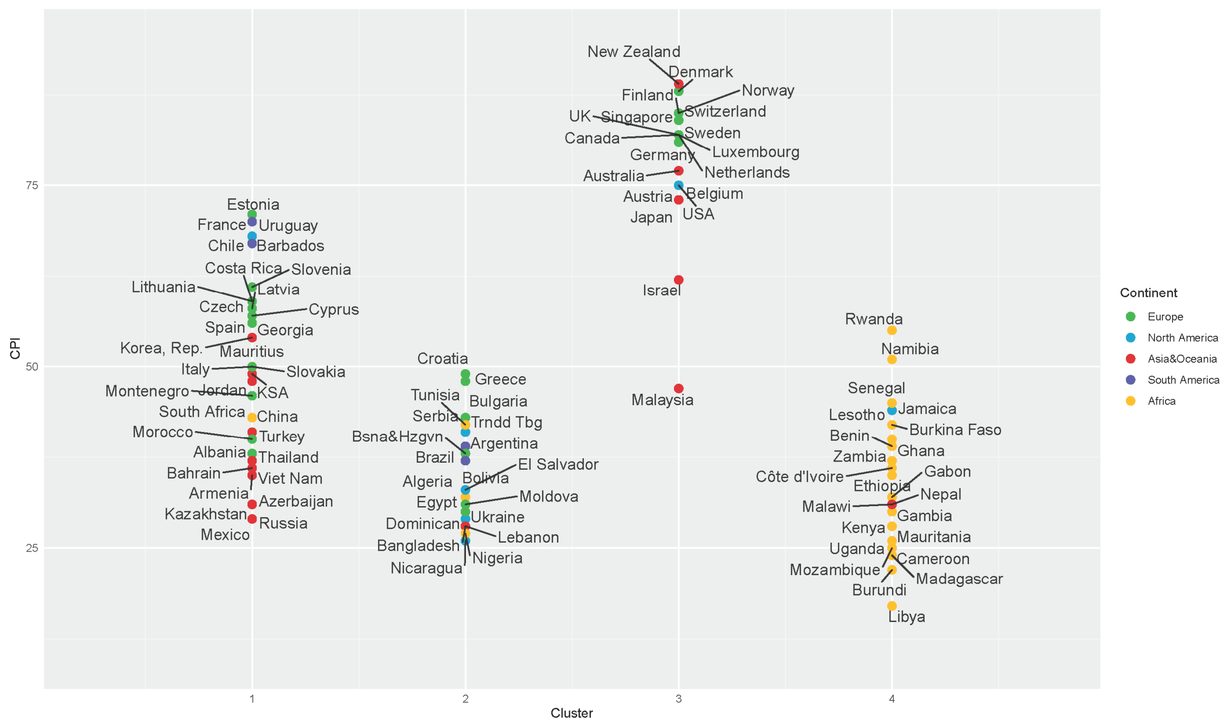


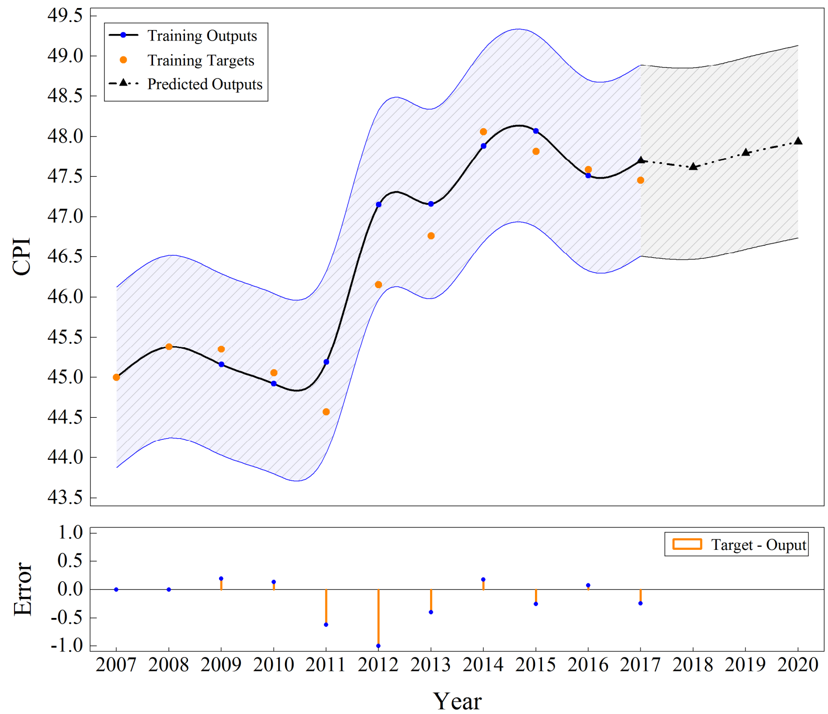
Figure 3.3. Position of countries in each cluster considering CPI values

Finally, the results of the NARX analysis using the world-level data and the clusters are discussed in this section of this chapter. The NARX ANN time series response for the world-level data is presented in Figure 3.4. Figure 3.4.a. indicates the training, target, and predicted outputs and the corresponding errors (target output – training output) with a 97.5% confidence band. This figure also presents the predicted values for the 2017–2020 period. Figure 3.4.b. presents the optimum ultimate epoch that is selected for obtaining the optimum results regarding the world-level data. The best training performance is identified as occurring at 0.10020 MSE and at the epoch 298 with no observable overfitting. This means that after the initial training of the first neural network model, it retrained the network for 298 epochs to reach a near-zero MSE change.

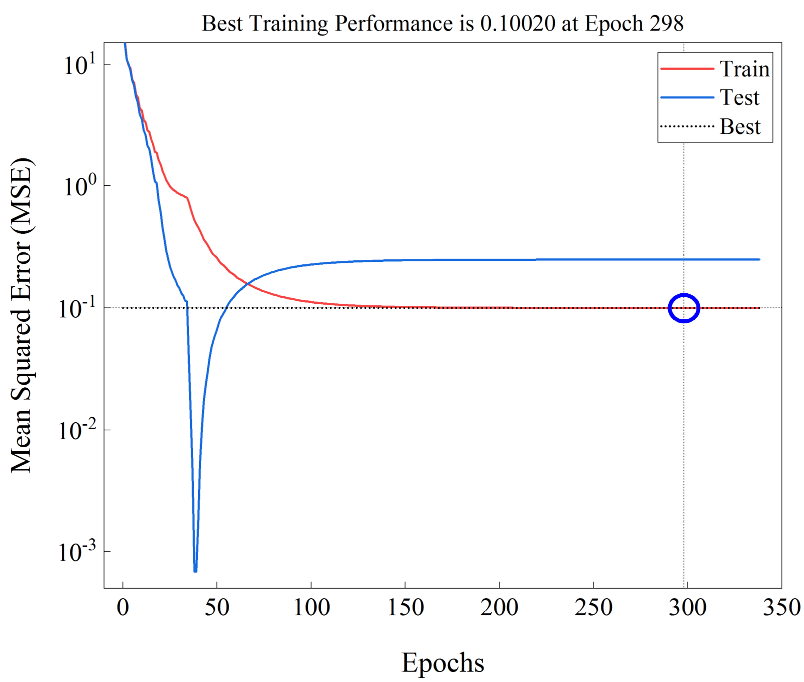
According to the results, the highest difference between the training target and training outputs is calculated for 2012 with a value of –0.999, and the second-highest error is achieved for 2011 with a value of –0.619 due to the significant change in the average CPI values from 2011 to 2013. The results show that the predicted CPI values for 2018, 2019, and 2020 (shown in black triangles connected with a dashed line) are comparatively close to the real values reported by Transparency International for those specific years (TI, 2020). Table 3.8. presents the actual and forecast values of CPI, and shows generally insignificant error between the two; the differences between the CPI forecasts and actual values in 2017, 2018, 2019, and 2020 are calculated at 0.25, 0.04, –0.07, and –0.08, respectively. Figure 3.4.a. also indicates that the overall CPI value of the world is increasing. Although a 0.18% decrease in CPI value is seen from 2007 to 2010, the general trend is positive with a 6.71% increase in the CPI value from 2010 to 2020.

Figure 3.5. presents the NARX ANN time series response for the first cluster. Figure 3.5.a. illustrates training, target, and predicted outputs and the corresponding errors (target output – training output) with a 97.5% confidence band. Also, this figure presents the predicted values for the 2017–2020 period. Figure 3.5.b. illustrates the optimum epoch chosen for calculating the optimum results for Cluster 1; the best training performance is set at 0.2135 MSE and epoch 151 with no observable overfitting. This denotes the fact that after the initial training of the first neural network model, it retrained the network for 151 epochs until it reached a near-zero change in MSE.

Based on the results, the maximum difference between the training target and training outputs is in 2013 with a value of 0.835, and the second-highest error is in 2011 with a value of -0.690. This could be due to the considerable change in the average CPI values from 2011 to 2013 for this cluster. The predicted CPI value results for 2017, 2018, 2019, and 2020 are close to the real values reported by Transparency International for those specific years (TI, 2020). Table 3.8. presents the actual and forecast CPI values. The results show 0.01, 0.26, 0.21, and 0.39 differences between the forecast and actual CPI values in 2017, 2018, 2019, and 2020, respectively. Furthermore, Figure 3.5.a. shows that the overall CPI value for Cluster 1 is increasing. Despite a 1.67% decrease in CPI value from 2008 to 2010, the general trend is positive with a 7.41% increase in the CPI value from 2010 to 2020.

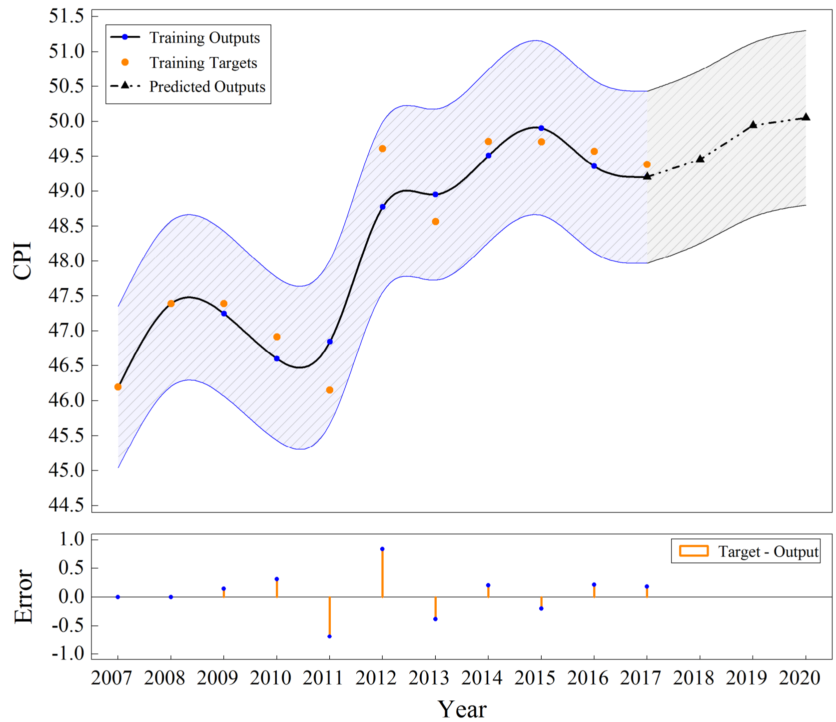


(a) Training, target, and predicted output results and errors

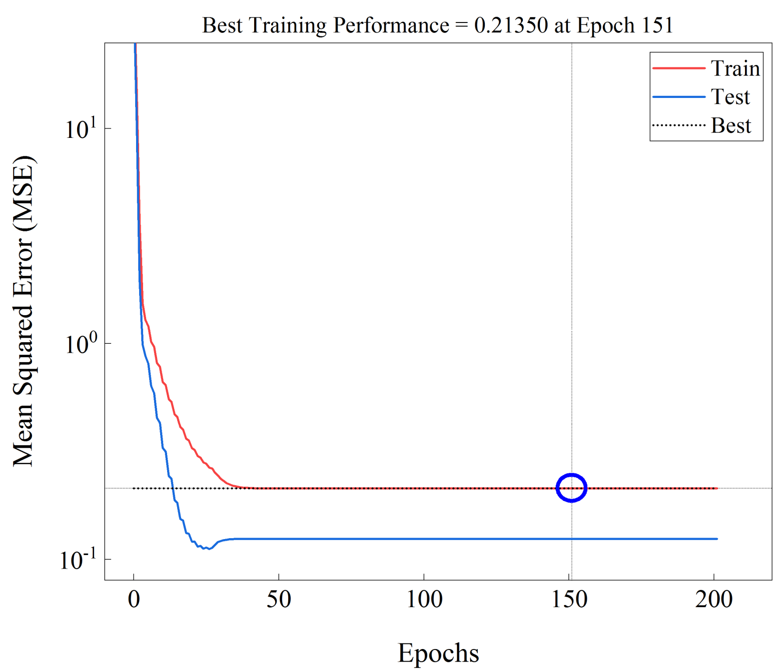


(b) Epoch and learning rate

Figure 3.4. NARX ANN time series response for the world level data



(a) Training, target, and predicted output results and errors

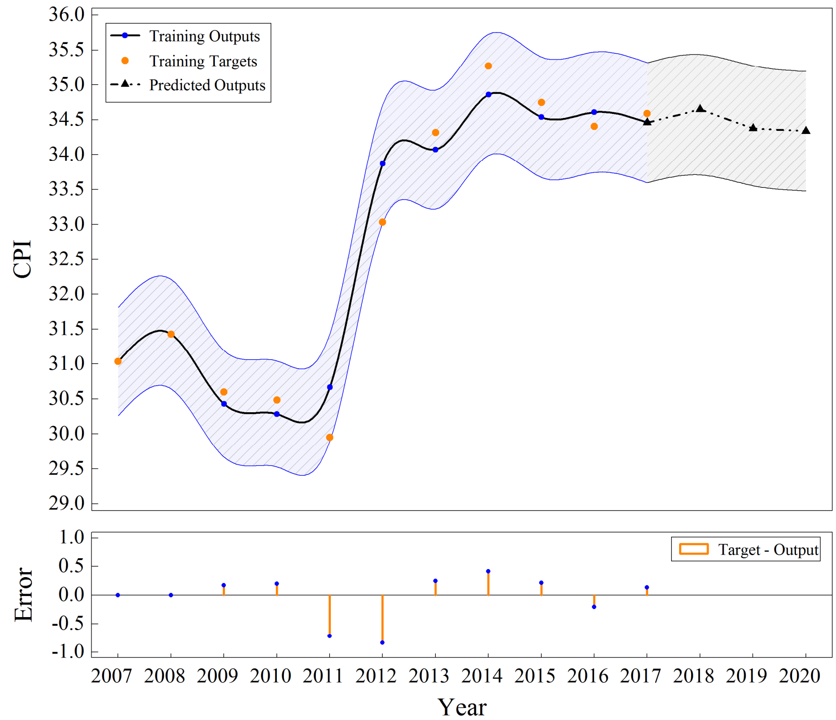


(b) Epoch and learning rate

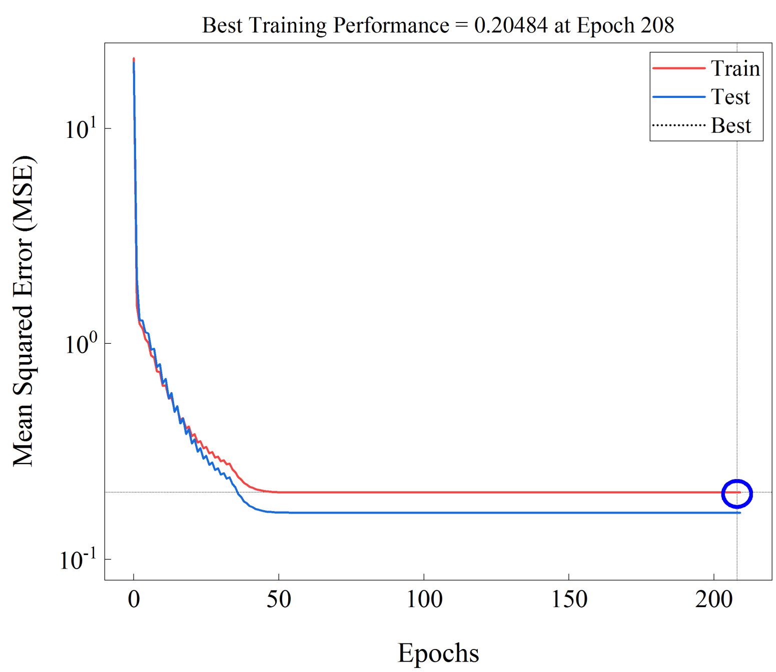
Figure 3.5. NARX ANN time series response for Cluster 1

The NARX ANN time series analysis results for Cluster 2 are presented in Figure 3.6. Figure 3.6.a. shows training, target, and predicted outputs and the corresponding errors (target output – training output) with a 97.5% confidence band. Furthermore, this figure shows the predicted values for the 2017–2020 period. Figure 3.6.b. denotes the optimum ultimate epoch selected in this analysis in order to obtain the optimum results. The best training performance is caught at epoch 248 and 0.20484 MSE with no observable overfitting. This shows that after the initial training of the first neural network model, it retrained the network for 248 epochs until it reached a near-zero change in MSE.

The results show that the highest training target and training outputs difference is in 2012 and 2011 with values of –0.833 and –0.714, respectively, which could be due to the significant change in the average CPI values from 2011 to 2013. The results indicate that the predicted CPI values for 2017 to 2020 are relatively close to the real values reported by Transparency International (TI, 2020). The values presented in Table 3.8. indicate a minor error between the real CPI values and the predicted CPI values. Differences between the predicted and real CPI values for 2017 to 2020 are calculated as 0.23, –0.01, –0.35, and –0.21, respectively. Moreover, Figure 3.6.a. shows an overall increase in the CPI values in this cluster. Although a 3.64% decrease in the CPI value is seen from 2008 to 2010, the general trend is upward with a 13.37% increase in the CPI value from 2010 to 2020.



(a) Training, target, and predicted output results and errors



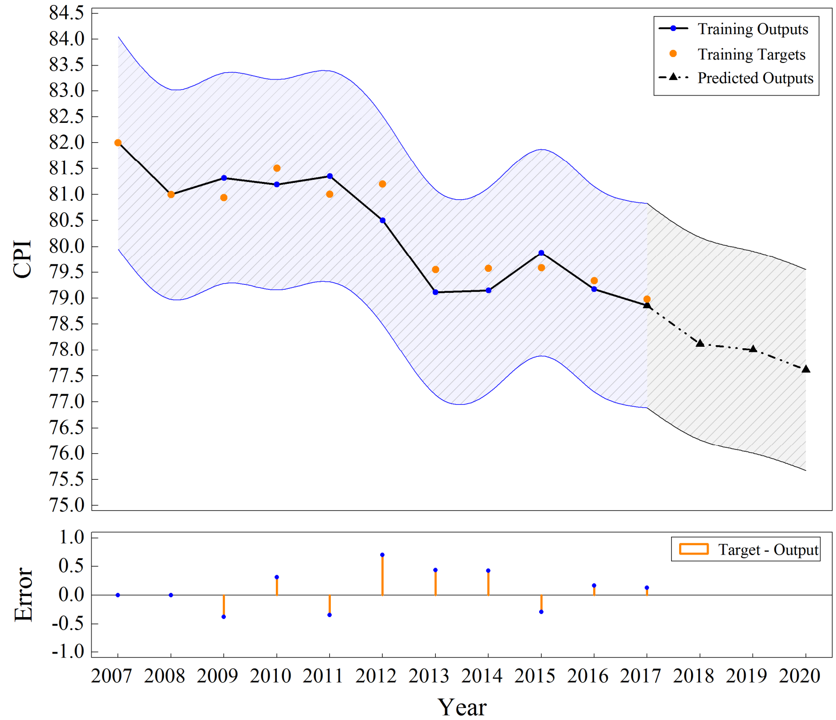
(b) Epoch and learning rate

Figure 3.6. NARX ANN time series response for Cluster 2

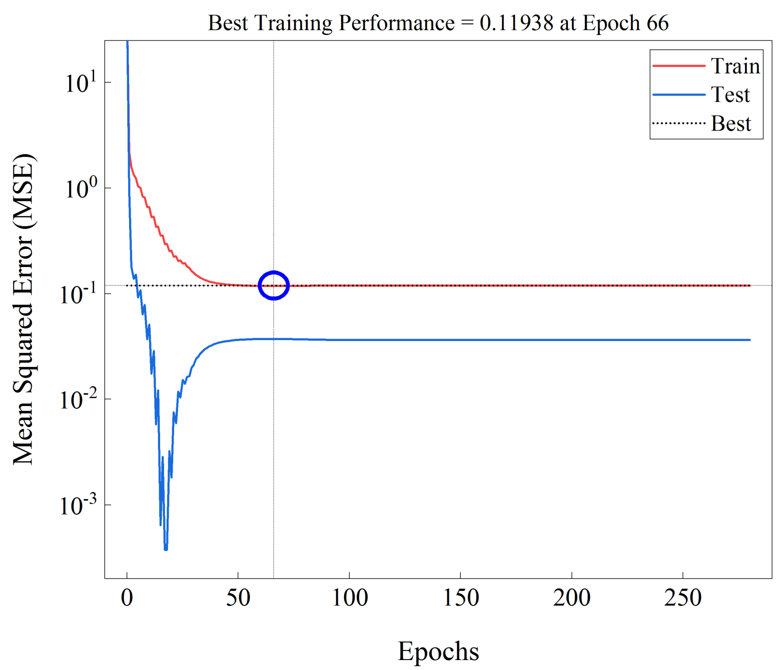
Figure 3.7. presents the NARX ANN time series response for the third cluster. Figure 3.7.a. shows training, target, and predicted outputs and the corresponding errors (target output – training output) with a 97.5% confidence band. This figure also illustrates the predicted values for 2017, 2018, 2019, and 2020. Figure 3.7.b. shows the optimum epoch chosen for calculating the optimum results for Cluster 3; the best training performance is obtained at 0.11938 MSE and epoch 66 with no observable overfitting. This indicates that after the initial training of the first neural network model, it retrained the network for 66 epochs until it reached a near zero change in MSE.

Based on the results, the difference between the training target and training outputs is at its maximum value of 0.696 in 2012, and the second-highest error at 0.436 in 2013, which could be due to the significant change in the average CPI values in 2012 and 2013 for this cluster. The predicted CPI value results for 2017 to 2020 are relatively close to the real values reported by Transparency International for those specific years (TI, 2020). Table 3.8. presents the actual and forecast CPI values. The results show differences of –0.63, –0.32, –0.35, and –0.16 between the forecast and actual CPI values in 2017 to 2020, respectively.

Figure 3.7.a. also illustrates that the overall CPI value for Cluster 3 is decreasing. The general CPI trend in this cluster is negative, with a 5.35% decrease in the CPI value from 2007 to 2020. Considering the fact that Cluster 3 mainly includes developed countries, reduction in CPI can be extremely alarming, and the underlying causes of the down trend need to be deeply studied. Taking another look at Figure 3.3. suggests that Israel and Malaysia might also belong to other clusters as they look like outliers for Cluster 3. Hence, the clustering of countries might need a revisit by changing the NARX hyperparameters for determining lags, number of hidden layers, number of neurons, etc. or the Random Forest hyperparameters for determining the top four influential attributes.



(a) Training, target, and predicted output results and errors

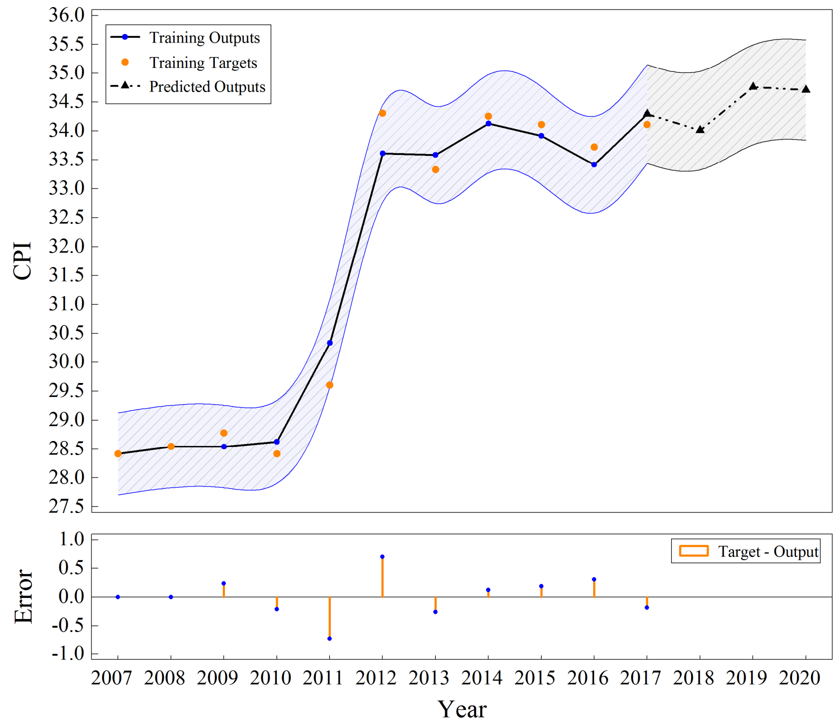


(b) Epoch and learning rate

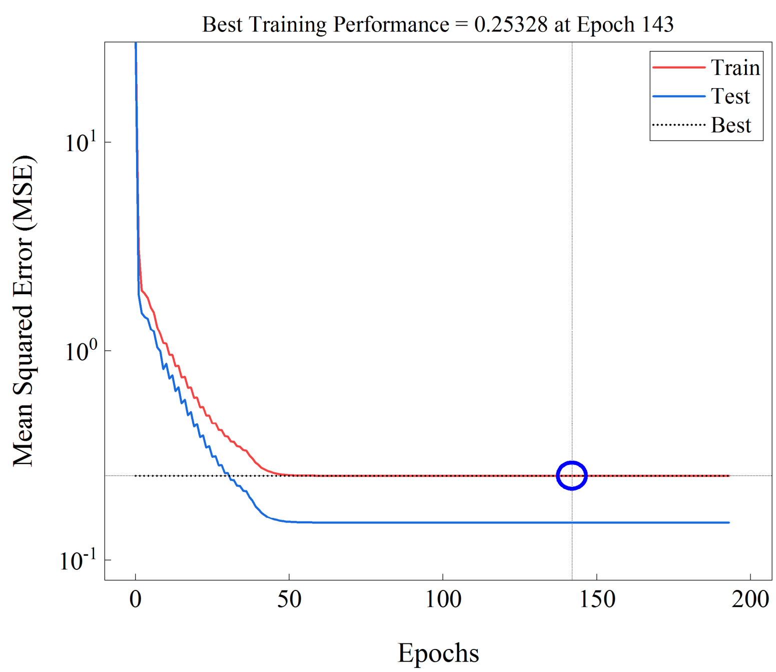
Figure 3.7. NARX ANN time series response for Cluster 3

Figure 3.8. presents the NARX ANN time series analysis results for Cluster 4. Figure 3.8.a. shows training, target, and predicted outputs and the corresponding errors (target output – training output) with a 97.5% confidence band. This figure also illustrates the predicted values for 2017 – 2020. Figure 3.8.b. shows the optimum ultimate epoch selected in this analysis to obtain the optimum results; the best training performance is caught at epoch 143 and 0.25328 MSE with no observable overfitting. This means that after the initial training of the first neural network model, it retrained the network for 143 epochs until it reached a near-zero change in MSE.

The results indicate that the highest training target and training outputs difference are in 2011 and 2012 with values of –0.733 and 0.696, respectively, which could be due to the significant change in the average CPI values from 2010 to 2012 in this cluster. The results denote that the predicted CPI values for 2017 - 2020 are relatively close to the real values reported by Transparency International (TI, 2020). The values are presented in Table 3.8. indicating a minor difference between the real CPI values and the predicted CPI values. The differences between the predicted and real CPI values for 2017 - 2020 are calculated at 0.18, 0.17, –0.17, and 0.08, respectively. Furthermore, Figure 3.8.a. indicates an overall increase in the CPI values. The general trend in this cluster is upward with a 21.25% increase in the CPI value from 2010 to 2020.



(a) Training, target, and predicted output results and errors



(b) Epoch and learning rate

Figure 3.8. NARX ANN time series response for Cluster 4

Table 3.8. CPI actual and forecast value

Year	Category	Actual CPI	CPI Forecast	Error (Forecast - Actual)
2017	World level	47.70	47.45	0.25
	Cluster 1	49.39	49.38	0.01
	Cluster 2	34.82	34.59	0.23
	Cluster 3	78.35	78.98	-0.63
	Cluster 4	34.29	34.11	0.18
2018	World level	47.65	47.61	0.04
	Cluster 1	49.71	49.45	0.26
	Cluster 2	34.64	34.65	-0.01
	Cluster 3	77.80	78.12	-0.32
	Cluster 4	34.17	34.00	0.17
2019	World level	47.73	47.80	-0.07
	Cluster 1	50.15	49.94	0.21
	Cluster 2	34.11	34.37	-0.26
	Cluster 3	77.65	78.00	-0.35
	Cluster 4	34.58	34.75	-0.17
2020	World level	47.86	47.94	-0.08
	Cluster 1	50.44	50.05	0.39
	Cluster 2	34.14	34.35	-0.21
	Cluster 3	77.45	77.61	-0.16
	Cluster 4	34.79	34.71	0.08

3.6 Concluding Remarks

Artificial neural networks (ANNs) are effective tools for non-linear mapping of multiple variables on one or more outputs. In this chapter, a well-known ANN method − the nonlinear autoregressive recurrent neural network with exogenous inputs (NARX), was used to model and forecast corruption in clusters of countries. The analysis was carried out using the data on 113 countries from 2007 to 2017. The development-related attributes that have significant influence on the levels of corruption in countries, as measured by CPI, were identified from the literature. The countries were split into four clusters based on their development-related attributes, and developed corruption forecasting models in each cluster. The NARX neural network training was performed on 70% of the data, 15% of the data was used for validation, and the rest of the data was used for testing the output.

Any reliable neural network model needs precise hyperparameter fine-tuning before training. The variation of the number of hidden layers, lags, and the number of neurons were selected as: 1 to 7, 1 to 3, and 1 to 20, respectively. Considering MSE as a baseline for the hyperparameter tuning process showed that 1 lag, 4 hidden layers, and 5 neurons would give an optimum NARX model for forecasting CPI values for the world-level data. For Cluster 1 and Cluster 4, the number of hidden layers were found to be 4, versus 3 for Cluster 2 and Cluster 3. At the same time, the number of neurons for Cluster 1, Cluster 2, and Cluster 4 were chosen to be 6, versus 5 for Cluster 3. Epochs and learning rates were found to have no significant influence on the initial hyperparameter MSE values for the NARX models. It was observed that when the number of neurons and hidden layers increased, a relatively lower prediction accuracy was obtained, due to model overfitting.

As expected, the NARX NN prediction models showed different results for the world-level data analysis and the cluster-level data analysis. For the world-level data, it was found that there is a general uptrend momentum in the value of CPI showing a 6.71% increase in CPI from 2010 to the predicted value of CPI in 2020. Cluster 1, Cluster 2, and Cluster 4 showed the same uptrend with 7.41%, 13.37%, and 21.25% increase in CPI from 2010, despite having a relatively minor downtrend in CPI from 2007 to 2010. However, Cluster 3 – despite containing developed countries mostly – showed a 5.35% decrease in CPI from 2007. For countries within the clusters developed in this chapter of the dissertation, the results can be valuable to policymakers, governments, and NGOs as they continue to assess the efficacy of their current or prospective future corruption-mitigation policies, programs, and initiatives.

In this chapter, one of the main limitations was the lack of adequate data on development-related attributes. In future studies, access to other data sources will be helpful to develop more confident conclusions. Another limitation was the reliance on only one attribute (CPI) as the indicator of corruption. Suggested directions for future research include (a) a detailed investigation of the causes of the uptrend and downtrend momentum in CPI values in each cluster; (b) adequate and explicit assessment of corruption-mitigation initiatives implemented in countries in each cluster, and identifying solutions that have worked well as those that failed, and an overall assessment of the extent to which these solutions succeeded or failed. Further, future studies could investigate project-level data (instead of country-level in this study). In this regard, researchers could examine the effect of corruption on infrastructure delivery quality, time delay, and cost overruns, and thereby measure, for example, the portion of overrun cost that could be attributed to corruption and the portion that could be attributed to inefficiency.

CHAPTER 4. CORRUPTION - IMPACT OF E-GOVERNANCE: NEW EVIDENCE USING PANEL VECTOR AUTO REGRESSION ANALYSIS

[A portion of this chapter is presented at the 2018 GIS Conference[1]]

4.1 Introduction

Corruption, the abuse of public power for private benefit (TI, 2017; WBG, 2020), exists in a myriad of forms (Heywood, 2014) and typically occurs at the interface of the public and private sectors (Ackerman, 1978; Heidenheimer et al., 1989). Corruption is not only damaging to the entire society from a political, social, and economic perspective (Heywood, 2014; Nur-Tegin & Czap, 2012; Tran, 2021) but also is associated with impacts that are inequitable, as low-income groups are more adversely affected (Paul, 1997; Thanh et al., 2021). It has been found, for example, that in developing countries such as Paraguay and Sierra Leone, higher-income persons generally pay a lower percentage of their income in bribes compared to low-income persons (Wright et al., 2007). From an economic perspective, the effects of corruption include short-term economic inefficiency, specifically in the private market, and long-term dynamic inefficiency and instability in economic growth (Mauro, 1995; Sulemana & Kpienbaareh, 2018; World Bank, 1997).

Irisova (2014) determined that at least 5% of the world's GDP (worth $2.6 trillion) is lost annually due to corrupt practices globally. This is "lost" money that not only denied use for development purposes but also is largely being used in crimes involving drugs and human trafficking (Integrity Vice Presidency, 2016). From a social standpoint, corruption degrades societal or traditional values of honesty, equity, and transparency, weakens social cohesion, and damages the integrity of the civil service. The political impact of corruption is even more destructive. In corrupt environments where government's administrative decisions are not merit-based, and its functions and decisions are neither transparent or objective, public distrust of government is exacerbated, and the civil society becomes less engaged. This leads to diminished capacity for law enforcement and compromised political legitimacy of the government (Johnston, 1998), (Mauro, 1995; Sulemana & Kpienbaareh, 2018; World Bank, 1997).

[1] Ghahari, S., Ghotbi, S., Labi, S., & Naderpajouh, N. (2018). Is Corruption Influenced by Human Development Index and Transparency? A Global Spatial Assessment Using GIS. In *2018 GIS Conference. GIS, Geoinformatics, and Remote Sensing at Purdue.*

The problem of corruption continues to plague several countries (Baker et al., 2019; Tanzi, 1998), and several mitigation initiatives, programs, and polices have been implemented to fight the disease (Doig & Riley, 1998). However, these have generally had rather limited or short-lived efficacy (Locatelli et al., 2017). The advent of the information and communication technologies (ICT) age, accompanied by the inherent openness and transparency it offers to all spheres of human activity (Bannister & Connolly, 2011) has led to renewed hope in the fight against corruption (Davies & Fumega, 2014; Shim & Eom, 2008).

An example of ICT applications is electronic governance (e-governance) (Bertot et al., 2010). The use of ICT, while promising, needs to be initiated or supported by the government rather than an NGO or the private sector for it to be effective. However, doing this with a coalition of various stakeholders (governmental officials, politicians, contractors, non-governmental organizations (NGOs), journalists, and the general public) can be useful. Rossel and Finger (2007) defined e-governance as "the use of the technologies that both help to govern and have to be governed". These governance applications include distribution of government amenities, exchange of data, incorporation of systems between government and citizens, government-to-business, government-to-government, and government-to-employees (Saugata & Masud, 2007). Consequently, these systems, if designed properly, could yield an integrated transparent system that is amenable to open monitoring where irregular actions can be quickly identified. Having access to public information and transparency has been found to be crucial for any economy to thrive in international trade (Bertot et al., 2010; Bertot et al., 2012; Cuillier & Piotrowski, 2009).

Clearly, the visibility of a government's administrative functions has been found to enhance transparency as it helps citizens monitor government activities and track the actions of government employees. As such, researchers have identified a need to investigate the relationship between e-governance and corruption level. It is anticipated that if such a relationship is identified, any causal effects of e-governance on corruption reduction can be identified and measured, and this could help provide greater justifications for investments in e-governance.

The main objective of this chapter of the dissertation is to investigate the association between the e-governance and the level of corruption in a country. The analysis is carried out at two levels, first, at a global level where all countries are considered as one group, and second at the group level where the countries were clustered based on their gross national income per capita. E-governance is represented using the e-governance index (EGI) and corruption using the

Corruption Perceptions Index (CPI). To what extent does a unit change in EGI associated with CPI changes? Does the direction and intensity of this relationship vary across the continents, or is it valid for all countries with specific income levels? This research sets out to address these questions using panel vector autoregression (PVAR) analysis involving Orthogonalized Impulse-Response Functions (IRF), Granger-causality, and variance decomposition analysis on data from 133 countries from the year 2007 to 2017 using the EGI and the CPI. The analysis considered the low- and medium-income level and high-income level countries based on their gross national income per capita (GNI). In the next section, a review of the relevant literature is presented, followed by a description of the data collection and methodology. The results of the analysis are then discussed, and suggestions for the use of e-governance to reduce corruption are made. The chapter ends with concluding remarks and recommended directions for future work in this research area.

4.2 Literature Review

This chapter of the dissertation seeks to identify any relationship or association between e-governance and corruption. As such, the review of literature focuses on only corruption factors that could potentially be mitigated by e-governance (as the corruption factors that are pertinent in this study) and past use of promising analytical methodologies that could be used to address the study objective. The first of the pertinent corruption factors is the lack of government accountability (Paul, 1997). Klitgaard (1991) stated that "illicit behavior flourishes when agents [public servants] have a monopoly power over clients [citizens], when agents have great discretion, and when accountability of agents to the principal is weak." Ackerman (1978) and Dininio et al. (2005) argue that the removal of corrupt officials, per se, is not likely to mitigate the problem, and that systemic changes in the decision-making processes are needed. E-governance, by enabling free and easy access and flow of data among government offices, public and private organizations and businesses, and citizens can enhance the transparency of government functions (Bertot et al., 2010; Rossel & Finger, 2007; Saugata & Masud, 2007).

The second pertinent corruption factor is the difficulty of clients (the public) to access basic government services and to process various forms associated with their business, travel, health care, and so on. Such difficulty not only makes the clients willing to pay a bribe to facilitate their official requests and processes, but also creates a fertile ground for the concerned government employees to demand such bribes. In India and Cameroon, for example, obtaining licenses, construction authorizations, and labor inspections are considered to be the main sources of corruption (Kenny, 2009b). E-governance can make available user-friendly and easy-to-use online portals where stakeholders and citizens can access and submit forms (Kenny, 2009b) and where corruption watchdogs can monitor the integrity of government functions (Northrup & Thorson, 2003).

Other pertinent corruption factors that can be mitigated using e-governance are discussed in (Andersen, 2009; Garcia-Murillo & Ortega, 2010; Mauro, 1995; Mistry, 2012). Certain indicators of macroeconomic performance can be influenced by e-governance, and therefore, can impact corruption where e-governance is adopted. Saha and Su (2012) investigated the integration effect of democracy and economic freedom on corruption, and Policardo and Carrera (2018) found that income inequality could be responsible for high corruption levels in a region.

Regarding the analysis technique used in this chapter of the dissertation, the literature review showed that a few studies have applied panel vector autoregression (PVAR) to data similar to the one used in the present study. Sadorsky (2010) used the technique to analyze the impact of financial development on energy consumption in emerging economies. The technique has also been used in other concepts including examination of the dynamic relationship between corruption and inflation (Sassi & Gasmi, 2017), the relationship between asset prices and global excess liquidity (Brana et al., 2012), assessment of the influence of external shocks on output stability in low-income countries (Raddatz, 2005), and analysis of financial development and dynamic investment behavior (Love & Zicchino, 2006).

4.3 Data

The data are from 133 countries from 2007 to 2017 using CPI and EGI. In order to cover the wide variety of variables, four different databases were used in this study: the databases from the World Bank Group (WBG) (the Gross National Income per Capita) (World Bank, 2017b), Transparency International (TI) (Corruption Perceptions Index) (TI, 2017), the United Nations Department of Economic and Social Affairs (UNDESA) (the E-Governance Index) (UNDESA, 2017), and the United Nations Development Programme (the Human Development Index) (UNDP, 2017). Table 4.1. presents the breakdown of the data used in this study.

Table 4.1. The breakdown of the data included in the study

Organization	WBG ($/Capita)	TI (0-100 (best))	UNDESA (0-1 (best))	UNDP (0-1 (best))
Database	Gross National Income per Capita (GNI)	Corruption Perceptions Index (CPI)	E-Governance Development Index (EGI)	Human Development Index (HDI)

Data on the gross national income per capita (GNI) were obtained from the World Bank Atlas method (World Bank, 2020b) (shown in Table 4.2.). GNI is defined as the "sum of value added by all resident producers plus any product taxes (fewer subsidies) not included in the valuation of output plus net receipts of primary income from abroad (WHO, 2020)." It is the main indicator of how "rich" or "poor" a country is. The World Bank (2020b) places countries into four GNI-based tiers: low-income (below $1,006), lower-middle-income (between $1,006 to $3,955), upper-middle-income (between $3,956 to $12,235), and high-income (over $12,235). In this study, the GNI per capita data for the year 2017 is used to place the countries into two clusters: low- and middle-income (or developing countries) and high-income (or developed countries). The analysis also consider the countries as a whole group (global level) and the countries with different level of income, i.e., developing (83 countries) and developed (49 countries).

Table 4.2. List of the countries and income levels used in this study

	High-Income Level (Over $12,536 GNI per Capita)			Low- and Medium- Income Level (Bellow $12,536 GNI per Capita)		
Europe	Austria	Belgium	Croatia	Albania	Armenia	Bosnia & Herzegovina
	Cyprus	Czech Republic	Denmark	Bulgaria	Georgia	Moldova
	Estonia	Finland	France	Montenegro	Romania	Serbia
	Germany	Greece	Hungary	Turkey	Ukraine	
	Iceland	Ireland	Italy			
	Latvia	Lithuania	Luxembourg			
	Malta	Netherlands	Norway			
	Poland	Portugal	Slovakia			
	Slovenia	Spain	Sweden			
	Switzerland	UK				
North America	Barbados	Canada	Panama	Costa Rica	Dominican Republic	El Salvador
	Trinidad and Tobago	USA		Guatemala	Honduras	Jamaica
				Mexico	Nicaragua	
Asia & Oceania	Australia	Bahrain	Brunei Darussalam	Azerbaijan	Bangladesh	Cambodia
	Israel	Japan	South Korea	China	India	Indonesia
	Kuwait	New Zealand	Oman	Iran	Jordan	Kazakhstan
	Qatar	KSA	Singapore	Kyrgyzstan	Lebanon	Malaysia
	UAE			Mongolia	Nepal	Pakistan
				Philippines	Russia	Sri Lanka
				Tajikistan	Thailand	Timor-Leste
				Viet Nam		
South America	Argentina	Chile	Uruguay	Bolivia	Brazil	Colombia
				Ecuador	Guyana	Paraguay
				Peru	Venezuela	
Africa				Algeria	Benin	Botswana
				Burkina Faso	Burundi	Cameroon
				Cape Verde	Chad	Côte d'Ivoire
				Egypt	Ethiopia	Gabon
				Gambia	Ghana	Kenya
				Lesotho	Libya	Madagascar
				Malawi	Mali	Mauritania
				Mauritius	Morocco	Mozambique
				Namibia	Nigeria	Rwanda
				Senegal	South Africa	Tanzania
				Tunisia	Uganda	Zambia
				Zimbabwe		

Transparency International, a leader in assessing perceived levels of corruption globally, developed the Corruption Perceptions Index (CPI) − an annually reported index that is based on thousands of surveys conducted each year on the perceived degree of corruption in governments. CPI ranges from zero ("highly corrupt") to 100 ("very clean") (GFI, 2020; TI, 2017). It should be noted, however, that CPI is perception-based and that is often considered a limitation of that index. For example, it does not capture "legalized" corruption, such as excessively high salaries that legislators legislate for themselves, lobbying, and so on. Moreover, the number of participants, their income level, occupation, school of thought, and many other qualitative variables related to the participants and the questionnaires can cause variances and biases in the assessment, which need to be studied carefully. Nevertheless, CPI is generally considered a good approximation of the level of corruption in a country, according to an extensive study on the reliability of this index performed by Lambsdorff (1999). Figure 4.1. presents a spatial heatmap of CPI distribution globally. As of 2017, two-thirds of the countries around the globe are ranked under 50, and the overall average is 43. Table 4.3. presents the descriptive statistics. The E-governance Development Index (EGI), developed by the United Nations, is a survey-based indicator that shows the extent of digital interaction of a country's government and its citizens, at all scales and levels of a government authority (U.N., 2018). The e-governance index data was obtained from the United Nations Survey (Department of Economic and Social Affairs, 2018). This index takes values from 0 to 1. Figure 4.2. presents an EGI heatmap.

Table 4.3. Summary statistics of EGI and CPI - 133 countries from 2007-2017

Variable	Observations	Mean	Std. Dev.	Min	Max
All Countries					
EGI	1854	0.533	0.196	0.1	0.946
CPI	1854	45.122	20.167	14	95
Low- and Middle-Income Countries					
EGI	1193	0.426	0.140	0.1	0.797
CPI	1193	33.727	9.949	14	72
High-Income Countries					
EGI	661	0.728	0.117	0.1	0.946
CPI	661	65.664	4.460	17	95

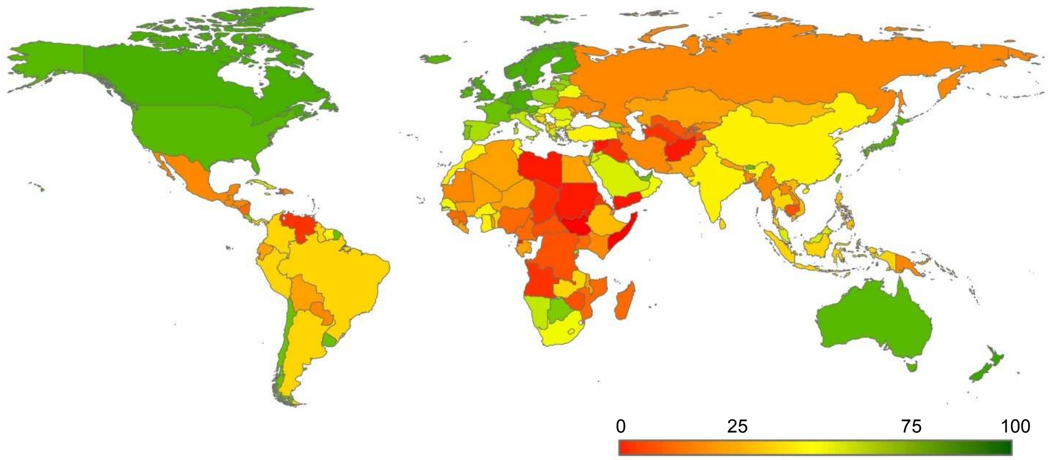


Figure 4.1. Corruption Perceptions Index map (TI, 2017)

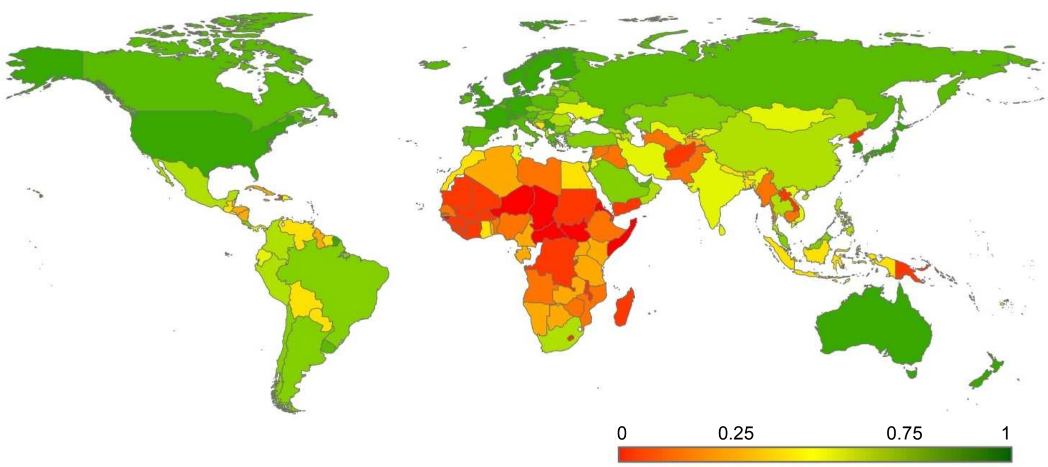
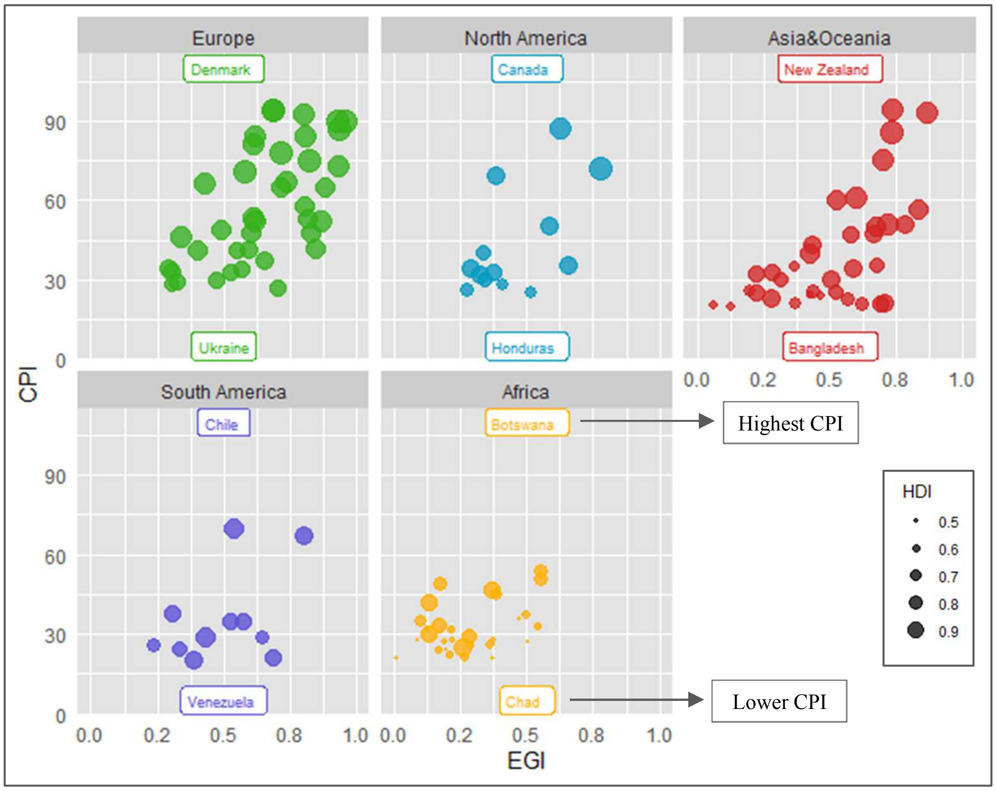
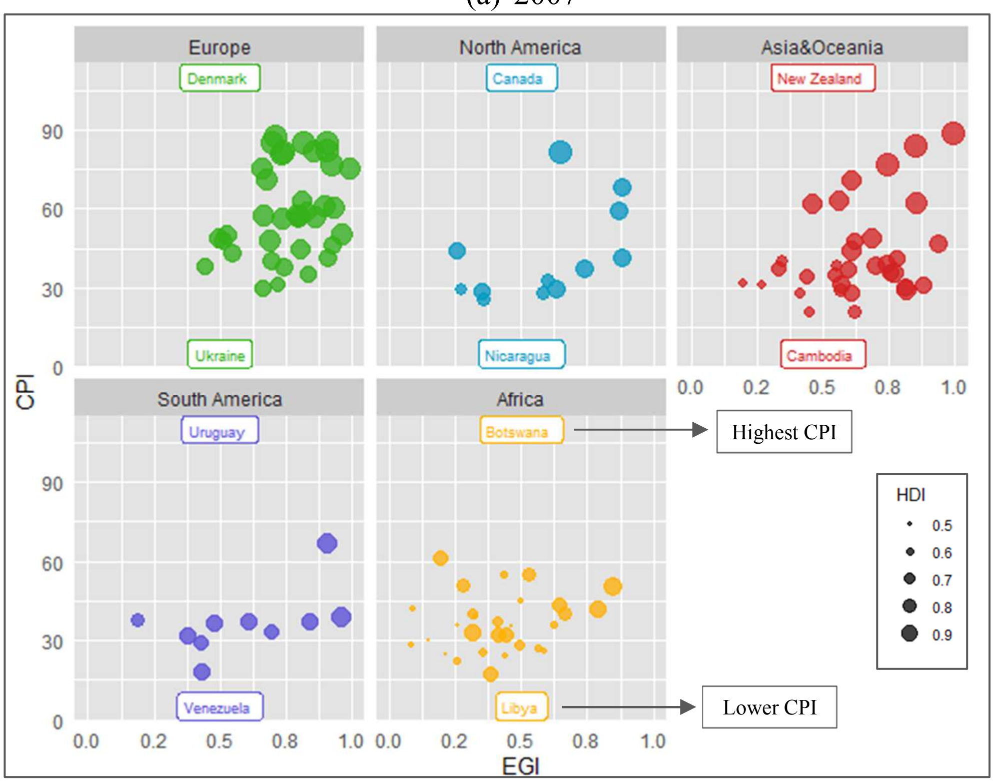


Figure 4.2. E-Governance index map (Department of Economic and Social Affairs, 2018)

The Human Development Index (HDI) was created by the United Nations Development Programme (UNDP, 2017) to assess a country's development in terms of their potential and capabilities (da Silva et al., 2020). Figure 4.3. presents the distribution, from 2007 to 2017, of countries with respect to CPI (y-axis), EGI (x-axis), and HDI (data point circle size). The highest CPI and lowest CPI values of the countries are shown at the top and the bottom of each cell, respectively. From the figure, it can be observed that over the study period, 4 out of 5 continents shifted towards up and right with a minimal change in HDI levels. However, the countries in South America did not follow these trends.



(a) 2007



(b) 2017

Figure 4.3. CPI, EGI, and HDI trends

4.4 Methodology

An autoregressive statistical model has the ability of predicting its future values based on its past values. In this type of model, the assumption is that past values influence current values. Vector autoregression (VAR) models simplify single-variable autoregressive models while considering panel data and multivariate time series. Analogous to autoregressive models, each variable in a VAR model (known as a "vector") is assigned to an equation which contains an error term and two lagged values. Hence, the model identifies all variables as endogenous variables. Compared to the conventional structural system-of-equations model, a VAR model needs relatively little information on the factors that affect a variable; what a VAR model needs is a list of the variables that hypothetically influence each other over time (Sims, 1980). Therefore, VAR is considerably helpful when it predicts multiple time series variables using a single model.

In this study a panel data is involved: panel data is data that is comprised of datapoints for various cross sections across time. Therefore, instead of a simple VAR model, a model capable of dealing with panel data is required: panel vector autoregression (PVAR) extends the VAR model by integrating it with a panel-data technique thereby including (explicitly) fixed effects in the model (Holtz-Eakin et al., 1988; Jouida, 2018). A PVAR model was chosen in this study to analyze the data in the present study for several reasons: first, it is a dynamic panel analysis that includes fixed effect outcomes in its time-series analysis. Second, it accommodates static and dynamic properties of interdependent models, and helps to link heterogeneous units considering the variations in their attributes over time (Liu & Kim, 2018). Third, PVAR analysis inherently incorporates a cross-variable dimension where the variable is the country.

PVAR consists of "a multivariate panel regression of each dependent variable on lags of itself, lags of all other dependent variables, and exogenous variables (the estimation is done by generalized method of moments (GMM)" (Abrigo & Love, 2015)). Without performing a PVAR analysis, it is not feasible to consider the integration of (a) panel data, (b) time series, and (c) impulse response and shocks that our variables may have on each other in the future. Hence, PVAR can be considered far superior to traditional regression analysis (Boubtane et al., 2013; Pesaran & Shin, 1998).

To illustrate this, consider Figure 4.4. the results of a regression analysis of CPI and EGI. Although the regression gives some insights into the nature of the CPI-EGI relationship, it does not provide insights regarding the effect that each side of the equation (EGI or CPI) would have on each over time. Therefore, this result cannot help determining the magnitude of EGI change on CPI in the years ahead, or vice versa. Hence, traditional regression is unable to address the objectives of this chapter. In this chapter of the dissertation, panel vector autoregression (PVAR) is performed to identify any association or causal relationship and shock effects between e-governance and corruption.

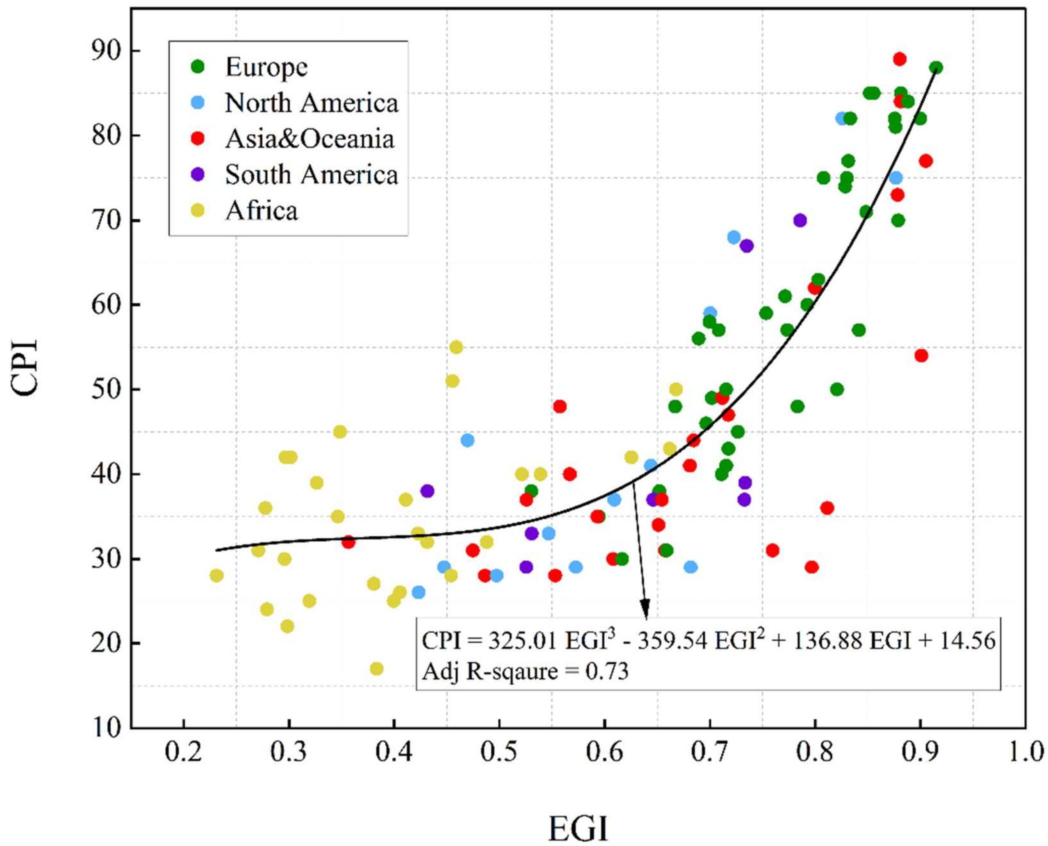


Figure 4.4. Preliminary CPI versus EGI model, countries color-coded by continent of location

Further, the PVAR technique allows three crucial identifications with our analysis: Granger-causality (Granger, 1969), variance decomposition (Bernanke, 1986; Sims, 1986), and impulse-response functions (IRF) (Koop et al., 1996). For these reasons, PVAR is considered appropriate for addressing the research questions in this study. Next, the structure of the PVAR model is described. A *k*-variate PVAR model of order *p* with panel-specific fixed effects can be written as follows:

$$Y_{it} = Y_{it-1}\,\tau_1 + Y_{it-2}\,\tau_2 + \ldots + Y_{it-p+1}\,\tau_{p-1} + Y_{it-p}\,\tau_p + f_{it} + \gamma_i + \varepsilon_{it} \qquad \text{Eq. 4.1.}$$

where, i is the observation/entity (country), t is the time period, Y_{it} is a $1*k$ vector dependent variables, f_{it} is 1*k vector dependent variable fixed effects, ε_{it} is $1*k$ vector idiosyncratic errors. γ_i is $1*k$ vector of forward mean-differencing. β $k*k$ matrix and α $1*k$ matrix are the estimated parameters (Abrigo & Love, 2016).

For the present study, the following PVAR model specification was used (Eq. 4.2.):

$$Y_a=\tau_0+\tau_i Y_{a-1}+f_i+\gamma_i+\varepsilon_i \qquad \text{Eq. 4.2.}$$

where, Y_a is a two-variable vector: EGI and CPI. f_i denotes the fixed-effects variable that covers unobserved individual heterogeneity, i.e. country fixed effects. The lags in the dependent variables cause the regressors to be correlated with fixed effects, and need to be accounted using other terms. γ_i is the forward mean-differencing to preserve the orthogonality between the transformed variables and the lagged regressors (Arellano & Bover, 1995; Love & Zicchino, 2006). That way, the lagged regressor can be used to estimate the parameters using GMM. ε_i is a vector of errors. The Im-Pesaran-Shin panel unit root test (Im et al., 2003) is performed on the dataset to ascertain the appropriate temporal properties of the data. This test helps detect the existence of stationarity in the panel data, for dependent and independent variables. Eq. 4.3. is used for the unit root test:

$$\Delta Y_t = \tau_0+\vartheta Y_{t-1}+\sum_{i=1}^{p} \gamma_i \Delta Y_{t-1}+\varepsilon_t \qquad \text{Eq. 4.3.}$$

where Y_t is a vector for the time series variables, p is the optimal lag length, and ε_t is a vector of errors. The null hypothesis is: “all panels include unit roots”, versus the alternate hypothesis (“at least one panel is stationary”).

To identify the optimum lag length, the likelihood-ratio test was used. These involved Akaike’s information criterion (AIC) (Akaike, 1969), Schwarz’s Bayesian information criterion (BIC) (Schwarz, 1978), and Hannan and Quinn’s information criterion (QIC) information criteria (Hannan & Quinn, 1979). These criteria are given by Eq. 4.4. - Eq. 4.6.:

$$\text{AIC}=\frac{2}{T}pK^2 + ln\left|\widehat{\sum_u (p)}\right| \qquad \text{Eq. 4.4.}$$

$$\text{BIC}=\frac{2ln ln(T)}{T}pK^2 + ln\left|\widehat{\sum_u (p)}\right| \qquad \text{Eq. 4.5.}$$

$$\text{QIC}=\frac{\ln(T)}{T}pK^2 + ln\left|\widehat{\sum_u(p)}\right| \qquad \text{Eq. 4.6.}$$

where, T is the number of observations in the time series data, p is the lag order, $\left|\widehat{\sum_u(p)}\right| = T^{-1}\sum_{t=1}^{T}\widehat{u_t}\widehat{u'_t}$, and K denotes the number of parameters in the statistical model (Albert & Logubayom, 2014). It may be noted that in this chapter's analysis, AIC, BIC, and QIC determine the optimum maximum lag order. In fact, these criteria are estimators of prediction error. These criteria provide a means for model selection by assessing the quality of each model, relative to each of the other models (Sakamoto et al., 1986). In assessing the amount of information lost by a model, these criteria perform a trade-off between the model's goodness-of-fit and simplicity (Akaike, 1985), and they deal with both the risk of overfitting or underfitting in time series models (Akaike, 1969; Schwarz, 1978).

To quantify the shock of the variables in question on each other, the impulse-response functions (IRFs) (Koop et al., 1996) associated with EGI and CPI is determined. The IRF measures the shock of one variable on the present and future values of other endogenous variables while the null hypothesis is suspended (Henriques & Sadorsky, 2008). The shocks for 10 consecutive years are observed. The error residuals produced by IRF may have a correlation issue. As such, it is useful to investigate the IRF along with the forecast error variance decomposition (FEVD) (Bernanke, 1986; Sims, 1986). FEVD orthogonalizes the shocks using Cholesky's decomposition method (Sassi & Gasmi, 2017); in this method, orthogonalization constraints are imposed on the variance-covariance matrix of errors. This way, the residuals are separated from common components. FEVD provides an indication of the cumulative contribution of each variable on the fluctuation of the shocked variable. In other words, the variance decomposition determines the amount of information each variable contributes to the other variable in the autoregression (Lütkepohl, 2005). FEVD for the variables can be calculated using Eq. 4.7., as follows:

$$\psi_{jl,h} = \sum_{i=0}^{h-1}\left(e_j'\theta_i e_l\right)^2 / MSE\left[y_{j,t}(h)\right] \qquad \text{Eq. 4.7.}$$

where, $\psi_{jl,h}$ is the FEVD for the variable j accounted for by exogenous shocks to variable l. y_t is a dimensional column vector, h is the forecast step size, e_j is the j^{th} column of I_k in the dimensional matrix (Seymen, 2008). After performing IRF and FEVD analysis, the PVAR Granger-cause analysis is studied (Granger, 1969). This causality analysis identifies the casual impact of shocks and shows the causal relationship between the variables in question. In other words, this test determines if one time series is beneficial in forecasting another. To investigate the Granger causality, i.e., to test the null hypothesis that n (a stationary time series) does not Granger-cause m (another stationary time series), the lagged values of m is included in a univariate autoregression of m as shown below (Eq. 4.8.):

$$m_t = \alpha_0 + \alpha_1 m_{t-1} + \alpha_0 m_{t-2} + \cdots + \alpha_\tau m_{t-\tau} + \varepsilon_t \qquad \text{Eq. 4.8.}$$

Then, the lagged values of n is included in the autoregression (Eq. 4.9.):

$$m_t = \alpha_0 + \alpha_1 m_{t-1} + \alpha_0 m_{t-2} + \cdots + \alpha_\tau m_{t-\tau} + \beta_1 n_{t-1} + \cdots + \beta_\sigma n_{t-\sigma} + \varepsilon_t \qquad \text{Eq. 4.9.}$$

The null hypothesis in our study is the left-hand side variable (LHS) does not cause the right-hand side (RHS) variable. In the Granger Causality Wald test, the null hypothesis is that "the excluded variable does not Granger-cause the Equation variable," versus "the excluded variable Granger-causes Equation variable."

The entire analysis is carried out at two levels: the global level, where all countries are considered as one group, and the country level where the countries are clustered based on their gross national income per capita.

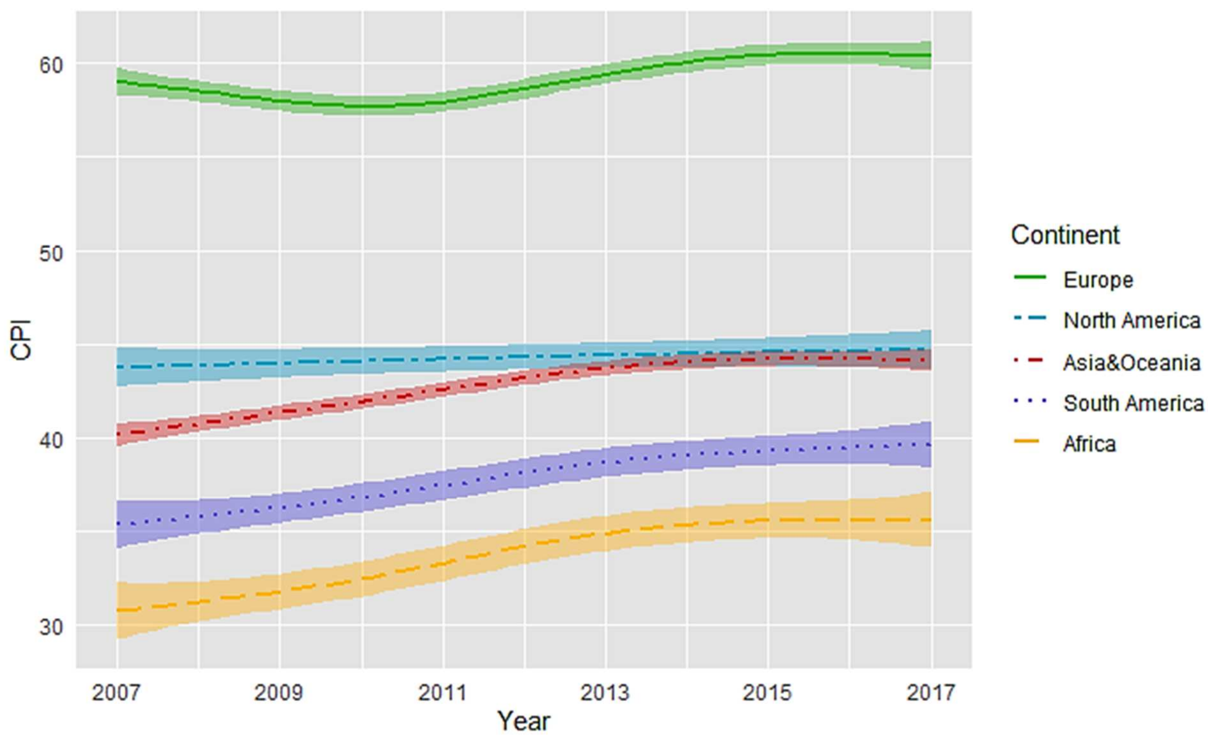
4.5 Results and Discussion

4.5.1 Spatial-Temporal Trends of CPI

The global spatial-temporal CPI trends (Figure 4.5.a.), suggest that although there has been a slight decrease in corruption (that is, slight increase in the Corruption Perceptions Index (CPI)) for all continents, a majority of the continents still have an average CPI below 45. Figure 4.5.b., a distribution of CPI observations (each observation represents a country in a specific year) in each continent, indicates a bimodal distribution in at least three of the five continents. It is observed that except for Europe, all other continents have many countries with CPI values less than 30. This exploratory analysis seems to provide some indication of the extent to which corruption (using CPI) prevails in each continent, and the distribution of corruption across the countries in a continent. This provides some indication of which continent(s) appear to be in immediate need of attention regarding corruption control.

Figure 4.5.c. presents the median and quartiles for each continent. Africa's median CPI is approximately 35, with 1st and 3rd quartiles of 25 and 40, respectively. There are very few countries

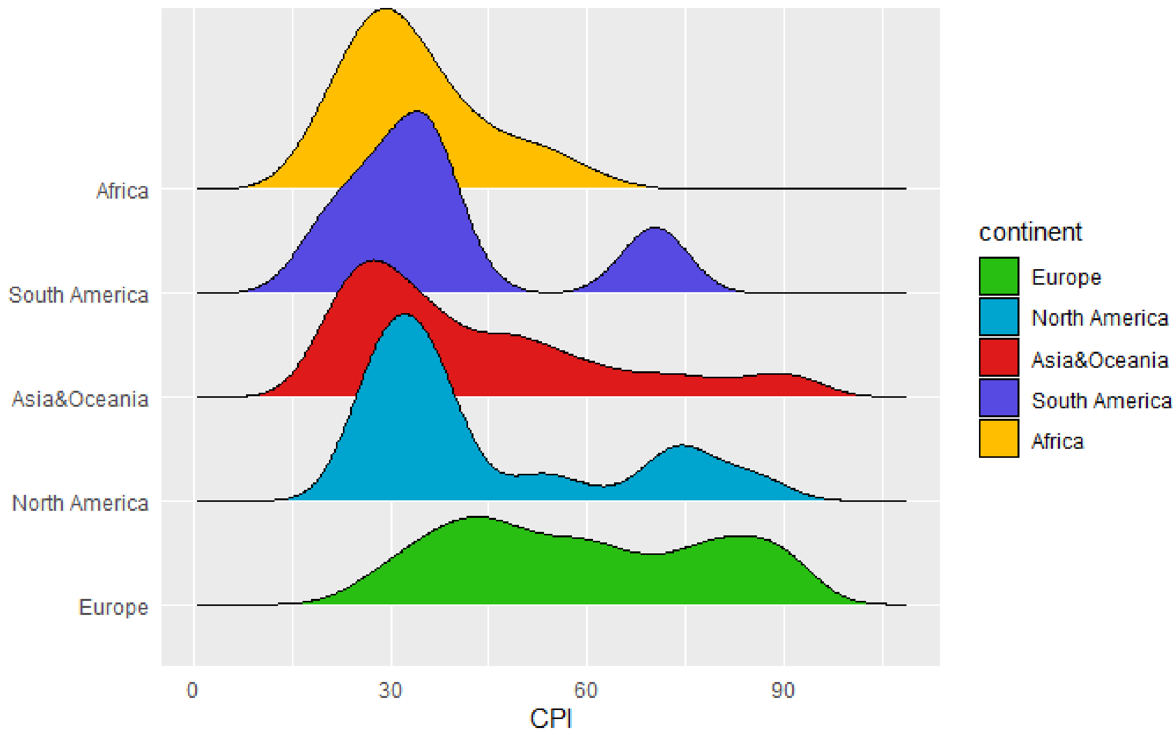
with CPI over 60. For South America, the median CPI value is 38 with the 1st and the 3rd quartile about the same as those of Africa, and this continent has few countries with CPI over 70. Compared to Africa and South America, Asia & Oceania has similar median and 1st quartile values; however, the 3rd quartile (approximately 50) is significantly higher and that continent has one country at the top levels of CPI. North America has a slightly higher 1st quartile value (approximately 30) and the same 3rd quartile value as Asia & Oceania. Europe's 1st and 3rd quartiles are approximately 45 and 75, respectively, with a median approximately 60. In sum, these broad trends suggest that Africa and South America are in critical need of effective policies and actions to control corruption.



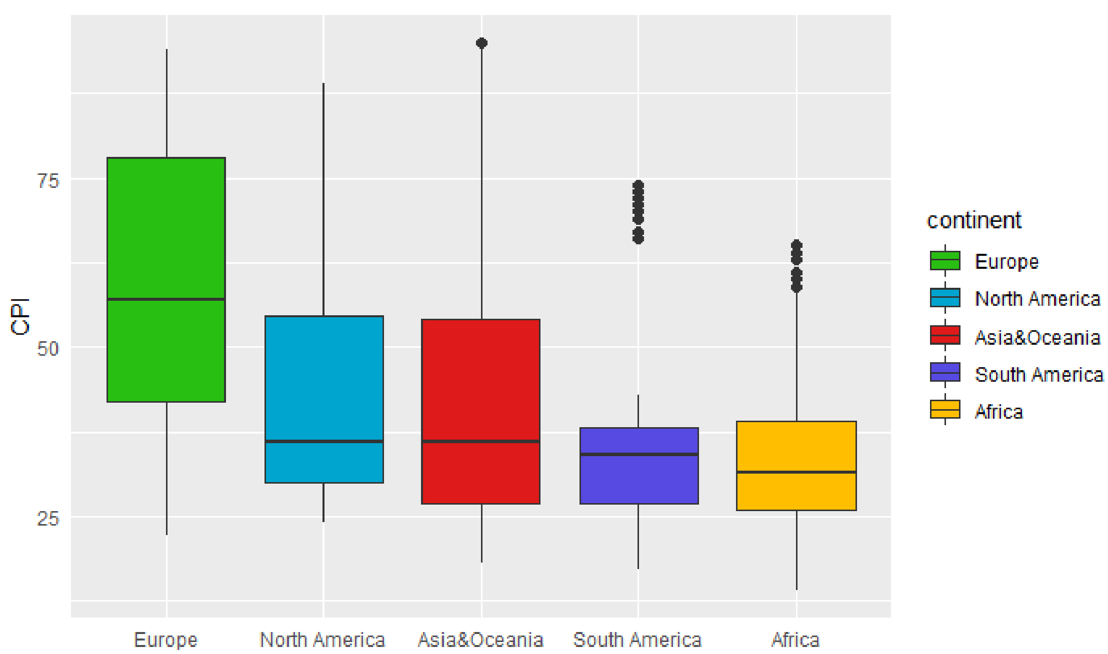
(a) Trends of Average CPI across the Continents, 2007 to 2017

Figure 4.5. CPI trends 2007 to 2017

Figure 4.5. continued



(b) Frequency Distribution of Average CPI from 2007 to 2017, across the Continents



(c) Boxplot for the Continents' CPI from 2007 to 2017

4.5.2 PVAR Analysis Results

Impulse-Response Functions

Table 4.4. presents the results of the Im-Pesaran-Shin panel unit root test (Im et al., 2003) (carried out to show the appropriate temporal properties of the data). A time series is considered to be stationary if a shift in time does not cause a change in the shape of the distribution (Marbaniang, 2020). As seen in the table, all the variables are at stationary levels (without unit-roots) because the null hypothesis (which postulates that all panels contain unit roots) is rejected. The model selection criteria are presented in Table 4.5. which helps in identifying the optimal lag order in our PVAR analysis. The Akaike's information criterion (AIC), Bayesian information criterion (BIC), and quasi information criterion (QIC) information criteria show first-order lag - with the smallest criteria - which denotes that one year of lag for EGI and CPI is appropriate for this specific analysis.

Table 4.4. Panel unit root testing

	Fixed Effects		Fixed Effects and Trends	
Variable	Statistic	P-value	Statistic	P-value
EGI	-5.119*	0.000	-4.430*	0.000
CPI	-3.674*	0.000	-3.162*	0.000

*Note: *The null hypothesis of panels, which contain unit roots, is rejected at the 5% significance level.*

Table 4.5. Model lag selection criteria

	Interactions between EGI-CPI		
Lag	AIC	BIC	QIC
1	-17.962	-64.539	-17.221
2	-13.384	-46.790	-27.554
3	-7.102	-24.546	-13.952

Table 4.6. presents the results of the PVAR analysis. In a PVAR analysis, IRF and FEVD are used to justify the results and discuss the potential outcomes. With IRF, it is possible to ascertain how endogenous variables react to certain structural shocks over time. The table presents the IRF for EGI and CPI, for all the three clusters (that is, all countries, countries with low and middle income, and countries with high income). This is done with the 95% confidence interval bands of the Monte Carlo simulation outcomes.

Figure 4.6. presents the IRF Curves for E-Governance Index (EGI) and Corruption Perceptions Index (CPI) interactions for 10-year intervals on the abscissa: (a) response of CPI to EGI shock, (b) response of EGI to CPI shock, (c) response of CPI to CPI shock, and (d) response of EGI to EGI shock. The confidence intervals are obtained using Gaussian estimation based on a Monte Carlo simulation. The results indicate that one-unit positive shock on EGI - meaning moving towards a society with an overall better e-governance - causes around 0.6 increase in CPI, i.e. less corruption, in two years (Figure 4.6.I.a). It is observed that this effect will be is damped through the time and after 8 years it becomes negligible.

As expected, the same shock on EGI causes a slight increase in EGI, and causes a persistent change in EGI over time (long-term effect) (Figure 4.6.I.d). In the short run, an EGI variation has a relatively negative shock on corruption, which could be due to the following reasons: at the beginning of any policy changes, (a) official representatives and people in charge are not fully aware that new anti-corruption policy has been implemented; (b) corrupt officials and organizations are aware of this initiative and know that the remaining time before the initiative is implemented is their last chance to earn illicit gains through corruption.

As observed, in a long run, the EGI changes still need persistent attention of the policymakers and governments. This could be because when new technology or new policy is implemented, the corrupt actions are paused or lowered for a while until the culprits identify new ways of getting around the new initiatives. Therefore, it will be beneficial for governments and policymakers to evaluate the efficacy of their corruption-mitigation policies and initiatives periodically, to keep ahead of individuals and organizations that seeking to continue this practice. In addition, from the results for the one-unit positive shock on CPI (that is, moving towards a less-corrupt situation), it is observed that there are no significant changes in EGI over the analysis period (Figure 4.6.I.b). The same shock causes a considerably positive increase in CPI: it seems to have a long-term and permanent effect on reducing overall corruption in countries (Figure 4.6.I.c). This result suggests that the effects of corruption reduction will likely linger on in the long term.

Table 4.6. First-order PVAR model results

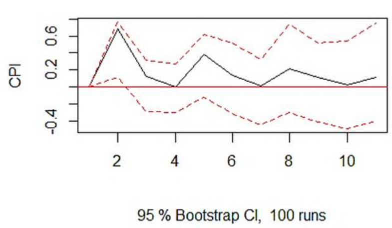
Response of	EGI	
Response to	CPI (t-1)	EGI (t-1)
All Countries		
CPI	0.569*** (3.82)	5.378** (1.58)
EGI	0.016** (1.31)	1.37*** (3.28)
Number of observations	1,854	
Number of countries	133	
Low- and Middle-Income Countries		
CPI	0.501*** (4.53)	0.017** (1.76)
EGI	1.56*** (2.73)	0.983*** (3.19)
Number of observations	1,193	
Number of countries	83	
High-Income Countries		
CPI	0.225** (1.64)	0.008 (0.89)
EGI	0.711** (1.57)	1.29*** (2.33)
Number of observations	661	
Number of countries	50	

Note: t-Student statistics are reported in parentheses.
*, **, *** *reflect 10%, 5%, and 1% significance levels, respectively.*

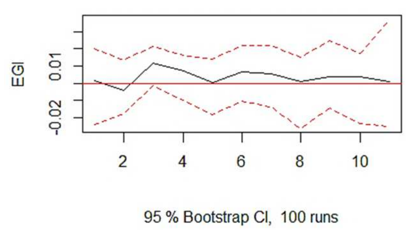
For developing (low- and middle-income) countries, the analysis results are even more significant. Figure 4.6.II.a-d illustrates the outcome of the IRF curves for these countries. From the results, a one-unit shock on EGI will lead to an immediate increase in CPI, and such an effect seems to persists over time (Figure 4.6.II.a). This CPI increase is 20% greater compared to that for all countries together. This result suggests that the e-governance efficacy in corruption control at developing countries is considerably higher compared to developed countries. The same shock causes a slight increase in EGI, and it considerably causes EGI to improve persistently over time (Figure 4.6.II.d). This results also supports the hypothesis that e-governance implementation can help control corruption in these countries. Furthermore, observing the results for the one-unit positive shock on CPI for this cluster suggest findings that are similar to those of the first cluster:

there are no significant changes in EGI over the time (Figure 4.6.II.b). The same shock leads to a significant positive increase in CPI with a long term and persistent effect as seen from the "all countries" category. In the case of high-income countries, it is noted that the shocks from either of the two variables, are not significant.

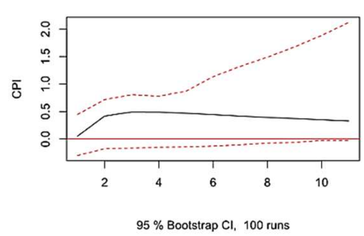
Figure 4.6.III.a-d shows the IRF curves for the developed countries. According to the results, one-unit EGI shock leads to an almost 0.5 increase in CPI (for the first two years) (Figure 4.6.III.a) with a damping pattern after almost 8 years. The same shock causes a slight increase in EGI with a negligible change on EGI over time (Figure 4.6.III.d). This finding shows that although developing new e-governance models and techniques are beneficial for developing countries, a dramatic change in the control of corruption in those countries cannot be expected. Hence, there must be other underlying means and methods that need to be used to reduce corruption in that category. This could be addressed in future research. Furthermore, the results for the one-unit positive shock on CPI for countries in this cluster suggest that findings similar to those above, are made: there are no significant changes in EGI over time (Figure 4.6.III.b). The same shock causes a relatively low increase in CPI with a long-term effect.



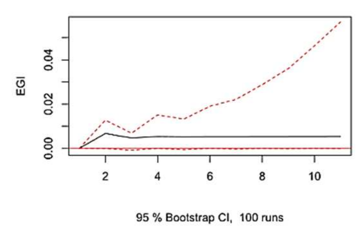
(a) response of CPI to EGI shock



(b) response of EGI to CPI shock



(c) response of CPI to CPI shock

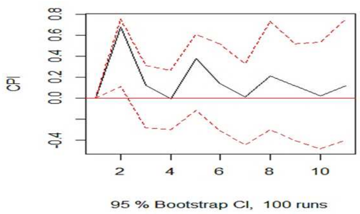


(d) response of EGI to EGI shock

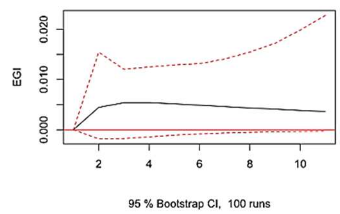
I: All Countries

Figure 4.6. IRF Curves: E-Governance Index and Corruption Perceptions Index interactions

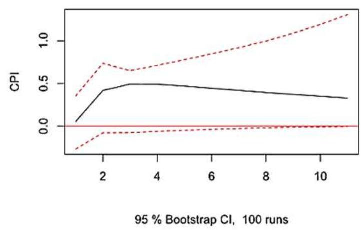
Figure 4.6. continued



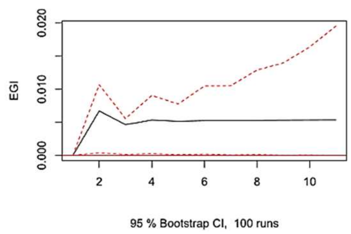
(a) response of CPI to EGI shock



(b) response of EGI to CPI shock

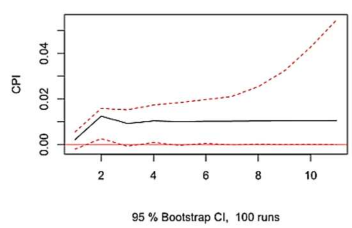


(c) response of CPI to CPI shock

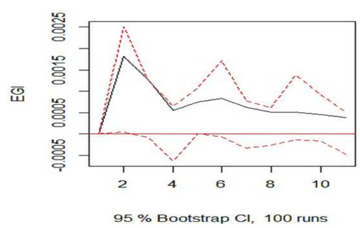


(d) response of EGI to EGI shock

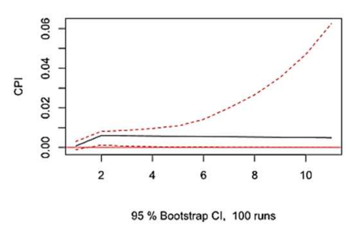
II: Low- and Middle-Income (or Developing) Countries



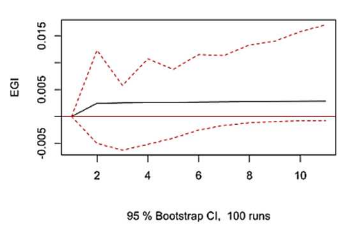
(a) response of CPI to EGI shock



(b) response of EGI to CPI shock



(c) response of CPI to CPI shock



(d) response of EGI to EGI shock

III: High-Income (or Developed) Countries

**Note: 10 years steps (x axis).*
***Confidence intervals are obtained using Gaussian estimation based on a Monte Carlo simulation.*

Determining the Direction of Influence using the Forecast Error Variance Decomposition (FEVD) & Granger Causality Test

Table 4.7. presents the results of forecast error variance decomposition (FEVD). In this table, the percentage of variation in the row variable is explained by the column variable for a ten-year period. The e-governance index explains the corruption perceptions index over ten years with a value of 38.7%. For the low- and middle- income level countries, this value is 45.2% and for high-income countries it is reduced to 16.3%. This suggests that EGI can explain 16.3% of the total CPI variations in high-income countries over the ten years. CPI contributes to 2.8%, 1.8%, and 9% of the variation of EGI in the first, second, and third categories, respectively – a negligible influence as seen previously. The findings from FEVD confirm the one-way relationship between EGI and CPI – as seen in the IRF analysis – thereby corroborating the notion that the former influences the latter to a greater extent compared to the vice versa case. This causal relationship can be verified by performing a panel Granger causality test. As shown in Table 4.8., causality between the two variables is one way. A robust causal relationship between EGI and CPI with a relatively negligible feedback from CPI to EGI is observed.

Table 4.7. Forecast Error Variance Decomposition (FEVD)

Response Variable		Impulse Variable	
		CPI	EGI
All Countries	CPI	0.613	0.387
	EGI	0.028	0.972
Low- and Middle-Income Countries	CPI	0.548	0.452
	EGI	0.018	0.982
High-Income Countries	CPI	0.837	0.163
	EGI	0.090	0.910

Table 4.8. Panel Granger-Causality results

Equation/Excluded		Chi2
All Countries	CPI/EGI	0.011**
	EGI/CPI	0.492*
	N observations	1,854
	N countries	133
Low- and Middle-Income Countries	CPI/EGI	0.015**
	EGI/CPI	0.693*
	N observations	1,193
	N countries	83
High-Income Countries	CPI/EGI	0.006
	EGI/CPI	0.155**
	N observations	661
	N countries	50

*Note: * and ** reflects 5% and 10% significance level.*

4.6 Concluding Remarks

E-governance, as an emerging application of information and communication technology, has been suggested in the literature to be a promising tool to reduce corruption. E-governance potentially not only fosters transparency but also encourages citizen participation in governance, among other benefits. It has been suggested or ascertained that by providing citizens access to information on the functionality of public entities and providing open media for public debate, e-governance can help improve openness and accountability associated with government functions, and ultimately significantly reduce instances of corruption.

In this chapter of the dissertation, the focused was made on finding the associative or causal relationships between e-governance and corruption. The hypotheses developed in this chapter included the efficacy of e-governance in developed countries comparted to developing countries. In this chapter, a panel vector autoregression (PVAR) analysis was performed to identify the associative or causal relationships and shock effects of e-governance and corruption. To quantify the shock effects, the impulse-response functions (IRFs) associated with EGI and CPI along with the forecast error variance decomposition (FEVD) were performed to find how much EGI contributes cumulatively to CPI fluctuations. The accuracy of the results was confirmed using PVAR Granger-causality analysis.

The analysis showed that e-governance can significantly help to reduce the levels of corruption. The results of forecast error variance decomposition (FEVD) suggest that EGI explains

38.7% of the CPI variation of the ten-year period. For low- and middle- income level countries, this value was 45.2%, and for high-income countries it was 16.3%; these results indicated that EGI can explain 45.2% and 16.3% of the total CPI variations in developing and developed countries, respectively, over the ten-year analysis period. The results of IRF showed that a one-unit positive shock on EGI leads to a 60% increase in CPI in two years. The results suggest that this effect fades off after eight (8) years.

The results for the low- and middle-income countries were more significant statistically compared to the results for all countries or the high-income countries. In addition, the results indicated that one-unit shock on EGI would lead to an immediate increase in CPI, and that the effects persist over time. This level of increase in CPI is approximately 20% higher compared to that of all countries together. This suggests that in developing countries, the efficacy of EGI will be more profound compared to developed countries. Moreover, it was shown that electronic governance can have permanent positive effects on controlling corruption in developing countries.

The results for high-income countries indicated little or no significant shocks from CPI to EGI or vice versa, suggesting that the beneficial effects of EGI may have already reached a plateau, and other corruption reduction initiatives may be more effective in those countries. In addition, it was found that in the short run, EGI has a relatively low shock on corruption. However, in the long run, it needs a fresh effort to become as effective. This indicated that policymakers and executive administrations should evaluate their policies periodically to “stay ahead of the curve” as corrupt entities will seek new channels when corruption-control initiatives are implemented. The IRF analysis suggested that low- and middle- income countries are in immediate need of attention regarding corruption, and that effective e-governance can provide an effective and lasting solution.

CHAPTER 5. CORRUPTION - PROPENSITY AND MITIGATION AT DIFFERENT INFRASTRUCTURE DEVELOPMENT PHASES

[A version of this chapter is presented at the Transportation Research Board 100th Annual Meeting[1]]

5.1 Introduction

Civil infrastructure systems, including transportation of all modes, water and wastewater plants and distribution networks, are developed with the intention of satisfying some specific objectives. These objectives can be traced back to overarching goals including human welfare and well-being, quality of life, and livability, within the social, economic and ecological environment, in which the infrastructure is situated or has an influence (Khisty et al., 2012; Labi, 2014). These overarching goals, in turn, emanate from a set of principles that govern the behavior of humans or corporate entities that can be described as values. The values serve as a moral compass to identify whether an action is good or bad, and often serve as the basis for a religion, culture, laws, or ethical behavior in a professional society. Hence, the development of civil infrastructure, which enhances the lives of thousands or millions of people, is inherently a noble and selfless endeavor, and the often far-reaching and longstanding future societal benefits are a source of great pride to the civil engineer. Unfortunately, in the development of civil infrastructure, some humans engage in selfish behaviors that not only betray this honorable purpose but also lead to significantly reduced societal benefits of the new infrastructure. As Transparency International (TI) notes, "Corruption erodes trust, weakens democracy, hampers economic development and further exacerbates inequality, poverty, social division, and the environmental crisis" (International, 2020).

Every year, more than 5% of the world GDP ($2.6 trillion) is lost due to collusion, corruption, and fraud (Irisova, 2014). Given that 1.2 billion people live on $1.25 or less per day, the magnitude of these losses are a reminder of their far-reaching impacts. Furthermore, these losses are not only diverted from development but are also used to support criminal activities such as drugs and human trafficking (Integrity Vice Presidency, 2016). Irrespective of location, corruption imposes losses, and exacerbates social issues and inequities. Hence, formulating

[1] Ghahari, S.A., Alabi, B. N.T., Queiroz, C., Labi, S., & McNeil, S. (2021). Corruption Propensity and Mitigation at the Various Phases of Infrastructure Development – An Exploratory Discussion. *Transportation Research Board 100th Annual Meeting.*

mitigation strategies on a global basis to identify, minimize, and even prevent misconduct is practical (Integrity Vice Presidency, 2009).

In this chapter of the dissertation, the corruption propensity at each phase of infrastructure development is considered. Moreover, the problem of corruption in the context of infrastructure systems delivery is discussed to show how corruption can be minimized and how engineering ethics could be leveraged to help in the fight against corruption. The chapter is organized as follows: first, the broad background concepts for the study and the motivation for the dissertation are presented. Then corruption is defined, and its impacts are identified. Next, the role of engineering ethics is discussed followed by the corruption propensity at each phase of infrastructure development. This leads to the next section where recommendations are made on corruption mitigation from strategic, tactical, and operational perspectives. In the last section, some concluding remarks are offered, the study limitations are listed, and possible avenues for future work are presented.

5.2 Study Background

5.2.1 Values and Value Systems

Any discussion of corruption needs to be set in the context of the values of the society in question. Values can be defined as the set of preferences regarding what is appropriate and what is not, and the types of values held by society including ethical, moral, religious, political, cultural, social, and aesthetic values (McCuen et al., 2011). A community's value system is a set of consistent values that are drawn from multiple types of values, and unlike personal values, those are generally stable across time or situations. In either of these two cases, values represent an internal gauge for what is right or wrong.

Over several millennia, societal values led to the development of customs, traditions, and laws within communities; and with the formation of professions and organizations of common interest, values also led to the development of rules of behavior for members of that organization. Values that ultimately underlie the code of ethics of most professional societies include honesty, stewardship, and discipline. For example, engineers should be loyal to society, their clients, and their employers and ensure that the products of their engineering designs do not impair the welfare of others, be truthful in testimony or public statements regarding their work, and ensure that their work is done diligently according to standards and specifications. In this chapter of the dissertation, values and ethics are addressed from the perspective of a civil engineer, but these concepts are also applicable to other professions (Labi, 2014).

5.2.2 The Properness Triad – Morality, Ethics, and Law

Those who engage in corruption are very much aware of what they are doing, and lack of knowledge is not a good excuse. As discussed in the previous section, the values of an individual or community often ultimately evolve into morality, ethics, and law. Morality is what distinguishes between actions that are considered right by society and those that are wrong, and is heavily influenced by religion and culture, particularly where explicit moral codes are established to guide human behavior. The most famous example of a moral code is the Golden Rule: "Treat others how you wish to be treated." Ethics is a branch of philosophy that addresses what can be considered a right or a wrong behavior. Law is a collection of rules that are enforced through social institutions to govern the behavior of individuals and organizations, and thus protect the individual or natural resources from the malicious actions of others. The importance of law in society is underscored by the fact that in most countries, the law-making body (or legislature) constitutes one of the three arms of government (the other two are the executive and the judiciary). As civil engineers plan, design, and operate civil systems, they constantly encounter situations related to morality, ethics, and law (Labi, 2014). For this reason, corruption is not only a legal issue, but also a moral and ethical issue.

5.2.3 Revisiting the Definition of Corruption

Nye (1967) defines corruption as "... behavior that deviates from the formal duties of a public role (elective or appointive) because of private-regarding (personal, close family, private clique) wealth or status gains." Werlin (1973) characterizes corruption as "… the use of public office for private needs", and Blackburn et al. (2004b) consider public sector corruption as the "illegal, or unauthorized, profiteering by officials who exploit their positions for personal gain." Regarding a specific narrow context, Shleifer and Vishny (1993) defines it as "… the sale by government officials of government property for personal gain". In echoing Nye's definition, Khan (1996) defined corruption as "... behavior that deviates from the formal rules of conduct governing the actions of someone in a position of public authority because of private-regarding motives such as wealth, power, or status.” Treisman (2000) offers what is consistent with what is probably the most common definitions of corruption: “... the misuse of public office for private gain.”

Corruption is generally motivated by personal gain, which may not be only monetary but also power or prominence. Given these definitions, a broad notion of corruption is used: the exploitation of public authority with the intention of achieving personal benefits. When shared public goods are transformed into private settlements, corruption occurs in both private and public entities (Corvellec & Macheridis, 2010; Heidenheimer et al., 1989). Acts of corruption can be seen as either a cultural moral issue and/or a structural issue of economics or politics. Moreover, moral decay, misuse of public power, bribery, and transfer of tangible resources all can be considered as acts of corruption.

5.3 The Role of Engineering Ethics

In this section, corruption is characterized in infrastructure systems delivery and solutions to the problem are sought through the lens of engineering ethics to connect actions to the responsibility for safety, equity and societal outcomes. Ethics is a branch of philosophy that deals with the values associated with human behavior, and addresses the wrongness or rightness of motives, the badness or goodness of actions in terms of their consequences (Josephson & Hanson, 2002). Ethics is closely related to morality and can be defined as a collection of moral principles or rules of conduct that guides the behavior and attitudes of a specific group of people, such as engineers, medical practitioners, or members of a religious group (Labi, 2014). Professional engineering organizations in most countries have established codes of ethics by which their members regulate their work practices, conduct and relationships. These organizations also urge engineers to hold themselves to the highest standards of professional and ethical conduct and recognize explicitly the obligation of individual engineers to uphold the integrity, self-respect, and honor of the engineering vocation by honest and impartial service to their employers, patrons, and the community (ASCE, 2020).

In the United States, ethical behavior is guided by codes established by professional organizations, including the National Council of Examiners for Engineering and Surveying (NCEES), the American Society of Civil Engineers (ASCE), and the National Society of Professional Engineers (NSPE). In Asia, codes of ethics have been established by the Chinese

Academy of Engineering, the Engineering Academy of Japan, and the National Academy of Engineering of Korea. Similar codes have been established by engineering professional organizations in other countries, including New Zealand, Australia, Canada, Brazil, and Russia, to regulate the behavior of engineers. The World Federation of Engineering Organizations (WFEO) (2001) has established a model code of ethics where professional engineers are expected to demonstrate an ethical and honorable conduct, and to uphold the values of integrity and honesty, and to hold sacrosanct all human life, the public welfare, and the natural environment.

These professional codes of conduct govern the obligations of registered engineers to society, their employers, and their clients and to other registered engineers. These codes exhort members of the engineering profession to uphold high principles of integrity and honesty, that in providing their services, engineers must ensure fairness, impartiality, and equity, and always seek the safeguard of the public safety, health, and welfare. Engineers must therefore be guided by a standard of professional conduct that adheres to the top levels of honorable behavior.

The preamble to NSPE's Code of Ethics for Engineers (2019) states that "members of the profession recognize that their work has a direct and vital impact on the quality of life for all people." Furthermore, any services rendered by engineers require "honesty, impartiality, fairness, and equity, and must be dedicated to the protection of public health, safety, and welfare" and "perform under a standard of professional behavior that requires adherence to the highest principles of ethical conduct." ASCE (2020) released an updated code of ethics in 2020 to reflect technological changes by focusing on "behavioral intent, rather than prescriptive rules." The preamble states, "Members of the ASCE conduct themselves with integrity and professionalism, and above all else protect and advance the health, safety, and welfare of the public through the practice of civil engineering." Building on fundamental principles, responsibilities to (1) society, (2) the natural and built environment, (3) the profession, (4) clients and employers, and (5) peers are articulated in the code of ethics. Specific responsibilities are directly associated with corruption (ASCE, 2020):

- "have zero tolerance for bribery, fraud, and corruption in all forms, and report violations to the proper authorities" (responsibility to society);
- "reject practices of unfair competition" (responsibility to the profession);
- "promote and exhibit inclusive, equitable, and ethical behavior in all engagements with colleagues" (responsibility to peers); and

- "act with honesty and fairness on collaborative work efforts" (responsibility to peers).

Other examples of responsibilities related to the four fundamental principles, shown in Table 5.1., are impacted by corruption.

The NSPE and ASCE code of ethics are similar to the engineering codes of other countries and other professions. Below, some of these rules of practice that are associated with civil engineering ethics, and how they are related to corruption are discussed. The discussion is built around the ASCE Code of Ethics but could also be applied to codes from other countries or professional organizations.

Engineers aware of potential infringements of any of the regulations of professional conduct are expected to deliver information to the governing board and assistance, when required. Most engineering professional societies worldwide recognize that the practice of professional engineering is not a right but a privilege. Also, these societies invariably charge engineers with the accountability of "adhering to the highest standards of ethical and moral conduct in all aspects of their professional practice" (Institution of Engineers, 2019), and in certain cases, their personal lives. As such, this privilege (in the form of a license to practice) could be withdrawn in the event of behavior deemed unethical or immoral by the professional society. In some countries such as Australia, there is explicit recognition in the code of ethics that engineers need to respect the dignity of the individual, and to act only on the basis of a "well-informed conscience" (Institution of Engineers, 2019).

Table 5.1. Fundamental principles and examples of responsibilities in the ASCE code of ethics (ASCE, 2020)

Fundamental Principle	Examples of Responsibilities
Create safe, resilient, and sustainable infrastructure	• First and foremost, protect the health, safety, and welfare of the public • Enhance the quality of life for humanity • Adhere to the principles of sustainable development
Treat all persons with respect, dignity, and fairness in a manner that fosters equitable participation without regard to personal identity	• Treat all persons with respect, dignity, and fairness, and reject all forms of discrimination and harassment • Recognize the diverse historical, social, and cultural needs of the community promote and exhibit inclusive, equitable, and ethical behavior in all engagements with colleagues
Consider the current and anticipated needs of society	• Consider the capabilities, limitations, and implications of current and emerging technologies • Consider and balance societal, environmental, and economic impacts, along with opportunities for improvement • Mitigate adverse societal, environmental, and economic effects • Use resources wisely while minimizing resource depletion • Present clearly and promptly the consequences to clients and employers if their engineering judgment is overruled where health, safety, and welfare of the public may be endangered
Utilize knowledge and skills to enhance the quality of life for humanity	• Uphold the honor, integrity, and dignity of the profession • Promote mentorship and knowledge-sharing equitably with current and future engineers • Educate the public on the role of civil engineering in society

5.4 Corruption Propensity at Each Phase of Infrastructure Development

An examination of corruption in infrastructure development through the phases of infrastructure development or stages in the life cycle helps to identify opportunities for mitigating corruption. Figure 5.1. presents the phases of infrastructure development. As stated in a World Bank report (World Bank, 2020a), "Every phase in an infrastructure project involves distinct combinations of institutions and stakeholders, each with their own vulnerabilities to particular types of misconduct." Building on the work of Sohail and Cavill (2008), the specific areas where corruption could occur within each phase (or stage) are discussed, and examples are presented.

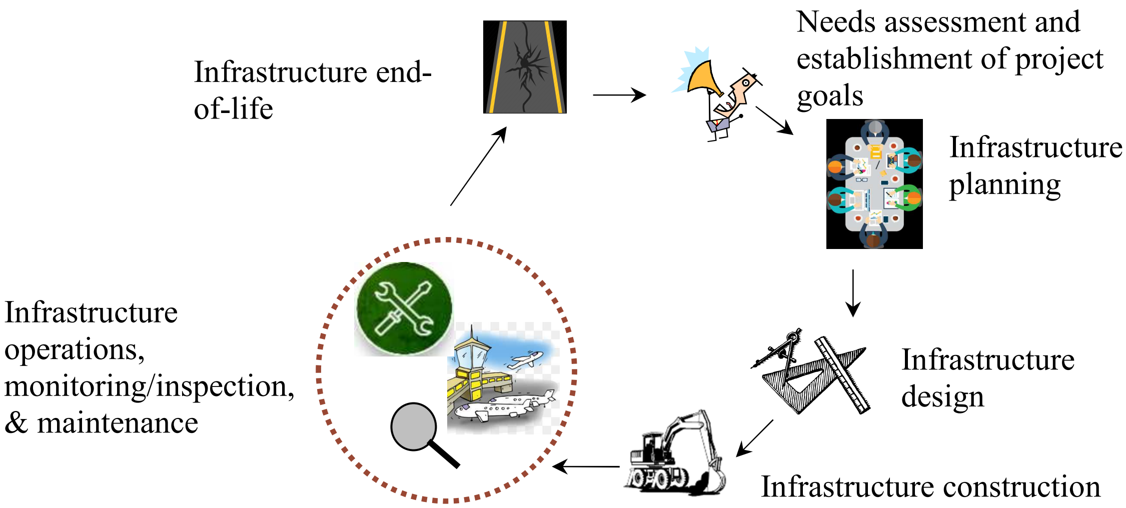


Figure 5.1. Phases of infrastructure development

5.4.1 The Needs Assessment Phase

At this phase, the infrastructure agency determines whether an infrastructure deficit exists and the magnitude of the deficit, identifies the stakeholders that will be affected by the infrastructure, and establishes the infrastructure goals and objectives of the system. New proposed construction projects themselves can be a sign of corruption as investment in maintenance for the existing infrastructure may be a better solution (Kenny, 2006; Labi, 2014).

Corruption in the needs assessment phase could be motivated by tribal, partisan, or pecuniary reasons. For example, a government decision maker may decide that a need exists to build infrastructure at a location not in response to a genuine socio-economic need, but because the decision-maker seeks to curry favor with residents of the area, to show that the decision maker has not "forgotten his roots", or to support the operations of a business venture that is not only located near the site of the proposed infrastructure but also would benefit from the proposed infrastructure. A good example is the infamous "bridge to nowhere" in Alaska, a proposed bridge earmarked for funding which was never built as it did not really serve any real need (Egan, 2004). Examples in other countries include election-time promises, where vote-seeking politicians seek to initiate "progress and development" infrastructure projects as pre-election gifts to their constituencies. In such cases, the need is not identified by an appropriate professional but some vote-seeking politician, often one who is a member of the ruling party and is therefore in a position of power to allocate or disburse funds. In certain cases, consultants are hired to assess the existence and magnitude of the infrastructure deficit; however, they could be influenced to skew the results to what the politician seeks. Such influence may be in the form of promises, rewards, or blacklisting regarding future contracts.

5.4.2 The Planning and Financing Phase

Planning includes assessment not only of the infrastructure impact (to the environment, economic development, air quality, noise, land-use, social equity, and so on) but also of the impact of the natural and built environment on the infrastructure. Also, in this phase, the technical and financial feasibility of the proposed infrastructure are determined; the latter is done by comparing costs and benefits of the infrastructure that are expected over a planning horizon that is often a function of the infrastructure service life.

The responsibility for systems planning is often borne by agencies that have been granted statutory authority for a specific type of infrastructure. In many countries, a formal and distinct unit of the national government carries out or supervises planning for public infrastructure systems. In other countries, such as the United States, most public infrastructure planning is carried out by regional, state, or local governments, and the federal government's role is to provide the funds and to ascertain that all the subsequent phases of the system development are consistent with legislation. The infrastructure agency carries out the planning task in-house or outsources it to consultants. The infrastructure planners liaise with other engineering professionals in the transportation, water, energy, and environment sectors, and also solicit input from other professionals and stakeholders including the general public (Sinha & Labi, 2007).

This phase is susceptible to corruption in a variety of ways, and for several reasons. For example, the planning analysis methodologies tend to be esoteric and rather difficult to comprehend by non-experts or the general public. Stakeholders of the planning process include the infrastructure owner or agency, the infrastructure financiers (such as financial institutions, non-governmental organizations, and governments of all levels, national regional, and city), residents of the area of the infrastructure location, and the general public (Labi, 2014). The planning process is an interplay of these stakeholders, and a great deal of trust and integrity is required. However, any one of these stakeholders, or faithful or unfaithful agents acting on their behalf, may gain some financial advantage (at the expense of other stakeholders and more importantly, at the expense of the long-term interest of the infrastructure).

Examples of such instances of corruption are as follows: (a) A financial institution, seeking to be selected as the financier of the infrastructure, may influence monetarily, a decision maker at the infrastructure agency. To make matters worse, the financial institution may seek to recover such payments by financing the project at an interest rate that exceeds the normal rate. (b) A representative of the prospective financier may conceal unfavorable data to receive a bonus associated with a decision to fund the infrastructure. (c) A representative of the prospective financier may be influenced monetarily by the infrastructure owner to influence the selection of a financier for the infrastructure. (d) An official employed by the infrastructure agency may secretly purchase or inflate the value of the land which is intended to serve as part of the right of way, and later sell it to the agency project owner at a profit. (e) An official employed by the infrastructure agency may purchase stocks associated with the proposed infrastructure after receiving inside information regarding the project.

Other areas of corruption at the planning phase are: permits, regulations, rules, and authorizations, public expenditure decisions, provisions of services and resources at below-market prices, discretionary foreign investments, and financing political party operations (Tanzi, 1998). Indirect factors that promote corruption include low quality of bureaucracy, low levels of the public sector wages, absence of or unenforced penalty systems, the absence of institutional controls, lack of transparency of rules, laws, and procedures, and leaders not setting an example (Sadiqi et al., 2017; Tanzi, 1998).

5.4.3 The Design Phase

Engineering design may be defined broadly as a creative problem-solving process in which the engineer works within the budget, time, legal, institutional, and other constraints to convert data, information, and technical know-how to translate ideas into a product or service. In this phase, detailed designs are generated by engineers, who also calculate the associated costs. Here is an ideal time to choose gratuitously high specifications for the method of construction, the materials, and the design. The amount of bribe money can be maximized when the total cost of the project is set to be higher than needed. Another way of bribery maximization is to allow for considerable low-quality design, materials, and/or methods of construction, and in the meantime increasing the contract price. This way, a considerable fraudulent profit will be potentially available to the beneficiaries in various occasions.

One specific method of construction might be falsely chosen in order to let one specific qualified bidder win the contract. This fraudulent activity is also possible when it comes to choosing materials. Specific materials might be selected to favor some selected suppliers. Engineers might perform or might be instructed to perform an incomplete design in order to enable the manipulation of any future changes and bribery or fraudulent claims.

The design phase is vulnerable to corrupt practices, for example, (a) The designer selects specific materials to favor some selected suppliers, particularly where there exist other superior materials to play that role in the design, (b) Deliberate submission of an incomplete design with the expectation that the client will return to the designer, at the construction phase, to carry out additional design work for a fee, (c) Incomplete or superficial analysis of loading, or usage scenarios resulting in an inadequate design, and (d) Influencing (monetarily or in kind), the public official responsible for permits to approve designs that do not conform to government regulations. In some countries with the highest reported level of corruption, such as India and Cameroon, attaining licenses, construction authorizations, and labor inspections are known to be the main sources of corruption (Kenny, 2007b).

5.4.4 The Construction Phase

The construction phase can be defined loosely as the process of “translating the design into reality” and involves the physical assembly of the infrastructure system. The multiplicity of the contractual parties involved in construction, often provides opportunities for corrupt actions. For this reason, this phase is often considered the most corrupt phase, and the construction industry in general, the most corrupt sector (Kenny, 2009b; Kottasova, 2014; Locatelli et al., 2017; Suen et al., 2007).

The propensity for corrupt actions manifests at each stage of the construction phase. At the stages of tender, bidding, and contract award, there could be collusion in the selection of the contractor, often with kickbacks paid to the client's personnel responsible for the pre-construction stage. Other areas of potential corruption at this stage include: (a) The client's personnel, seeking to favor a specific bidder in return (or in expectation) of a monetary or in-kind illicit payment, leak confidential information (such as the engineers estimate) or impose unduly strict and unnatural requirements in the biding process that can be met by that bidder only, (b) Collusion between bidders, where the bidders bid collaboratively such that one of them wins the contract. (c) In order to win the contract, the bidder submits false bidding data, such as much reduced unit prices of certain items, with the expectation that they can make up for such "losses" through change orders or other illicit ways during the construction process. An example of corrupt practices at the pre-construction stage was the 2009 conviction of a major U.S. construction firm of foreign bribery charges regarding a bidding for the construction of liquefied natural gas in a developing country and the imposition of a $402 million criminal fine. According to court documents, the firm "pleaded guilty to conspiring with its joint-venture partners and others to violate corruption legislation by authorizing, promising, and paying bribes to a range of government officials of that country to obtain contracts (United States Department of Justice, 2009). Another example was kickbacks paid to the Chief Executive Officer of the Lesotho Highland Development Authority (Darroch, 2003). A survey of international construction firms revealed that the main reason why these firms attempt to influence the owner's officials is the fear of not getting new contracts or losing existing contracts awarded to them.

The Odebrecht case in Brazil is particularly notable as the corruption was involved in the planning and financing, construction and operation phases but had the most impact in the construction phase (GPO, 2019). Extending beyond Brazil, Odebrecht bribed high-ranking officials to get initial contracts that were later renegotiated (Morales & Morales, 2019). This is also a reminder that corruption extends beyond infrastructure in many countries, and context plays an important role as evidenced by the Lava Jato (Car Wash) investigation in Brazil (The Economist, 2019). Bowen et al. (Bowen et al., 2015; Bowen et al., 2012b), Oyewobi et al. (Oyewobi et al., 2011), Sichombo et al. (Sichombo et al., 2009), and Ling et al. (Ling et al., 2014) provide several examples of corruption in this phase.

The global construction industry is dominated by large firms. In developing countries, the relatively large construction companies are often owned by government-related corporations. According to a comprehensive research performed in 2006, in Vietnam, 60% of the construction sector's revenue comes from 900 construction firms owned by states, and about 40% of the revenue is captured by 7,000 private firms (Copplestone, 2006).

Corruption, particularly for international projects and foreign transactions, is mostly driven by the host country conditions. According to a comprehensive survey on international company practices, the fear of losing contracts is the main reason firms attempt bribery (Søreide, 2006).

Technical challenges in the actual process of construction, for example, decision-making and planning with insufficient information, design inadequacies and uncertainties, project change of scope, incomplete estimations, and unreliability in price forecasting are factors that increase vulnerability to corrupt actions. Examples of corrupt actions at this stage include: (a) The project owner's site representative is influenced by the contractor to (i) issue a not-needed scope change, (ii) sign a payment certificate for a work that is not done, not completed, or not carried out to material or workmanship specification, (iii) approve an extension of time for the wrong reason or to state falsely that the delay is not the fault of the contractor; and (b) Potential deviations from specification (with regard to material or workmanship quality) may be associated with defective finished surfaces, use of low quality materials, and incorrect dimensions (widths, thicknesses, heights, depths) of the final product.

5.4.5 Operations, Monitoring, and Maintenance Phase

At this phase, the activities of the triad – operations (use of the infrastructure), monitoring (assessing changes in condition of the infrastructure, threats imposed by the natural and built environments and opportunities for change), and maintenance (carrying out physical repairs to address imminent defects or to correct existing ones) - are carried out synchronously (Ghahari et al., 2019d). Where the infrastructure operations, monitoring, and maintenance are carried out in house, inefficiency, rather than corruption, seems to be the bane. On the other hand, where these tasks are contracted out, then the nature of the corruption and the instance of corrupt activities are similar to those discussed for the construction phase.

Tangible evidence of the cost of corruption in this phase is presented in an analysis of asphalt concrete and road rehabilitation and reconstruction costs based on data from Europe and Central Asia, and corruption has been identified as a cause of significant cost variability of the materials and processes associated with those projects (Cirilovic et al., 2014).

Renegotiation of Public-Private Partnerships (PPP) in this phase also has the potential for abuse in this phase as the contracting process is less open (Ling et al., 2014; Wang et al., 2019; World Bank et al., 2020). The Global Infrastructure Hub (2018) found 48 instances of renegotiation in 146 PPPs studied. Of the renegotiated projects, the cause of renegotiation was cited as increased operation costs (9%), wrong demand forecasts (7%), other inaccurate projections (9%), and government strategy shift (19%).

5.4.6 The End-of-Life Phase

One cannot refer to infrastructure end of life without specifying what constitutes end of life. Lemer (1996) defined system life as the time between construction and its subsequent replacement, due to any of several reasons including technological obsolescence, substandard performance, regulatory changes, or changes in consumer behavior and values. Hence, the reasons for demolishing an infrastructure system (and in many cases, rebuilding it) could include the need to accommodate the changing nature, patterns, or levels of user demand; to mitigate user or community safety or security problems associated with the infrastructure operations; or to avoid excessive maintenance or operating costs associated with its current infrastructure. In many cases, infrastructure systems provide service during their design lives, and may even be doing so at a cost of economic efficiency and safety. Therefore, the lack of definite standards to specify what end-of-life really means can open opportunities for corrupt actions.

At the end-of-life phase, the infrastructure material may be reused, modified, and repurposed, recycled, dismantled, sold, upgraded, and/or integrated with the proposed new infrastructure. Examples of corrupt activities at this phase include: (a) Representatives of the infrastructure owner declare that an infrastructure system has reached its end-of-life due to the expectation of receiving prospective illicit benefits associated with the reuse or recycling of the physical infrastructure, or to make way for alternative developments; (b) The infrastructure owner's representatives specify the disposal of construction waste to unapproved sites for their personal gain; and c) Hazardous materials are improperly disposed of. For example, Doshi and Ranganathan (2017) document the premature demolition of housing in Chennai and Bangalore, and the subsequent land grabbing.

5.5 Corruption Mitigation Initiatives

The international attention on anti-corruption attempts – particularly, developing countries – is a relatively new development. Since the delivery of the "Cancer of Corruption" speech in 1996 by the 9th World Bank President, the development-related financial institutions dropped inhibitions and started using the "c-word" in public (Wolfensohn, 1996). Since then, billions of dollars have been spent to assist governments tackle corruption challenges (Wang, 2020). This investment in corruption mitigation is relatively small compared with the investments in development. International development banks (IDBs) help with the social and economic development of developing countries by providing loans with favorable interest rates (Nelson, 2015). For example, the World Bank finances 20,000 to 30,000 contracts with total worth of more than $60 billion per year and is the largest IDB in the world (World Bank, 2016). The contracts fund infrastructure, agriculture, education, and health, and are provided to countries with low and middle incomes. In some of those countries, the government is unstable, and given that the value of these transactions are high, several contracts are susceptible to collusion, corruption, and fraud (Integrity Vice Presidency, 2016).

The Business Environment and Enterprise Performance Survey (BEEPS) indicates that 14% of all firms attempted to secure government contracts through unofficial payments to public officials, and the median amount spent by firms from all sectors for this purpose represented about 7% of the contract value (Kisunko & Ponomariov, 2014). For instance, in Indonesia, losses due to employee theft were reported to be 24% of expenditures for road construction projects overseen by heads of the villages (Olken, 2007). Strategies and initiatives to mitigate corruption include policy statements, guidelines and codes, organizational and political structures, and monitoring and penalties. These types of strategies and initiatives are discussed followed by examples of initiatives in each phase of the infrastructure life cycle. The discussion is also associated with the ASCE Code of Ethics.

5.5.1 Policy Statements, Guidelines, and Codes

Concerns regarding corruption has an international scope and is not limited to developing countries. For this reason, efforts to fight corruption, at least from a strategic perspective, have largely been international in nature. Several international organizations have published policy statements, guidelines, codes, and manuals on the issue.

On the global scale, international agencies produce official publications, and engage in various ways to address the problem of corruption:

- The Organization for Economic Co-operation and Development (OECD) released the "Recommendation for Further Combating Bribery of Foreign Public Officials," or Anti-Bribery Recommendation in 2009 (OECD, 2009c). Currently, OECD is reviewing this policy, following a broad public consultation carried out in 2019 (OECD, 2019).
- The World Economic Forum, Transparency International, and a collection of engineering and construction firms initiated a "zero tolerance" policy on bribery in 2004 (WEF, 2016). The policy promotes the monitoring of all payments, donations, gifts, and charitable payments, to individuals associated with projects. The policy also protects the rights of the firms that refuse to give bribes, and encourages strict audits and penalties for violators and more auditing for those firms.
- The World Bank Group (WBG) has in place procedures that scrutinize all prospective projects and collaborates with member countries to reduce the risks of any potential corruption. The WBG has established a Sanctions System (which includes an Integrity Vice Presidency) that investigates any reports or allegations of corruption and fraud in the projects they support (Integrity Vice Presidency, 2016). WBG is a leader in this effort (World Bank, 2016) insisting on zero-tolerance toward corruption in the infrastructure projects it supports. Their corruption fighting approach consists of proactively anticipating risks and avoiding them. Avenues are available for the public to make complaints about planned, ongoing, or completed projects, and the project implementation receives rigorous oversight and is supervised by WBG-financed consultants with satisfactory records.
- The International Chamber of Commerce (ICC) published Rules and Recommendations to Combat Extortion and Bribery in 1977 and revised this document in 2005 (International Chamber of Commerce, 2005, 2011, 2015). The ICC encourages enterprises to self-regulate themselves in the drive to fight corruption, bribery, and extortion, and provides

critical perspectives from the business sector, towards international corruption-fighting programs, policies, and initiatives (International Chamber of Commerce, 2011).

- Transparency International has worked with multi-stakeholders and an global operating committee of firms, business organizations, scholars, union commissioners, and civil society associations to issue an anti-corruption code entitled Business Principles for Countering Bribery (Transparency International, 2010). This code created the foundation for the Partnering Against Corruption Initiative (PACI) Principles, developed with the World Economic Forum (WEF) (WEF, 2007). Transparency International organizes workshops in various countries to develop and train individuals on tools that support the development and implementation of anti-corruption policies and to monitor the effectiveness of these tools.
- The United Nations, in 2004, published its Global Compact to include a 10th "principle" that sent a power message to the private sector that is partially responsible for fighting corruption (Brun et al., 2011; UN Global Compact & Transparency International, 2009). The principle stated that "Businesses should work against corruption in all its forms, including extortion and bribery." The United Nations continues to encourage the private sector to not only prevent bribery, extortion and other forms of corruption, but also to cultivate strategies and solid programs to tackle it (Brun et al., 2011; United Nations, 2018).
- The World Bank, OECD and UNODC (2020) published principles for avoiding and controlling conflicts of interest in the public sector.
- The World Economic Forum (WEF) runs a Partnering Against Corruption Initiative (PACI), a multi-national and multi-industry private sector driven platform where organizations create, maintain, implement and monitor their anti-corruption initiatives (International Chamber of Commerce et al., 2008; WEF, 2007, 2009).

Strategic-level corruption mitigation initiatives are consistent with the fundamental principles or canons in the codes of ethics of engineering organizations in many countries. The responsibility to "have zero tolerance for bribery, fraud, and corruption in all forms, and report violations to the proper authorities" in the ASCE Code of Ethics (ASCE, 2020). When these initiatives are systemically instituted across all phases of the infrastructure development life cycle, it becomes easier to address corruption.

5.5.2 Organizational and Political Structures

Montinola and Jackman (2001) found that partisan rivalry, a feature of democracies, can help lessen corruption: monitoring the activities of public officials is easier in freedom-of-information environment, therefore, it can restrict the chances of corrupt activities. Moreover, the potential power reversal at the ballot box is beneficial to corruption mitigation because it helps ensure that politicians involved in corruption may lose the election and will become subject to investigation and punishment following their election defeat. Kunicova and Rose-Ackerman (2005) asserted that a viable electoral procedure can provide politicians a motivation not only to divulge the corrupt activities of their rivals but also to make certain that they themselves are truthful. The researchers addressed issues of honesty and trust in relation to the operation of the parliamentary government and markets.

Bribery may happen in construction firms who seek to unethically raise profit margins by reducing their actual project spending through reduction in quantity or quality. Therefore, it seems that if projects are delivered on time, with the anticipated quality and cost, the instances of corruption can be limited. Hence, any tool, method, or intervention that could guarantee the quality, on-time delivery, and cost, can help as an anti-corruption tool. Overall, improving planning and budgeting processes and the transparency of the project cycle, raising awareness and civil society contribution and financial auditing agencies, reducing the unrestricted power of individual bureaucrats and unnecessary regulation, could significantly lower corruption (Lederman et al., 2005; Svensson, 2005; Van Rijckeghem & Weder, 2001).

Government ownership of construction firms adds more complexity to the transparency of contracts and bidding process. Governments that function as the regulatory sector and do not participate in construction activities can institute a more merit-based selection and less politically influenced environment of contract award, and more importantly, quality monitoring. Two clear indications of the impact of the government ownership of projects are (ILO, 2005; Mkenda & Aikaeli, 2015): (1) Indonesian road construction projects corrupted by local government employees involved in theft of materials, and (2) violation of labor standards in 11 large construction sites in Tanzania, reported by the National Housing Corporation .

The privatization of firms can cause its own problems and related corruption, and when there is an opaque privatization procedure, few will benefit from the privatization process, as was experienced in Vietnam (Copplestone, 2006). Where the bureaucratic values are not merit-based, the competitive politics are not institutionalized, the government processes are not transparent, and the active media is not fostered and is filtered, corruption takes place more often. For example, in most developing countries where the civil society is generally less engaged, the capacity for law enforcement is diminished (Johnston, 1998). Moreover, compared to the cost of human capital, corrupted countries invest more in tangible assets (De la Croix & Delavallade, 2009).

The Infrastructure Transparency Initiative (CoST) is a multi-stakeholders effort that leverages earlier efforts (for example, Integrity Pacts), and tools (such as Open Government Partnership and Open Contracting Partnership) to enhance public accountability (World Bank et al., 2020). CoST is a membership organization that supports national and subnational governments to implement the multi-stakeholder approach to transparency. The four key elements are the formation of multi-stakeholder working groups, disclosure, and social responsibility. The World Bank (2020) describes the experiences and results with the CoST program in Thailand, Ukraine and Honduras. In each instance, gains have been documented (World Bank et al., 2020) in the form of savings (Thailand), more projects for less money (Ukraine), and additional smaller project with significant social impacts (Honduras).

The institutional and organizational structures are strategic initiatives aiming to produce tactical responses. These structures provide frameworks in which ethical responsibilities related to unfair competition, equity, honesty, and fairness are practiced consistent with the codes of ethics of the engineering professional bodies of most countries.

5.5.3 Monitoring and Penalties

Establishing transparent, accountable, capable organizations and institutions that can moderate anti-corruption programs is a major step in fighting corruption. Where the monitoring, reporting and enforcements are insignificant, the electronic governance is poor, and there are benefits that can be gained by exploiting a position of control, the instances of corruption are likely to be high. Monitoring and penalties that leverage advanced technologies can help in corruption mitigation (Ghahari et al., 2018b).

Contractors and private firms experience several different types of issues related to financing, building, and/or operating highways. By providing well-established contract agreements that have pricing flexibility, a sound debt structure, and transparency, and by reducing the project risks contractors and private firms face, the risk of corruption will be lowered. Li and

Cai (2017) showed that the incentives from the government such as lump-sum subsidy, concession period extension, fee subsidy (e.g., shadow toll), and revenue guarantee can reduce the investment risks of the private partner. Offering private partners, during the bidding phase, a wide range of government incentives related to investment timing, capacity, and pricing, can be a viable approach to reduce corruption. The incentives are structured to benefit the contractor and there is a freedom to select from several alternatives. Under the competitive bidding process, the risk of corruption can be reduced. In such circumstances, the cost of corruption would be more than the net outcome, and that would lower the instances of projects involving corruption (Li & Cai, 2017).

Corruption is often exacerbated by excessive bureaucracy, for example, the number of licenses that are required to get permission for construction. Upper-income countries require 16 on average, and developing countries require 20 (Djankov et al., 2002). It is likely that with more licenses required, the risk of fraud and corruption is increased.

A useful strategy that helps ensure quality is output-based aid (OBA). It supports supplying basic services using unequivocal performance-based subsidies. By clearing "who" receives the grant, "why" it is given, and "what" it is going to be spent on, the aid is less likely to be associated with misinterpretations, low quality, and possible corruption (Kenny & Mumssen, 2007).

Involving more audits and required licenses does not always reduce corruption. Sometimes, a long process leads firms to attempt bribery to accelerate the procedure. Simplifying the health and safety regulations, and working closely with labor syndicates, consumers, and industry to craft an enforceable code can lower the likelihood of corruption. Other simple but crucial cultural changes need to be established and initiated with the reform of government agencies overseeing construction affairs. These changes include, but are not limited to, the prohibition of ghost-workers, defining specific roles, responsibilities and the levels of staffing, institutional budgeting in a transparent way, and digitalized ways of tracking and auditing of expenses. For example, over 1999-2000, Tanzania's Treasury changed the way of transferring funds from central to local government after a considerable leakage in the system (Sundet, 2004).

Predicting the outcome of projects using the existing models generated from previous similar projects can be another way of selecting projects that lead to the best outcomes. Doing this requires a comprehensive technical, economic, social, and environmental analysis. This way, the accuracy of the bidders can be revealed, a trustful relationship formed, and all results publicized for further discussion, debate, and/or detailed review. In the meantime, by sharing the risk of having unsatisfactory outcomes with the private partners, fewer projects with such problems might be seen. Reduction in the risk of having a low-quality project increases the returns to public investments. This entails comprehensive reform on pricing and regulations to make financial returns transparent and let the private sector make robust decisions based on the costs and benefits, which would lead to more reliable bids. These punitive and educational strategies are tactical and operational strategies. They are less directly tied to the engineering codes of ethics but provide some of the tools for enforcement.

5.5.4 Leveraging Advanced Technologies

Evidence from the literature suggests that advanced technologies can be used as an effective tool in the fight against corruption. These technologies include information and computer technologies, blockchain, artificial intelligence, big data analytics, and civic technologies (OECD, 2021). Each of these technologies and their potential role in corruption mitigation, are presented below.

Blockchain technology

Blockchain is a database technology for storing verified and trusted financial transactions. This technology provides transparency and helps build trust in financial systems. Also, by reducing the need for intermediaries, it lowers the risk and opportunities for corruption of the financial system (Mackey & Cuomo, 2020; Rangel et al., 2019). Nevertheless, because it does not disclose the identities of sender and receiver, blockchain may be misused for money laundering, illicit trade, and criminal activities (Adam & Fazekas, 2018; OECD, 2021).

Artificial intelligence (AI)

The reduction of corruption starts by identifying corruption, and as demonstrated in preceding chapters of this dissertation. AI can also be leveraged to help learning from past corruption incidents, improving the accuracy of financial and technical inspections and reviews, and detecting loopholes within project finance procedures. Yet still, AI could lead to biased predictions (and hence, decisions), and therefore fine-tuning and careful training of the AI algorithms are vital.

Big Data Analytics

As shown in this dissertation, statistical data analysis can help in detecting and measuring corruption in numerous ways. The availability of additional data is expected to yield more accurate analysis outcomes, and can afford oversight agencies a holistic view of the efficacy of their policies (Silveira, 2016). Big data and its associated analytics, on the other hand, may jeopardize individual privacy and cause threats to personal security, and therefore may constitute a concern for citizens (Ashenden et al., 2018).

Civic Technologies

E-governance can enhance communications between governments and citizens, and provides a foundation for citizens to have greater participation in government decision making and activities, and greater citizen engagement in public service policy making is another benefit of civic technologies is that they can encourage and facilitate greater public participation in government affairs and increase transparency. An example mechanism for this is crowdsourcing of data collection (via digital platforms such as cell phones) regarding infrastructure-related performance (Garcia-Molina et al., 2016; OECD, 2021).

Information and communication technologies (ICT)

Defined by the international federation of global and green information communication technology (IFGICT) as the integration of telecommunications and computers (IFGICT, 2020), ICT has helped not only facilitate government and citizen interaction but also educate citizens and reduce barriers in information delivery to and from governments (Köbis et al., 2021). Accordingly, ICT has helped citizens to become more engaged in bureaucratic processes and more aware of public service schedules and levels of service (Vrasidas et al., 2009). Other potential benefits of ICT in combating corruption are: automation (reduce chances of corruption in repetitive processes), transparency (reduce the probability of discretion), anomaly detection (including underperforming jurisdictions and outliers), passive defense (through networks of monitoring individuals), reporting systems, raising awareness (educating citizens) and deterrence (through public announcement of corruption cases) (Grönlund et al., 2010; Wickberg, 2013; Zinnbauer, 2012). However, despite all the advantages of ICT, it must be noted that some citizens with limited access to technologies, due to lack of knowledge of using devices, may be unable to effectively report any infrastructure abnormalities. In addition, some limitations from political environments may inhibit citizen attempts to access ICT capabilities and functionalities (Hellström, 2010). One other important challenge is the potential misuse of such technologies; the 2007/2008 presidential election crisis in Kenya is a clear example of the misuse of ICT against citizens (Goldstein & Rotich, 2009). ICT may be associated with risk of reduced security and confidentiality and protection from malicious individuals or repressive governments (LaFraniere, 2010).

The Christian Michelsen Institute (CMI) and TI (2012) provided some insight on how mobile phones can help to detect and deter corruption. The report suggests ways that mobile phones and camera/satellite technologies implemented in various countries, can help corruption reduction in the areas such as social accountability and mobilization (Mexico), communication and citizen-to-government interaction (South Africa), budget tracking (Kenya), whistleblowing and reporting (Panama and Georgia), and land transfer transaction monitoring (Pakistan) (Bailard, 2009; Fung et al., 2010; Hellström, 2010). The examples include "community monitoring of health and education services, public monitoring of budgets, and contrasting performance between government bodies in different districts (TI, 2012)." In addition, smart phone applications, e-tools, and e-procurement systems are now being used more for anti-corruption purposes (Mackey & Cuomo, 2020; Wellisz, 2018; Wickberg, 2013).

The corruption mitigation potential of ICT exists at all phases of infrastructure development. At the construction phase, for example, connectivity (communication) capabilities between the infrastructure being constructed and a central monitoring office (or construction inspector's mobile device such as cell phone) could be established. Through such connectivity, the inspection engineer could carry out a variety of activities in data collection (using image-processing, GPS, GIS, remote sensing) and analysis (using machine learning, heuristics, and mathematical models) to monitor the quality and quantities associated with the construction project in real time (Wellisz, 2018). In addition, data on the dimensions and quality of in-progress or completed work could be collected using sensors installed in intelligent construction equipment or connected and automated vehicles during post-construction use of the facility.

Sensing

The sensors that could be used in construction inspection fall into two categories: active and passive. Active sensors send out energy in the form of a wave and characterizes the features of the target based upon the returning information. Examples of sensor technologies include radar, LiDAR, and ultrasonic (Dubayah & Drake, 2000; Massaro et al., 2014). An example is the ground penetrating radar (GPR) which can be used to measure the quality and thicknesses of constructed layers of soil, aggregate, or asphaltic concrete. Passive sensors, on the other hand, take in information from the environment without emitting waves, such as regular cameras (Reindl et al., 1996). As discussed in the preceding paragraph, sensors facilitate real-time monitoring of physical construction (in progress or completed work). They are typically fitted on tall structures overlooking the construction site, mounted on drones, or fitted on construction equipment or passing traffic vehicles to collect data on the construction as it progresses or when it is completed.

Overall Discussion

An integrated system to mitigate corruption at the construction phase would typically consist of several of the technologies described above, as portrayed in Figure 5.2. To provide the contexts and the applications of this integrated system that is, some practical examples related to the infrastructure construction are discussed herein.

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Figure 5.2. Schematic figure of leveraging advanced technologies for fighting corruption at the construction phase

For example, aerial photos of the project site could be taken before the construction starts, and before and after each day's activities. In addition, the entire construction process (not only the overall site but also areas of specific tasks) can be recorded on video. These tasks include excavation, filling or embankment construction in layers, concrete pouring, asphalt laying, assembly of steel or precast concrete members, and so on. Using artificial intelligence techniques, the construction images can be processed to ascertain the quantities of materials used, the dimensions of the constructed product, and in certain cases, the quality of the material used in the constructed product, such as the level of soil compaction, moisture content of fresh concrete, and so on. The aerial photos can be used in conjunction with photogrammetric techniques to ascertain the dimensions and positions (heights, depths, angles) of constructed elements. Ground Penetration Radar (GPR) can help verify the quality of materials used in the construction including asphalt and concrete. Remote sensors installed in the crane buckets and trucks, used with GPS (Teizer et al., 2007) can measure the exact amount of soil that is hauled from one site to another. Intelligent compactors can help ascertain if the appropriate compaction levels have been achieved.

Concrete and asphalt mixer trucks equipped with GPS systems can alert the engineer at the laying site if they encounter undue delays between the batching plant and the site. Sensors installed inside their rotating drums report to the central monitoring office, the amount of concrete they are carrying, any changes in the concrete properties along their haul trip, and the mixture design of their load. Connectivity features also enable comparison of material specifications and in-situ properties of the materials after construction, and any deviations can be addressed.

Smart sensors implemented in workers' vests can capture the number of times they have moved objects during the day and show the calories burnt in that day, thereby monitoring workers' overall health and performance (Navon & Goldschmidt, 2003). Finally, in such an integrated autonomous and connected system for construction inspection, the collected and analyzed data can be stored in a data cloud, processed according to established standards and guidelines that are consistent with a secure cyber environment, and given access to all relevant stakeholders including corruption mitigation personnel.

5.6 Examples of Mitigation Initiatives

Corruption mitigation measures may be preventive, educational, or punitive. Examples of mitigation initiatives applicable to specific phases of project development that also support the relevant codes of ethics are outlined. The examples include both tactical and operational strategies that are supported by strategic initiatives.

5.6.1 The Needs Assessment Phase

Journalists and NGOs could play a role as watchdogs. Also, an anonymous public complaint and whistleblower program, could lead to less corruption. Projects that have used these approaches have slashed costs by 50% to 66% in competitive bidding strategies for a community-based construction of schools in Zambia and Mauritania (Theunynck, 2002), and savings of 25% to 56% compared with conventional infrastructure projects (Wong & Guggenheim, 2005).

Establishing transparent, accountable, capable organizations and institutions that can implement anti-corruption programs is a major step for this movement. Where the discretion is extensive, the monitoring system and reporting are deficient, the electronic government is poor, and the benefits that can be gained by exploiting a position of control are large, the instances of corruption are likely to be high.

As an example of applying a penalty system, South Korea's road sector applied the sanction policy on the firms that had broken laws and had agreed not to bribe or collude. Such firms can be subjected to comprehensive oversight by a self-regulating inspector with access to classified, internal documents (Lee & Larnemark, 2007). Accordingly, by publicizing detailed information about contract awards, so that all have access to the documents, the level of corruption will be lowered. Argentina, Turkey, Philippines, and Uganda are among the countries that have embraced this initiative (Kenny, 2007a). The disclosed information includes when and how the funds are going to be spent, by whom, and at what unit price the project is going to be delivered. Besides, the government officials who are auditing and monitoring the quality of the project should specifically be identified and announced.

5.6.2 The Planning and Financing Phase

To address corruption at the planning phase, it is important to ensure transparency throughout the planning process. All the options, as well as the merits and demerits of each option, should be made available to all stakeholders using the same dissemination platform. The agency should raise awareness of the proposed infrastructure and should facilitate the participation of the general public in the decisions made at this phase. The selection of the project financier should be done openly and the reasons for selection should be shared with the general public. In addition, the discretionary power of individual bureaucrats should be reduced. The infrastructure agency should undertake comprehensive fiscal reform to reflect transparency in agency's planning processes. Other initiatives could include procurement procedure reform in the rules and audit processes, mechanisms for competitive selection of planning consultants and infrastructure financiers, and legal reform that could lead to a significant increase in the society's awareness about the proposed infrastructure. Also, as the planning phase involves an *ex-ante* assessment of the infrastructure project outcomes (technical, economic, social, and environmental), and an open evaluation process can help verify whether the chosen plan was indeed the optimal, and this information could help guide the selection of plans for similar future infrastructure systems.

5.6.3 The Construction Phase

The Convention on Combating Bribery in International Business Transactions, which were enacted in 1999 by the Organization for Economic Cooperation and Development (OECD), would alleviate the ongoing culture of bribing foreigners (OECD, 1999). A "zero tolerance" policy on bribery initiated by WEF, TI, and other known engineering, and construction firms in 2004 is another approach. The policy also monitors payments (particularly, donations, gifts, and charitable payments) to make sure they are not an indication of bribery. It protects the rights of the firms, which refuse to bribe, and, in the meantime, it considers penalties for violators and more auditing for those firms. At a more local level, the Colombia Society of Civil Engineers supported open contracting using standard documents (World Bank, 2020a). This initiative has also leveraged new technology to make data more publicly available resulting in more competitions.

5.6.4 Operations, Maintenance, and Monitoring Phase

When there is a joint venture which includes entities from different countries, the joint venture might initiate an agency agreement through the entity that resides in the host country. This entity has less risk to be discovered for the corrupt activities. This entity is usually associated with a government official, project owner or their relatives. The entity will receive a larger portion of the profit (as a bribe) than it should normally receive.

Using well-documented best practices for operations, maintenance, and monitoring are the most obvious tactical and operational corruption mitigation measures. There is also evidence that digital reporting of issues added accountability and improved road conditions in Moscow (Gorgulu et al., 2020). Limiting the opportunities for renegotiation of PPPs, using moratoria, prescriptive language in the original contract, or letting the market respond, has proved effective in Brazil, Colombia, Peru, India, Australia, and Chile (World Bank et al., 2020).

5.6.5 The End-of-Life Phase

When it comes to the last project development phase, there are numerous ways to gain revenues through corruption. Excavation/removal of materials from the site is a very sensitive step and it is susceptible to corruption. Confirmation notes and documents might be falsely generated inflating the amount of material being removed. Site inspectors/surveyors/engineers might ask for bribe from contractors or vice versa to issue a proper record. Moreover, false invoicing for an equipment purchased/rented for a specific task of the project, e.g. a mid-size bulldozer to build road embankments, is another ground for fraud activities. In this case, site inspectors are offered bribes or threatened by contractors to falsely record the activities.

Corruption in the end-of-life phase can be symptomatic of larger issues. Premature demolition is often driven by new development and mitigation strategies are required, accordingly. Similarly, the improper management of materials can be addressed through regulation and best practices (Yeheyis et al., 2013). Early consideration of sustainable options can increase opportunities to optimize economic, environmental, and social indicators. Design engineers and decision makers can specify materials and designs that can be reused, modified and repurposed, recycled, dismantled, sold, upgraded, and/or integrated with new systems. This foresight can minimize landfill deposits and increase usability and salvage values. However, many end-of-life sustainability opportunities can still be taken advantage of without foresight and planning during early infrastructure development phases (OECD, 2009a).

5.7 Concluding Remarks

This chapter of the dissertation sought to identify the common ways that corrupt actions may occur in the development of infrastructure systems. The findings from publications related to corruption, projects, and infrastructure systems were condensed. The chapter's contents may be used to develop guidelines to measure, detect, and address corruption in the infrastructure sector. The fight against corruption is clearly not an easy one. For example, there have been several cases where government officials appointed to lead the fight against corruption have been ensnared in corrupted practices they had been tasked to eliminate. On the other hand, actions grounded in the appropriate value systems and codes of ethics should be adopted, and such implementations require optimism and persistence.

Corruption, in all forms, skews incentives and could lead to the loss of expert workforces, engineers, and people who do not want to be involved in such activities. In a corrupt industry, disqualified people will take the lead and will often overrule qualified experts, which in turn will cause economic loss. Corruption causes inefficiency in both public and private sectors. Corruption conflicts with fundamental values of honesty, equity, and transparency; it gradually weakens the unity of a society and ethical aspects of the civil service, which in turn, inhibits the capability of governments to enact public policies that promote social welfare. In this chapter, different aspects of corruption were reviewed and discussed. The study outcomes can be used to guide corruption mitigation efforts throughout the infrastructure lifecycle.

CHAPTER 6. INEFFICIENCY – ANALYTICAL MEASUREMENT METHODS

6.1 Introduction

Efficiency analysis is associated with the development of analytical tools that assist policy makers and agencies in measuring the efficiency of a system. Such tools contribute to the decision-making processes and help reduce inefficiencies accordingly. The proposed frameworks assess the productivity of the objectives as a whole as well as the relative productivity of the individual contributors to the objective. The analytical methods for efficiency measurement may be placed in at least two categories: (a) non-parametric vs. parametric, and (b) stochastic vs. deterministic (Kringos et al., 2010). In this chapter, the focus is made on deterministic non-parametric methods of efficiency measurement.

Other analytical methods for efficiency measurement include, corrected ordinary least squares (COLS), stochastic frontier analysis (SFA), and data envelopment analysis (DEA) are well-known in the field (Pelone et al., 2015). COLS is a parametric deterministic approach that uses ordinary least squares regression in estimating the relationship between inputs and outputs (Agbelie et al., 2015). The resulting residuals from COLS correspond to the inefficiency of the system. SFA is a stochastic parametric approach where the unknown parameters of the efficiency factors are estimated using maximum likelihood models. In an SFA model, the residuals are split into symmetric and asymmetric errors, which translate into statistical noise and inefficiency, respectively. DEA is a deterministic non-parametric approach which uses linear programming models to evaluate the relative productivity of organizational units. Due to the fact that DEA models are non-parametric, they can capture the convexity and monotonicity of data. Recently, a stochastic DEA has been introduced that adds the characteristics of both DEA and SFA together to increase the capabilities of DEA models. This reduces the potential limitations of DEA models by releasing the deterministic characteristic limitation of those models (Olesen & Petersen, 2016).

Frontier method applications have been studied in numerous fields, such as human resource management, transit agencies, public administration, management control system, health care system, etc. DEA is a well-known frontier analysis method. The main difference between DEA and other parametric methods is that DEA does not need an ex-ante specification of a production or a cost function, and therefore involves no functional relationship between inputs and outputs.

6.2 DEA Models for Efficiency Measurement

DEA uses a non-parametric mathematical programming to determine optimal individual frontiers. DEA is particularly efficient when the problem includes multiple inputs and outputs with uncontrollable factors. Moreover, it does not assume any functional form for the frontier or the distribution of productivity, therefore, the productivity analysis outcome is relatively easy to be interpreted by decision makers (Olesen & Petersen, 2016).

DEA is used to empirically quantify the effectiveness of decision-making units (DMUs) (Charnes et al., 1978). Emrouznejad et al. (2008) reported over 4000 studies on DEA models in their review dissertation on the very topic, and found that this technique is used particularly for benchmarking in operations management, and its applications have become widespread through the time.

Organizational units are typically eager to identify the sources of any inefficiencies in their agencies. Inefficiencies can be identified by breaking down the productivity components into the elements that contribute to efficiency. An influential capability of a DEA model is that it can be decomposed into those components when needed. Figure 6.1 presents the architecture of a general multi-stage model for efficiency assessment. This model takes direct inputs at each stage, and similarly, it gives direct outputs at each stage. Intermediate measures can toggle between two stages, common inputs can be given at each level, and shared inputs can be given to the stages at each level. In DEA models, there is no predefined distinction among inputs and outputs, therefore, all variables equally influence an organization's productivity (Epstein & Henderson, 1989).

In a DEA model, DMUs must be homogeneous; this means that the units of comparison must be similar in technology, have similar market conditions, and have similar tasks and objectives (Dyson et al., 2001; Golany & Roll, 1989). Another advantage of a DEA model is that it does not require all factors to have a common unit of measurement (Cook et al., 1994), and therefore, the inputs and outputs can be comprehensive as noted by Ozbek et al. (2010a). On the other hand, too many inputs and outputs will lead to larger values for the DMUs with high productivity scores. Hence, there is a rule of thumb in determining the number of inputs and outputs: number of inputs times number of outputs times 2 roughly determines the optimum number of DMUs (Dyson et al., 2001).

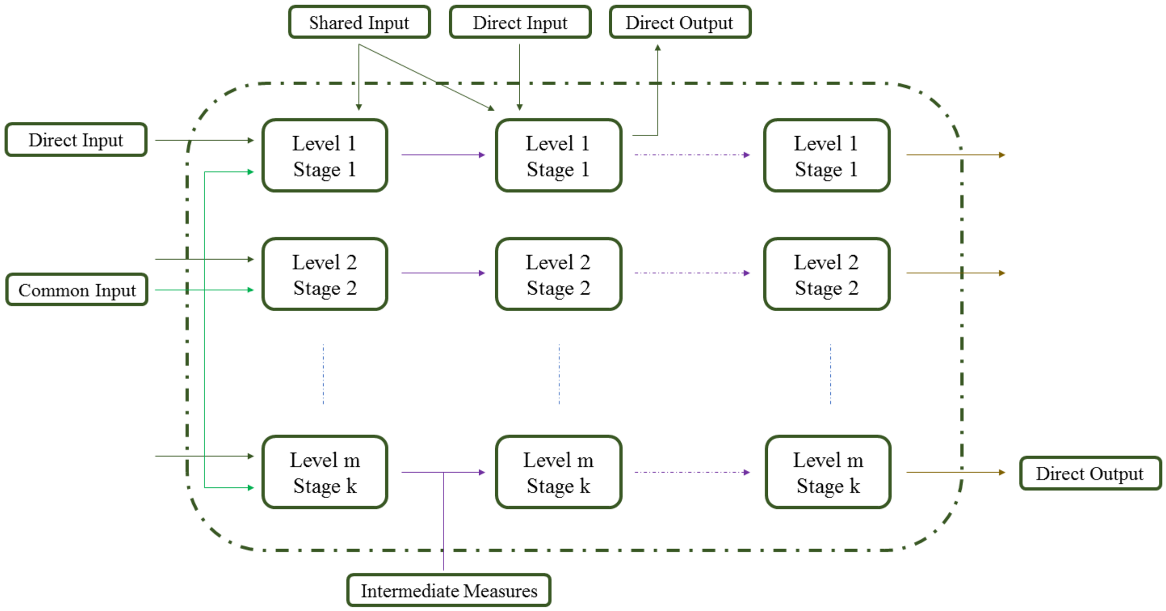

Figure 6.1. Architecture of a general multi-stage DEA model for efficiency assessment

6.3 Network DEA

The concepts in this section focuses on one of the most applicable DEA methods in real data called network DEA. In a traditional, typical DEA, the internal architecture of DMUs are typically disregarded. As such, the efficiency of a DMU is assumed to be a function of the inputs and outputs as a whole. To overcome this limitation, Färe and Primont (1984) proposed the assessment of productivity by considering internal factors. Later, Färe and Grosskopf (2000) developed a general multi-stage DEA model (i.e. network DEA) including internal inputs and outputs. They also used a network model to assess the performance of an organization (Färe & Grosskopf, 1996). In a similar effort, Cook et al. (2000) suggested a non-linear DEA model to assess the efficiency of a financial sector with the consideration of shared resources. Building upon this model, Jahanshahloo et al. (2004b) linearized the model by considering flexible and non-flexible share resources for their specific model.

Yang et al. (2000) considered a system containing several independent parallel subsystems. They suggested a DEA assessment model to measure the productivity of systems based on the efficiency of subsystems. Golany et al. (2006) proposed a similar approach to assess the productivity of a system as a whole as well as within its subsystems. Chen (2009) suggested a dynamic network DEA by proposing another productivity assessment for estimating the efficiency of hierarchical levels in a dynamic system. Later, Chen and Yan (2011) discussed returns to scale based on mixed organization, centralized and decentralized systems, and the relationship between productivity among systems.

Of all network DEA models, the two-stage DEA covers a large set of real data productivity assessment studies (Castelli et al., 2010). The two-stage DEA model was suggested by Wang et al. (1997) for productivity assessment in firms. Charnes et al. (1986) used a two-stage DEA model in the U.S. army recruitment system. Later, Seiford and Zhu (1999) used the same concept in measuring efficiency and marketability of the U.S. financial sector. In their model, independent constant returns to scale (CRS) models were used to assess the overall productivity (Eq. 6.1), productivity of stage 1 (Eq. 6.2), and productivity of stage 2 (Eq. 6.3). The overall productivity measurement equations are presented below:

$$\begin{array}{lll} \text{Max} & E^0(X_1.Y_2.Z.crs)^{sz} = uY^0{}_2, & \text{Eq. 6.1.} \\ \text{s.t.} & \gamma X^0{}_1 = 1, & \\ & \tau Y_2 - \gamma X_1 \leq 0, & \\ & \gamma,\tau \geq 0. & \end{array}$$

where, X_1 is the input for stage1, Z is an intermediate input for stage 2, and Y_2 is the output for stage 2. Accordingly, stage 1 is modeled according to the following equation:

$$\begin{array}{lll} \text{Max} & E^0{}_1(X_1.Y_2.Z.crs)^{sz} = \psi Z^0, & \text{Eq. 6.2.} \\ \text{s.t.} & \gamma X^0{}_1 = 1, & \\ & \psi Z - \gamma X_1 \leq 0, & \\ & \gamma,\psi \geq 0. & \end{array}$$

where, X_1 is the input for stage1 and Z is an output for stage 1, and an intermediate input for stage 2. Finally, stage 2 is calculated based on Eq. 6.3:

$$\begin{array}{lll} \text{Max} & E^0{}_2(X_1.Y_2.Z.crs)^{sz} = uY^0{}_2, & \text{Eq. 6.3.} \\ \text{s.t.} & \psi Z^0 = 1, & \\ & \tau Y_2 - \psi Z^0 \leq 0, & \\ & \psi,\tau \geq 0. & \end{array}$$

where, X_1 is the input for stage1, Z is an intermediate input for stage 2, and Y_2 is the output for stage 2. The overall architecture for a two-stage network DEA model is shown in Figure 6.2.

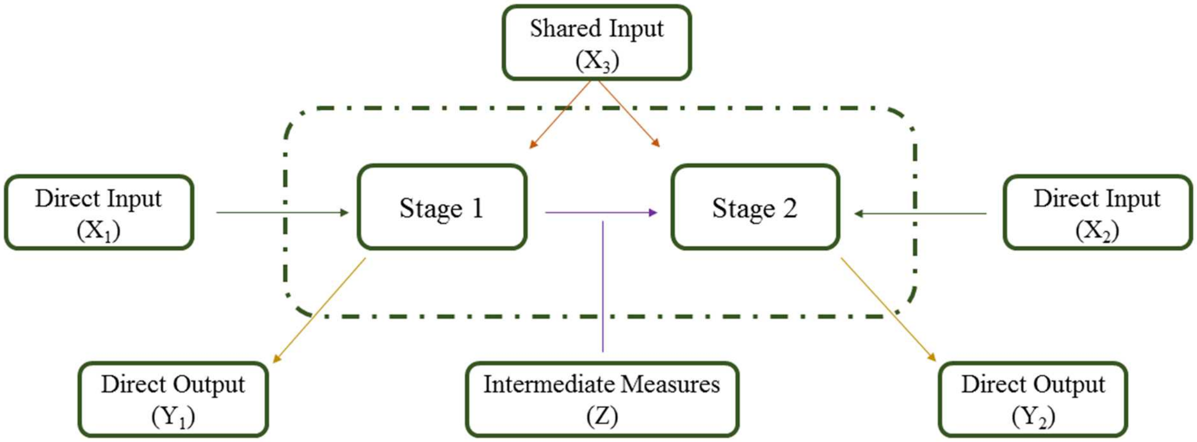

Figure 6.2. The architecture for a two-stage network DEA model

Chen and Zhu (2004) demonstrated that the conventional two-stage network DEA model, shown above, can potentially characterize the stages incorrectly due to the probable conflict that Z (intermediate measures) can create; this happens when $Z+Y_2$ is used as an output in assessing the overall productivity. In other words, Eq. 6.1. lacks the ability to correctly measure the efficiency of the two stages, since it only reflects the inputs and outputs of the whole procedure, and it disregards Z (intermediate measures) related to the two stages. Accordingly, in order to reduce the inaccurate assessments, Zhu (2014) suggested using the following method that takes an average productivity of the stages:

$$\text{Max} \quad E^0(X_1.Y_2.Z.\text{crs})^{sz} = \frac{1}{2}\left[\frac{\psi_1 Z^0}{\gamma X_1^0} + \frac{\tau Y_2^0}{\psi_2 Z^0}\right], \qquad \text{Eq. 6.4.}$$

$$\begin{aligned} \text{s.t.} \quad & \psi_1 Z - \gamma X^0{}_1 \le 0, \\ & \tau Y_2 - \psi_2 Z \le 0, \\ & \gamma, \tau, \psi_1, \psi_2 \ge 0. \end{aligned}$$

This approach still does not contemplate the connection among the two stages due to the fact that it decouples the stages via different multipliers. Hence, a variable returns to scale (VRS)-like linear DEA model is required to solve the problem (Chen et al., 2006; Chen & Zhu, 2004):

$$
\begin{aligned}
\text{Min} \quad & E^{0}(X_1.Y_2.Z.vrs)^{cz} = \theta_1\alpha - \theta_2\beta, && \text{Eq. 6.5.} \\
\text{s.t.} \quad & \left.\begin{aligned} & X_1\delta \leq \alpha X^{0}_{1} \\ & Z\delta \geq Z^{0} \\ & 1\,\delta = 1 \\ & \delta \geq 0 \end{aligned}\right] \text{Stage 1,} \\
& \left.\begin{aligned} & Z\delta \geq Z^{0} \\ & Y_1\vartheta \leq \beta Y^{0}_{2} \\ & 1\,\vartheta = 1 \\ & \vartheta \geq 0 \end{aligned}\right] \text{Stage 2.}
\end{aligned}
$$

where, Θ_1 and Θ_2 are pre-set weights signifying the productivity of the stages, and Z^0 is a decision variable that characterizes an intermediate measure for a particular DMU. Eq. 6.5., accordingly, measures both overall productivity and optimal values for Z (intermediate measures). Chen et al. (2006) used this approach to measure the productivity of firms considering of the impact of information technology (IT). Similarly, Saranga and Moser (2010) implemented the same approach in assessing the performance of supply managements. Table 6.1. presents other types of network DEA models including those mentioned above.

6.4 DEA Applications

DEA is a non-parametric and deterministic approach and it determines the most efficient objective in the system. Moreover, it captures the relative efficiency of other influential units in the system, and since it is non-parametric, it can capture convexity and monotonicity of the data. Furthermore, DEA does not take any functional form for the frontier or the distribution of efficiency, therefore, the analysis output is comparatively straightforward to be construed by decision makers.

DEA application has been investigated in various sectors such as health care system, public administration, transit agencies, human resource management, etc. Table 6.2. presents the application of DEA techniques in performance assessment in various industries. Note that a limitation in DEA analysis is that the results are sensitive to the selection of inputs and outputs. Hence, the variables have to be comprehensive, and they must include the relevant factors to cover the essence of the objective. On the other hand, when the number of inputs and outputs increase, the number of DMUs increase as well. In fact, an increase in the number of inputs and outputs makes the between DMUs much harder. Hence, although increasing the factors may seem to enhance the analysis, the presence of agencies within one sector that have considerably different types of services may provide flawed results and explanations. In the following sections, the focus is made on introducing the studies that have concentrated on the application of DEA in performance assessment of supply chain and manufacturing, healthcare system, energy sector, and transit agencies.

Table 6.1. Selected network DEA methods

Method	Application	Reference
Initial DEA Generation	Multi-plant firms	(Färe, 1991; Färe & Primont, 1984)
	Production	(Färe & Whittaker, 1995)
Seminal Study	Power Plant	(Cook et al., 1998; Yang et al., 2011)
Radial Method	Financial sector	(Cook et al., 2000; Jahanshahloo et al., 2004a)
	Supply chain	(Chen & Yan, 2011)
Non-radial Method	Supply chain	(Avkiran, 2009; Chang et al., 2014; Tone & Tsutsui, 2009)
Two-stage	Supply chain	(Chen et al., 2006; Chen & Zhu, 2004; Saranga & Moser, 2010; Wang et al., 1997)
	Financial sector	(Seiford & Zhu, 1999)
	Multi=plant firm	(Chen & Zhu, 2004; Wang et al., 1997)
Dynamic DEA	Supply chain	(Färe & Grosskopf, 1997)
	Ψ - efficiency	(Chen, 2009)

6.4.1 Supply Chain & Manufacturing

In the manufacturing industry, Hoopes et al. (2000) used a goal-programming model to assess the performance of serial manufacturing process. In the oil and petroleum industry, Ross and Droge (2002) applied an integrated DEA model to a large-scale supply chain distribution network. They used a benchmarking methodology on data from over 100 distribution centers to assess temporal productivity in the industry. Vas et al. (2010) used a network DEA to assess the efficiency of retail stores considering the interdependencies of each store.

Talluri and Baker (2002) suggested a three-phase DEA model for designing a productive supply chain. In their approach, the first phase included DEA models along with an efficiency game to assess the productivity of distributors, manufacturers, and suppliers. In the second phase, building upon the previous stage, they chose nominees for supply chain model using an integer programming model with a hindsight on location, capacity, and demand constraints. Finally, the third phase included a transshipment model with minimum cost to choose ideal routing decisions.

Using a two-stage method, Sexton and Lewis (2003) assessed the productivity of baseball teams' management. In this approach, productivity was identified per stage, therefore, inefficient stages could be pinpointed by managers to increase the productivity. In another study, Narasimhan et al. (2004) used a two-stage DEA approach to investigate the relationship between productivity and flexibility in manufacturing. In order to consider productivity at each stage, they used the reduced DEA model under the constant returns to scale (CRS) approach.

6.4.2 Healthcare System

DEA in the context of primary care (PC) is an important topic and the attention to this efficiency assessment technique in healthcare systems has been increased over the years. Two main DEA approaches of constant return to scale (CRS) or variable returns to scale (VRS) have been taken by researchers in this field (Amado & Dyson, 2008). The CRS approach is applicable when analysis needs to be performed through policy makers' perspectives. In other words, when the assessment of productivity of a whole system is the objective of the analysis, regardless of any other managerial factors, it has been suggested to use the CRS approach. On the contrary, when a managerial viewpoint is required from the analysis and it is important to investigate the influential factors and elements, the VRS approach has been suggested (Jacobs et al., 2006).

Building upon the Färe and Grosskopf model, Löthgren and Tambour (1999) investigated the (in)efficiency of the pharmaceutical industry in a European country using a network DEA model. Also, Amado and Dyson (2009) explored the use of a CRS DEA model in assessing the productivity of a primary diabetes care system. Similarly, Wagner et al. (2003) performed a DEA analysis in finding the overall efficiency of physician practices in a large primary care organization in the United States. They found a linear relationship between inputs and outputs in their CRS DEA study. Salinas-Jimenez and Smith performed a similar CRS DEA analysis considering adjusted values for DMUs by normalizing those based on sizes (Salinas-Jiménez & Smith, 1996).

Rahman and Capitman (2012) adopted a VRS DEA model to investigate the effect of an increase in the use of supporting PC health practitioners on the productivity of health clinics. The study was followed by a Tobit regression analysis in order to identify the factors that affect productivity. In another similar study using a VRS DEA model, Guiffrida and Gravelle (2001) investigated the performance of English Family Health Services Authorities (FHSAs) in providing PC for patients. It was found that the correlation among the variables of the regression methods and among the variables of the DEA model were significant. Moreover, it was noted that assumptions about the fundamental technology of PC cause a relatively more changes in rankings.

6.4.3 Energy Sector

In this sector, Lansink and Silva (2003) used DEA models to assess the CO_2 and energy efficiency of a production line in Netherlands. Building upon the previous study, Sarkis and Talluri (2004) investigated the feasibility of using DEA models in ecoefficiency measurement of the energy industries. Gomes and Lins (2008) improved a CO_2 emission model using a DEA approach by considering non-parametric productivity assessment methods. Similarly, Mo et al. (2005) applied DEA approaches in determining the ecological productivity assessment in agriculture.

Amalnick et al. (2007) assessde the efficiency of energy-intensive sectors using an integrated DEA principal component analysis (PCA) numerical taxonomy approach for energy efficiency assessment and consumption optimization in energy intensive manufacturing sectors. Later, Azadeh et al. (2007) implemented an adaptive neural network algorithm on performance assessment of electric power generation to confirm the previous results obtained from the integrated DEA PCA assessment.

Hu and Kao (2007) performed an extensive research on improving the sustainability of the Asia-pacific economic cooperation (APEC) economies. They suggested a DEA model for the sustainable development of 17 APEC economies based on energy saving target ratios (ESTR). Yang and Pollitt (2009) incorporated unwanted outputs and uncontrollable attributes into DEA to assess the productivity of coal-fired power plants in China. They proposed six DAE models to evaluate the efficiency of the power plants. In a similar study, Yeh et al. (2010) considered two undesirable outputs - SO_2 and CO_2 releases – in their energy use performance assessment by means of a DEA method. They found that 11.28% less CO_2 emission is attainable for China assuming the optimal efficiency is achieved.

6.4.4 Transportation and Transit Agencies

In the realm of transportation and transit, Sheth et al. (2007) used a network DEA and goal programming approach to assess the productivity of bus routes. Yu an Lin (2008) investigated the productivity of railway firms in terms of freight and passenger service efficiency using a multi-activity DEA technique, and Yu and Fan (2009) suggested a two-stage DEA model to assess the efficiency of a bus transit system on a national scale. Rouse (1997) proposed a methodology of performance measurement with applications using DEA, and investigated the feasibility of using modified input-oriented variable returns to scale (VRS) model. Similarly, Zhang et al. (2015) assessed the efficiency of bridge management in the U.S. using the DEA VRS model.

Humphrey et al. (1993) analyzed the feasibility of DEA in estimating the operational productivity of highway agencies. Also, comprehensive analysis on the operational performance of public transportation agencies by Arman et al. (2013) showed that although an improvement may be achieved when the number of inputs and outputs increase, considering multiple transit agencies with considerably different services may provide erroneous results. Later, Olesen and Petersen (2016) found that such limitations can be alleviated by combining SFA and DEA techniques, which translates into stochastic DEA models.

Ozbek (2007) investigated the application of DEA in road maintenance in general and they continued the study in bridge and road maintenance afterward. Ozbek et al. (2010b) studied the efficiency measurement of bridge maintenance using DEA and proposed DEA as a decision-making tool for transportation professionals (Ozbek et al., 2009). Similarly, Fallah-Fini et al. (2009) proposed the performance measurement of highway maintenance operation using DEA along with environmental considerations. Wang and Tsai implemented the same technique to evaluate the highway maintenance performance in Taiwan (Wang & Tsai, 2009). London (2011) assessed the application of DEA in exploring state transportation infrastructure performance and economic health.

Table 6.2. Selected DEA applications in performance assessment in various industries

Method	Application	Reference
Multi-criteria decision models	Supply chain	(Talluri et al., 1999)
	Transportation	(London, 2011; Ozbek, 2007; Ozbek et al., 2010b; Wang & Tsai, 2009)
	Energy	(Yang & Pollitt, 2009)
Integer Programming Models	Supply chain	(Talluri & Baker, 2002)
	Manufacturing	(Azadeh et al., 2007)
	Energy	(Azadeh et al., 2007)
Throughput Planning	Supply chain	(Troutt et al., 2001)
Network	Pharmaceutical Industry	(Löthgren & Tambour, 1999)
	Energy	(Gomes & Lins, 2008; Mardani et al., 2017)
	Retail stores	(Vaz et al., 2010)
	Transportation	(Sheth et al., 2007) (bus transit) (Taboada & Han, 2020; Yu & Lin, 2008) (rail transit)
Two-stage Modeling	Transportation	(Yu & Fan, 2009) (bus transit) (Yu, 2008) (rail transit)
	Recruitment	(Charnes et al., 1986)
	Sports	(Fukuyama & Weber, 2010; Sexton & Lewis, 2003)
	Socio-economic	(Ünsal & Nazman, 2018)
	Infrastructure	(Cook et al., 1994; Fallah-Fini et al., 2009; Ozbek et al., 2009)
Goal-programming	Manufacturing Industry	(Hoopes et al., 2000) (Narasimhan et al., 2004)
	Recruitment	(Charnes et al., 1986)
	Sports	(Sexton & Lewis, 2003)
Constant returns to scale (CRS) models	Manufacturing	(Narasimhan et al., 2004)
	Primary care	(Amado & Dyson, 2009; Salinas-Jiménez & Smith, 1996; Wagner et al., 2003)
	Supply chain	(Hu & Kao, 2007)
	Energy	(Yeh et al., 2010)
Variable returns to scale (VRS) models	Primary care	(Lansink & Silva, 2003; Rahman & Capitman, 2012)
	Energy	(Lansink & Silva, 2003)
	Infrastructure	(Arman et al., 2013; Zhang et al., 2015)
Integrated constant returns to scale (CRS) & (VRS) Models	Oil & Petroleum	(Ross & Droge, 2002)
	Healthcare	(Giuffrida & Gravelle, 2001; Rouse et al., 2011)

6.5 Concluding Remarks

Efficiency measurement analytical methods were assessed in this chapter. Corrected ordinary least squares (COLS), stochastic frontier analysis (SFA), and data envelopment analysis (DEA) are among the productivity assessment techniques, which can be implemented to acquire reliable measures in such cases. COLS is a parametric and deterministic approach and the resulting residuals correspond to the level of unproductivity of the system. SFA is a parametric and stochastic approach and the residuals are separated into symmetric errors (statistical noise indicators) and asymmetric errors (inefficiency indicators).

It was noted that as the significant efficient efficiency measurement analysis, Data Envelopment Analysis is a pioneer method in the realm. DEA can take multiple inputs and multiple outputs in the transformation process. It does not need significantly reliable assumptions about the fundamental technology that relates inputs to outputs. The incorporation of various inputs and outputs in the productivity assessment models, such as DEA, could assist policy makers and managers in figuring out the relative efficiency of their agencies with respect to the individual units of the subsystems. Due to having such unique characteristics, DEA has widely been used in performing accurate productivity measurements in various sectors. Its applications have been investigated in various sectors, namely public administration, health care system, human resource management, transit agencies, etc.

A limitation to DEA models is its deterministic characteristic. This means that unproductivity is assessed compared to a deterministic frontier; therefore, the assessment errors (noises) and the specification errors will not be included in the results. SFA, in turn has this capability to consider both errors. Hence, a stochastic DEA approach is necessary to gain more accurate and interpretable results. This limitation can be significantly controlled by performing a non-parametric and stochastic DEA, which is achieved by combining SFA and DEA methods. The combination of SFA and DEA method provides DMU-based inefficiency and noise distributions, which in turn, makes the assessment simpler to be interpreted by decision makers, especially when multiple inputs and outputs need to be included. A future work the stochastic DEA method could focus on making the territory between inefficiencies and errors – in models with composite error term – clearer.

The next two chapters are dedicated to analytical efficiency measurement methods in finding inefficiencies in infrastructure projects. The background of non-parametric and parametric methods as well as stochastic and deterministic approaches to each methods with a focus on non-parametric deterministic approaches are investigated. The chapters examine the relationship between infrastructure investment and performance using state-level data, and conclude with a nonparametric efficiency methodology for comparative assessment of infrastructure agency performances. The methodology presented the following chapters of this dissertation can help oversight agencies to promote the overall accountability of infrastructure agencies by establishing a clearer connection between infrastructure investment and performance, and by carrying out comparative assessment of infrastructure performance across the jurisdictions under their oversight or supervision.

CHAPTER 7. INEFFICIENCY - EXAMINING THE RELATIONSHIP BETWEEN INFRASTRUCTURE INVESTMENT AND PERFORMANCE USING STATE-LEVEL DATA

[A version of this chapter is published in the Journal of Infrastructure Systems[3], presented at the Transportation Research Board 98th Annual Meeting[4], and published in the proceedings of the 11th International Bridge and Structures Management Conference[5]]

7.1 Introduction

Most development sectors have in place oversight processes where oversight bodies monitor the performance of jurisdictions (agencies, divisions, units, etc.) under their purview. These sectors include agriculture (Anríquez et al., 2016), healthcare (Levitt et al., 2014; Schieber et al., 1992), local administration (FMPO, 2017), education (Boser, 2011). Irrespective of the jurisdiction or sector type in question, the oversight body monitors the overall accountability of each jurisdiction's by (a) assessing whether the jurisdiction's outcomes are consistent with their spending levels, and (b) measuring and tracking the expenditures and performance of each jurisdiction. In certain cases, the oversight body plays a purely observatory role; in other cases, it carries out both observatory and presecretory roles. In the specific context of the infrastructure sector, performance of the jurisdictions can be measured in terms of physical preservation (enhanced condition) which translates into greater longevity, reduced frequency and intensity of repairs, reduced user costs, enhanced mobility and safety, and other benefits. It is useful to duly recognize that there often exists a time lag between such expenditure and the resulting performance outcomes in any system.

[3] Ghahari, S.A., Alabi, B. N.T., Alinizzi, M., Alqadhi, S., Chen, S., & Labi, S. (2019). Examining relationship between infrastructure investment and performance using state-level data. *Journal of Infrastructure Systems*, *25*(4), 04019026.
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[5] Ghahari, S.A., Qiao, Y., & Labi, S. (2017). Exploring the US Interstate Highway Bridge Maintenance Expenditure Versus Condition Trade-Off Relationship Using Aggregate Data. In *Eleventh International Bridge and Structures Management Conference*.

7.2 Legislative and Executive Backing

The monitoring of infrastructure performance earned due to expenditures is motivated by legislative actions intended to promote agency accountability in terms of their spending outcomes (Agbelie et al., 2015; Ghahari et al., 2019c). In the United States, for example, a significant watershed related to government supervision and responsibility of infrastructure agencies was the Government Performance and Results Act (GPRA) passed by the U.S. Congress in 1993. The GPRA caused the government to pay increased attention to the outputs and outcomes that are expected from federal programs. According to GPRA, federal agencies were required to define "levels of achievements" in order to be able to compare the outputs from the programs to the quantified goals (GAO, 2001). This legislation helped provide support to local, state, and federal legislators who were eager to identify the benefits of public expenditures in terms of performance outcomes within the system.

The 1995 National Performance Review (NPR) ushered in a broader definition for performance management, which corresponds with evaluating progress toward achieving pre-defined objectives. NPR fostered examination of the relationship between how well the outcomes are delivered and the extent to which intended goals are achieved by investment expenditures; thus, NPR facilitated the "tying of the knot" between the efficacy of actual government operations and program goals and objectives (Shaw, 2003). In 2012, the Moving Ahead for Progress in the 21st Century Act (MAP-21) required state agencies to focus more on monitoring performance and target outcomes. MAP-21 specifically requested the DOT secretary to ensure that all states implement performance measurement in order to adequately monitor the condition of interstate highway infrastructure and the national highway system. This call was consistent with the need for systemwide monitoring of expenditures and performance. It is expected that by developing such a monitoring system that identifies the relationship between expenditures and performance outcomes, the states will be placed in a better position to track their progress toward national goals and targeted outcomes, and that this will enhance the accountability of agency spending.

In the United States, the Department of Transportation (USDOT) is one of the agencies that has responded most effectively to all these legislations. This federal body oversees the transportation infrastructure investments and the performance of state highway agencies. Through its policies and actions, the USDOT has indicated recognition of the importance of monitoring the expenditures and performance of the states' transportation infrastructure. For example, the

USDOT's Federal Highway Administration (FHWA), in initiatives that align with the NPR vision, continues to evaluate the level of consistency and progress toward targeted outcomes, and assesses the efficiency of projects from perspectives of resource-outcome efficiency. A similar position was espoused by the National Surface Transportation Policy and Revenue Study Commission (NSTPRSC) which aims at fostering proper assessment of infrastructure performance early in the life cycle (NSTP, 2007). The U.S. Government Accountability Office (GAO) has emphasized that spending should be tied to outcomes (GAO, 1999). In a similar move, the National Performance Management Advisory Commission (NPMAC) stated that the relation between expenditures and predetermined outputs as organizational objectives needs to be realized (NPMAC, 2010).

These instances of legislative and executive backing have been corroborated by infrastructure management research. For example, a study sponsored by the National Cooperative Highway Research Program (Cambridge Systematics, 2000) indicated that significant insights can be earned by establishing a relationship between project spending and project performance. They argued that a clearer link will "foster greater allocation of resources to highways, make the overall effectiveness of highway projects more visible, and improve financial management" and reported that such benefits are already becoming manifest in states including Florida, Minnesota, and Washington (Cambridge Systematics, 2000).

7.3 Motivation and Objectives

As evidenced by past practice in this area, there seems to exist the need for a general methodology that characterizes the relationship between infrastructure expenditures in a specific area of infrastructure management (preservation, safety, and mobility, for example) and the resulting performance in terms of enhanced condition or longevity, crash reduction, reduced travel delay and travel time reliability, and so on). In this chapter of dissertation, the focus is made on infrastructure condition only, for purposes of demonstration. Also, it is useful to ensure that such methodology is robust in the sense that it duly accounts for extenuating factors that could explain better the nexus between expenditure and performance at certain jurisdictions. The benefits of such a methodology could include the ability of individual jurisdictions to assess their performance (duly "normalized" by their inventory size or investment thereof, and other extenuating factors) compared to their peer jurisdictions. This could also help the oversight body to compare the relative performance across the jurisdictions under the supervision of the oversight body.

This chapter of the dissertation, therefore, presents and demonstrates a methodology to address part of this research need, namely, infrastructure condition impacts of preservation expenditures. The chapter carries out a literature review of past studies that have attempted to characterize the expenditure-performance relationship, develops a methodology to account for this, and uses data from highway interstate bridges in the USA to demonstrate the methodology.

7.4 A Synthesis of the Literature

From the perspective of the management level of the data used for analyzing the expenditure-performance nexus, such relationship can be examined in one of three dimensions: (a) at the project level using project-level data, (b) at the network level using project-level data, or (c) at the network level using network-level data. At the network level, Hartgen and Krause (1993) used aggregate data to investigate the link between spending and performance of highway infrastructure. Also, for over two decades, Hartgen and Krause have reported the overall ranking of 50 state DOTs based on resource-related factors and performance-related factors of each state.

Some researchers subsequently stated that Hartgen and Krause's series of reports do not provide an adequate characterization of the relative performance across the various transportation agencies because they do not account for the differences in the key prevailing conditions or performance factors across the agencies. For example, Goode et al. (1993) argued that the Hartgen et al. reports yielded a "simple listing" of the highway agencies of the various states. In a study similar to Hartgen et al's, Spears clustered peer states using key factors from each state including VMT, population, highway inventory size (mileage), and the number of bridges (Spears, 1995). The Spears study, data for which spanned only one year (1993), used variables that were the subject of discussion in a subsequent study (Hendren & Niemeier, 2006). In the literature, Agbelie et al. (2015) commented that the Spears study could nevertheless be credited for raising awareness regarding state agency placement into peer groups for purposes of assessing the agencies overall performance relative to others.

In past work in this domain, it has been acknowledged that the unique characteristics of specific states, as such local climate conditions are important for comprehending the relationship between a state's expenditures and its performance outcomes. Using data from at least 10 state highway agencies, Hendren and Niemeier (2006) investigated this relationship using spending amounts of specific project types and the resulting performance in terms of safety and congestion

(Hendren & Niemeier, 2006). The results of their analysis not only provided evidence that it is possible to establish the link between spending and performance but also established a platform upon which highway agencies could make their highway planning functions more transparent and accountable. In a subsequent expansion of their 2006 research, using empirical data on at least forty (40) indicators related to the inventory, climate and topography associated with transportation infrastructure at state level, the same researchers applied cluster and principal components analysis to establish nine "peer state" groups (Hendren & Niemeier, 2008).

At least one researcher used Data Envelopment Analysis (DEA) techniques to examine states economies (instead of their infrastructure investment levels) and the performance of their transportation infrastructure (London, 2011). In this aggregate analysis of data, their objective was to compare the efficiencies across the states, and the input variables for their analysis included environmental conditions, gross state product, mortality rate, debt per capita, and an index of "transportation performance". The London et al. study established DEA scores for each state that was then used to rank the states in terms of their overall performance. In a similarly-themed study, a group of researchers developed a DEA efficiency frontier to establish the overall pavement performance of interstate highways in the USA (Zhang et al., 2015). They developed a productivity model over time (years), to measure the changes in the efficiency of the state highway agencies and the nationwide change in productivity. It has been pointed out that for investigating the investment-outcome connection, a limitation of DEA is the paucity of input and output variables at the state level. Where such data are available most of them such as traffic load intensity and climate severity, are largely uncontrollable by the highway agency and therefore cannot be used as a basis for developing remedies to enhance the performance of deficient states.

Researchers in Indiana used historical network-level highway expenditure and performance data from the Indiana DOT capital program to carry out an ex post assessment of the state's program outcomes (Everett et al., 2013). They characterized the relationships between investment and performance for highway physical assets (pavement and bridge condition), highway operations (safety and mobility), and community impacts (short-term changes in economic development).

In addition, researchers in pavement management have attempted to quantify the relationship between interstate highway pavement preservation expenditures and their resulting performance (Agbelie et al., 2015). Using 2000–2008 data and lagged panel model specifications, the researchers developed an econometric model that quantified the expenditure–performance connection. They then used the resulting model parameters to develop an overall performance index and attempted to explain for the differences that were observed in the states' overall performance levels.

Overall, the existing literature, clearly, has not only highlighted the usefulness of investigating the relationship between expenditure and performance but also has proceeded to attempt to quantify such relationship using some (albeit limited number of) evaluation criteria.

7.5 Methodology

This section presents a general methodology that characterizes the link between expenditures and the resulting infrastructure performance. The methodology duly recognizes that it takes a few years before the effect of infrastructure spending becomes manifest in the form of increase condition of the infrastructure. This time lag is due to the period between the end of the project duration and the time of the condition measurement. A number of researchers have ascertained that a time lag of 2 years is often appropriate (Ghahari et al., 2019c; Ghahari et al., 2018d; Oh et al., 2007). This chapter therefore used a 2-year time lag between the infrastructure investment and subsequent performance.

This chapter's methodology for characterizing this expenditure-performance relationship duly recognizes that the integrity of such relationship could be jeopardized by situational and measurement biases. Situational bias refers to the differences in the existing jurisdiction-specific attributes, namely, climate severity, loading, average age of the infrastructure inventory, that could influence the expenditure-performance relationship. Measurement bias refers to the differences in the measurement scale of the attributes, which if left unaddressed, could result in distortion of the relationship in favor of attributes that are measured using large numerical units. To remove the measurement bias, the attributes of each jurisdiction are normalized by expressing them as a ratio of the average value of the variable across all the jurisdictions. With respect to the situational and measurement bias, the study considers four scenarios:

Scenario 1 (Raw2): The first scenario for the analysis involves the raw (not normalized) values of infrastructure performance and expenditure only. After that, the chapter proceeds to hypothesize that such expenditure-performance relationship does not account for biases, and hence, it could lead to misleading conclusions regarding the relationship and subsequently jeopardizes any comparative analysis of the infrastructure agencies in various jurisdictions. Regarding performance, two jurisdictions that are similar in size could show very different levels of spending due to differences in climate severity, coastal location, traffic loads, average age of the infrastructure inventory. Therefore, Scenario 2 (below) was established to account duly for the various recuperative factors and deterioration factors or stressors.

Scenario 2 (Raw5): This uses the raw values of a wider range of the evaluation criteria: infrastructure performance, truck traffic, climatic conditions, age, and expenditure. The dissertation tests the hypothesis that incorporating a larger number of evaluation criteria can influence the evaluation outcome.

Scenario 3 (Norm2): In the third scenario for the analysis, the methodology for the two evaluation criteria (as in Scenario 1) is repeated using scaled or normalized values instead of raw values, albeit for only two evaluation criteria: infrastructure performance and expenditure only.

Scenario 4 (Norm5): In the fourth scenario, the methodology for the wider range of evaluation criteria (as in Scenario 2) is repeated using scaled values instead of raw values. Scenarios 3 and 4 were established in a bid to remove the measurement scale bias associated with the different units of measurement of these factors. The factor values in each jurisdiction are normalized by expressing them as a ratio of the average value of the variable in the nation (across all the jurisdictions).

For each of the scenarios, the chapter carries out the quadrant analysis (Figure 7.1.) using the infrastructure performance on one hand, and various criteria related to the infrastructure deterioration/recuperation. The y axis (ordinate) of the quadrant analysis plot is the average condition of the infrastructure in a jurisdiction. The x axis (abscissa) represents the overall net effect of the recuperative factors. In its simplest form, the x axis is the repair expenditure per area of inventory. In a more refined form, it is the reciprocal of the stress factors (climate severity and traffic loading) (Ghahari et al., 2018d).

In this chapter of the dissertation, it is taken as the product of the average expenditure per inventory size and the reciprocal of the stress factors. Each jurisdiction is plotted using its coordinates (its corresponding values of the ordinate and abscissa variables). The average value of the ordinate and abscissa values of all the jurisdictions is calculated and plotted as a horizontal and vertical line, respectively, on the Quadrant Plot. The two lines intersect with each other and yield the four quadrants. Then, quadrant locations of each jurisdiction are determined. The dashed line represents the average values of the evaluation criteria across all the jurisdictions.

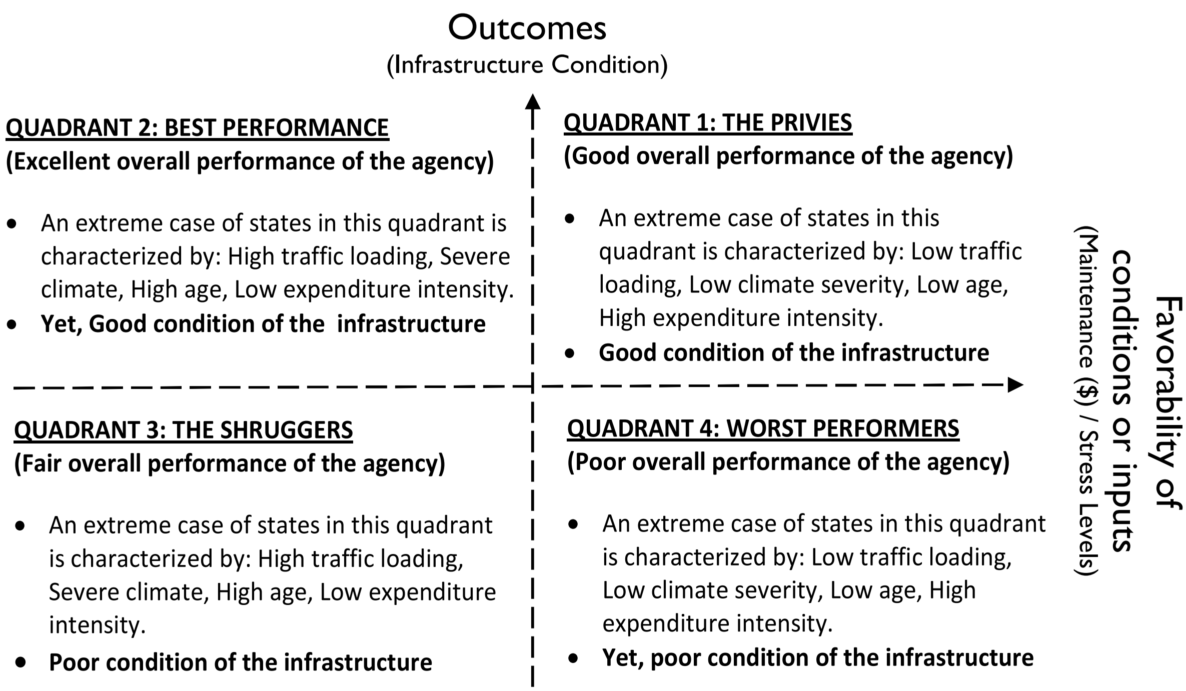


Figure 7.1. Interpretations of quadrant positions

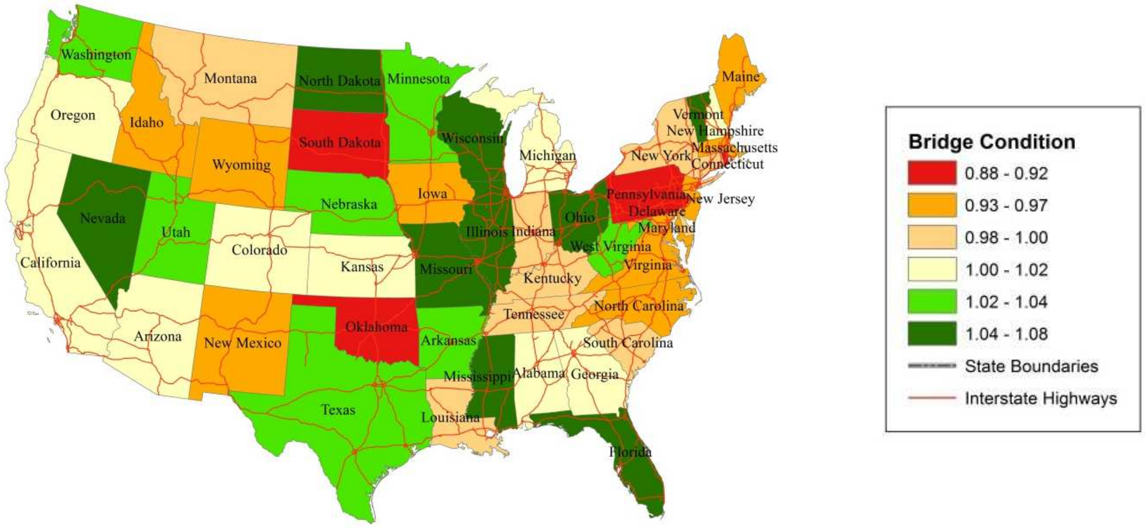
The first quadrant represents the jurisdictions with generally favorable environments (low volume of truck traffic and mild climate), low spending levels and good condition of infrastructure. These states can be considered to be “privileged” in that they generally possess relatively auspicious conditions (low value of stressors). Their good performance may not necessarily be attributed to superior management of funding but is likely due to the good conditions they enjoy. They are fair-good performers. The second quadrant represents the jurisdictions with good condition of infrastructure in spite of their generally unfavorable environments (high truck traffic volume and severe climate) and low expenditure levels. They are the best performers. The third quadrant represents the jurisdictions with poor condition of infrastructure and generally unfavorable environments and high expenditure levels. The relatively poor performance of jurisdictions in this quadrant could probably be “shrugged off” as a consequence of the high stress encountered by their infrastructure. Clearly, the high spending level of these jurisdictions are unable to offset the effects of the stressors. The fourth quadrant represents jurisdictions with poor condition of infrastructure in spite of their generally favorable environments (low volume of truck traffic and mild climate) and high expenditure levels. Clearly, the jurisdictions in this quadrant are facing serious problems associated with the management of their funding and they are the poorest performers. In sum, the quadrant position of a jurisdiction, after correcting the biases in both categories, could be used to reflect how "well" the infrastructure agency in that jurisdiction is using the funds allocated to it. Later in this chapter, some possible extenuating circumstances that could cause a jurisdiction to be misjudged as poorly performing is discussed.

7.6 Data for the Case Study

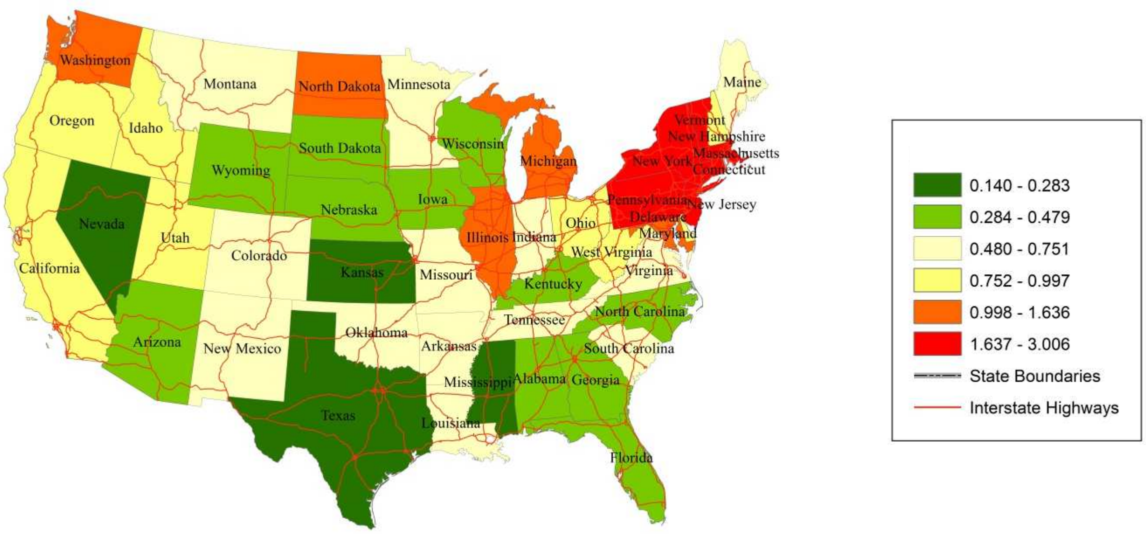
To demonstrate the methodology, the chapter uses a case study involving interstate highway bridges. The jurisdiction level used is the state, so the data is for each of the fifty states in the USA. This analysis is "aggregate" in the sense that it is the jurisdictions (agencies), not individual assets that are being evaluated, and this is appropriate from the perspective of the oversight body. The FHWA National Bridge Inventory (NBI) database, which contains bridge information from the year 1992-2016, served as a primary source of data for this dissertation. The bridge attributes considered in this chapter include the weighted average condition rating of all components, truck traffic volume, bridge structure length, and bridge width. The metadata for this database is available in FHWA's Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges(FHWA, 1995). The database is updated using information submitted annually by the individual states to the FHWA. Other data sources used in this chapter include FHWA's Highway Statistics reports and the National Climatic Data Center. The FHWA's Office of Highway Policy Information (USDOT, 2016) provided information of state highway expenditures on highway construction and maintenance. The National Climate Data Center (NCDC) database (NCDC, 2016) described climate information. Among the primary and secondary indicators of climate, freeze index is used in this dissertation since past researchers have found that the freeze index (Liao et al., 2018) is one of the most significant climate factors of infrastructure deterioration. For each state, the average freeze index from 1992 to 2012 (Liao et al., 2018) was used in this dissertation. To adjust for the spatial variation in infrastructure costs, the expenditures in each state was duly adjusted using spatial cost adjustment factors from the literature (Sinha & Labi, 2007).

7.7 Descriptive Analysis of the Input Data

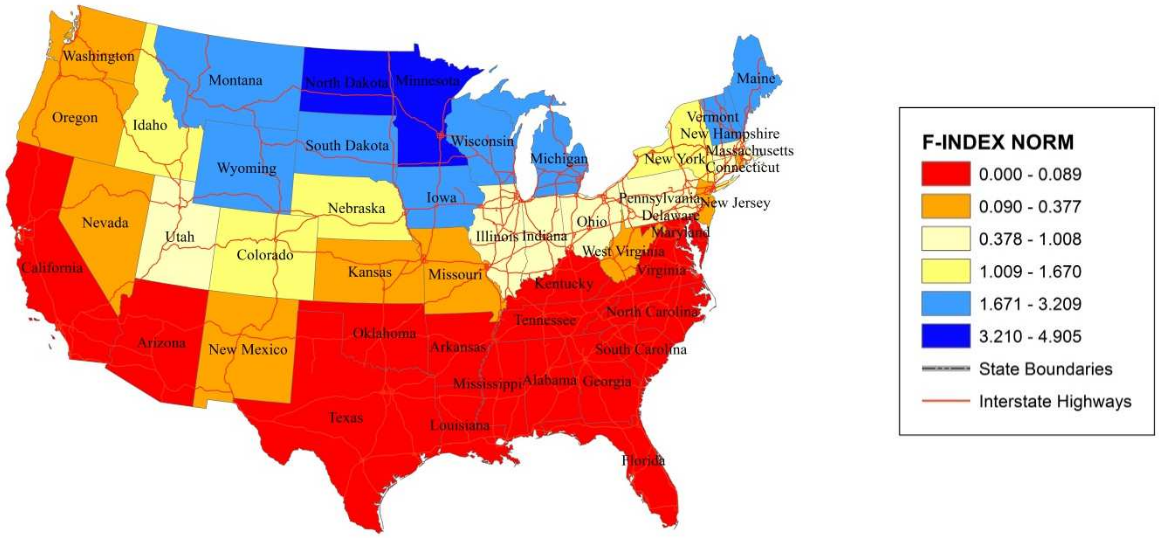
Figure 7.2a. presents the distribution of the weighted average interstate bridge condition across the States. The states with highest weighted average condition of bridges include Nevada, North Dakota, Vermont, Florida, Illinois, Missouri, Mississippi, Wisconsin, and Ohio, while Pennsylvania, South Dakota, and Oklahoma have on average, bridges in poor condition. Figure 7.2b. presents the distribution of normalized interstate highway bridge repair expenditure ($\$/m^2$ of bridge deck area) for the states in the US. The data suggests that 70% of the states have a lower climate severity (in terms of freeze-index) than the US average. Alaska and North Dakota have climate severity that is approximately 80% over the US average, whereas Oklahoma and Alabama have climate severity less than 2% of the US average. Regarding traffic loading, 68% of the states have truck traffic less than the US average. Arizona and Maryland each have 77% truck traffic more than the US average, whereas Nebraska and Montana has 7% truck traffic compared with the US average. Figure 7.2c. and Figure 7.2d. present the distribution of weighted average levels of the key evaluation attributes (climate severity in terms of freeze index, expenditure per m^2 of deck, freeze index, and age) of the interstate highway bridges. The interstate highway bridges in Hawaii and District of Columbia are 32% older than the U.S. average, whereas, in Nevada and Alaska the age is 25% lower than the U.S. average. States with older bridges are expected to incur higher repair expenditures. Figure 7.3. presents the average age of interstate highway bridges by state. Nationwide, the average age is 43 years. About 50% of the states are have an average bridge age that exceeds the national average.



(a) Normalized average condition ratings



(b) Normalized average expenditure per m^2 of bridge deck area



(c) Normalized average climate severity (Freeze Index)

(d) Normalized average age

Figure 7.2. Distribution of normalized weighted average levels of the key evaluation attributes

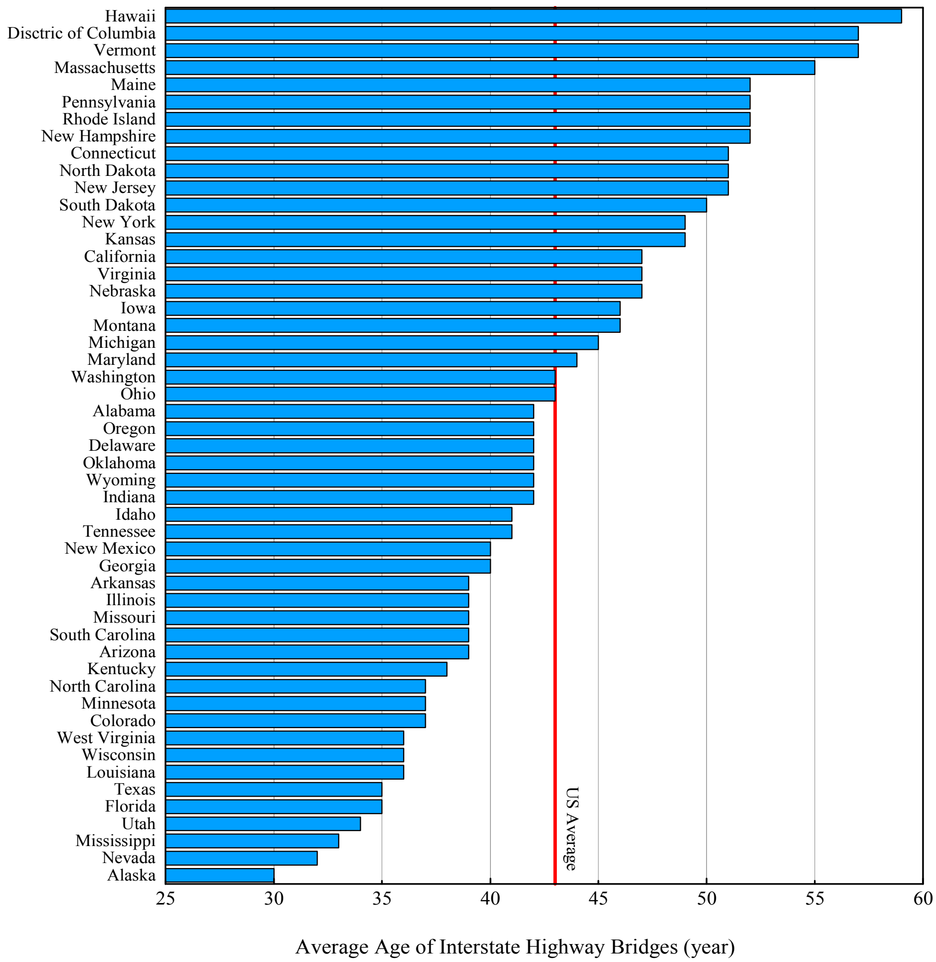
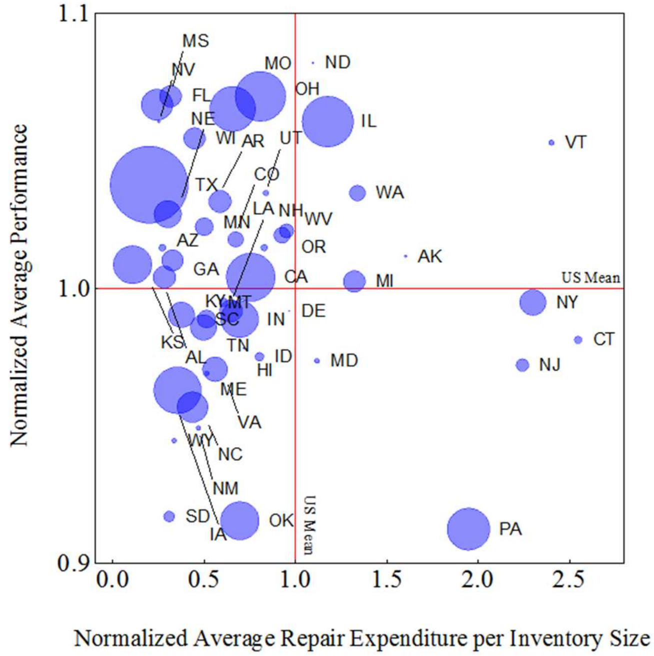


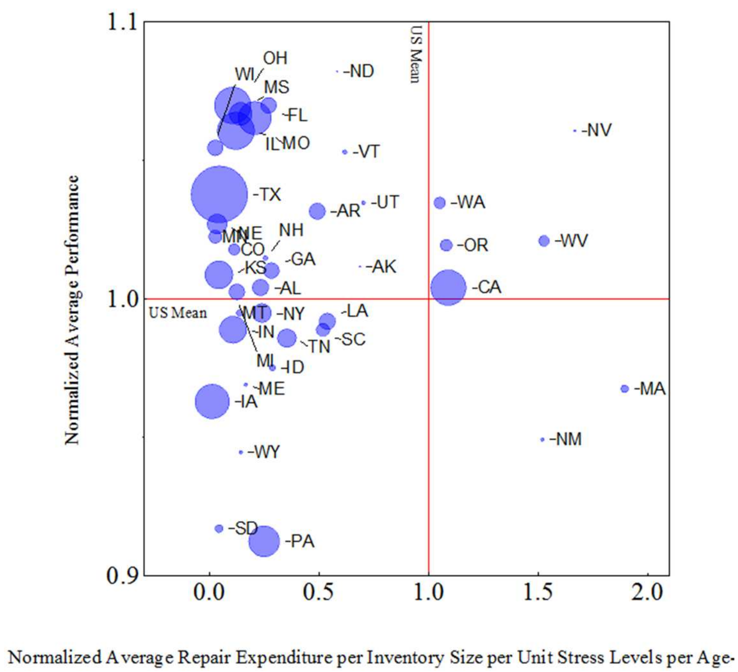
Figure 7.3. Average age of interstate highway bridges by state

7.8 Results and Discussions

Figure 7.4. presents the states' positions on the normalized performance-expenditure plot. The red lines represent the criteria values averaged across all the states. The dot size for each state represents the size of the interstate bridge inventory (m^2) in that state. For example, Texas (TX) has the largest inventory. Figure 7.4.a. unlike Figure 7.4b., considers only performance and does not account for differences in climatic conditions, bridge age, and traffic loading. In Figure 7.4a., it can be seen that most states are in Quadrant 2 (that is, relatively lower expenditure and higher stress factors, yet higher performance). These include Nevada, Texas, and Florida. A few states including Pennsylvania, New York, and New Jersey, are in Quadrant 4 (as they exhibit relatively higher expenditures and lower stress factors, yet relatively lower performance). Figure 7.5. presents the percentage of states in each quadrant (%).



(a) Performance vs. Expenditure only, Normalized



(b) Performance vs. Expenditure, Age, Climate, & Loading, Normalized

Figure 7.4. Quadrant positions by state

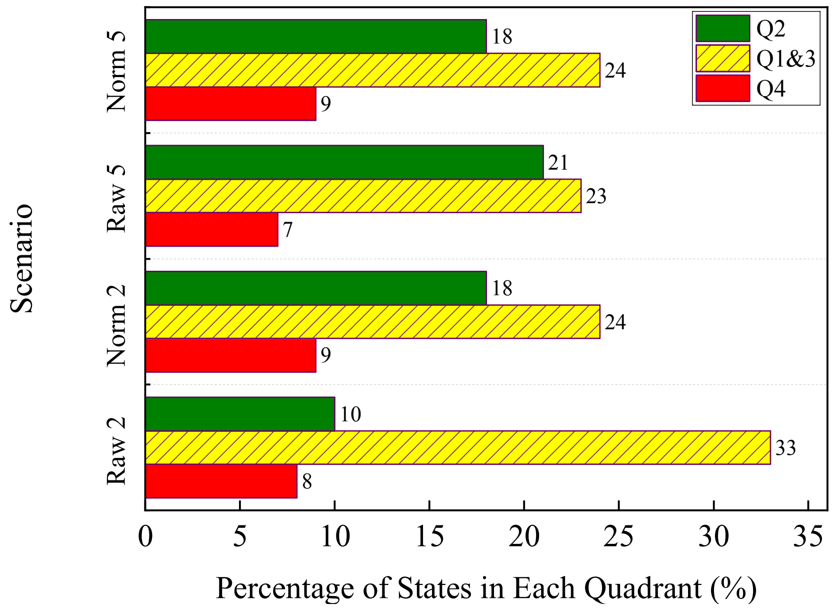


Figure 7.5. Percentage of states in each quadrant

7.8.1 Sample Calculations (for the State of Utah)

To clarify how the analysis was carried out, Table 7.1. presents sample calculations for the state of Utah. For the abscissa (the X axis), the amalgamated effect of all factors is: $= \frac{\text{EXP per m}^2}{\text{AADT}*\text{F}-\text{Index}*\text{Age}} = 4.24$. This value is what is shown for that state, on the abscissa of the plots. A higher value of this abscissa coordinate means a less favorable situation (higher spending, lower traffic, mild climate, and low age), that is, Quadrant 1 and 4. For the ordinate (the Y axis), the coordinate for that state is: 6.77/6.54 = 1.03.

Table 7.1. Example of calculations

	Raw values of the evaluation criteria (Mean), USA	**Raw** values of the evaluation criteria (Mean), Utah	**Normalized** values of the evaluation criteria, Utah
Annual freeze index (^{0}F-days)	4.17	4.20	4.20/4.17 = 1.007
Average age of the bridges	42.81 years	33.88 years	33.88/42.81 = 0.79
Average annual inventory Size	5,064,543 m^2 of bridge deck area	1,731,320 m^2 of bridge deck area	-
Average annual expenditure	\$391.4 M (in 2012 dollars, raw expenditure) \$401.03M (in 2012 dollars, national dollars)	\$99.58M (in 2012 dollars, Utah dollars) = \$120.49M (in 2012 dollars, national dollars)	-
Annual expenditure per m^2	\$401.03M/5,064,543m^2 = \$79.18/m^2	\$120.49M/1,731,320 = \$69.59/m^2	=\$69.59/\$79.18 = 0.87
Average annual daily truck traffic	8,569	2,226	2,226/8,569 = 0.26
Average NBI rating	6.54	6.77	6.77/6.54 = 1.03

7.8.2 State Shifts across the Quadrants

After accounting for the bridge age, climate severity, and traffic loading, the quadrant positions change somewhat. For example, Pennsylvania moves from a quadrant of poor performing states to a quadrant representing superior overall performance. Clearly, it is of interest to analyze the stability of quadrant positions when a full set of evaluation criteria is considered. Figure 7.6. presents the change in states' quadrant locations when the state performance is measured with and without accounting for measurement and situational biases, specifically, in their raw form, normalized form, and so on.

To avoid overcrowding the figure, these changes are presented for seven randomly-selected states only. The vertical axis represents the four quadrants, quadrant 2 as the best performers, quadrant 4 as the worst performers, and quadrants 1 and 3 falling in between these extremes. The four scenarios on the horizontal axis representing the extents to which measurement and situational biases were addressed: (a) Raw2 is un-normalized values of performance (NBI ratings) and expenditure (\$/m^2) only; (b) Raw5 is un-normalized values of performance (NBI ratings), truck traffic, climatic conditions, age, and expenditure (\$/m^2); (c) Norm2 is normalized values of performance (NBI ratings) and expenditure ($\$/m^2$) only; (d) Norm5 refers to the normalized values of performance (NBI ratings), truck traffic, climatic conditions, age, and expenditure ($\$/m^2$).

It can be observed that for certain states, there is significant shift of the state locations across the different scenarios. When a wider range of performance criteria are considered, Pennsylvania departs from the worst performance quadrant to a mid-performance quadrant; New Mexico moved from a mid-performance quadrant to the worst performer quadrant when it is analyzed with Norm5, and Illinois moved from a mid-performance quadrant to the best performance quadrant.

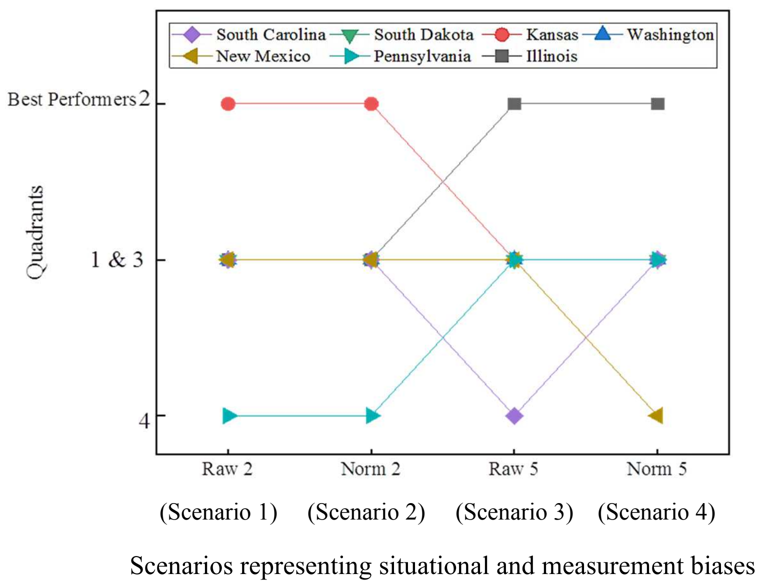


Figure 7.6. Stability quadrant positions (for a sample of 7 states)

A consistency analysis was carried out to measure the extent of shifts when situational and measurement biases were addressed (that is, from Scenario 1 to 4). A significant percentage of shifts were observed (Figure 7.7.). The results indicated that when situational and measurement biases were addressed, 24% of states moved from a lower-performance quadrant to a higher performance quadrant, 33% of states moved from a higher-performance quadrant to a lower performance quadrant, and 43% of states remained at their positions.

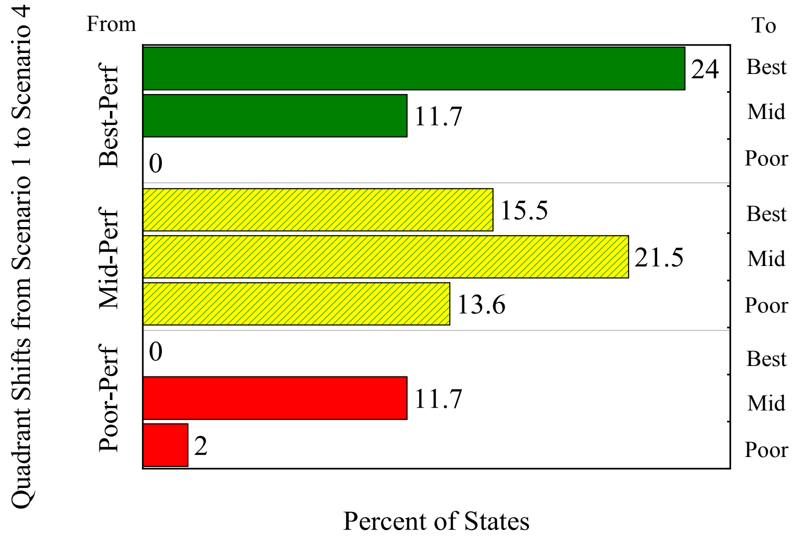


Figure 7.7. Quadrant shifts when situational and measurement biases are addressed

7.9 Practical Application of the Methodology

The chapter's methodology can be useful to oversight bodies that seek to not only monitor the performance of individual jurisdictions under their supervision but also compare their performance relative to each other. The oversight bodies may use the results not to penalize or pillory poor-performing jurisdictions but instead to establish a basis upon jurisdictional deficiencies can be identified and discussed, and any remedial measures recommended to address extenuating circumstances that are within the control of the agency in that jurisdiction. The methodology can also be used to establish peer jurisdictions (and possibly, to rank them) based on their expenditures and performance outcomes. Also, the individual jurisdictions themselves may use the methodology to compare their overall performance relative to their peers or other jurisdictions with which they share some common characteristic (such as regional location, design and maintenance philosophy and practices, and work culture) (Ghahari et al., 2019a). It is important to note that a jurisdiction may be observed from this analysis to be "low performing" due to some natural or anthropogenic factor beyond their control. At least one past researcher (Hendren & Niemeier, 2008) cautioned that it is useful to pay heed to state-specific conditions because such local conditions can be is vital in any effort to establish peer groups regarding the "overall performance of state transportation systems, the fairness of the interpretations, and the informative use of the resulting information". It is noteworthy that the chapter's case study involved interstate bridges which "enjoy" some uniformity in design across the various jurisdictions (states); Hence, it may be reasonable to posit that this chapter's analysis was not unduly compromised by unobserved variables of such nature. There are plentiful avenues, however, for extensions of this work in future research, as discussed in the next paragraph.

7.10 Potentially Influential Variables that could be Considered in Future Research

First, this chapter used, as the evaluation criteria, the normalized average levels of expenditure ($/m^2 of deck), climate, age, and truck traffic loading. Regarding expenditure, it can be argued that the level of expenditure is not always a good indicator of the actual work done, because it does not account for wastage, management and operational inefficiencies, and corruption. As such, the actual work done may be more or (often) less than what the expenditure records suggest. Regarding truck loading, it may be more accurate to use, instead of the average of the daily truck count, the average structural load imposed. From AASHTO bridge design equations, the structural load is a function of (a) the bridge design type and (b) for each truck that uses the bridge, its gross weight and axle distribution. Clearly, the calculation of the average structural loading across all interstate bridges in a state would require a tremendous amount of data related to each bridge and each of the thousands of trucks that use each bridge daily.

Regarding climate severity, the freeze index was used to represent climate severity; however, in certain cases, precipitation, and temperature are more influential factors of bridge deterioration. Furthermore, in this dissertation, it is assumed that the non-load factors of bridge deterioration (freeze index was used) has the same weight as the load factor. In other words, doubling the climate severity, for example, would have the same effect on deterioration as doubling the loading. If the actual split of the load and non-load share of bridge deterioration is known, this could be applied to the data to yield a more balanced performance evaluation of the jurisdictions. If, in reality, the non-load factors contribute a larger share of bridge deterioration, then by assuming an equal split share of, this dissertation underestimates the non-load effects and overestimates the load effects, and Hence underestimates bridge performance of states in colder regions. It has been reported that there is a 30%-70% split of load and non-load factors is reasonable (Everett et al., 2013). Also, cost allocation studies have reported various load and nonload splits for the different bridge components (FHWA, 1997; Oregon Department of Transportation, 2013).

Regarding the statistical issue of omitted variables, any performance comparison analysis such as that of this dissertation could be impaired by the absence of evaluation criteria that vary significantly across the jurisdictions being evaluated. These include administrative culture prevailing at the jurisdiction, the quality of available construction materials, the availability of effective technology for construction and maintenance, the extent of use (and efficacy) of innovative project delivery approaches (design-build, warranty, and so on), quality of audit processes, and operating policies such as overweight-vehicle restrictions. There is also the issue of coastal proximity – jurisdictions located near the sea have chloride-laden environments that accelerate the corrosion rate of reinforcement and accelerate the bridge deterioration.

For the reasons explained above, it may very well be that the position of a jurisdiction in the poor-performance quadrant is not necessarily a reflection of inadequate or inefficient infrastructure construction or maintenance practices in that jurisdiction but rather could be reflecting the omission of variables that are important in such analysis. Such unobserved heterogeneities, if identified but left unaddressed, could very well impair the integrity of any expenditure-outcome relationship.

7.11 Concluding Remarks

Oversight organizations seek to monitor regularly the expenditures and the resulting performance of infrastructure agencies under their authority. A context of this expenditure-performance connection is that of infrastructure preservation spending and the physical condition of the infrastructure. This chapter presented a methodology for examining this relationship. The chapter duly recognized that the integrity of the expenditure-performance relationship could be impaired by situational and measurement biases associated with these attributes, and attempted to correct for these biases. The methodology is demonstrated using aggregate (state-level) data on repair expenditures and performance for interstate highway bridge infrastructure in the USA. The methodology can help oversight agencies to promote the overall accountability of infrastructure agencies by establishing a clearer connection between infrastructure investment and performance, and by carrying out comparative assessment of infrastructure performance across the jurisdictions under their oversight or supervision.

The methodology uses aggregate data on infrastructure investment condition and age, environment, expenditures (normalized by their inventory size) and performance outcomes to quantify this relationship. The chapter's analysis duly recognized that the integrity of the expenditure-performance relationship could be jeopardized by situational and measurement biases. Measurement bias refers to the differences in the measurement scale of the attributes. If left unaddressed, measurement bias could result in distortion of the relationship in favor of attributes that are measured using large numerical units. To remove the measurement bias, the analysis normalized each attribute by expressing it as a ratio of the average value of the variable across all the jurisdictions. Based on these attributes, the methodology ultimately placed the jurisdictions in one of four quadrants or peer groups.

This case study used in this chapter created only four peer groups. However, it is possible to subdivide these into a greater number of groups that may take the shape of rectangular blocks or any other shape whose boundaries are established by the oversight body. The methodology can be used by oversight agencies to monitor the overall accountability of individual jurisdictions with respect to their expenditures and performance outcomes and to identify poor-performing jurisdictions as a first step towards improvement. It can also be used by agencies to carry out critical self-assessment to identify the possible causes of such performance as a first step towards their resolution.

CHAPTER 8. INEFFICIENCY - A NONPARAMETRIC EFFICIENCY METHODOLOGY FOR COMPARATIVE ASSESSMENT OF INFRASTRUCTURE AGENCY PERFORMANCE

[A portion of this chapter is presented at the Transportation Research Board 98th Annual Meeting[1]]

8.1 Introduction

Past and current highway-related government legislation emphasize the need for continual assessment of performance outcomes vis-à-vis expenditures, not only at the project level but also systemwide (entire state or district networks or specific classes therefrom). Such legislation includes the Government Performance and Results Act (GPRA) of 1993, which advocates the assessment of the outcomes of federal programs (GAO, 2001) and the National Performance Review (NPR) Act of 1995, which requires evaluation of the extent to which intended goals are achieved by investment expenditures (Shaw, 2003). The Moving Ahead for Progress in the 21st Century Act (MAP-21) similarly requires that state agencies focus on monitoring performance and target outcomes, particularly for highway infrastructure on the national highway system.

In response to these pieces of legislation, the US Department of Transportation (USDOT) has emphasized monitoring the expenditures and performance of transportation infrastructure and continual assessment of the efficiency of programs in terms of resources and outcomes. Other agencies in the executive branch that have espoused assessment of agency expenditures and resulting performance include the National Surface Transportation Policy and Revenue Study Commission (NSTPRSC) (NSTPRSC, 2007) and the National Performance Management Advisory Commission (NPMAC) (NPMAC, 2010). The US Government Accountability Office (GAO) has similarly emphasized that spending should be tied to outcomes (GAO, 1999). A study sponsored by the National Cooperative Highway Research Program (Cambridge Systematics, 2000) indicated that these oversight agencies can obtain significant insights if they possess knowledge of the relationships between spending and performance and that a clearer link will

[1] Chen, S., Ghahari, S.A., Miralinaghi, M., & Labi, S. (2019). Assessing Performance Outcomes and Ranking of Jurisdictions–a Nonparametric Efficiency Approach for Asset Management. *Transportation Research Board 98th Annual Meeting.*

"foster greater allocation of resources to highways, make the overall effectiveness of highway projects more visible, and improve financial management."

One way to carry out an assessment of performance outcomes with respect to expenditures at the highest level is to compare, across various organizational entities (jurisdictions) and for a defined domain of infrastructure, spending levels on the one hand and the resulting performance on the other. The jurisdictions of interest could be cities and towns, counties, sub-districts, states, or nations (Ghahari et al., 2018a). The infrastructure in question can range from specific assets to all assets combined within a jurisdiction. In studies of this nature, it is necessary to account for the differences in inventory size (that leads to scale effects) and measurement bias (due to the differences across the various units used to measure the levels of various performance criteria). It is also important to consider the effect of the differences across jurisdictions, of the average ages of infrastructure assets, climate severities, and traffic loading levels.

The objective of this chapter is to present and demonstrate a methodology for overall efficiency ranking of transportation organizations. The chapter first reviews similar past work and then presents a nonparametric efficiency methodology. The chapter uses empirical data on performance and expenditures that are duly adjusted for inventory size and measurement bias and the effect of the different average ages of infrastructure assets, different climate severities, and different traffic intensities across the jurisdictions. The scale of the evaluation is such that the analysis needs to be aggregate in nature and therefore devoid of project-level assessment; therefore, the analysis does not use detailed data on design, materials, and site characteristics. In the final section, the chapter discusses the results of the ranking and identifies the practical usefulness of the methodology.

8.2 A Review of Past Research

Over two decades ago, Hartgen and Krauss (1993) used aggregate data to assess the relationship between spending and the performance outcomes of state highway agencies and ranked agencies based on these two metrics. A number of researchers have subsequently argued that such analysis must account for differences in the key evaluation factors across agencies (Goode et al., 1993). Spears (1995) clustered states into peer groups based on data that included the amount of travel, population, and highway inventory size. In explicit recognition that different states' unique characteristics could impair an impartial comparison of states in terms of their expenditures and performance outcomes, Hendren and Niemeier (2006) used a sample of ten state highway agencies for which requisite data were available, to investigate this relationship more closely. In a subsequent study Hendern and Niemeier (2008), these authors used an expanded data set and carried out cluster analysis and PCA to establish nine “peer state” groups.

In more recent work, Agbelie et al. (2015) proposed a quadrant-based clustering method to compare investments and performance outcomes separately for pavement and bridge preservation across different states in the US. In these two studies, states were placed in four clusters, or quadrants, based on their expenditures and performance outcomes, duly normalized by traffic levels and climate severities. Ghahari et al. (2019c) demonstrated a similar methodology for interstate highway bridge infrastructure in the United States. The two studies, nevertheless, commented on the drawbacks associated with their approach and the clustering approach in general. First, is the limitation of classifying the states into groups based on excellent, good/fair, and poor overall performance. Within each cluster, there was no attempt to assess the relative performance of the states. Secondly, the quadrant or cluster boundaries were based on some rather arbitrary standard (often the mean values) for all states in the US. These values can and do change from year to year due to changes in the evaluation factors (namely, traffic, climate, infrastructure condition, expenditures, and so on). The stochastic nature of these factors implies that the boundaries of the peer groups (clusters or quadrants) are non-stationary. Regarding the states that are located close to the peer group boundaries, a small change in any of these factors can cause that state to shift into another peer group. Third, with regard to the states that are clustered within the “poor overall performance” peer group, the cluster method presented in their study does not provide any states worth emulating.

Although it may be argued that poorly performing states could learn from the states in the “excellent performance” peer group, there is no clear guidance on which states should be considered role models in terms of their investment levels, weather and traffic loading severity, and so on. For example, suggesting that a certain state should learn from the several states clustered in the “excellent overall performance” quadrant makes it difficult for that state to acquire insight from those states because they may be having very different investment and operational conditions.

A number of researchers have proposed nonparametric efficiency approaches. Sarıca and Or (2007) stated that the relative efficiency of similar jurisdictions (or organizational units) can be assessed objectively using nonparametric efficiency testing. As such, this approach has been implemented in a broad range of disciplines to estimate the efficiency of production units; these disciplines include civil engineering, agriculture, education, health, finance, and macroeconomics (Fancello et al., 2014; Jiang, 2009; Kuosmanen & Kortelainen, 2005; Ozbek et al., 2009; Shen et al., 2012). Anastasopoulos et al. (2011) used aggregate state-level data from 1999 to 2006 in the United States to examine the relationships among pavement performance (pavement roughness) on one hand, and pavement preservation expenditure, dominant surface geology, and climate on the other hand, using a random-parameters logit (mixed logit) to accounting for any random variations in the model parameters across geographic locations and time periods.

London (2011) applied a nonparametric method to assess transportation performance and the economies of state highway agencies in the U.S. (in terms of the state GDP, transportation performance index, mortality rate, and debt per capita) and ranked them based on their overall performance. Arman et al. (2013) presented a DEA-based framework to assess the operational productivity and efficiency of transit agencies in the State of Indiana; this involved non-parametric linear programming and input data including the transit agency's annual operating expenses, number of employees, and total fuel consumption to evaluate the efficiency of public transit agencies in terms of ridership and vehicle miles traveled, over an eight-year period (2002 to 2009). Zhang et al. (2015) used a nonparametric method to develop a productivity boundary across SHAs with regard to their interstate highway pavements. The authors implemented a productivity model over a horizon period to account for variances in the agencies' technical efficiencies and technological changes.

Nonparametric methods have also been used to assess the efficiency of transportation programs, including public transportation services (Barnum et al., 2007; Barros & Peypoch, 2010; Caulfield et al., 2013; Lao & Liu, 2009; Tran et al., 2017; Van Vuuren, 2002), and airports and airlines (Barros, 2011; Fung et al., 2008; Marques, 2011; Oum et al., 2005; Schaar & Sherry, 2008). Lan et al. (2014) used integrated fuzzy data envelopment analysis to compare the performance of bus transit companies. Further, Sampaio (2014) identified peer states for transportation policy analysis regarding application to handheld cell phone bans, using Synthetic Control Methods (SCM) to address bias. This line of research application was continued by Dong et al. (2017) who analyzed the effectiveness of implemented highway safety laws (related to handheld cellphone bans, speed limits, speed camera systems, and ignition interlock devices) across U.S. states using random-parameter zero-truncated negative binomial models.

8.3 Methodology

In this section, a nonparametric efficiency testing, a linear programming-based approach, is presented to evaluate the efficiency of organizational entities or jurisdictions (in this dissertation's case study, an entity or jurisdiction refers to a state highway agency) in terms of their investment levels and performance outcomes.

Decision variables:

$$\lambda^1, \lambda^2, \ldots, \lambda^K \qquad \text{Eq. 8.1}$$

objective function:

$$\text{Maximize} \quad u = \sum_{k=1}^{K} u^k \lambda^k \qquad \text{Eq. 8.2.}$$

subject to:

$$\sum_{k=1}^{K} x_n^k \lambda^k \le x_n^E \qquad n = 1, \ldots, N \qquad \text{Eq. 8.3.}$$

$$\sum_{k=1}^{K} \lambda^k = 1 \qquad \text{Eq. 8.4.}$$

$$\lambda^k \ge 0 \qquad k = 1, \ldots, K \qquad \text{Eq. 8.5.}$$

where:

k is the index of the organizational entity, $k = 1, \ldots, K$

n is the input index, $n = 1, \ldots, N$, which refers to *N* different types of inputs

u^k is the output of entity *k*

x_n^k is the type *n* input of entity *k*

x_n^E is a fixed value of type *n* input

u is the maximized output that can be produced given inputs x_n^E

λ^k is the weight associated with each entity *k*

The formulation used in this chapter is adopted from Preckel et al. (1997). The role of the decision variables λ^k as weights is to form a convex combination of the input and output vectors (Eq. 8.4. makes the weights non-negative and sum to unity). The first constraint $\sum_{k=1}^{K} x_n^k \lambda^k \le x_n^E$ is to ensure that no more type *n* inputs than x_n^E are used. The objective function $\sum_{k=1}^{K} u^k \lambda^k$ to be maximized represents the output that can be produced feasibly given the fixed amount of inputs $\boldsymbol{x^E} = (x_1^E, x_2^E, \ldots, x_n^E)$.

The feasible set of outputs u using inputs $\boldsymbol{x^E}$ is as follows:

$$T(x_1^E, x_2^E, \ldots, x_n^E) = \quad \{u | \textstyle\sum_{k=1}^{K} u^k \lambda^k = u; \qquad \text{Eq. 8.6.}$$

$$\textstyle\sum_{k=1}^{K} x_n^k \lambda^k \leq x_n^E \qquad n = 1, \ldots, N \qquad \text{Eq. 8.7.}$$

$$\textstyle\sum_{k=1}^{K} \lambda^k = 1 \qquad \text{Eq. 8.8.}$$

$$\lambda^k \geq 0 \qquad k = 1, \ldots, K\} \qquad \text{Eq. 8.9.}$$

It may be noted that this set is a function of the input levels $\boldsymbol{x^E}$. For a given entity indexed by *E*, the question of interest is as follows: Given the input and output vector $(\boldsymbol{x^E}, u^E)$, is it possible to achieve a higher output value (that is greater than u^E)? Figure 8.1. illustrates the goal of the proposed output-oriented efficiency test. In this example, entities 1, 2, and 3 are considered to be efficient entities because they are located on the efficiency frontier (shown as the dashed red line in the figure). In other words, it is not possible for any other entity with the same inputs as these entities to achieve a higher output value. Entity *E* is considered "inefficient" because it is not located on the efficiency frontier. It is assumed that inefficient entities could potentially learn from the entities located on the frontier so that the former could behave similarly to the latter (in terms of their efficiency in utilizing inputs and producing outputs). In real-life asset management practice, such learning takes place through peer exchanges jointly sponsored by FHWA, TRB, and AASHTO such as those held recently in Cheyenne, Wyoming (Park & Robert, 2011), Burlington, Vermont (Park et al., 2014), and Miami, Florida (Park et al., 2014).

Consider an inefficient entity, say, *E*. A path to utilize entity *E*'s inputs in a manner similar to that of the efficient entities (in this example, entities 2 and 3) can be represented by the vertical line shown in Figure 8.1. The vertical line reaches the efficiency frontier at a point that lies between entities 2 and 3. Hence, entity *E* can succeed in its efforts if it learns from entities 2 or 3. If entity *E* succeeds in reaching the efficiency frontier, then the maximized output u will be a value on the frontier (a convex combination of u^2 and u^3; in this example, $u = \lambda^2 u^2 + \lambda^3 u^3,\ \lambda^2 + \lambda^3 = 1$) that is larger than the original value u^E. The percentage improvement in this analysis can be then computed as $\frac{u - u^E}{u^E}$.

The weight λ^k indicates the degree to which organizational entity *E* should learn from or operate in a manner similar to entity *k* in order to achieve the maximized output. Therefore, a higher value of λ^k indicates that there is greater opportunity for entity *E* to learn more from and operate in a manner similar to entity k. For a given entity E, if $\lambda^E = 1$ and $\lambda^k = 0, for\ k \neq E$, entity E is on the frontier.

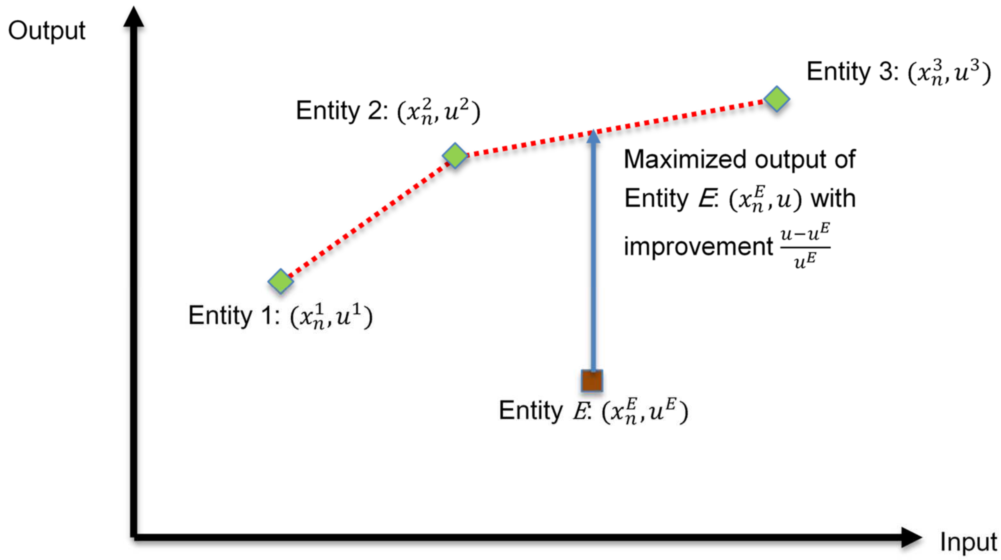


Figure 8.1. Conceptual illustration of the output-oriented nonparametric efficiency test

Based on these definitions, a method is proposed to rank entity efficiency using the framework shown in Figure 8.2. The premise of this ranking method is the assumption that the inefficient entities will seek to learn from the efficient entities. Initially, the list contains all the entities. In the first round of analysis, the optimization framework analyzes each entity on the current list to determine: (1) whether the entity is on the frontier, (2) how much more output the entity could achieve if it learns from and behaves like other entities on the frontier, and (3) the degree or extent to which the entity should learn from and behave similarly to the superior entities (λ_j^k indicates the degree to which entity j learns from entity k). Then, for each entity k that is currently on the list, the sum of weights according to which other entities should learn from this entity is computed as $\sum_j^J \lambda_j^k$ (only the entities that currently stay on the frontier have a positive value). The entity that has the largest value of $\sum_j^J \lambda_j^k$ receives the highest rank in the current list. After identifying the most efficient entity in the current list, this entity is removed from the list, and the analysis proceeds to the next round. This process is repeated until all of the entities are removed from the list, and the resulting list indicates the final ranking of all of the entities.

In this chapter, the organizational entities represent state highway agencies. State highway agencies are the U.S. equivalent of organizations in other countries that are termed regional or district departments of transportation or highways. These are public agencies that receive budgetary allocations from the government and are tasked with ensuring that the transport infrastructure is maintained in a state of acceptable physical condition (through reconstruction, rehabilitation, and maintenance) and operational performance (safety, mobility, and access). Depending on the administrative structure of a country, these regional agencies are overseen by an umbrella national oversight body (such as the federal department of transportation (in the U.S.), or the national ministry of transportation in certain countries, and so on. As explained in the introduction of this chapter, the oversight national agencies have a responsibility to make the agencies at the next jurisdictional level accountable for their stewardship of the public funds. The approach described in this methodology places them in a better position to carry out this duty.

8.4 Data

To demonstrate the methodology, this dissertation uses the states in the US as the jurisdiction of interest (with the oversight agency being the Federal Highway Administration [FHWA] or GAO). The infrastructure in question is the set of interstate highway bridges. The data on bridge performance were obtained from the National Bridge Inventory (NBI) database and are supplemented by the FHWA's recording and coding guide for the inventory and appraisal of the nation's bridges (FHWA, 1996). The NBI database contains inventory sizes (in terms of deck surface areas), condition ratings, and average daily truck traffic. The average traffic volume per bridge inventory size was calculated for this case study.

Other data sources include the Office of Highway Policy Information (OHPI) and the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NCDC, 2016). The climate data from the NCDC include the annual average temperature and precipitation records from 1992 to 2012. The climate data are used in this dissertation to provide the average number of freeze-thaw cycles as well as the average annual freeze index in each state. For each state, the average freeze index for the period from 1992 to 2012 is used in this study. The expenditure data (over three years) were obtained from the FHWA's highway statistics reports. To adjust the expenditures for inflation to their year 2014 equivalents, the FHWA construction price index (Sinha & Labi, 2007) was used.

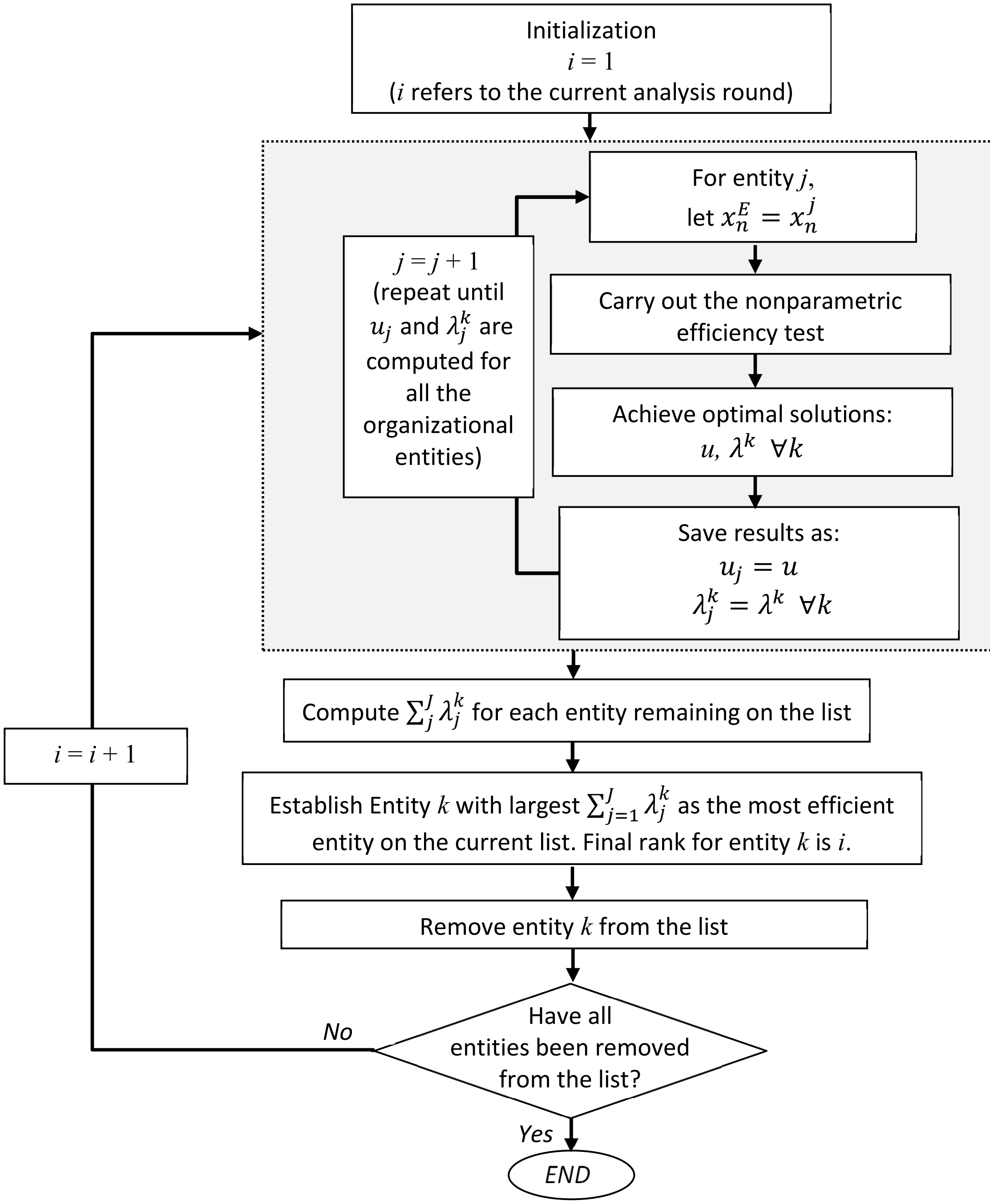


Figure 8.2. Ranking method for evaluating the performance efficiency of entities

To remove the measurement scale bias associated with the different units of measurement of these factors, each factor is normalized by expressing it as a ratio of the average value of the variable for all jurisdictions in the population (in this case, all states in the nation). Table 8.1. presents the normalized values for the key evaluation attributes (climate severity in terms of freeze index, expenditure per inventory size (m^2 of deck area), freeze index, and age) of interstate highway bridges in each state.

Table 8.1. Normalized values of the key evaluation attributes

STATE	Norm_COND	Nom_EXP/m²	Norm_AADT	Norm_F-INDEX	Norm_AGE
AL	1.00	0.28	1.11	0.00	0.978
AK	1.01	1.60	0.10	4.90	0.694
AZ	1.01	0.27	0.34	0.05	0.896
AR	1.03	0.59	1.09	0.00	0.909
CA	1.00	0.76	2.40	0.06	1.086
CO	1.02	0.67	0.77	1.67	0.849
CT	0.98	2.55	0.36	0.63	1.181
DE	0.99	0.97	0.07	0.00	0.966
DC	0.93	4.25	0.02	0.00	1.326
FL	1.07	0.32	1.07	0.00	0.794
GA	1.01	0.33	1.06	0.00	0.923
HI	0.98	0.72	0.09	0.00	1.356
ID	0.98	0.80	0.42	1.45	0.957
IL	1.06	1.18	2.53	0.83	0.908
IN	0.99	0.69	1.86	0.75	0.958
IA	0.96	0.36	2.33	2.24	1.055
KS	1.01	0.11	1.89	0.28	1.122
KY	0.99	0.38	1.28	0.01	0.882
LA	0.99	0.65	1.10	0.00	0.827
ME	0.97	0.52	0.23	2.90	1.211
MD	0.97	1.12	0.24	0.09	1.026
MA	0.97	2.97	0.50	0.69	1.267
MI	1.00	1.32	1.07	2.13	1.031
MN	1.02	0.50	0.89	4.21	0.857
MS	1.07	0.24	1.55	0.00	0.756
MO	1.07	0.66	2.24	0.31	0.903
MT	0.99	0.61	0.43	2.24	1.052
NE	1.03	0.30	1.34	1.31	1.074
NV	1.06	0.25	0.12	0.28	0.740
NH	1.01	0.83	0.32	2.22	1.195

Table 8.1. continued

STATE	Norm_COND	Nom_EXP/m^2	Norm_AADT	Norm_F-INDEX	Norm_AGE
NJ	0.97	2.24	0.62	0.19	1.173
NM	0.95	0.47	0.23	0.29	0.925
NY	0.99	2.30	1.28	1.64	1.139
NC	0.96	0.44	1.51	0.01	0.858
ND	1.08	1.10	0.09	4.78	1.180
OH	1.07	0.81	2.48	0.66	0.983
OK	0.92	0.70	1.89	0.00	0.962
OR	1.02	0.93	0.80	0.24	0.977
PA	0.91	1.95	2.09	0.81	1.210
RI	0.90	4.84	0.07	0.38	1.197
SC	0.99	0.51	0.91	0.00	0.902
SD	0.92	0.31	0.53	2.80	1.146
TN	0.99	0.50	1.28	0.00	0.950
TX	1.04	0.20	3.84	0.00	0.815
UT	1.03	0.87	0.26	1.01	0.791
VT	1.05	2.40	0.29	2.92	1.308
VA	0.97	0.56	1.22	0.04	1.076
WA	1.03	1.34	0.78	0.36	0.997
WV	1.02	0.95	0.71	0.19	0.835
WI	1.05	0.45	1.06	3.21	0.835
WY	0.94	0.34	0.23	2.17	0.961

8.5 Results and Discussion

Table 8.2. presents the final ranking for the top 26 performing states in the US using the proposed nonparametric efficiency method. The complete results of rankings are presented in Table 8.3: For a state in row *l*, the results show that by learning from and adopting practices similar to that of state *k* (represented by the weight λ^k), a relatively inefficient state could improve its bridge condition rating to the extent indicated by the percentage value shown in the respective cell. The table suggests that, for example, Hawaii (HI) could possibly achieve a 10% improvement in bridge condition if it operates (including the use of its resources) in a manner 48% similar to that of Florida in terms of administrative procedure. Fortunately, highway agencies in the United States, carry out peer exchanges that serve as valuable platforms through which the agencies continually interact and learn from each other (Park & Robert, 2011; Park et al., 2014).

Table 8.2. Final efficiency rank (regarding interstate highway bridges): the top 26 states

Rank	**State**		**Rank**	**State**
1	ND		14	AZ
2	OH		15	KS
3	MO		16	CO
4	IL		17	VT
5	WI		18	WA
6	NE		19	WV
7	FL		20	OR
8	MS		21	NH
9	NV		22	AK
10	TX		23	GA
11	MN		24	AL
12	AR		25	CA
13	UT		26	MI

Table 8.3. presents the first-round analysis results (without any state removed from the frontier) when efficiency levels of all 50 states (including the District of Columbia) are compared. Of the 51 jurisdictions, 10 states lie on the frontier (as shown in Figure 8.3). It may be noted that a state's position on the frontier does not necessarily indicate they are unequivocally efficient overall; rather, it means that they are most efficient from at least the perspectives considered in this chapter of the dissertation (that is, this study's infrastructure "strength" and "stress" factors) for which their operational and resource allocation experiences could serve as useful knowledge to other states that seek to learn and make improvements (Chen et al., 2019). For the 41 jurisdictions that are not on the frontier, the percentage values that indicate the possible amount of improvement that these states can achieve by learning from other states range from 0.3% to 20.4%. Figure 8.4. presents the distribution of possible percentages of improvement for the 41 inefficient states. More than half of these states could improve by less than 10% if they use their resources more efficiently.

Table 8.3. Percentage of the opportunities for learning

λ^k (%)

STATE	Improvement could achieve (%)	AL	AK	AZ	AR	CA	CO	CT	DE	DC	FL	GA	HI	ID	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
AL	6	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AK	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AZ	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	82	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR	4	0	0	0	0	0	0	0	0	0	65	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CA	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	56	0	0	11	0	0	0	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CO	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	22	0
CT	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DE	9	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	83	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DC	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FL	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GA	6	0	0	0	0	0	0	0	0	0	64	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HI	10	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ID	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	64	0	0	0	0	0	0	0	0	32	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IL	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	64	0	0	0	0	0	0	0	0	0	0	0	0	0	36	0
IN	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	57	0	0	0	0	0	0	0	0	0	0	0	0	0	23	0
IA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KY	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	54	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
LA	8	0	0	0	0	0	0	0	0	0	57	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ME	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	65	0
MD	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MA	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MI	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	73	0
MN	0.9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	75	0
MS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MT	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	36	0
NE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NH	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	21	53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NJ	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NM	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0
NY	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	75	0
NC	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	55	0	0	0	23	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OK	17	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OR	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	21	0	0	9	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PA	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	51	0
RI	20.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SC	9	0	0	0	0	0	0	0	0	0	75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SD	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	77	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0
TN	9	0	0	0	0	0	0	0	0	0	55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TX	0.6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	30	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
UT	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	37	0	0	8	0	0	0	0	0	55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VT	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VA	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32	0	0	47	0	0	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WA	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WV	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	83	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0
WY	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	66	0

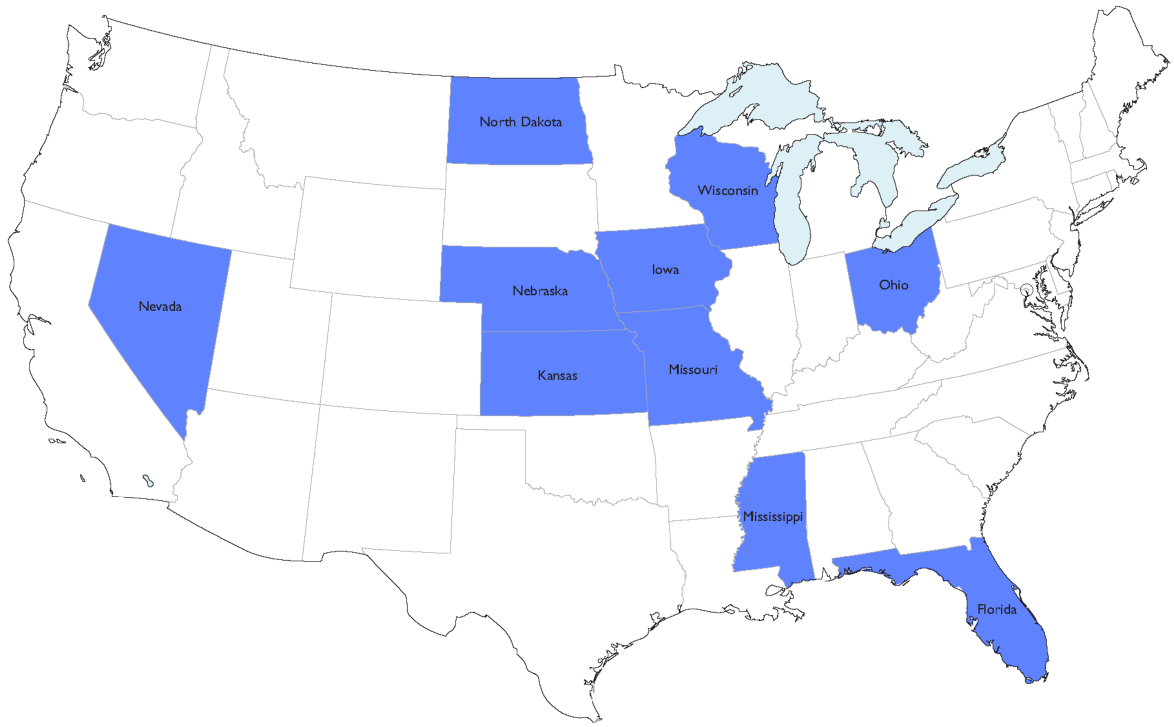


Figure 8.3. The frontier states after the first round of the evaluation

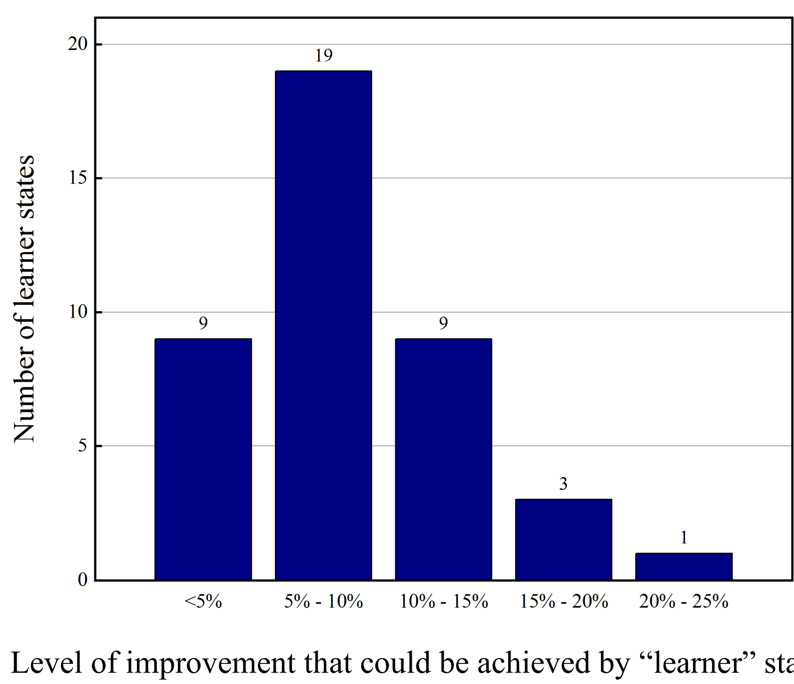


Figure 8.4. Distribution of the extent of possible improvement across the "learner" states

After the data had been adjusted duly for biases associated with inventory size and deterioration factors (age, climate, and traffic), the analysis identified the following states as the top performers: North Dakota, Ohio, Missouri, Illinois, Wisconsin, Nebraska, Florida, Mississippi, Nevada and Texas. Further research will be necessary to assess the consistency of these rankings across the years and to identify the reasons why certain states have relatively high ranking.

It may be noted that a state may exhibit superior efficiency due to extenuating factors that may be within or outside of its control but are not considered in the analysis. Factors that are within a transportation agency's control may exist at several levels of management and may be loosely categorized as strategic, tactical, and operational:

- Strategic factors include the agency's mission and goals (such as system preservation) in the years in which data were collected, as well as policies that promote transparency and accountability.
- Tactical factors include policies on overweight trucking and minimum performance standards in the agency's asset preservation manuals, enforcement of penalties for substandard road work by contractors, and the level of maturity of management systems for the individual asset types.
- Operational factors include the quality of contract documents, frequency of staff training, and quality of supervision of contractual or in-house workmanship. The prudent use of technology to enhance efficiency is an influential factor at all three management levels.
- Factors outside the transportation agency's control include the quality of available materials (from local borrow pits and quarries) and frequency and severity of natural disasters (e.g., floods, earthquakes, and landslides).
- Other factors that cut across all the three categories include the prevailing work culture, design- or material-related resilience of the infrastructure to man-made or natural threats, and political instability.

8.6 Concluding Remarks

In this chapter, for the proposed ranking method, the output was bridge condition rating and the inputs include strength and stress factors. The strength factors are those whose higher levels cause an increase in infrastructure performance; the strength factor was preservation expenditure, which is the sum of the costs of all treatments applied to any component of a bridge. To avoid bias due to inventory size, the statewide total expenditure was divided by inventory size. The stress factors are those whose higher levels cause a decrease in infrastructure performance; stress factors included traffic (truck) loading, climate severity, and age. Climate severity was described in terms of the freeze index in degree-days and was calculated by subtracting the number of degree-days between the highest point and lowest point on a cumulative degree-day curve for one freezing season.

It was found that a jurisdiction may exhibit extremes of efficiency due to prevailing levels of factors that are within or are outside of the control of its infrastructure agency. As stated in the discussion section of this chapter, factors within the control of the agency may be classified as strategic, tactical and operational factors. Strategic factors include the agency's mission and goals, and policies that promote transparency and accountability. Tactical factors include policies such as overweight limits and asset performance standards, quality assurance of roadwork, maturity level of management systems. Operational factors include the quality of contract documents, frequency of staff training, and quality of supervision of contractual or in-house workmanship, and use of technology. Factors outside the agency's control include the quality of available materials (from local borrow pits and quarries) and frequency and severity of natural disasters. Other factors may include the work culture in the agency, resilience of the infrastructure to man-made or natural threats, and political instability. The effect of these factors on the efficiency of a jurisdiction's agency, can be investigated in future research in this domain.

CHAPTER 9. CONCLUDING REMARKS

9.1 Introduction

This chapter provides a summary of the conclusions, the contributions of the dissertation, policy recommendations regarding corruption and inefficiencies reduction actions at the global level and at the infrastructure project level that may be useful for government and non-government agencies, study limitations, and recommendations for future work.

9.2 Summary and Conclusions

This dissertation addressed the issues of corruption and inefficiencies associated with the provision of transport infrastructure. Part 1 of the dissertation investigated and assessed attributes that influence corruption levels among countries from 2007 to 2017. Using principal component analysis (PCA), and K-means machine learning and hierarchical structure cluster analysis, groups of countries that share similar levels of development-related attributes were identified. The cluster analysis helped identify countries where corruption control initiatives should receive high priority. Also, using a machine learning technique (random forest algorithm) the Corruption Perceptions Index (CPI) for each cluster were predicted based on development-related attributes. Furthermore, building upon the results from the first chapter the corruption levels at countries were also forecasted using an artificial neural network time series analysis - a nonlinear autoregressive recurrent technique with exogenous inputs (NARX).

Transparency can help address corruption. With information and communication technologies (ICT) advancements, it is possible to enhance transparency. One way to use ICT to increase transparency is electronic governance. This dissertation used a panel vector autoregression (PVAR) to analyze the relationship and shock effects between electronic governance and corruption. In the final chapter of Part 1, this dissertation identified the ways where corrupt actions may occur in the development of infrastructure systems, and by setting the discussion of corruption in this context, it connected the propensity for corruption in each phase of infrastructure development to strategic, tactical, and operational mitigation actions supported by examples in practice. The dissertation's contents may be used to develop guidelines to measure, detect, and address corruption in the infrastructure sector.

Part 2 began with a discussion of various methods used in the literature to measure the performance efficiency of organizational units. Part 2 of the dissertation also addressed inefficiencies associated with transportation infrastructure management. In the United States, oversight agencies such as the U.S. Department of Transportation, the Federal Highway Administration, and the Government Accountability Office are responsible for the measuring and monitoring the overall accountability of state highway agencies. To help these oversight bodies to carry out this task, it is often useful to show the extent to which the infrastructure expenditures influence infrastructure performance. Further, oversight agencies typically seek to establish a methodology to assess how well the individual states are doing compared to each other. In response to these two issues, this part established an empirical relationship between expenditures and performances, using Interstate highway bridge decks as a case study. The unit of observation in this dissertation was the state level (each state contains a collection of bridge decks whose average annual expenditures and average condition rating are known). The dissertation recognized that there exist jurisdiction-specific variables that affect infrastructure performance, and therefore attempted to remove some of this bias by normalizing the expenditure as a ratio of the inventory size and by considering state-specific values of the key deterioration variables. Also, the dissertation identified the factors found significant in the condition-expenditure relationship and used these factors as a basis for assessing the performance of state highway agencies.

The concluding chapter of Part 2 performed a nonparametric efficiency methodology for comparative assessment of infrastructure agency performance by duly adjusting for inventory size and measurement bias and the effects of the different average ages of infrastructure assets, different climate severities, and different traffic levels across jurisdictions. The methodology involved the development of an efficiency frontier using optimization, identification of frontier-located jurisdictions (FLJs), removal of the FLJs and re-development of the next frontier, and continuing this cycle until all jurisdictions have been removed. The dissertation presented an overall efficiency ranking of the US states regarding the performance of the infrastructure used as a case study. Oversight agencies can implement the methodologies presented in this study to monitor the accountability of jurisdictions regarding their performance outputs and expenditures.

9.3 Overall Strategic Practical Implications of this Research

There are several strategic practical implications of this dissertation's results that can provide governmental and non-governmental oversight agencies with some guidelines for policies regarding corruption and efficiencies in the future.

9.3.1 Corruption

In Part 1 the attributes that have a significant influence on the corruption levels in countries was determined. PCA biplot showed that GNI (C1), EGI (C2), human development index (C3), public-sector performance (C5), and labor market efficiency (C9) are the most determining and influential attributes for countries' development-related attributes when plotted with regards to the first two principal components.

Partial dependence plots from the random forest analysis showed that when considering countries altogether, there is a positive relationship between technological readiness (C11) and human development index (C3) in improving CPI values. The Gini charts obtained from the random forest machine learning technique showed that among the attributes C1 to C13, technological readiness (C11), human development index (C3), and e-governance index (C2) are of the highest importance in predicting CPI values. This outcome indicated that efforts to reduce corruption need an emphasized attention to these factors.

The cluster-based analysis showed that the most influential attributes of corruption in each cluster are:

- Cluster 1: Technological readiness (C11), GNI (C1), and security (C6)
- Cluster 2: Human development index (C3), undue influence (C4), and e-governance index (C2)
- Cluster 3: Public-sector performance (C5), labor market efficiency (C9), and e-governance index (C2)
- Cluster 4: Undue influence (C4), public-sector performance (C5), and security (C6)

The NARX NN prediction models showed different results for the world-level data analysis and the cluster-level data analysis. Using world-level data, it was found that there is a general reduction in corruption over the years studied (a 6.71% increase in CPI from 2010). Cluster 1, Cluster 2, and Cluster 4 showed the same uptrend with 7.41%, 13.37%, and 21.25% decreases in perceived corruption from 2010, despite having a comparatively minor increase in perceived corruption from 2007 to 2010. However, Cluster 3, despite containing developed countries in major, showed a 5.35% increase in perceived corruption from 2007.

The results of PVAR impulse response function (IRF) showed that a one-unit positive shock on EGI leads to a 60% increase in CPI in two years. This effect was shown to fade off in 8 years. The results were more significant for the low- and middle-income countries. The results indicated that a one-unit shock on EGI would lead to an immediate increase in CPI, and it persisted over time. This level of increase in CPI is around 20% higher than that of the CPI increase when all countries were considered together, meaning that in developing countries EGI would have a more critical effect in controlling corruption than in developed countries. When analyzing the results for high-income countries, it was noted that the shocks from neither CPI nor EGI were significant, indicating there must be other underlying reasons that cause corruption in those countries.

9.3.2 Inefficiency

Consistent with the principles of transportation asset management, government legislations emphasize the need for continual assessment of performance outcomes vis-à-vis expenditures. One way to do this is to compare, across various organizational entities (jurisdictions) and for a defined domain of infrastructure, spending levels on one hand and the resulting performance on the other hand. The jurisdictions of interest could be cities and towns, counties, sub-districts, states, or nations. The infrastructure in question can range from specific assets (or parts thereof) to the combination of all assets within a jurisdiction.

In Part 2 of this dissertation, the framework and results showed how oversight agencies can monitor the overall accountability of individual highway agencies. The observed differences in the state performance could be due to extreme differences in construction cost across states, differences in agency audit quality, work culture, poor geotechnical conditions in a state, unfavorable design–construction practices, and possibly, poor quality of quarry or borrow pit materials available in or near a state. The relative rankings could also prompt those agencies seen as not well performing, to carry out critical self-assessment to identify the possible causes of such performance as a first step towards their resolution.

The dissertation identified the highest efficiency states after the data had been adjusted duly for biases associated with inventory size and deterioration factors (age, climate, and traffic). It was found that based on the data, 10 of the 51 U.S. jurisdictions (i.e., the 50 states plus the District of Columbia) lie on the efficiency frontier in the first round of analysis, indicating that they are efficient from one or more perspectives considering their strength and stress factors for which their operation experiences could be useful to other states to make improvements. It was also determined that for each of the 41 non-frontier states, an increase in efficiency ranging from 0.3% to 20.4% could be earned by learning from the frontier states. For more than half of these states, an up to 10% increase in efficiency can be gained by more efficient use of their resources.

9.4 Contributions of the Dissertation

The main contributions of this dissertation for the two main parts are as follows:

9.4.1 Corruption

In a pioneering effort to determine the attributes that have a significant influence on the corruption levels in countries using advanced statistical techniques, this dissertation used three approaches: principal component analysis (PCA), hierarchical structure cluster analysis, and regression tree analysis and random forest (RF) machine learning (ML) technique. In addition, the dissertation applied an artificial neural network (ANN) technique − a nonlinear autoregressive recurrent method with exogenous inputs (NARX) to analyze the level of corruption in any country.

This dissertation also addressed the efficacy of e-governance in reducing Corruption Perceptions Index (CPI) in any country. To what extent does a unit change in EGI cause CPI changes? Is the trend valid for all continents, or is it valid for all countries with any category of gross national income per capita (GNI)? This dissertation answered this question using a panel vector autoregression (PVAR) analysis, including Orthogonalized Impulse-Response Functions (IRF), Granger-causal, and variance decomposition analysis on data from 133 countries from the years 2007 to 2017.

9.4.2 Inefficiency

The dissertation addressed the requirements of past and current highway legislation that emphasize the need for continual assessment of performance outcomes vis-à-vis expenditures. The dissertation showed that one way to do this is to compare, across various jurisdictions and for a defined domain of infrastructure, spending levels on the one hand and the resulting performance on the other hand, and to rank the jurisdictions duly considering their spending levels and performance outcomes.

The dissertation reviewed past work and presented a nonparametric efficiency approach based on linear programming by developing an efficiency frontier using optimization, identification of frontier-located jurisdictions (FLJs), and re-development of the next efficient frontier by removing the FLJs. In addition, based on the linear programming approach, this dissertation proposed a method to rank US states using the optimization results. The proposed methodology can be used by individual jurisdictions to learn from each other and estimate the expected benefits they could earn if they move up to the efficiency frontier through enhanced utilization of their resources.

9.5 Study Limitations

In Part 1 of this dissertation, there are several limitations that could be addressed in future research studies. First, the amount of data is significantly limited, which might cause bias in the results. Consequently, including more data in the analysis makes the results more accurate and reliable. Moreover, relying on only one attribute as the indication of corruption in countries, i.e. CPI, was another major limitation of this study. Hence, providing more data and giving more access to the public would be significantly beneficial for policymakers, governments, and NGOs that are active in this important field. Another study limitation is due to the intrinsic machine learning hyperparameters. Fine-tuning the hyperparameters in machine learning techniques plays a significant role in finding the most accurate results. This is mainly important in small scale analysis such as, state-level predictions, where the scales are smaller, and more accuracy is required, accordingly.

In Part 2 of this dissertation, the limitations include the assumption that the recorded bridge repair expenditures reflect the actual work done, and the split share of deterioration caused by load and non-load factors. Regarding the inputs and outputs, the inefficiency analysis assumed that all states are independent of each other. This means that, for example, the condition of bridges in a state is assumed to be a function only of that specific state's input factors (such as the level of maintenance spending, traffic, weather, and so on). In reality, factors such as traffic may often be correlated between or across states, particularly where the states are adjacent to each other. Certain states (particularly, those that share borders) depend on each other in various ways including cross-border commuting and truck movements associated with agriculture and industrial operations between workstations that straddle the border, for example. Such interdependency could be benefitting some states to a larger extent, compared to others, and if this can be measured, the analysis can be modified accordingly. Furthermore, nonparametric methods generally tend to assume a linear relationship between inputs and outputs. This assumption may not be valid because of returns to scale and other effects that are inherently non-linear. For example, not only do larger states generally enjoy the benefits of scale economies but also the rate of change in such benefits depends on the size of the state.

9.6 Recommendations for Future Work

There are several opportunities for future work related to corruption analysis. First, as seen from the results, the policymakers need to focus on a specific cluster in terms of the corruption level and development-related attributes. Hence, as a future work, it is suggested that the focus to be made on each individual country in that cluster and investigate the further needs in reducing corruption in the countries. The starting attributes can be undue influence, public-sector performance, and security for this cluster. Secondly, reduction of corruption in a country cannot be achieved without comprehensive cooperation of entities within its society. Such cooperation includes, for example, a coalition of government officials, politicians, and NGOs who can help reveal or present surreptitious acts of corruption. Corruption reduction can happen through raising awareness, which includes an integrated public digital portal where data is captured through crowd sourcing and processed, and is organized for easy comprehension by citizens. The feasibility of implementing such approaches could be assessed in future work (Ghahari et al., 2019e).

Other suggestions for future work include (a) a thorough investigation of the reasons behind the uptrend and downtrend momentum in CPI values in each cluster of countries; (b) considering the policies applied to the countries in each cluster, finding the solutions that have been applied to those countries, and assess the effectiveness and the impacts of the policies; (c) finding out how much portion of the overestimated costs in projects is associated with corruption and how much is related to inefficiencies.

Also, future work could include a greater number of data points (a longer analysis period) as additional annual data become available. Also, data on additional factors that affect corruption, and other corruption indicators, can be collected and analyzed. Secondly, the study results suggest that enhancing electronic governance in developed countries will not be as effective compared to developing countries. Hence, future studies could identify other initiatives that could be more efficacious at developed countries.

Finally, e-governance may be accompanied by increased surveillance of private-sector activities and records that are associated with government functions. Therefore, even though this may be originally intended for the greater good, there is the downside of potentially reduced privacy and greater opportunity of an overbearing government to use the e-governance platforms to suppress the populace. Both the negative, as well as, the positive implications of enacting this remedy may be worth investigating in future studies.

In Part 2 of the dissertation, the suggested future work is as follows. First, in the absence of reliable research-driven split numbers between the recorded expenditures and the actual work done, sensitivity analysis can be carried out in the future research to establish, the jurisdictions status (locations on a Cartesian axis of efficiency factors, such as quadrants) and position shifts or different splits. Furthermore, future studies could consider other model specifications such as the lagged panel model, not just a one-year lag (t–1) as done in this dissertation but also t (same year), t–2, t–3, and so on, to confirm the investment-performance lag time that best captures the field conditions.

Future work could also consider including omitted variables as valuation criteria where such data are available, and also extend the work to the other bridge components (superstructure and substructure) and other asset types. The methodology could also be extended to infrastructure management in other sectors where oversight bodies seek to monitor the performance of jurisdictions associated with agriculture, healthcare, energy, education and other sectors. Another future research in this area could be the improvement of the optimization framework by duly accounting for spatial and situational interdependencies.

In addition, for the ranking method proposed in this dissertation, the weights λ_j^k (the degree to which agency or entity j learns from entity k) were considered to be equally weighted across all entities j. For example, when computing $\sum_j^J \lambda_j^k$ for a state that other states can learn from, if the learning weights of both New York State and New Mexico are 30%, both states' contributions to $\sum_j^J \lambda_j^k$ are considered equal. However, using equal weights may not be ideal because some entities possess certain attributes that make them inherently more efficient compared to others.

Furthermore, research projects are needed to focus on assessing the consistency of these rankings across the years and to identify the reasons why certain states have a high ranking. Also, the analysis could be replicated for another transport asset type and other jurisdictional levels.

Finally, there is continuing evolution of not only transportation *per se* (autonomous and connected vehicle operations, ride sharing, aerial transport units, focus on resilient and sustainably developed infrastructure) but also the transportation environment (climate change, infrastructure interdependencies, and smart cities). These developments are expected to cause shifts in the number and intensity of the factors that either exacerbate or ameliorate the rate of infrastructure deterioration, and cause redistributions of budgets and expenditures across the various infrastructure program areas. These and other related developments will likely lead to changes in the relative inputs and outputs (and hence, relative efficiencies) that are associated with infrastructure jurisdictions at any level of government. For this reason, in the future, performance efficiency analysis will need to be conducted regularly.

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APPENDIX A. PUBLICATIONS ON CORRUPTION ASSOCIATED WITH EACH CATEGORY

Table A.1. List of the publications associated with each category

Category	Description	References
Impact of the corrupt behaviors on governance of commons	Types of impact (emerging from the literature)	(Ades & di Tella, 1997; Aghion et al., 2016; Ahsan & Gunawan, 2010; Aisen & Veiga, 2013; Alexeeva et al., 2011; Alzahrani & Emsley, 2013; Ameyaw et al., 2017a; Amoako & Lyon, 2014; Amoatey et al., 2015; Amponsah, 2010; Anderson & Tverdova, 2003; Asunka, 2016; Ateloye et al., 2016; Athanasouli & Goujard, 2015; Babos, 2015; Bardhan, 1997; Bob-Milliar, 2012; Bose et al., 2008; Bowen et al., 2012a; Boycko et al., 1996; Castro et al., 2014; Chan et al., 2015; Cheng, 2014; Collier et al., 2015a, 2015b; Damoah et al., 2018; Del Monte & Papagni, 2001, 2007; Dobson & Ramlogan-Dobson, 2012; Esfahani & Ramírez, 2003; Farooq et al., 2013; Fazekas & Tóth, 2018; Fiorino et al., 2012; Fredriksson & Svensson, 2003; Frey, 1994; Gillanders, 2014; Guasch et al., 2008; Guiso et al., 2004; Gupta et al., 2002; Hall & Lobina, 2004; Hellwig & Samuels, 2008; Hessami, 2014; Hofstede, 1983; Hunt, 2005; Jetter et al., 2015; Kaliba et al., 2009; Kenny, 2009a; Leff, 1964; Leys, 1965; Mauro, 1995; McGee, 1999; Méon & Sekkat, 2005; Morse, 2006; Neeman et al., 2008; Paunov, 2016; Percoco, 2014; Picur & Riahi-Belkaoui, 2006; Porter & Graycar, 2016; Rădulescu et al., 2016; Rose-Ackerman, 1996a; Rui et al., 2008; Saha & Gounder, 2013; Slemrod & Katuščák, 2005; Thillairajan & Menon, 2014; Transparency International, 2015; Von Hirschhausen, 2002; Wei, 2000; Yehoue et al., 2006)
Causes of Corruption		(Abdulai, 2009; Aghion et al., 2016; Amadi & Higham, 2016; Ameyaw & Chan, 2015; Asenova & Beck, 2003; Ateloye et al., 2016; Ball et al., 2003; Baumol, 1996; Bildfell, 2018; Boase, 2000; Bruzelius et al., 2002; Button, 2016; Castro et al., 2014; Collier et al., 2015b; Czibik et al., 2014; Damoah et al., 2018; Edomah et al., 2016; Estache et

		al., 2009; Fazekas & Tóth, 2018; Frank & Martinez-Vazquez, 2014; Gillanders, 2014; Golden & Picci, 2005b; Guasch et al., 2007; Hall & Lobina, 2007; Halpern et al., 2008; Kenny, 2009a; King & Pitchford, 2008; Klemperer, 2007; Kwak et al., 2009; Laffont & Tirole, 1991; Lengwiler & Wolfstetter, 2006b; Makoni, 2014; Maskin & Tirole, 2008; North, 2007; Oyewunmi & Olujobi, 2016; Percoco, 2014; Piga, 2011; Porter & Graycar, 2016; Rebosio & Wam, 2011; Rose-Ackerman, 1999; Şentürk et al., 2004; Treisman, 2007; UNECE, 2004; Yehoue et al., 2006; Zábojník, 2002)
Level of corruption		
	Individual	(Abdulai, 2009; Africa Research Bulletin, 2008; Aghion et al., 2016; Ameyaw et al., 2017a; Benitez et al., 2012; Bowen et al., 2007b; Brown & Loosemore, 2015; Bruzelius et al., 2002; CDD Ghana, 2000; Collins et al., 2009; Damoah et al., 2018; Dewatripont et al., 1999; Felix & Hines, 2013; FMI/CMAA, 2004; Mensah et al., 2003b; Munavar Ali, 2017; Nordin et al., 2011; Osei-Tutu et al., 2010b; Porter & Graycar, 2016; Rafi et al., 2012; Saenz & Brown, 2018; Wilson & CFE, 2004; Yan & Oum, 2014; Zou, 2006)
	Organization	(Ahsan & Gunawan, 2010; Ameyaw et al., 2017b; Brass et al., 1998; Cheng, 2014; Clarke & Xu, 2004; Damoah et al., 2018; de Jong et al., 2010; Doh et al., 2003a; Graycar & Villa, 2011; Jon, 1999; Kaliba et al., 2009; Kaniki & Gwatidzo, 2012; Kivyiro & Arminen, 2013; Krackhardt, 1999; Locatelli et al., 2017; Luo, 2005; Marcel & Heller, 2012; Martin et al., 2007; Munavar Ali, 2017; Osei-Tutu et al., 2010b; Otairu et al., 2013; Otairu et al., 2014; Percoco, 2014; Pinto, 2013; Saenz & Brown, 2018; Sohail & Cavill, 2008; Sovacool, 2017; Transparency International, 2011; Vee & Skitmore, 2003; Winch & Leiringer, 2016; Wu, 2009; Yan & Oum, 2014; Zhang et al., 2017)
	Project	(Alam & Ahmad, 2013; Alexeeva et al., 2011; Ameyaw et al., 2017a; Armijo & Rhodes, 2017; Bajari, 2001; Bildfell, 2018; Bowen et al., 2007a; Chan et al., 2014; Cheung et al., 2006; Chotibhongs & Arditi, 2012; Collier et al., 2015b;

		Collins et al., 2009; Damoah et al., 2018; Doh et al., 2003b; Dorée, 2004; Fazekas & Tóth, 2018; Frank & Martinez-Vazquez, 2014; Golden & Picci, 2005a; Gordon & Miyake, 2001; Hall & Lobina, 2004, 2007; Hardon & Heinrich, 2011; Husted, 1999; Jiménez et al., 2017; Krishnan, 2009; Lewis-Faupel et al., 2016; Locatelli et al., 2017; Mahmud, 2007; Makoni, 2014; Martin et al., 2007; May et al., 2001; Munavar Ali, 2017; Osei-Tutu et al., 2010a; Sachs et al., 2007; Signor et al., 2016a; Sultana et al., 2013; Thillairajan & Menon, 2014; Vee & Skitmore, 2003; Wu & Liu, 2013a; Zarkada-Fraser & Skitmore, 2000; Zou, 2006)
	Society	(Ades & di Tella, 1997; Aghion et al., 2016; Aidt, 2003; Alam & Ahmad, 2013; Ameyaw et al., 2017a; Anderson & Tverdova, 2003; Assiotis & Sylwester, 2014; Bildfell, 2018; Boubaker & Nguyen, 2014; Bremer & Kok, 2000; Charron et al., 2017; Choi, 2009; Damoah et al., 2018; Della Porta & Vannucci, 2016; Edwards et al., 2014; Fazekas & Tóth, 2018; Frank & Martinez-Vazquez, 2014; Godinez & Liu, 2015; Graycar & Prenzler, 2013; Huther & Shah, 2000; Jankauskas & Šeputienė, 2007; Jensen & Smith, 2000; Jiménez et al., 2017; Khlif et al., 2016; Knox, 2009; Laurance, 2004; Lee & Weng, 2013; Li & Mayraz, 2017; Locatelli et al., 2017; Owusu-Ababio & Acheampong, 2018; Piquero & Albanese, 2011; Porter & Graycar, 2016; Putnam, 2001; Rădulescu et al., 2016; Rafi et al., 2012; Sampson et al., 1999; Sohail & Cavill, 2008; Sumkoski, 2016; Tabish & Jha, 2012b; UNDOC, 2010; Unruh & Shalaby, 2012; Wagner et al., 2009; Zimring & Johnson, 2007)
Institutional elements		
	Regulation	(Abbott & Snidal, 2002; Abramowitz, 1998; Ameyaw et al., 2017b; Berg, 2000; Bildfell, 2018; Bird et al., 2007; Bukovansky, 2006; Coffé & Geys, 2005; Damoah et al., 2018; Donohoe, 2011; Edwards et al., 2014; Estache et al., 2009; Feld & Frey, 2007; Gasmi et al., 2009; Getz, 2006; Gilardi, 2002; Hansen, 2011; Huther & Shah, 2000; IPMA, 2015; IWA, 2010; Kaniki & Gwatidzo, 2012; Kenny, 2009a, 2009b; Kivyiro & Arminen, 2013; Kuperan & Sutinen, 1999;

		Laurance, 2004; Le et al., 2014a; Lengwiler & Wolfstetter, 2006a; Locatelli et al., 2017; Maggetti, 2009; Makoni, 2014; Mensah et al., 2003a; Miranda Sarmento & Renneboog, 2017; Mitnick, 1980; Munavar Ali, 2017; Nordin et al., 2011; Osei-Tutu et al., 2010a; Pressman, 1997; Rafi et al., 2012; Rodrik et al., 2004; Rose-Ackerman, 2002; Saenz & Brown, 2018; Seim & Søreide, 2009; Shapiro et al., 2006; Signor et al., 2016a; Sohail & Cavill, 2008; Sovacool, 2017; Stansbury, 2009; Sumkoski, 2016; Transparency International, 2011; Tun et al., 2012; USSC (US Sentencing Commission), 2015; Vannucci, 2009; Vee & Skitmore, 2003; Weaver, 2001; Wei, 2000; Wrage & Wrage, 2005; Wu, 2009; Yan & Oum, 2014; Zábojník, 2002)
	Normative	(Alm et al., 1999; Ameyaw et al., 2017a; Amponsah, 2010; Anderson & Tverdova, 2003; Armijo & Rhodes, 2017; Beets, 2005; Bob-Milliar, 2012; Bowen et al., 2007b; Brown & Loosemore, 2015; Choi, 2009; Christensen & Lægreid, 2005; Colledge, 1999; Damoah & Akwei, 2017; Damoah et al., 2018; Estache & Martimort, 1999; Felix & Hines, 2013; Husted, 1999; Kivyiro & Arminen, 2013; Knox, 2009; Li & Mayraz, 2017; Maingot, 1994; Makoni, 2014; Munavar Ali, 2017; Owusu-Ababio & Acheampong, 2018; Pinto, 2013, 2014; Pinto & Patanakul, 2015; Posner, 2000; Robertson & Watson, 2004; Saenz & Brown, 2018; Signor et al., 2016a; Sumkoski, 2016; The Hofstede Insights, 2019; Wagner et al., 2009; Wibowo & Wilhelm Alfen, 2014; Zarkada-Fraser & Skitmore, 2000; Zou, 2006)
	Cognitive	(Asmar et al., 2013; Brass et al., 1998; Damoah et al., 2018; Kent & Becerik-Gerber, 2010; Munavar Ali, 2017; Vee & Skitmore, 2003)
Geographic location (the focus of the study)		
	East Asia and pacific	(Brown & Loosemore, 2015; Chan et al., 2014; Hartley, 2009; Jones, 2006; Li & Mayraz, 2017; Ling et al., 2014; Macdonald, 1997; May et al., 2001; Phillips, 2006; Sha, 2004; Vee & Skitmore, 2003; Wang et al., 2000b; Zarkada-Fraser & Skitmore, 2000)

	Europe and central Asia	(Alexeeva et al., 2011; Armeanu et al., 2018a; Auditors, 2013; Becker et al., 2013; Bologna & Del Nord, 2000; Bremer & Kok, 2000; Castro et al., 2014; Charron et al., 2017; Choi, 2009; CIOB, 2006; Coopers, 2013; Day, 2012; Doig & McIvor, 2003; Donohoe, 2011; Dorée, 2004; Fazekas & Tóth, 2018; Golden & Picci, 2005a; Golden & Picci, 2005b; Jiménez et al., 2017; Kanin, 2003; Ke et al., 2011; Kenny, 2009b; Kersan-Škabić, 2013; Lai et al., 2004; Miranda Sarmento & Renneboog, 2017; Priemus, 2004; Rădulescu et al., 2016; Sachs et al., 2007; Schamis, 2002; Shan et al., 2015; Sohail & Cavill, 2008; Vazhenin & Gerasimov, 2011; Wang et al., 2000a; Winch, 2000; Wu & Liu, 2013a; Xu et al., 2010; Zhang et al., 2017; Zhu, 2017; Zou, 2006)
	Latin America and Caribbean	(Armijo & Rhodes, 2017; Auriol et al., 2016; Estache et al., 2009; Martimort & Straub, 2009; Regis et al., 2017; Saenz & Brown, 2018; Schamis, 2002; Signor et al., 2016a; Takano, 2017)
	Middle east and north Africa	(Fallahnejad, 2013)
	North America	(Abramowitz, 1998; Bajari, 2001; Chotibhongs & Arditi, 2012; Doran, 2004; Felix & Hines, 2013; Gardiner, 1970; Globerman & Shapiro, 2003; Meier & Holbrook, 1992; Porter & Graycar, 2016; Pressman, 1997; The Economist, 2002; USSC (US Sentencing Commission), 2015; Yan & Oum, 2014)
	South Asia	(Abdulai, 2009; Alam & Ahmad, 2013; Arnold & Buchanan, 2008; Davis, 2004; Dutta, 2005; Fox & Treakle, 2003; Gulati & Rao, 2006; IWA, 2010; Jones, 2006; Knox, 2009; Mahmud, 2007; Olken, 2007; Rafi et al., 2012; Seligson, 2006; Sumkoski, 2016; Tabish & Jha, 2011, 2012b; Thillairajan & Menon, 2014; Unruh & Shalaby, 2012; Wei, 2000; Wibowo & Wilhelm Alfen, 2014; Yeoh et al., 2007)
	Sub-Saharan Africa	(Abdulai, 2009; Abdullahi & Usman, 2013; Adinkrah, 2017; Africa Research Bulletin, 2008; Alexeeva et al., 2008; Alutu,

		2007; Amadi & Higham, 2016; Ameyaw et al., 2017a; Ameyaw et al., 2017b; Anyanwu, 2006; Ateloye et al., 2016; Babalola & Odunowo, 2010; Bowen et al., 2007a; Bowen et al., 2012a; Bowen et al., 2007b; CDD Ghana, 2000; Clark, 2003a, 2003b; Damoah et al., 2018; Demuijnck & Ngnodjom, 2011; Edomah et al., 2016; Edwards et al., 2014; Effah & Chan, 2015; Ibimilua, 2011; Ibrahim et al., 2006; ILO, 2005; Kaliba et al., 2009; Kaniki & Gwatidzo, 2012; Kivyiro & Arminen, 2013; Makoni, 2014; Mawenya, 2008; Mensah et al., 2003a, 2003b; Mlambo, 2005; Nwankwo & Richards, 2001; Osei-Tutu et al., 2010a; Osei-Tutu et al., 2010b; Otairu et al., 2013; Otairu et al., 2014; Owusu-Ababio & Acheampong, 2018; Oyewunmi & Olujobi, 2016; Sonuga et al., 2002; Utzinger et al., 2005; World Bank, 2009b)
Methodology of the study	Types (emerging from the papers)	(Aghion et al., 2016; Ahsan & Gunawan, 2010; Alam & Ahmad, 2013; Amadi & Higham, 2016; Ameyaw & Chan, 2015; Ameyaw et al., 2017a; Armeanu et al., 2018a; Ateloye et al., 2016; Atkinson, 1999; Banerjee et al., 2006; Benitez et al., 2012; Bildfell, 2018; Castro et al., 2014; Chan et al., 2014; Chang & Chu, 2006; Collier et al., 2015b; Damoah et al., 2018; Edomah et al., 2016; Estache et al., 2009; Fazekas & Tóth, 2018; Felix & Hines, 2013; Flyvbjerg & Molloy, 2011; Galilea & Medda, 2010; Gillanders, 2014; Glaeser & Molloy, 2006; Golden & Picci, 2005b; Grace et al., 2016; Graff, 2013; Hall & Jones, 1999; Jiménez et al., 2017; Kaniki & Gwatidzo, 2012; Ke et al., 2011; Kenny, 2009a; Kenny & Musatova, 2010; Kersan-Škabić, 2013; Khlif et al., 2016; Kivyiro & Arminen, 2013; Law & Bany-Ariffin, 2008; Li & Mayraz, 2017; Lin & Zhang, 2009; Locatelli et al., 2017; Ma & Xu, 2009; Martimort & Straub, 2009; Miranda Sarmento & Renneboog, 2017; Mukabeta Maumbe et al., 2008; Munavar Ali, 2017; Nordin et al., 2011; Osei-Tutu et al., 2010a; Otairu et al., 2013; Owusu-Ababio & Acheampong, 2018; Porter & Graycar, 2016; Rădulescu et al., 2016; Rafi et al., 2012; Regis et al., 2017; Rodrik et al., 2004; Saenz & Brown, 2018; Schneider et al., 2010; Scott et al., 2011; Signor et al., 2016a; Signor et al., 2016b; Sohail &

		Cavill, 2008; Sovacool, 2017; Sumkoski, 2016; Takano, 2017; Vazhenin & Gerasimov, 2011; Wibowo & Wilhelm Alfen, 2014; Wu & Liu, 2013b; Wyatt, 2003; Xu et al., 2010; Yan & Oum, 2014)
Types of corruption		
	Bid rigging	(Ameyaw et al., 2017b; Bajari, 2001; Ballesteros-Pérez et al., 2015; Chotibhongs & Arditi, 2012; Dorée, 2004; Le et al., 2014b; Lockard & Tullock, 2001; Priemus, 2004; Regis et al., 2017; USSC (US Sentencing Commission), 2015)
	Bribery	(Ades & Tella, 1996; Africa Research Bulletin, 2008; Aidt, 2003; Alam & Ahmad, 2013; Alam, 1989; Ameer, 2015; Ameyaw et al., 2017a; Amundsen, 2000; Armeanu et al., 2018b; Beets, 2005; Benitez et al., 2012; Bildfell, 2018; Blackburn et al., 2004a; Boycko et al., 1996; Bray, 2004; Brinkerhoff & Goldsmith, 2002; CIOB, 2006; Collier et al., 2015b; Collins et al., 2009; Damoah et al., 2018; Doh et al., 2003b; Fazekas & Tóth, 2018; Globerman & Shapiro, 2003; Goel & Rich, 1989; Gordon & Miyake, 2001; Guasch et al., 2005; Hamel, 2007; Hardon & Heinrich, 2011; ISO 37001, 2016; Kaniki & Gwatidzo, 2012; Ke et al., 2011; Kenny, 2009b; Leff, 1964; Lengwiler & Wolfstetter, 2006a; Lin & Zhang, 2009; Lui, 1985a; Lui, 1985b; Ma & Xu, 2009; Mahmud, 2007; Martimort & Straub, 2009; Mawenya, 2008; Meier & Holbrook, 1992; Mensah et al., 2003a; Nordin et al., 2011; Osei-Tutu et al., 2010b; Otairu et al., 2013; Rafi et al., 2012; Rashid, 1981; Sachs et al., 2007; Saenz & Brown, 2018; Shah, 2006; Shleifer & Vishny, 1994; Sohail & Cavill, 2008; Tanzi, 1994; Tanzi, 1998; The Economist, 2002; UNDOC, 2010; United Nations Global Compact, 2012; Unruh & Shalaby, 2012; Wang et al., 2000a; Wells, 2013)
	Collusion	(Ameyaw et al., 2017a; Bajari, 2001; Bildfell, 2018; Bowen et al., 2012a; Chotibhongs & Arditi, 2012; Collier et al., 2015b; Damoah et al., 2018; Dorée, 2004; Klitgaard, 2012; Lai et al., 2004; Le et al., 2014b; Messick, 2011; OECD, 2009b; Regis et al., 2017; Rose-Ackerman & Truex, 2012; Zarkada-Fraser & Skitmore, 2000)

	Embezzlement	(Ameyaw et al., 2017a; Damoah et al., 2018; Fazekas & Tóth, 2018; Hartley, 2009; Lin & Zhang, 2009; World Bank, 2009a; World Bank et al., 2007)
	Facilitation of payments and fraud	(Alutu, 2007; Damoah et al., 2018; Greame Hamilton, 2014; Osei-Tutu et al., 2010a; Sohail & Cavill, 2008; Tabish & Jha, 2011; UN, 2006; Vee & Skitmore, 2003)
	Fronting	(Ameyaw et al., 2017a; Bowen et al., 2007a; Jong et al., 2009; Le et al., 2014b)
	Gerrymandering	(Munavar Ali, 2017)
	Rent seeking	(Acemoglu et al., 2003; Acemoglu & Verdier, 2000; Aidt, 2016; Auriol et al., 2016; Bahmani-Oskooee & Nasir, 2002; Banerjee, 1997; Bardhan, 1997; Brown & Loosemore, 2015; Buchanan, 1980; Congleton, 2015; Gradstein, 1993; Hauk & Saez-Marti, 2002; Hodges & Dellacha, 2007; Iossa & Martimort, 2013; Isaac Ehrlich & Francis T. Lui, 1999; Kenny, 2009a; Krueger, 1974; Laffont & Martimort, 1994; Leung et al., 2006; Linster, 1993, 1994; Ma & Xu, 2009; Maskin & Tirole, 2008; Mensah et al., 2003a; Miraftab, 2004; Mueller, 2003; Osei-Tutu et al., 2010b; Ostrom et al., 1961; Posner, 1975; PPIAF, 2014; Rafi et al., 2012; Rose-Ackerman, 1996a; Schamis, 2002; Takano, 2017; Tang et al., 2003; Tanzi, 1998; Tullock, 1967, 1980, 2001; Vee & Skitmore, 2003; Wu & Liu, 2013b)
	Theft	(ILO, 2005; Kenny, 2009b)

APPENDIX B. ASCE PREPRINT PERMISSION

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VITA

SeyedAli Ghahari holds a B.Sc. in railway engineering (concentration in railway infrastructure systems) from Iran University of Science and Technology, Tehran, Iran (2007 – 2011), and three M.S. degrees in Construction Engineering and Management from Tehran Polytechnique (Amirkabir University of Technology), Tehran, Iran (2011-2013), Construction Materials from Purdue University, Indiana, U.S. (2015-2016), and Applied Economics from the alma matter (2018-2020). Ali started his Ph.D. program in Civil Engineering (concentration in Infrastructure Transportation Systems) and completed his Ph.D. in 2021 with two internships at Illinois Department of Transportation as an Engineering Intern, and at the NSF CONVERGE COVID-19 workgroup in NY as a Data Science intern. Ali's research interests are diverse and span multiple knowledge domains. He uses niche multivariate statistical analysis, econometrics, applied economics, finance, machine learning techniques, and neural network time series analysis, systems engineering, operations research, etc. to detect and monitor inefficiencies and corruption at the global and at the agency levels.

Ali has published more than 30 peer-reviewed publications on different aspects of civil engineering in well-reputed journals including, the Journal of Infrastructure Systems, Journal of Transportation Engineering, Journal of Advanced Transportation, Journal of Infrastructure Asset Management, and Journal of Cleaner Production. During his doctoral program, Ali has been the recipient of numerous competitive awards, scholarships, and a fellowship including Essam and Wendy Radwan Graduate Fellowship, ITE Edward J. Cox for Excellence in Infrastructure Transportation Systems Scholarship, ASCE Jack E. Leisch Fellowship, Magoon Scholarship for Excellence in Teaching, Civil Engineering Graduate School Outstanding Service Scholarship, MIT Scholarship to attend "Transportation Networks and Smart Mobility" program at MIT, NSF Emerging Educator award to investigate "Making Academic Change Happen" strategies in academia, and Bilsland doctoral dissertation fellowship based on his outstanding academic and research accomplishments.

Ali has served as a teaching assistant and advisor in the Engineering Projects in Community Service (EPICS) for more than four years where his teams received multiple grants from the Office of Provost including India Mobile Science Labs Development, Gary Indiana Green House Restoration, Small-House Building Project for Native Americans, Gary Indiana Urban Farming Project, Wabash Special

Needs Center Interactive Tools for Disabled Individuals, LAKOTA Green House Project for Native Americans, Indiana Riley Hospital Interactive Wall Project, City of West Lafayette Smart City Project, Camp Riley Interactive Tools for Disabled Kids, and West Lafayette Park Erosion Control Project.

Along with his academic achievements, Ali has been actively pursuing professional development skills. Ali has been a mentor to graduate students at the Engineering Academic Career Club (EACC) in 2020-2021, where has organized and coordinated EACC's mentoring circles in this role. Ali has helped the President of this club in holding numerous workshops on teaching statement, research statement, diversity and inclusion statement, etc. for preparing graduate students for academic jobs. Ali has mentored the next generation of students through the K-12 outreach events with Duke Energy Academy – Purdue Regional Clean Energy Innovation Forum (in Association with Argonne National Laboratory) where he mentored the students, who were enrolled in the Energy Academy program, to inspire talented high school students and teachers in energy sciences and engineering. He also has been serving as a judge at Science Olympiad Regional Competition in 2016 where he helped assess and rank individual participants. Ali was the chair of the 2nd Annual Conference on Next-Generation Transport Systems (NGTS 2020) in 2020 where he helped every aspect of the conference organization, including logistics, marketing, and registration. He also was a volunteer member for Purdue COVID-19 medical supplies response team in 2020 where he was part of the university-wide initiative to make and donate gowns, hats, and booties for healthcare workers. Ali also co-chaired the 13th Annual Inter-University Symposium on Infrastructure Management (AISIM) in 2017.

Ali is a member of the ITE Purdue Student Chapter, where he has served as Secretary. He has served as a Senator for Purdue's Graduate Student Government and has served as President of Purdue's Civil Engineering Graduate Student Advisory Council (CEGSAC) where he worked closely with the CE graduate students in 6 committees (Outreach, Health & Wellness, Advocacy, Sports, Professional Development, and Cultural Committees) and held more than 50 events for the department in 2017-2018. He is a member of Habitat for Humanity and volunteered at the World Bank Group Youth Summit in 2017. Ali is currently a member of the TRB standing committee on Tunnels and Underground Structures s (AFF60) and the secretary of ASCE T&DI's economics and finance committee where he prepares and sends newsletters to the Economics & Finance committee, provides the agenda for the annual meetings, and broadcasts the news and events for the organization.

PUBLICATIONS

Selected journal articles are listed in the following.

S.A. Ghahari, B.N.T. Alabi, C. Queiroz, S. Labi, S. McNeil, "Corruption Propensity and Mitigation at Different Phases of Infrastructure Development", Submitted to the Journal of International Project Management, 2021.

S.A. Ghahari, C. Queiroz, S. Labi, S. McNeil, "Cluster Analysis of Global Corruption Using Principal Component Analysis and Machine Learning Methods", Submitted to the Journal of Computational Economics, 2021.

S.A. Ghahari, C. Queiroz, S. Labi, S. McNeil, "Cluster Forecasting of Corruption Using Nonlinear Autoregressive with Exogenous Variables (NARX) – An Artificial Neural Network Time Series Analysis", Submitted to the Journal of Sustainability, 2021.

S.A. Ghahari, C. Queiroz, S. Labi, S. McNeil, "Impact of E-Governance on National Corruption Indexes: New Evidence Using Panel Vector Auto Regression Analysis", Submitted to the Journal of Economic Analysis and Policy, 2021.

S.A. Ghahari, S. Chen, S. Labi, "A Nonparametric Efficiency Methodology for Comparative Assessment of Infrastructure Agency Performance", Preprint, 2021.

A. Alsalman, L. Assi, S. Ghotbi, **S.A. Ghahari,** A. Shubbar, "Users, Planners, and Governments Perspectives: A Public Survey on Autonomous Vehicles Future Advancements", Journal of Transportation Engineering, 2021.

J. Rostami, O. Khandel, R. Sedighardekani, A.R. Sahneh, **S.A. Ghahari,** "Enhanced Workability, Durability, and Thermal Properties of Cement-based Composites with Aerogel and Paraffin Coated Recycled Aggregates", Journal of Cleaner Production, 2021

E. Ghafari, **S.A. Ghahari,** D. Feys, K. Khayat, A. Baig, R. Ferron, "Admixture Compatibility with Natural Supplementary Cementitious Materials", Journal of Cement and Concrete Composites, 2020.

S.A. Ghahari, L.N. Assi, A. Alsalman, K.E. Alyamac, "Fracture Properties Evaluation of Cellulose Nanocrystals Cement Paste", Journal of Materials, 2020.

S.A. Ghahari, N. Alabi, M. Alinizzi, S. Alqadhi, S. Chen, S. Labi, "Examining Relationship between Infrastructure Investment and Performance Using State-Level Data", Journal of Infrastructure Systems, 2019.

S.A. Ghahari, P. Ha, S. Chen, M. Alinizzi, B. Agbelie, S. Labi, "Inputs for Bridge Painting Decision Support – A Synthesis", Journal of Infrastructure Asset Management, 2018.

S.A. Ghahari, M. Volovski, S. Alqadhi, M. Alinizzi, "Estimation of Annual Repair Expenditure for Interstate Highway Bridges," Journal of Infrastructure Asset Management, 2018.

S. Alqadhi. **S.A. Ghahari**, W. Woldemariam, M. Volovski, S. Chen, "Costs and Benefits of Highway Pavement Resurfacing: Interstate 456 Case Study", Journal of Infrastructure Asset Management, 2018.

Z. Tang, S. Chen, J. Cheng, **S.A. Ghahari**, S. Labi, "Highway Design and Safety Consequences: A Case Study of Interstate Highway Vertical Grades", Journal of Advanced Transportation, 2018.

S.A. Ghahari, E. Ghafari, L. Assi, "Pore Structure of Cementitious Material Enhanced by Graphitic Nanomaterial: A Critical Review", Journal of Frontiers in Structural and Civil Engineering, 2017.

S.A. Ghahari, A. Mohammadi, A.A. Ramezanianpour, "Performance Assessment of Natural Pozzolan Roller Compacted Concrete Pavements", Vol. 7. Journal of Case Studies in Construction Materials, 2017.

L. Assi, **S.A. Ghahari**, E. Deaver, D. Leaphart, P. Ziehl, "Improvement of the Early and Final Compressive Strength of Fly Ash-Based Geopolymer Concrete at Ambient Conditions", Vol. 123. Journal of Construction and Building Materials, 2016.

E.Ghafari, **S.A. Ghahari**, H. Costa, E. Julio, A. Portugal, L. Duraes, "Effect of Supplementary Cementitious Materials on Autogenous Shrinkage of Ultra-High Performance Concrete", Vol. 127. Journal of Construction and Building Materials, 2017.

S.A. Ghahari, A.M. Ramezanianpour, A.A. Ramezanianpour, M. Esmaeili, "An Accelerated Test Method of Simultaneous Carbonation and Chloride Ion Ingress: Durability of Silica Fume Concrete in Severe Environments", Journal of Advances in Materials Science and Engineering, Vol. 2016. 2016. ISI - ISSN: 1650979 – Hindawi Publication.

S.A. Ghahari, A.A. Ramezanianpour, M. Esmaeili, S. Mohammadzade, A. Khazaie, "Sustainability in Mass Production of Concrete Sleepers Using Fiber Reinforced Concept Based on a Value Engineering Survey", Under review at the Journal of Construction and Building Materials, 2016. ISSN: 1943-555

A.A. Ramezanianpour**, S.A. Ghahari**, M. Esmaeili, "Effect of Combined Carbonation and Chloride ion Ingress by an Accelerated Test Method on Microscopic and Mechanical Properties of Concrete", Journal of Construction and Building Materials, 2014. ISI - ISSN: 0950-0618- Elsevier Publication.

A.M. Ramezanianpour, Kh. Esmaeili, **S.A. Ghahari**, A.A. Ramezanianpour, "Effect of Steam Curing on Durability of Self-Consolidating Concrete", Journal of Construction and Building Materials, 2014. ISI - Elsevier Publication.

A.A. Ramezanianpour, M. Esmaeili, **S.A. Ghahari**, M.H. Najafi, "Laboratory Study on the Effect of Polypropylene Fiber on Durability, and Physical and Mechanical Characteristic of Concrete for Application in Sleepers", Journal of Construction and Building Materials, 2013. ISI - ISSN: 0950-0618- Elsevier Publication.

M. Esamaeili, **S.A. Ghahari**, "Laboratory Study on the Effect of Poly-Propylene Fiber on Mechanical Properties of Concrete for Application in Sleeper ", OmraanModarres Journal, 2012.

Selected International Conference Papers and Posters:

S.A. Ghahari, C. Queiroz, M. Alinizzi, S. Ghotbi, S. Labi, "Anti-Corruption Activities in Infrastructure Project Delivery by Implementing Technology", International Conference on Transportation & Development (ICDT). PA, USA, 2019. *(Poster Session)*

S.A. Ghahari, L. Assi, K. Carter, S. Ghotbi, "Hydrogen Fueling System Challenges and Opportunities for the Fully Automated Vehicles", International Conference on Transportation & Development (ICDT). VA, USA, 2019.

B. Fulk, **S.A. Ghahari,** K. Kang, M. Hastak, "Construction Engineering Students Cognitive Apprenticeship Approach", 126th Annual Conference of American Society for Engineering Education. FL, USA, 2019.

S.A. Ghahari, S. Ghotbi, S. Labi, "The Future of Electric Automated Fleets and Contribution to Sustainable Development", 1st Annual Conference on Next-Generation Transport Systems (NGTS 2019). Indiana, USA, 2019.

S.A. Ghahari, M. Alinizzi, S. Ghotbi, S. Labi, "Feasibility of Using CAV Monitoring Capabilities to Combat Corruption Related to Infrastructure Project Delivery", 1st Annual Conference on Next-Generation Transport Systems (NGTS 2019). Indiana, USA, 2019. *(Poster Session)*

S.A. Ghahari, B. Alabi, H. Kemaw, S. Labi, "Reducing Pavement Project Delivery Inefficiency, Irregularity, and Cost Using Lean Construction, Information Modeling, and Monitoring Systems", International Airfield and Highway Pavements Conference. Illinois, USA, 2019. *(Poster Session)*

S. Chen, **S.A. Ghahari**, S. Labi, "Assessing Performance Outcomes and Ranking of Jurisdictions – A Nonparametric Efficiency Approach for Asset Management", Transportation Research Board (TRB 2019), TRB 98th Annual Meeting, Washington D.C., USA, 2019.

S.A. Ghahari, N. Alabi, S. Chen, B. Agbelie, S. Labi, "The Bridge Investment-Performance Nexus at an Aggregate Level–Accounting for Situational and Measurement Biases", Transportation Research Board (TRB 2019), TRB 98th Annual Meeting, Washington D.C., USA, 2019.

S.A. Ghahari, S. Labi, N. Naderpajouh, S. Ghotbi, "Is Corruption Influenced by Human Development Index and Transparency? A Global Spatial Assessment Using GIS", 2018 GIS Conference, Indiana, USA. *(Poster Session)*

S. Ghotbi, **S.A. Ghahari**, "A Curriculum Design on Electronic Devices Design Laboratory", 2018 IEEE Frontiers in Education Conference (FIE), California, USA, 2018.

S. Labi, **S.A. Ghahari**, A. Marfo, Y.J. Ha, "Evaluation of Automated Transit Systems -- Assessment Criteria, Methodologies, and Case Studies", 16th International Conference on Automated People Movers and Automated Transit Systems (APM-ATS 2018). Florida, USA.

S.A. Ghahari, S. Labi, S. Ghotbi, M. Alinizzi, "Leveraging Advanced Technologies for Fighting Corruption in Infrastructure Project Delivery", International Conference on Transportation & Development (ICDT). PA, USA, 2018. *(Poster Session)*

S.A. Ghahari, W. Woldemariam, Y. Qiao, S.Labi, "Assessing the Relative Performance of Highway Bridge Decks Across States – A Preliminary Aggregate Analysis" TRB Best Presentations from the Annual Interuniversity Symposium on Infrastructure Management, Transportation Research Board (TRB 2018), TRB 97th Annual Meeting, Washington D.C., USA, 2018.

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