PhD Dissertation

EMPIRICAL ANALYSIS OF TRANSPORT DEMAND AND EFFICIENCY OF DIFFERENT TRANSPORT MODES IN PAKISTAN

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2021

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I, Muhammad Zamir Khan, hereby state that my Ph.D thesis titled **"Empirical Analysis of Transport Demand and Efficiency of Different Transport Modes in Pakistan"** is my own work and has not been submitted previously by me for taking any degree from this University (Quaid-i-Azam University, Islamabad) or anywhere else in the country/world.

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Muhammad Zamir Khan

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No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the School of Economics, Quaid-i-Azam University, in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the field of Economics, School of Economics, Quaid-i-Azam University, Islamabad.

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Muhammad Zamir Khan

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SYMBOLS AND VARIABLES

PKM_t	passenger-kilometers
TKM_t	ton-kilometers
FP_t	fuel-price (high-speed diesel)
FPI_t	fuel-price index (high-speed diesel and gasoline)
IPI_t	industrial production index
GDP_t	gross domestic product
FR_t	average freight-rate
TR_t	international trade (as a percentage of GDP)
$Route_t$	route density (ratio of route-km to country's total area)
POP_t	total population
RD_t	road density (ratio of road length to country's total area
UR_t	urban population

USE OF ABBREVIATIONS

KM	Kilometers
TOE	Tons of Oil Equivalent
ADF	Augmented Dickey-Fuller Test
ARDL	Autoregressive distributed lag model
CUSUM	Cumulative sum
CUSUMSQ	Cumulative sum of squares
PP	Phillips-Perron Test
IEA	International Energy Agency
Rs.	Rupees (Currency of Pakistan)
LPI	Logistic Performance Index
OLS	Ordinary Least Square
OECD	Organization for Economic Cooperation and Development
VAR	Vector autoregressive
PR	Pakistan Railway
DEA	Data envelopment analysis
DMU	Decision making unit
GMM	Generalized method of moments
GDP	Gross domestic product
LOS	Level of service
IRF	Impulse response function
2SLS	Two stage least square
3SLS	Three stage least squares
WDI	Word development indicators
VMT	Vehicle miles travelled
EU	European Union
US	United States
UK	United Kingdom

ABSTRACT

It is well known that empirical analysis of transport demand is important in terms of making effective decisions regarding transport demand management and planning. Therefore, this thesis uses two objectives, in which the overall objective is to increase the understanding of how aggregate freight and passenger (travel) demand for rail and road in Pakistan is determined by various factors. Therefore, first objective investigates the demand for rail (freight and passenger) transport in Pakistan within Johansen's multivariate co-integration framework using annual time series data over 1978-2018. Similarly, second part analyzes the determinants of the demand for both road freight and passenger demand. For that, annual time series data is used from 1980 to 2016, and ARDL bounds test of co-integration is employed because variables have different order of integration (I(0) and I(1)). The second objective estimates the (technical) efficiency of rail, road, and rail vs. road transport in Pakistan with a non-parametric approach of data envelopment analysis (DEA), and efficiency patterns are traced over time from 1980 to 2018.

The empirical results show that rail freight (passenger) demand is relatively more inelastic in the long-run, offering important policy implications for Pakistan-railways to manage its operations through changes in freight-rate and fare. Similarly, the long-run passenger demand for rail and road is positively related to real per-capita GDP, which means that the demand for road and rail travel can be treated as the normal goods. Moreover, income elasticities of travel demand and output elasticities of freight demand across both rail and road are positive and relatively more elastic in the long-run, which implies that a significant increase in transport demand is expected in future as economic growth in Pakistan increases. Cross-price elasticities of rail and road transport demand are found positive and significant, indicating that both road and rail transport are substitutes. The demand for road transport is inelastic to its own-price, particularly passenger demand, which means that the role of market instruments is relatively less effective in terms of controlling the future growth of road transport demand. Although it is found that population and the passenger demand for rail and road are positively related in long-run, the effect of (urban) population on road travel demand is far more dominant than the impact of population on rail travel demand. Similarly, rail (road) densities are positively related to passenger demand for respective transport modes in the long-run. However, rail passenger demand is far more sensitive to rail density than road travel demand to road-density. In the short-run, a comparison of error-correction terms of passenger demand for rail and road indicate that road passenger demand adjusts relatively quickly than rail travel demand to restore

the long-run equilibrium, while error in rail freight demand is corrected at a relatively faster-rate than road freight demand to re-establish the long-run relationship. Finally, the results based on efficiency scores indicate that, in general, the technical efficiency of rail transport has increased over time, as Pakistan-railway has gradually shifted from inefficient coal-traction to a more efficient diesel-traction. A similar pattern is observed for road transport due to a relatively faster growth in its outputs than inputs. However, efficiency of road transport is higher than rail transport when relative efficiency comparisons are made.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Transportation industry plays a very important role in country's economic growth and development. At macro level, it makes an important contribution of 6% to 12% of gross domestic product (GDP) in many developed economies, and logistics costs can represent a share of 6% to 25% of the gross domestic product (GDP). Moreover, for an advance country, value of all transport assets (vehicles, infrastructure, etc.) can make up to the half of its GDP. On the other hand, the importance of transport at micro level can be assessed through its links to consumer, producer, and production costs of various subsectors. On average, the share of transport in household spending is around 10% to 12%, and it also represents 4% of the costs of producing each unit of manufacturing output (Rodrigue, 2016).

The transport sector stimulates economic growth through various direct and indirect channels. For instance, an efficient transport system, through improvements in quantity and quality of transport infrastructure, not only reduces transport and production costs via gains in delivery time and improvements in economies of scale in production process but also integrates markets, boosts trade, and creates economic opportunities and communication links. Moreover, it also creates employment opportunities, promotes foreign investment and tourism. There is an ample empirical evidence on the positive contribution of transport infrastructure on economic growth (see, for example, Aschauer, 1989; Farhadi, 2015; Goetz, 2011; Mohmand et al., 2017; Munnell, 1990; Saidi et al., 2018; Vlahinić Lenz et al., 2018, and many others).

Although transport infrastructure is commonly treated in its physical form like roads, railroad tracks, pipelines, ports, bridges, etc., its real output can be defined in terms of services it renders for efficient and smooth facilitation of transport demand (movements of goods and people). Therefore, effectiveness of transport infrastructure not only depends on transport infrastructural investments but also on the quality of service offered (Looney, 1998). Transport activity or demand is further classified into two components such as freight and passenger transport. Freight transport is related to the movements of all logistic components (raw materials, intermediate and finished goods, etc.) from their origins to final destinations using a specific transport mode or a combination (road, rail, air, etc.) in a cost-efficient manner.

Similarly, passenger transport is usually acquired by the people for a number of reasons such as work or job, education (school, college, university), shopping, tourism, etc. Several indicators or metrices are used to represent or measure transport demand. They can be defined as the total number of passengers carried (passenger transport) or total tons lifted (freight transport), total passenger-kilometers (PKM, it accounts for both passengers and distance travelled simultaneously) or ton-kilometers (TKM, it covers both weight and distance of freight), vehicle-kilometers or total vehicles, distance-travelled (in miles or km), and revenue generated per-passenger-kilometer or per-ton-kilometer, which traces both economic and financial effect of a particular transport activity (European Commission, 2010).

Since a number of transport modes (such as road, rail, air, waterways, etc.) are generally used to facilitate the demand of freight and/or passenger transport, the relative importance of each transport mode (in terms of its share in total transport) may vary across countries, and further depends on various factors such as individuals income or purchasing power, degree of competition among transport modes, whether or not national government offers subsidies for specific modes of transport (such as railways, metro or buses), the amount of transport infrastructure available for each mode, trips distances and country-size (Profillidis, 2016). Cross-country comparisons of a modal-split of each transport mode (road, rail, air, inland waterways and pipelines, etc.) reveals some interesting facts. For passenger transport (measured in terms of passenger-kilometers (Billion)), road sector (passenger cars) has a dominant role for EU-28 (average share of 72.9%), Japan (59.6%) in 2014, US (78.9%) in 2015, while rail transport is also important for these countries (6.8% share of rail in EU-28 countries and 29% for Japan including bus, metro, etc.) except for US (0.5%), because railways in US are not subsidized. On the other hand, rail and road, along with air transport mode, dominate the passenger transport in other countries due to their larger size such as China (38% share of rail, 35% of road, 24.2% share of air) and Russia (34.5% share of air, 19.3% for road, and 18.4% for railways). Similarly, road sector also plays a leading role for handling freight transport in many European countries with an average share of 49% in EU-28 countries, US (44%), Japan (50.7% in 2014)) and China (32.4%), while the share of sea transport is also very important for many EU-28 countries (31.6% average share), Japan (44.2%), and China (32.4%), because they are surrounded by sea (EU Statistical Pocketbook, 2017). According to some estimates of transport sector in developing countries, particularly in South Asia (such as Bangladesh, India, Pakistan and Sri-Lanka), the road-based mode has the largest share in domestic freight and passenger transport, followed by rail, waterways or air, respectively (see, for example, data on share of transport modes used by Ahmed and Fujiwara, 2010; Asian Development Bank, 2010, 2015; Tiwari and Gulati, 2013).

Increasing transport demand for relatively faster transport modes, particularly the demand for road transport, have also resulted in higher energy consumption. Currently, worldwide transport sector consumes about 29% of total final energy consumption (TFC), of which road, domestic aviation, rail, world marine and aviation bunkers use 76%, 4%, 2%, 8% and 7%, respectively (IEA, 2018b). Moreover, since transport sector's energy consumption mostly comes in the form of petroleum products, higher energy consumption in transport has also accounted for an increase of the environmental emissions (especially CO_2 emissions). Transport sector is also the second largest source of global carbon emissions, and produces 7866 million-tones of CO_2 emissions, with 24.34% share in total global emissions. Within transport sector, road transport emits most (75%) of transport related CO_2 emissions (IEA, 2018a).

Growing transport demand (especially road) is a major obstacle to reduce energy consumption and associated greenhouse-gas emissions. Therefore, an accurate empirical assessment of transport demand is crucial for a careful planning of transport sector. A major objective of transport demand analysis is to investigate the impact of main influencing factors such as price, income, and quality-related variables on travel behavior. The empirical literature on transport demand has received more attention in 1970s and 1980s. Since then, transport demand is extensively investigated by many empirical studies (see, for instance, Goodwin, 1992; Graham and Glaister, 2004; Lewis and Widup, 1982; Oum et al., 1992). In a review article, Goodwin (1992) summarizes the own-price (petrol price) elasticities of transport demand from 150 studies. The study finds that, on average, the short and long-run elasticities of traffic levels with respect to petrol price is -0.16 and -0.33, respectively, while the average fare-elasticity of the demand for rail travel is -0.79. Over time, studies of transport demand improve in terms of both model specification and methodology used to specify the demand relationships. Subsequent studies, at an aggregate level, adopt modern time series econometric methods of co-integration and error-correction models to analyze the transport demand of different modes (Ahern and Anandarajah, 2006; Fouquet, 2012; Kupfer et al., 2017; Melo et al., 2019; Milioti and Karlaftis, 2014; Ramli and Graham, 2014; Tong and Yu, 2018; Wang and Lin, 2019; Wijeweera et al., 2014, and others). For instance, Fouquet (2012) employs Johansen's multivariate co-integration approach to analyze the relationship between aggregate passenger transport (cars, buses and railways), price and GDP in UK from 1850 to 2010, and traces the trends/patterns in income and price elasticities over time. The results show that price and income elasticities of land transport in UK are very high (-1.5 and 3.1) during 1850s, which are decreased over time to -0.6 and 0.8 in 2010, respectively. In a recent past, Chi (2016) utilizes nonlinear ARDL co-integration approach on monthly data from 2002 to 2013 to examine the short and long-run asymmetric behavior of vehicle travel demand (various indicators such as total vehicle-trips, no. of passenger vehicle-trips (buses, passenger-cars), passenger vehicle-kilometers, vehicle-kilometers) in Korea to variations in fuel prices, with real GDP and total road length are used as additional explanatory variables in the model. The results indicate that travel demand, in the long-run, is more sensitive or responsive to fuel price cuts than to price increases. Wang et al. (2019) use panel data on 31 Chinese provinces (further divided into three regions central, eastern and western) from 2000 to 2015 to analyze the connection between freight transport (measured in terms of ton-kilometers) and economic growth (per-capita GDP) in a panel co-integration framework. The results show that, for all three regions, the long-run relationship exists between economic growth and freight transport, with long-run elasticity of economic growth with respect to freight transport ranges from 0.35 to 0.89 among three regions.

Empirical studies on transport demand are widely conducted for developed countries for reasons such as availability of quality data on transport in developed countries, researchers' own association with those countries, etc. On the other hand, although some empirical estimates of transport demand (especially road and rail) are indeed available for some less developed countries, the issue has not been formally investigated for a country like Pakistan as per author's best knowledge. Therefore, present study aims to estimate the transport demand for Pakistan. Next section provides the study's background and objectives of the study will be reported thereafter.

1.2 Background of the Study

Till 1970s, rail was considered as the predominant mode of transport in Pakistan. However, the performance of rail transport has decreased over time due to both sub-optimal planning and diversion of (public) resources from rail infrastructural development to investments in road infrastructure (See, for example, Li et al., 2018; Looney, 1998). Consequently, share of rail freight has declined from 73% to less than 4%, and rail's passenger share has reduced from 41% to 10% (Government of Pakistan, 2009). Shifting most of inland freight and passenger traffic on roads have also raised major concerns of planners and policymakers in terms of higher energy consumption (mostly petroleum products) and associated emissions, deteriorating urban air-quality and road conditions. For instance, road sector consumes 15.24 Million tons of oil-equivalent (MTOE) energy as of 2016, which accounts for about 97% of total energy consumption in transport (IEA, 2018a). Since road's energy consumption mostly comes in petroleum products, it also importantly contributes to (national) environmental (especially CO_2) emissions. Therefore, it accounts for about 29.30% of total (national) CO_2 emissions from fuel combustion in 2016 (IEA, 2018b).

Recognizing the importance of rail transport (especially for long-distances), the Government of Pakistan, in an official document of vision-2025 in 2014, aims to increase the share of rail transport to 20% over the period 2015-2025 (Planning Commission of Pakistan, 2014). Among other strategies related to investments in rail infrastructure, analysis of transport (both rail and road) demand is also important for an appropriate planning of transport sector.

1.3 Objectives of the Study

i. The main objective of the present study is to estimate and analyze the demand for both passenger and freight transport of rail and road in Pakistan using time series data.

ii. This study also intends to estimate the efficiency of road and rail transport using data envelopment analysis (DEA) and traces the patterns of efficiency over time.

To fulfill these objectives, the following policy issues or research questions will be addressed by the present study:

- What are the main influencing factors of road/rail's freight and passenger demand for Pakistan in the long-run? Are these factors also important in affecting/determining the short-run transport demand?
- What are the long-run output/income and price elasticities of freight/passengers' demand?
- Does the responsiveness of freight/passenger demand to its determining factors vary across transport modes such as road and rail?
- Is each demand system (freight and passenger) of road/rail transport stable? How does demand respond to variable specific shocks and system-wide shocks? Which variables respond to shocks through error correction mechanism and which do not?
- What type of policy implication can be drawn from the nature (elastic or inelastic) of relationship between transport demand and price (i.e., freight-rate, rail-fare, fuel-price, etc.), which is an important policy variable?

- Are road and rail transport modes efficient in terms of facilitating freight and passenger traffic using minimum possible inputs such as labor, vehicles, and infrastructure? What types of efficiency patterns one can observe for road and rail transport modes over time? Which years are considered relatively more efficient, and which are not?

1.4 Contribution of the Study

The present study contributes to the understanding of the empirical transport demand behavior of different modes such as rail and road in a developing country such as Pakistan. We estimate the demand for both rail's freight and passenger transport separately with Johansen's multivariate co-integration approach using aggregate time series data on freight and passenger transport. The results show that price and income elasticities of long-run rail passenger demand are between -0.26 to -0.34 and 1.02, respectively, and that of rail's freight demand elasticities with respect to price and industrial production are -0.43 and 0.87, respectively. It implies that the demand for rail's freight (passenger) transport is relatively sensitive to changes in industrial production (real per-capita GDP), which has an important implication that the demand for rail's freight/passenger transport is expected to increase if industrial production/income rises.

On the other hand, since the demand for freight and passenger transport is relatively more inelastic to its price, a rise in average price (freight-rate and fare) of rail's freight and passenger transport will result in more revenue earnings, without decreasing most of the demand for rail's freight and passenger transport and vice-versa. Similarly, we also identified a positive relationship between the long-run demand for rail's freight/passenger transport and road's trucking/passengers' costs, which indicates that road transport is the substitute of rail transport. Moreover, the impact of rail infrastructural development on rail's passenger demand is captured through its route-density, and it is found that demand for passengers' transport is highly correlated to rail's route-density, which implies that as rail's route-density increases, rail's passenger demand is expected to grow faster than the route-density of rail. However, although we identified a positive effect of population on rail's passenger demand, the co-efficient is significantly less than one and the impact is marginally significant at traditional significance levels.

Later, we also carried out econometric analysis of the determinants of road's freight and passengers' demand with ARDL bounds test of co-integration, as variables exhibit different order of integration (I(0) and I(1)). The empirical results indicate that real per-capita GDP, fuel-price, rail-fare (cross-price effect), road density and urban population are key determinants of long-run road's passenger demand in Pakistan. Similarly, fuel-price, industrial production, and rail's freight-rate are important determining factors of road freight demand. An important policy implication of empirical findings can be derived from the long-run relationship between road's transport demand and fuel-price, which is less elastic, particularly for passenger demand. This shows that market policy instruments (fuel-prices) are less effective in terms of reducing the growth of road's transport demand, especially passenger demand. Similarly, demand for road's passenger transport is highly responsive to urbanization (measured by urban population), which implies that as urban population increases, road's passenger demand will grow faster than the urban population. On similar lines, since long-run road's freight demand is highly responsive to changes in industrial production, which also indicates that the demand for road's freight transport is expected to increase more proportionately with growth in industrial production.

In addition, the efficiency of rail and road transport modes is also investigated by the present study in terms of how much they are effective in facilitating outputs (such as freight and passenger transport) with minimum possible consumption of inputs (energy, labor, and infrastructure). The efficiency analysis is conducted with a non-parametric approach, known as data envelopment analysis (DEA). The efficiency patterns of rail and road sectors are derived over time. The empirical results show that efficiency of rail transport has increased over time, as it has experienced a positive growth in its outputs (especially passengers), while registering a negative growth in its inputs. However, the estimated efficiency of rail transport is lower than road transport when efficiency analysis is conducted across transport modes of rail and road. On the other hand, efficiency of road transport is relatively higher than rail transport, as there is no considerable difference between the efficiency scores of most efficient and inefficient years.

1.5 Organization of the Study

The following organization will be used for this thesis. Chapter 2 will provide a brief overview of transport sector in Pakistan. Chapter 3 will be related to the estimation of rail freight and passenger transport demand in Pakistan while the demand for road freight and passenger transport will be analyzed in chapter 4. Chapter 5 investigates the relative efficiency of different transport modes (road and rail) in Pakistan and chapter 6 provides the summary and conclusions of the study along with some policy implications and further directions of research.

CHAPTER 2

A BRIEF OVERVIEW OF TRANSPORT SECTOR IN PAKISTAN

2.1 Introduction

The transport sector in Pakistan is an important driver of economic growth. It accounts for about 13% of country's GDP, registering an annual average growth rate of 4.12% between 2011-12 and 2017-18. This sector significantly contributes to the services sector value additions of about 1590 billion (rupees), representing a share of 22% in the GDP of services sector. Transport sector generates 3.4 million jobs, which are 5% of employed labor force in Pakistan. Moreover, it also represents 20% of total (public and private) gross fixed capital formation, of which the share of private sector's infrastructure investment in transport is 17% while public's investment share is merely remaining 3% (Government of Pakistan, 2018).

2.2 Transport Infrastructure

The quality and quantity of transport infrastructure is an important enabler of a country's economic growth & development and is also considered as a crucial determinant of transport sector's performance. Transport infrastructure in Pakistan is broadly divided into different forms such as road, rail, airports, seaports and shipping, etc. World Economic Forum measures the Global Competitiveness Index (GCI) across countries of world, which assesses the level of competitiveness of an economy. The GCI is based on 12 pillars, in which the quality of transport infrastructure is an important component of a country's relative competitiveness position. The World Economic Forum, in its Global Competitiveness Report 2016-17, evaluates 137 countries of the world in terms of quality of their transport infrastructure such as roads, rails, air transport and ports, etc. The quality of transport infrastructure of some selected Asian countries, including Pakistan, is compared with some of the top performers of the World in Table 2.1. The quality of transport infrastructure in Hong Kong is the best in the world during 2016-17 as it has the highest score of 6.4 in a range from 1 to 7, whereas a score equal to 1 shows the poorly developed transport infrastructure and 7 indicates the best and efficient transport infrastructure.

Table 2.1: Indicators of Transport Infrastructural Quality across Countries (2016-17)

Country	Ranking by Overall Infrastructure Quality	Overall Infrastructural Quality	Quality of Roads	Quality of Railroad Infrastructure	Quality of Air Transport Infrastructure
Bangladesh	111/137	2.9	3.1	2.9	3.3
Hong Kong	01/137	6.4	6.2	6.3	6.6
India	66/137	4.6	4.3	4.4	4.6
Japan	04/137	6.2	6.1	6.6	5.6
Malaysia	22/137	5.3	5.3	5.0	5.7
Netherland	03/137	6.2	6.1	5.8	6.6
Nepal	119/137	2.9	2.8	n.a*	2.5
Pakistan	**110/137**	**3.8**	**3.9**	**3.3**	**4.0**
Singapore	02/137	6.4	6.3	5.9	6.9
Sri Lanka	85/137	3.9	4.2	3.2	4.2
Switzerland	06/137	6.6	6.3	6.6	6.2

Source: Global Competitiveness Report 2017-18

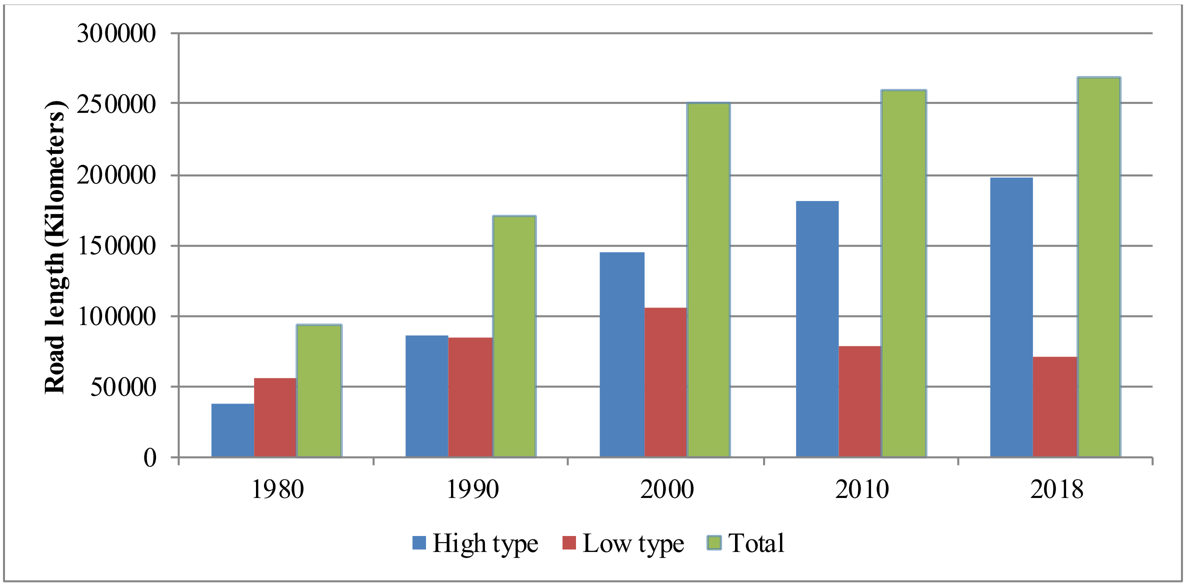
Note: Quality of overall infrastructure is (1= inefficient and poorly developed and 7= among the best in the world. The same scoring level is used for road, rail, and air transport infrastructure quality.

* Not assessed.

Other countries such as Singapore, Netherland, Japan, and Switzerland are among the top ten countries of the world in terms of highest transport infrastructural quality. Pakistan ranks at 110 and manages to receive a score of 3.8 regarding the overall transport infrastructural quality. The scores of roads, railroads, and air transport in Pakistan are relatively low at 3.9, 3.3 and 4, respectively, during 2016-17. In a cross-country comparison, Pakistan lags behind other similar developing countries such as India and Sri Lanka while performs better than others such as Bangladesh and Nepal. Similarly, the development of transport infrastructure in Pakistan is significantly lower than those of top performers.

Among other transport modes, roads are considered as the most important form of transport infrastructure as they carry most of the inland freight and passenger transport in Pakistan. The existing road infrastructure can be represented by the length of total road network (in kilometers). The national highway road network represents only 4% of total road network but carries 80% of commercial traffic in Pakistan (Goverment of Pakistan, 2011). The road network in Pakistan is further divided into high-type and low-type roads. The high-type roads are the paved roads while low-types are unpaved. The evolution of road network in Pakistan over the last four decades is given in Figure 2.1 below. It reveals that total road length has increased during this period, with the share of high-type roads in total road length has also increased. Total road network in 1980 was 93,960 km, which increased to 26,8935 km in 2018. Similarly, length of high-type road has increased from 38,035 km in 1980 to 19,7452 km in 2018, showing an annual average growth rate of 4.5%. Moreover, the share of high-type road has also moved up from 40% to 73% during the same period. On the other hand, low-type road length has depicted an upward trend in first two decades from 1980 to 2000, which then registered a negative growth thereafter. Its share has also decreased from 60% in 1980 to 27% in 2018. The main reason of decreasing both low-type road length and its share is due to the conversion of most of the low-type roads into high-type roads.

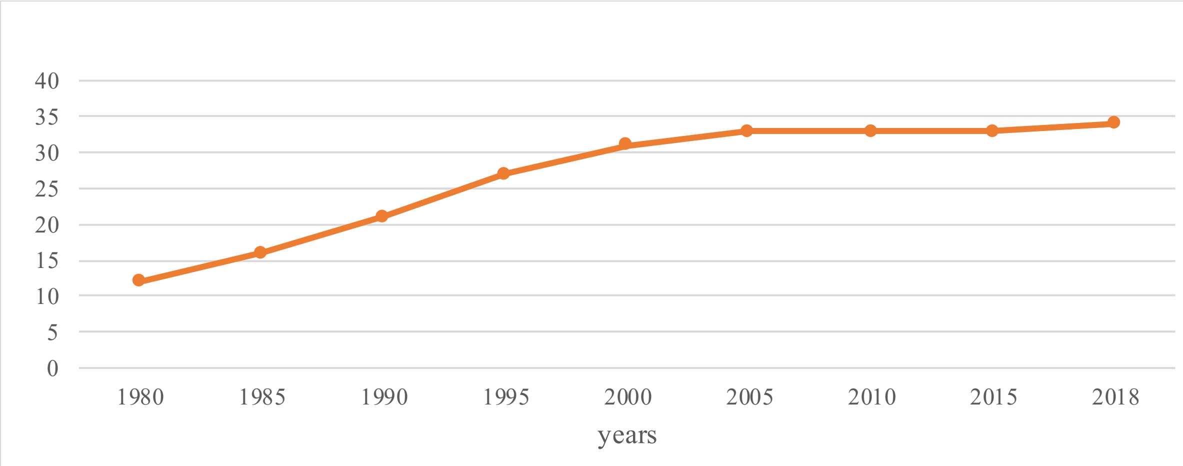
Figure 2.1: Road Network (Kilometers) in Pakistan Over 1980-2018



Source: Pakistan Economic Survey (various issues)

Road density, in general, is considered as an important indicator of quality of road infrastructure, country's economic development and prosperity. It can be defined as the ratio of total road length of a country to its total land area. Road density in Pakistan over the last four decades from 1980 to 2018 is provided below in Figure 2.2. The graph reveals that road density has increased over time in Pakistan. It has increased from 12-km/100 sq. km in 1980 to 34-km/100 sq. km in 2018, with annual growth rate of 2.8%. Surprisingly, road density has remained stagnant over the last two decades. Road density in Pakistan during 2018 is only 34-km/100 sq. km, which is significantly lower than the government of Pakistan's intended target of 64-km/100 sq. km (Government of Pakistan, 2008).

Figure 2.2: Road density in Pakistan over 1980-2018 (in km/100 Sq. km)



Source: Author's calculations using data from Pakistan Economic Survey (various issues)

Although road density has generally increased in Pakistan over time, it is still very low as compared to some other countries of South Asia and developed economies like OECD countries. A comparison of road density in Pakistan is made with other members of South Asian countries and developed countries in Table 2.2 during 2016-17.

Table 2.2: Cross-Country Comparisons of Road Density Over 2016-17

South Asian countries	Road Density (km/100 sq. km.)	Selected OECD countries	Road Density (km/100 sq. km.).
Afghanistan	6.1	Austria	168.1
Bangladesh	14.4	Belgium	510.5
Bhutan	29.1	France	198.8
India	166.5	Hungary	228.2
Maldives	NA	Japan	335.2
Nepal	59.2	Netherland	413
Pakistan	**33.2**	Switzerland	181
Sri Lanka	47.6	UK	174.8
		USA	72.8

Data sources: Data on South Asian countries is collected from respective countries' statistical yearbook and ADB statistic (2017) while the rest is obtained from OECD countries' database (OECD. Stat).

A comparison with member countries shows that Pakistan's road density is lower than India, Nepal, and Sri Lanka. Similarly, road density in South Asian countries is significantly lower than the selected OECD countries. For example, road density in Pakistan during 2017 is 33.2 km/100 sq. km while road density in some developed countries such as Belgium, Japan and Netherland is 510.5, 335.2 and 413 km/100 sq. km, respectively, which is 15, 10 and 12 times the road density in Pakistan.

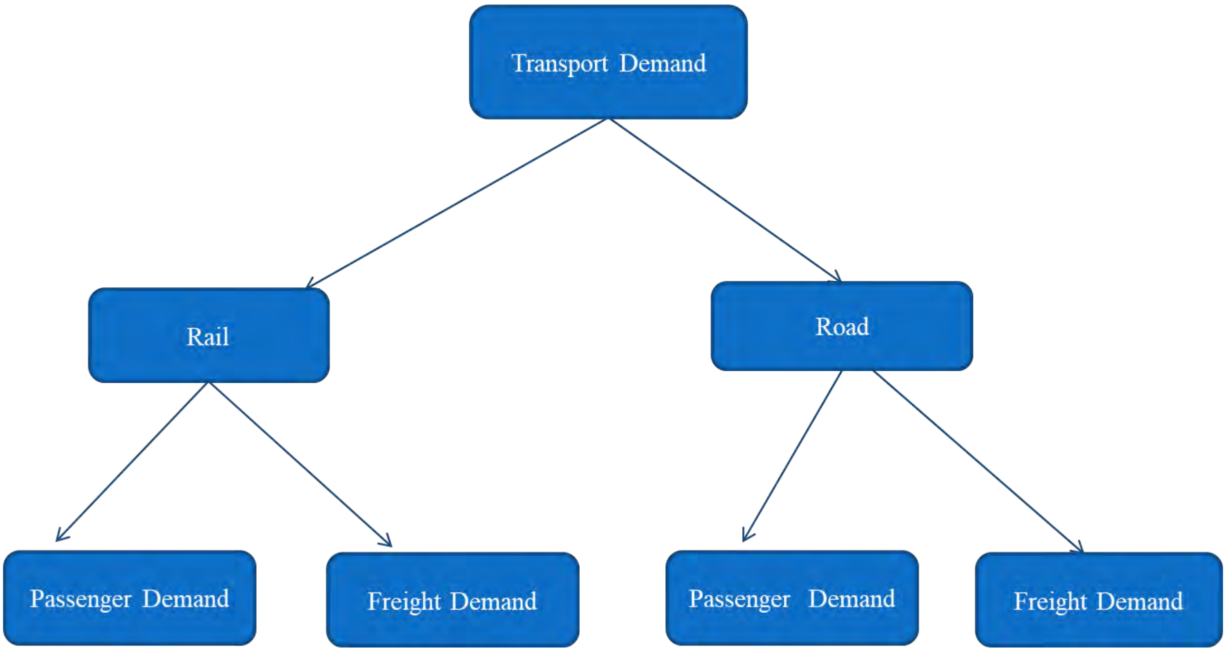
Improvements in investment climate of a country would promote economic growth through creation of world class business environment. Investors perceive trade and transaction cost as crucial for their competitiveness. Lack of both quality and inadequate infrastructure is one of the most important sources of high transaction costs, which may further affect the sustainable growth. Over the last few decades or so, logistics industry has been recognized as one of the most important enablers of economic growth. It is an important component of supply chain management process that deals with the planning, arranging, and organizing for the transportation of various resources (raw materials, people, equipment and inventories, etc.) from origin to the destination with the help of different transport modes (road, rail, air, etc.). Logistic services provide important linkages with the other sectors of an economy and connect local economy with the rest of the world. It contributes to an economy by generating additional income, create employment opportunities and facilitates foreign investment inflow (Tang and Abosedra, 2019). Moreover, it is also considered important in terms of improving the competitiveness and performance of firms and industries by reducing firm's costs. A considerable empirical literature has investigated the role of logistics in countries 'economic growth and observed that performance of logistics sector makes important positive contributions to the economic growth and development (see, for expample, Chu, 2012; Coto-Millán et al., 2013; D'Aleo and Sergi, 2017; Lean et al., 2014; Sezer and Abasiz, 2017, etc.).

2.3 Structure of Transport Demand

Transport demand relates to the movement of people and goods. It can be defined as the amount of transport people and firms are willing and able to choose under some specific conditions using a specific transport mode. A special characteristic of transport demand is that its demand is derived one, which implies that transport services are not demanded for their own sake but to fulfil some other economic objective at the end of trip or at the destination. For example, work or job-related activities involve people's travel from residence to workplace. Supply of work exists at one place (residence) while the labor demand exists at another location (workplace). So, transport demand in this case is directly derived from labor supply and demand relationship. Similarly, demand for freight transport is also derived because all supply chain components involve movements of finished goods, raw material, and parts. Therefore, transport demand is derived from consumption and distribution sectors of the economy and is considered as an important component of transport planning and management.

Basic structure of transport demand in Pakistan can be explained with the help of Chart 2.1 below. Currently, there are two inland modes of transport in Pakistan road and rail transport. The demand for each transport mode can be further classified into the demand for freight and passenger transport.

Chart 2.1: Basic Structure of Inland Transport Demand in Pakistan



Source: Bhattacharyya (2019)

2.3.1 Demand for Road Transport

Road is considered the most dominant mode of facilitating passenger and freight transport, followed by rail. On the other hand, air transport carries only a small proportion of domestic transport in Pakistan as compared to road and rail transport. Moreover, since time series data on domestic air transport in Pakistan in terms of passenger-kilometers (PKM) and ton-kilometers (TKM) is not available, we analyze the patterns of road and rail transport. In addition, oil pipelines carry about 37% of all petroleum products, rest being carried by road (61%) and rail (2%). They have diverted road and rail business. Therefore, the trends and an approximate modal-share of road and rail transport over time in Pakistan is given in Table 2.3.

Table 2.3: Profile of Road and Rail Transport during 1980-2018

Years	Rail transport (billion)		Road transport (billion)		Total (billion)	
	PKM	**TKM**	**PKM**	**TKM**	**PKM**	**TKM**
1980-81	16.38 **[20%]**	7.91 **[30%]**	65.99 **[80%]**	18.20 **[70%]**	82.37	26.125
1985-86	16.65 **[16%]**	8.27 **[24%]**	85.95 **[84%]**	26.36 **[76%]**	102.60	34.63
1990-91	19.96 **[13%]**	5.70 **[14%]**	128 **[87%]**	35.21 **[86%]**	147.96	40.92
1995-96	18.90 **[11%]**	5.07 **[6%]**	154.56 **[89%]**	79.90 **[94%]**	173.47	84.97
2000-01	19.59 **[9%]**	4.52 **[4%]**	208.37 **[91%]**	107.08 **[96%]**	227.96	111.60
2005-06	25.62 **[10%]**	4.97 **[4%]**	238.07 **[90%]**	124.45 **[96%]**	263.69	129.42
2010-11	20.61 **[7%]**	1.75 **[1%]**	263.72 **[93%]**	152.15 **[99%]**	284.34	153.91
2015-16	21.20 **[7%]**	4.77 **[3%]**	282.45 **[93%]**	167.02 **[97%]**	303.65	171.79
2017-18	24.90 [n.a]	8.08 [n.a]	n.a	n.a	n.a	n.a

Data sources: Pakistan railway yearbook (various issues), Pakistan economic survey (various issues), Pakistan statistical yearbook (various issues), Oil companies' advisory committee (various issues).
N.A stands for not available.

During 2015-16, both road and rail have approximately facilitated 304 billion passenger-kilometers (PKM) and 172 billion ton-kilometers (TKM) in Pakistan. Over the period 1980-2016, the total PKM have increased by 268%, with an average annual rate of 3.8%, while TKM have grown by 558% at an annual average growth-rate of 5.5%. Over the last few decades or so, a gradual shift has also witnessed from rail transport to road transport. From Table 2.3, the share of rail transport in PKM has decreased from more than 20% in 1980 to a less than 10% in 2016, while that of rail-TKM has declined from 30% 1980 to less than 5% in 2016.

Rail transport in Pakistan or Pakistan-railway (PR) only carries about 25 billion PKM and 8 billion TKM in 2018. The data on rail transport in Table 2.3 witness that either it has marginally increased over the last three decades or has remained stagnant. For example, over the period 1980-2018, rail-PKM has increased from 16.38 billion to 24.90 billion, with a mere rate of 1.1% per annum, while rail-TKM figure has remained stagnant at 8 billion. A more detailed analysis of rail transport will be presented in the next section.

Since income and population are growing in country, registered road vehicles have also experienced a strong growth over the last four decades, posing serious challenges for policy makers regarding road infrastructural quality, energy consumption and environmental sustainability. Table 2.4 describes the growth of various types of road vehicles from 1976 to 2018 in Pakistan.

Table 2.4: Trends in Registered Vehicles on Roads over 1976-2018 (in Thousands no.s)

Years	Two-Wheelers	Cars, jeeps, Taxis & Station-Wagons	Buses	Trucks	Total Vehicles
1976	254.7	226.9	39.4	62.2	674.5
1982	636.2	325.2	51.7	63.0	1339.0
1988	1094.0	603.1	79.6	94.3	2369.9
1994	1680.0	955.0	107.4	118.4	3537.9
2000	2260.8	1266.2	154.4	148.6	4701.6
2006	2757.8	1477.2	175.6	190.0	5633.4
2012	7500.2	2238.1	215.5	240.9	11788.6
2018	17465.0	3210.8	236.5	277.4	23588.0

Data source: Pakistan Economic Survey (various issues).

The road vehicle-categories are classified into two-wheelers, cars, jeeps, taxis and station-wagons, buses, trucks, and others. The total registered vehicles in Pakistan are 23,588 thousand as of 2018. Of this, two-wheelers constitute a major share in total vehicles at 17,465 thousand while cars, jeeps, taxis, etc. represent a total of 3,211 thousand, trucks at 277.4 thousand, buses at 236.5 thousand and remaining are represented by three-wheelers and others.

In terms of growth, all major road vehicle-types have recorded a significant increase over 1976-2018, showing an exponential trend as can be seen from Table 2.4. In 1976, total registered vehicles on roads were 674.5 thousand, which increased to 4706.1 thousand in 2000 (an increase of more than 700%) and increased to almost 8 million by 2012. The road vehicles have increased further to 23,588 thousand in 2018 at an annual average growth rate of 12.3%. Since most of road vehicles use petroleum products and natural gas, increasing motorization rates has severely affected the air quality in Pakistan. Therefore, road transport is a major source of air quality deterioration in Pakistan. According to a report by World Bank (2014), the urban air quality in Pakistan is the worst in the world and therefore recommends the Government of Pakistan to improve the quality of air in Pakistan on urgent basis.

On the other hand, rapid motorization may also create some additional social and economic costs in terms of road accidents, which may lead to deaths and/or injuries. According to World Health Organization (2020), road traffic crashes cause 1.35 million deaths each year, and around 20 to 50 million additional people suffer non-fatal injuries, leading to permanent disabilities of many as a result of their injury. For most countries, these road crashes account for about 3% of gross domestic product (GDP). The number of road fatalities in developed economies is very low as compared to low and middle-income countries. Although low and middle-income countries occupy approximately 60% of vehicles in the world, around 93% of the world's road fatalities occur in these countries.

Pakistan is also one of those countries where road accidents and associated fatalities are relatively high. For instance, data from Pakistan Statistical Yearbook (2018) reveals that the total number of road accidents in Pakistan as of 2016 are 9,100, causing 4,448 deaths and 11,544 injuries. The total number of reported road accidents is the ones registered with police authorities, which may be under-reported. According to some estimates, road traffic fatalities in Pakistan during 2016 are 27,582, with an estimated fatality-rate per 100,000 population at 14.2 (World Health Organization, 2018).

2.3.2 An Overview of Rail Transport in Pakistan

This section deals with the analysis of rail transport over the period from 1997-2018. Next section explains the rail freight transport, followed by rail passenger transport, and then the analysis of expenditures and revenues of Pakistan railway (PR) will be examined.

2.3.2.1 Rail Freight Transport

The Pakistan Railway (PR) is a national, state-owned enterprise of Pakistan, founded in 1861 and headquartered in Lahore. It works under the Ministry of Railways which is responsible for planning, administrating the passenger locomotive services, regulating the railway companies, industries, and associated organizations. The PR facilitates the movement of both passenger and freight transport throughout the country. It connects coastal ports (Karachi Port and Bin-Qasim Port) and dry ports to the interior parts of the country. It also generates revenues from the movement of various commodities such as petroleum oil, wheat, coal, fertilizer, cement, industrial and imported goods, etc. However, due to diversion of resources to the expansion of road network, the performance of Pakistan railway has declined over time. Therefore, its share of inland passenger traffic reduced from 41% to 10% and 73% to 4% for freight traffic (Government of Pakistan, 2009). Recognizing the importance of rail for transport, the Government of Pakistan, in its vision 2025, has planned to increase the share of rail transport from 4% to 20% (Planning Commission of Pakistan, 2014).

The performance of rail freight transport in Pakistan during the last two decades from 1997-98 to 2017-18 is provided in Table 2.5. Rail freight transport is measured in both total tons (millions) and ton-kilometers (millions). PR has carried a total of 5.97 million tons and 4,447.3 million ton-kilometers of freight in 1997-98, which, although not consistently, has increased to 7.23 million tons and 6187.3 million ton-kilometers after a decade. The improvement in most of this period was due to the development projects implemented by PR to improve its services (Government of Pakistan, 2008)[1].

Table 2.5: The Performance of Rail Freight Transport in Pakistan Over 1997-2018

Years	1997-98	2002-03	2007-08	2012-13	2017-18
Total Freight carried (Million tons)	5.97	6.18	7.23	1.01	8.35
Total Freight (Ton-km)[2] (Million)	4447.3	4819.8	6187.3	419.3	8080.3
Average rate per ton (Rs.)	757	820.5	846.5	1965.2	2232.6
Average rate per ton-km (Rs.)	1.01	1.05	0.989	4.73	2.31
Average kilometer carried by a ton	745.8	779.8	855.3	412.74	967.1
Freight Wagons (no.s)	24275	23460	18638	16635	16159
Locomotives (no.s)	611	577	555	493	478

Data Source: PR yearbook (various issues).

However, the performance of PR began to slow down after 2008, particularly from 2010 to 2013. PR has endured the worst crisis during this period, owing to the over-aged infrastructure, lack of locomotives, rolling stock and shortage of diesel-fuel. As a result, the number of freight trains from ports has dropped from 96 to merely 1 per day (Government of Pakistan, 2012). Besides, the number of terrorist attacks on PR has substantially increased from 2010 to 2013 (South Asia Terrorism Portal, 2018). Consequently, the amount of freight carried

[1] Allocations for PR has increased from Rs. 3 billion in 2000-01 to Rs. 11.65 billion in 2007-08. The development projects of PR include rehabilitating and manufacturing of diesel electric engines (Japan International Cooperation Agency, 2004).
[2] T-km represents ton-kilometers.

by PR declined sharply from 7.23 million tons in 2007-08 to 1.01 million tons in 2012-13, and also from 6187.3 to 419.3 in terms of million ton-kilometers. Since then, PR has adopted a number of strategies (increasing freight trains from ports, improvements in dry ports, etc.) to increase rail freight transport (Pakistan Railway, 2018). As a result, rail freight, measured in both tons and ton-kilometers, has considerably increased to 8.35 tons and 8080.3 ton-kilometers, respectively, in 2017-18.

Table 2.6 provides the information regarding rail freight transport (measured in thousand tons and thousand ton-kilometers) of five major commodities in Pakistan over the period 2012-13 to 2016-17. In addition, each commodity's share in total rail freight transport (measured in thousand tons) is also given.

Table 2.6: Rail Freight Transport of Five Major Commodities for Period 2012-2017

Commodities		Ton and Ton-kilometers (thousands) of a commodity				
		2012-13	2013-14	2014-15	2015-16	2016-17
Departmental commodities[3]	Tons	524	752	734	821	1036
	% share	52%	47%	20%	16%	18%
	Ton-km	20,634,2	30,981,4	25,725,2	25,056,1	33,473,7
Petroleum & other hydro-carbon oils (non-dangerous)[4]	Tons	115	305	668	857	829
	% share	11%	19%	19%	17%	15%
	Ton-km	10,297,3	28,706,8	57,954,8	77,723,1	65,435,3
Container traffic	Tons	57	50	524	1003	846
	% share	5.61%	3.11%	14.56%	20.06%	15.03%
	Ton-km	64,236	57,585	60,045,5	11,4675,2	96,163,0
Coal & Coke for public	Tons	-	161	596	881	1301
	% share	-	10%	16.5%	17.23%	23.14%
	Ton-km	-	20,570,8	74,176,8	10,504,01	15,460,12
Cement	Tons	159	160	255	283	239
	% share	15.6%	9.9%	7.1%	5.7%	4.2%
	Ton-km	25,809	22,018	31,121,9	35,384,3	29,681,0

Source: PR yearbook (2017)

[3] Include coal, coke, and patent fuel for railways (including H.S.D and durance oil) plus railway material and stores.

[4] Represents petroleum and hydro-carbon oils (non-dangerous i.e., having flashing point at above 76 FAHR (includes diesel & furnace oil).

In general, data indicates that most of the commodities show healthy growth (ton-km) over the period 2013-2017. However, share of only three commodities (Coke & coal for public, petroleum oil and container traffic) has generally increased during the five-year period while the shares of others (departmental commodities, cements) have declined.

2.3.2.2 Rail Passenger Transport in Pakistan

This section aims to provide the performance of rail passenger transport in Pakistan. Therefore, passenger related data of PR over the last two decades from 1997 to 2018 is provided in Table 2.7 below, which can be used to assess the main trends and performance of PR over time. The passenger performance is measured in terms of both total passengers and passenger-kilometers carried by PR on annual basis. Both figures reveal a strong growth over 1997-2018, except for the period 2010-13, when PR endured a worst crisis. Therefore, both passengers and passenger-kilometers have greatly declined during this period, which can be observed in Table 2.7.

Table 2.7: The Performance of Rail's Passenger Transport in Pakistan during 1997-2018

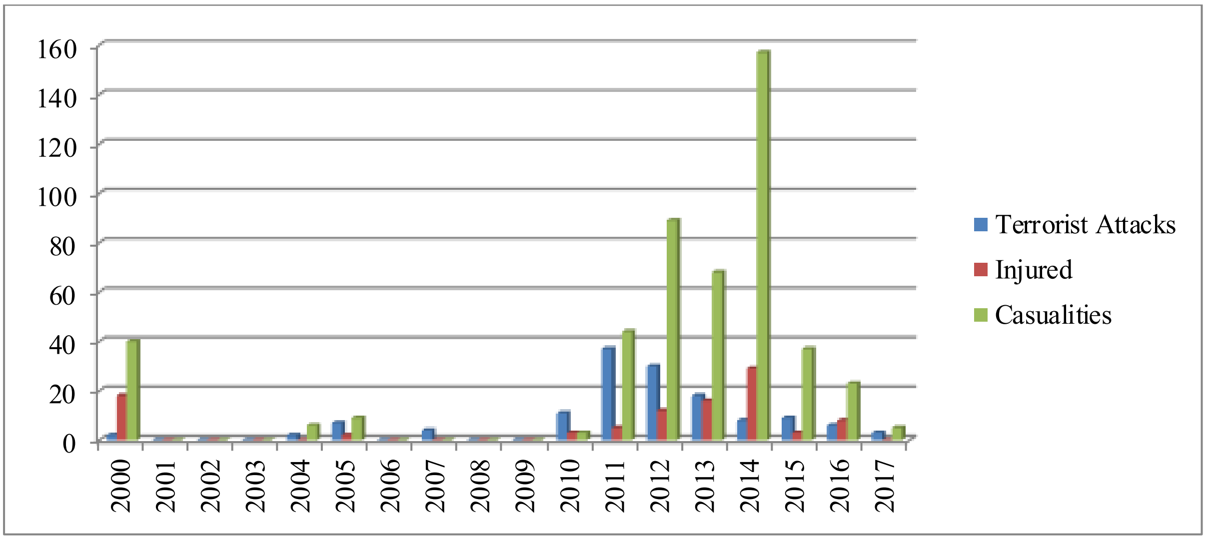
years	1997-98	2002-03	2007-08	2012-13	2017-18
Total Passengers (Million).	64.9	72.4	80	41.9	54.90
Passenger-kilometers (Million).	18,774	22,306	24,731	17,388	24,903
Average distance travelled by a passenger (km).	289	308	309	415	454
Average revenue per passenger (Rs.).	70.6	102.6	130.1	323.1	445.3
Average revenue per passenger-kilometer (Rs.).	0.244	0.333	0.421	0.778	0.982
Track-kilometers.	11,526	11,515	11,658	11,755	11881
Passenger coaches (no.s).	1768	1553	1627	1540	1460

Data Source: PR yearbook (various issues)

On the other hand, average distance travelled by a passenger has increased from 289-kilometers in 1997-98 to 454-kilometers in 2018, with annual average rate of 2.30%. Similarly, there is also a considerable tendency of growth in average rail fares, measured in terms of average revenue or rate per passenger and average revenue per passenger-kilometers. However, PR has not improved its track-kilometers and route-kilometers. Therefore, track-kilometers of PR have remained stagnant or marginally increased over the last two decades due to poor governance of PR. Moreover, passenger-coaches have also significantly reduced from 1768 to 1460 over 1997-2018 because of low infrastructural investment in rolling-stock.

The PR has also affected by the terrorist attacks from time to time since 2000. The data on terrorist incidents on PR, injuries of passengers and casualties is obtained from South Asian Terrorism Portal (2018) during 2000-2017 and is plotted below in Figure 2.3. The Figure 2.3 shows that terrorist activities have substantially increased from 2010 to 2013, which have accounted for a large number of passengers' injuries and casualties.

Figure 2.3: The Number of Terrorist Attacks on Pakistan Railway



Source: South Asia Terrorism Portal (2018)

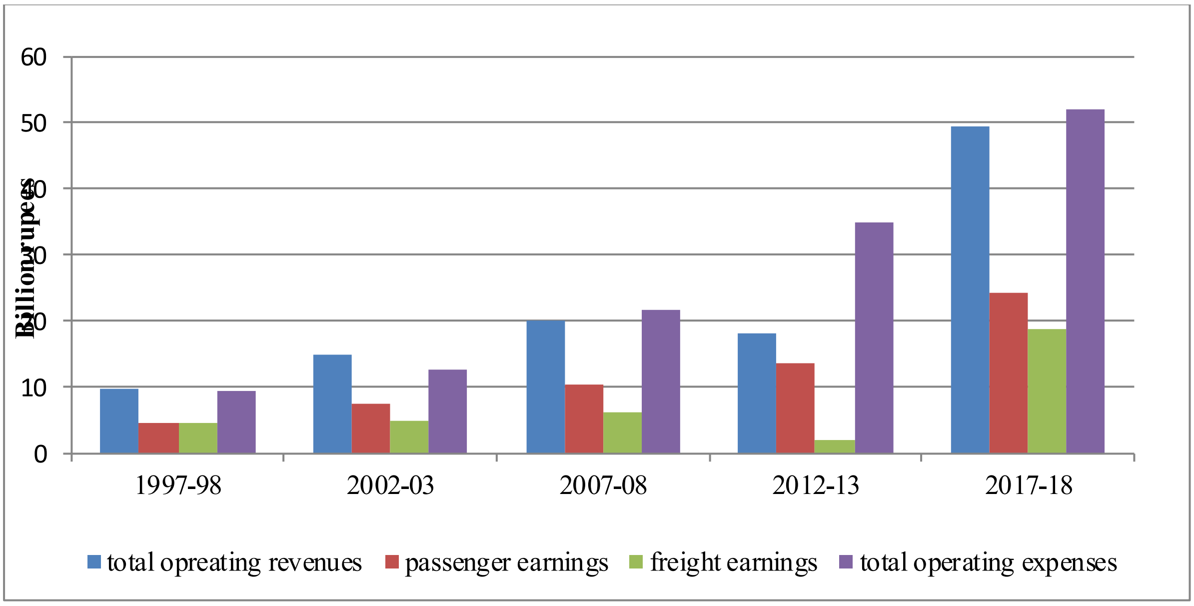
2.3.2.3 Expenditures and Revenues of Pakistan-Railway over 1997-2018

Finally, we have provided a comparison of total operating costs (billion rupees) and revenues (billion rupees) of PR in Figure 2.4 over the period 1998-2018. Moreover, earnings of PR are further classified into passenger and freight earnings (billion rupees). The graph shows huge disparity in expenditures and earnings. In particular, PR has experienced a budget surplus from 1997-98 to 2002-03, which turned into a significant deficit of 18 and 2.54 billion (rupees) during 2012-13 and 2017-18, respectively. Moreover, rail freight earnings were similar to passenger earnings in 1997-98 but decreased gradually overtime due to less favorable treatment of freight transport as compared to passenger transport (NTRC and JICA, 2006)[5]. As a result, freight earnings decreased to 2 billion (rupees) in 2012-13 from 6.13 billion (rupees)

[5] NTRC and JICA stands for National Transport Research Centre and Japan International Cooperation Agency, respectively.

in 2007-08. Recognizing its importance for rail earnings, PR has planned different strategies to provide rail freight a more balanced treatment with passenger transport (Pakistan Railway, 2018)[6]. In addition, as the PR gradually recovers from crisis during 2010-13, freight earnings have increased to 19 billion (rupees) in 2017-18, with annual average growth rate of 57% from 2012-13 to 2017-18.

Figure 2.4: The Financial Position of Rail Transport in Pakistan during 1997-2018



Data source: PR yearbook (various issues)

2.4 Energy Consumption of Transport in Pakistan

Transport sector is an important source of energy consumption. energy consumption in transport sector may also increase due to increasing transport requirements. The pattern of sectoral and aggregate final energy consumption in Pakistan is shown in Table 2.8 during the last four decades from 1980 to 2018. Total final energy consumption in Pakistan is dis-aggregated into six sectors such as industrial, transport, domestic, commercial, agriculture and other government's consumption. In 2018, total final energy consumption in Pakistan amounts to 54,992 thousand tons-of-oil-equivalent (TOE). Of this, industrial sector consumes about 20,602 TOE energy, and has the most dominant share of 37%. Transport sector (all modes) constitutes the 2nd largest share (34%) in final energy consumption after industry, followed by domestic or households (21%), commercial (4%) and agriculture (2%). Since both industry and

[6] Long-term agreements were signed with different companies for transporting cement, coal and high-speed diesel. Moreover, the carriage capacity of freight and freight productivity (in terms of loading freight wagons) has also increased over last five years.

transport sectors consume more than 70% of final energy, the priority should be given to these two sectors for energy management.

Table 2.8: Sector-Wise Final Energy Consumption & Petroleum Products in Pakistan during 1980-2018

Year	1980	1990	2000	2010	2018
Aggregate Energy Consumption (Thousand TOE)					
Aggregate	13,790 [100]	16,966 [100]	25,256 [100]	38,860 [100]	54,993 [100]
Industry	4,902 [32]	6,611 [39]	8,608 [34]	14,957 [39]	20,602 [37]
Transport	**2,717 [21]**	**5,097 [30]**	**8,686 [34]**	**12,019 [31]**	**18,637 [34]**
Domestic	1,583 [12]	3,506 [21]	5,826 [23]	8,725 [22]	11,660 [21]
Commercial	414 [3.0]	497 [3.0]	778 [3.0]	1,521 [4.0]	2,010 [4.0]
Agriculture	693 [5.0]	734 [4.0]	666 [3.0]	773 [2.0]	840 [2.0]
Other Govt.	3481 [27.0][a]	521 [3.0]	692 [3.0]	847 [2.0]	1,244 [2.0]
Consumption of Petroleum Products (thousand TOE)					
Transport	**2,717 [61.7]**	**5,093 [49.9]**	**8,581 [47.9]**	**9,374 [48.9]**	**16,989 [66.7]**
Power	180 [4.1]	2,397 [23.5]	6,326 [35.3]	7,933 [41.3]	6,224 [24.4]
Industry	257 [5.8]	1,124 [11.0]	1,889 [10.5]	1,356 [7.1]	1,786 [7.0]
Domestic	533 [12.1]	974 [9.5]	466 [2.6]	88 [0.5]	68 [0.3]
Agriculture	185 [4.2]	276 [2.7]	265 [1.5]	42 [0.2]	15 [0.1]
Other Govt.	533 [12.1]	344 [3.4]	386 [2.2]	392 [2.0]	407 [1.6]

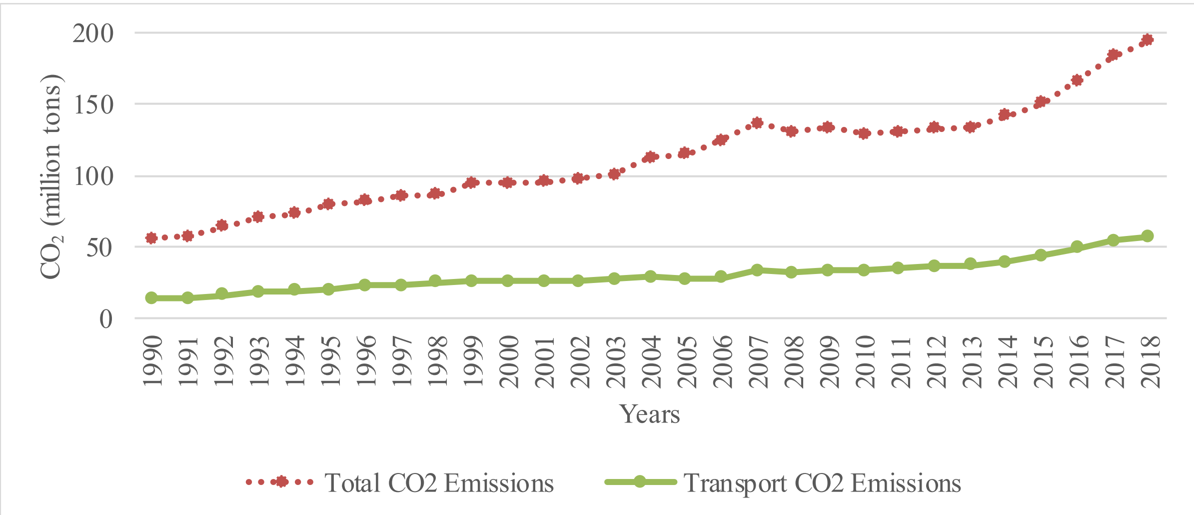
[a] it also includes the shares of power sector, fertilizer, and other Govt. purchases.
values in square-brackets are percentage-share of respective sector.
Data source: Pakistan Energy Yearbook (various issues)

In terms of growth, energy demand in all major sectors has substantially increased during the last few decades. For instance, total final energy consumed has increased from 13,790 thousand-TOE in 1980 to 25,256 thousand-TOE in 2000 (almost doubled), which further increased to 54,993 thousand-TOE in 2018, registering an annual average growth rate of 4.41% from 2000 to 2018. Energy consumed by the industrial sector has also shown impressive growth from 4,902 thousand-TOE to 20,602 thousand-TOE over 1980-2018 with an average annual growth-rate of 3.9%. Moreover, the share of industrial sector in total energy consumption has also increased from 32% to 37% during the same period. Similarly, due to increasing transport requirements, the transport sector's energy consumption has also moved up from 2, 717 thousand-TOE to 18, 637 thousand-TOE in the last four decades, and its share also has increased from 21% in 1980 to 34% in 2018. Other sectors have also experienced similar trends except for agriculture, whose share has decreased from 5% to 2%.

On the other hand, information regarding the consumption of petroleum products by these sectors is also reported at the bottom of Table 2.8. The data clearly indicates that transport sector consumes most of the petroleum products in Pakistan. It accounts for about 67 % consumption of petroleum products, leaving behind other sectors such as power (24.4%), industry (7%), domestic (0.3%) and agriculture (0.1%). Between 1980 and 2018, the consumption of petroleum products by transport sector in Pakistan has increased at an annual average growth rate of 5% from 2,717 thousand-TOE to 16,989 thousand-TOE. Since Pakistan imports huge amount of oil and petroleum products (fossil fuels) to meet its domestic requirements, increasing activities in all economic sectors, particularly industry and transport, have also resulted in higher fuel imports bill. Pakistan spends 14.5 billion US dollars on the import of fossil-fuels, which represents 20% of foreign exchange and also accounts for about 40 % of country's imports (Uddin et al., 2016).

Increasing transport sector's energy consumption in Pakistan has also resulted in higher environmental emissions, especially carbon-dioxide (CO_2) emissions. Figure 2.5 reports the total CO_2 emissions from fuel combustion and CO_2 emissions from Pakistan's transport sector during the last three decades from 1990 to 2018. The data is obtained from International Energy Agency (IEA).

Figure 2.5: Total and Transport Sector's CO_2 Emissions in Pakistan



Data source: IEA (Various issues).

The data shows that CO_2 emissions from transport sector are growing at an average compound growth-rate of 3.76% per annum from 14 million-tons in 1990 to 57 million-tons in 2018. The share of transport sector in total CO_2 emissions has also increased from 25% in 1990 to 29% in 2018.

2.5 Conclusion

This chapter provides an overview of transport sector in Pakistan and assesses the performance of its transport sector. It analyzes the past trends and current situation of various types of transport infrastructure such road, rail, logistic sector, etc. in Pakistan. Moreover, transport infrastructure situation in Pakistan is also compared with other similar developing countries in South Asia and developed countries. It reveals that transport infrastructure development in Pakistan is in poor condition as compared to other similar developing countries (such as India and Sri Lanka) and developed economies of the world. Since limited and poor quality of transport infrastructure facilities act as a major impediment to economic growth, Pakistan needs to improve the quality of its transport infrastructure on priority basis to reduce poverty and to promote its overall standard of living.

On the other hand, we also analyze the evolution of transport demand for two modes (road and rail) in Pakistan during the last few decades. For both road and rail, transport demand is further classified into the passenger and freight transport. The demand for freight and passenger transport is measured in terms of composite indicators ton-kilometers and passenger-kilometers, respectively. Both indicators not only measure the quantity demanded but also the distance over which a quantity is carried. Moreover, a modal-split of road and rail transport for freight and passenger transport is also highlighted over time, showing a favorable freight and passenger modal-splits towards road for medium to long-distance transport. Over the last few decades, transport demand in Pakistan has substantially increased, especially the demand for road freight and passenger transport while the share of freight and passenger transport of Pakistan-Railway has reduced. Increasing transport activity on roads has also raised major concerns of planners and policymakers such as massive expansion of road vehicles, higher energy consumption and associated environmental emissions, deteriorating urban air quality, road congestion, road accidents, etc. If current trends in transport demand continue, then it will have serious implications for country's future energy security and environment sustainability.

Shifting most of the domestic inland freight and passenger transport on road sector clearly suggest lack of long-run planning in transport sector of Pakistan. Therefore, Pakistan needs to develop a well-integrated transport system, that integrates the road and rail network to enhance the efficiency and reduce environmental impacts. In general, rail transport has lower costs and competitive advantage over road transport for long-distances. So, the strategy of developing a multi-modal transport system, that uses road for shorter distances and rail for long-hauls, will enhance the sustainability of transport. There is also an urgent need to expand and modernize rail infrastructure in Pakistan through investments to improve its capacity, provide connectivity across country, and improve the reliability of its services. For sustainability of road transport, priority should be given to improve the use of public transport and non-motorized transport. The use of public transport services should be made available, encouraged, and integrated to other transport modes.

CHAPTER 3

ESTIMATING THE DEMAND FOR RAIL FREIGHT AND PASSENGER (TRAVEL) TRANSPORT IN PAKISTAN: A TIME SERIES ANALYSIS[7]

3.1 Introduction

At macro level, mobility plays an important role in a country's competitiveness, economic growth and regional connectivity. A well-established transport system facilitates the smooth passenger and freight traffic movements in a cost-efficient manner from origins to destinations. There exist a number of transport modes such as road, rail and air to handle such traffic movements. However, road and rail are the two most dominant modes of a country's inland Passenger and/or freight transport (see, for exmample, European Environment Agency, 2019; Ramanathan, 2001; Shen et al., 2009). In general, railway has a potential advantage over road transport, in terms of long haul and mass scale traffic movements (freight and passenger). Besides, rail transport also contributes less significantly towards environmental degradation in comparison to road transport (Chapman, 2007; Givoni et al., 2009; Nelldal and Andersson, 2012). A country's effective railway transport system facilitates commerce and trade, reduces transportation costs and road congestion, promotes national integration and rural development (Government of Pakistan, 2013).

Both freight and passenger transport are the most important components of rail operations. An important characteristic of both demand components of rail transport is that their demand is a derived demand, and not the final one. For example, freight transport is usually considered as an input to the production process of firms and it is derived from the demand for goods spatially differentiated from the locations of production. Similarly, passengers do not use transport by simply for its own sake, rather transport services are acquired to satisfy a need at the end of a trip (such as education, work, recreation, etc.). The two important determinants of demand for rail passenger (freight) transport are real income (economic activity or output) and price, among other factors (see, for example, studies of Fitzroy and Smith, 1995; Kulsreshtha and Nag, 2000; Productivity Commission, 2006). The

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main objective of rail transport demand analysis is to identify the main factors that affect rail transport demand, which can further be used for rail transport planning and demand management. Empirically derived elasticity estimates provide valuable information to policymakers, transport planners, public agencies and transport operators and can help them to evaluate various policy options regarding the control of growth in future rail transport, modal-shift or emissions reductions. Furthermore, an accurate assessment of empirical rail transport demand model is crucial for making various key policy decisions such as price regulations, subsidies and taxes.

The empirical literature on rail passenger and/or freight transport dates back to the late 1960s and 1970s (see, for example, Evans, 1969; Morton, 1969; Tyler and Hassard, 1971). However, the studies of rail freight demand are relatively scarce in comparison to passenger demand studies. This has motivated and attracted the interest of researchers and academicians towards the analysis of rail freight demand and indeed some of the studies pertaining to freight demand are available. Most of the existing studies are often criticized on two grounds such as (i) Aggregate data bias and (ii) endogeneity bias (Wijeweera et al., 2014). Aggregate data bias occurs when data on total flows by modes at regional or national level is used while the information on selected freight commodities, routes and modes is ignored. On the other hand, endogeneity bias or problem arises due to the existence of possible simultaneity between freight transport and freight rate. Ignoring these endogenous relationships between price and quantity on rail freight demand may potentially bias the results. Some of the recent studies incorporate the possible feed-in-effects between freight rate and freight demand in their analysis of rail freight demand (see, for example, Kulshreshtha et al., 2001; Wijeweera et al., 2014). However, such empirical attempts are totally missing for a developing country like Pakistan, where rail transport has been the primary mode of handling most of freight transport. On similar lines, feedback effects from price to quantity demand may also be important for rail passengers or travel demand (see, for example, Kulsreshtha and Nag, 2000)

To the best of our knowledge, this is the first attempt of investigating the demand for rail freight transport in Pakistan. Similarly, empirical studies on rail passenger demand in Pakistan are also very limited as there is only one existing empirical study of Hussain et al. (2016) on rail passenger or travel demand So, the objective of the present study is to provide empirical analysis of rail passenger and freight transport demand in Pakistan using annual time series data from 1978 to 2018. To obtain elasticities, we utilize standard multivariate time series method such as Johansen co-integration and error correction model. The estimation results show that rail fare (freight rate) and real per-capita GDP (industrial production index) are important determinants of rail passenger (freight) demand in the long-run. Moreover, long-run cross-price elasticity of rail passenger and freight demand with respect to road transport costs is also positive, which means that road and rail transport are substitutes. Similarly, the impact of rail's route-density on rail passenger demand is positive and the most dominant in the long-run.

The organization of the chapter is as follows. Section 3.2 contains a survey of literature on rail freight and passenger transport demand whereas Section 3.3 deals with methodology and data. Results of the study are presented and discussed in Section 3.4. Finally, Section 3.5 concludes the study.

3.2 Review of Literature

This section is devoted to review the previous empirical studies on rail transport demand. Therefore, we first provide a review of empirical studies specific to rail freight demand and then explain studies on rail travel or passenger demand thereafter.

3.2.1 Literature Review of the Studies on Rail Freight Demand

The demand for freight transport has remained the focus of many empirical studies in the later part of the twentieth century. The empirical studies can be classified into several different ways. For example, Winston (1983) categorizes the empirical studies in two broad groups namely the aggregate or dis-aggregate demand models, which depend on the availability of data for estimation. The basic unit of observation in aggregate models is aggregate share of particular transport mode at a specific geographic location whereas dis-aggregate models involve the choice of particular transport mode by an individual decision maker (shipper) for a given shipment size. Regan and Garrido (2001) and Marcos and Martos (2012) summarize three approaches of modelling freight transport demand such as microeconomic models, econometric models and network-based models. The microeconomic models are based on the theory of firm, where firm's demand for transport service is treated as a demand for an input to the production process of a firm. The econometric models investigate the cause and effect relationships between freight demand and its determinants. On the other hand, network models use the optimal combinations of routing and (freight) traffic assignment, on a given network, to achieve network equilibrium (balancing supply-demand).

In a review article, De Jong et al. (2004) categorize the existing freight transport demand models on the basis of traditional four-step passenger transport modeling (Production and Attraction, Distribution, Modal split and Assignment). The Production and Attraction, Distribution and Modal split models are equally important part of other freight demand models, which further depend on the type of data used for the analysis. Both Production and Attraction and Distribution models can be classified on the basis of aggregate data. In general, gravity-type models are available for Distribution models. The Production and Attraction models are further divided into four types such as trend and time series models, system dynamics models, zonal trip-rate models and input-output models. On the other hand, modal split models are the dis-aggregate models, in which the allocation regarding freight flows to different modes (road, railway, inland waterway and combined transport) is determined. Modal split models are based on dis-aggregate (micro level) data at an individual level and are further categorized into aggregate modal split models, elasticity-based models, neo-classical economic models, econometric direct demand models, dis-aggregate modal split models, multi-modal network models and micro-simulation approach. Similar reviews of literature regarding freight transport modelling have also been offered in the following studies (Ben-Akiva et al., 2013; Chow et al., 2010; Nuzzolo et al., 2013; Tavasszy and De Jong, 2013).

The literature on freight transport demand is diverse in nature as it involves the choices of several decision makers (shipper, carrier(s), freight forwarder, and receiver) in the process of freight movements. So, we provide a brief survey of some previous aggregate rail freight demand studies.

In one of the earliest studies, Rao (1978) studies rail freight transport demand in Canada using simultaneous equations framework. The study's main objective is to quantify the effect of macroeconomic activity and inter-modal competition on rail freight demand. For that, he constructs a model for each commodity containing three simultaneous stochastic equations plus an identity to constitute a system. The first two equations in the system represent demand side while the third equation is of supply. The dependent variables in demand equations are volume (measured in million tons) of commodity carried by railway and average rail length of haul (measured as miles per ton) while the dependent variable in remaining third supply equation consists of rail freight rates (measured as average rail revenue per ton mile). To estimate the model using annual time series data from 1958-1973, two econometric methods such as ordinary least square (OLS) and two-stage least square (2SLS) are adopted. The results show that both export-share and commodity outputs are two significant determinants of rail freight demand, with estimated short-run output elasticity of rail freight demand is closer to unity. Similarly, the short-run inter-modal competition from trucking industry solely depends on the distance component of rail demand.

Oum (1979) formulates a derived demand model for Canadian intercity freight transport, based on three modes of transport such as railway, highway and waterway carriers, considering freight transport services as an intermediate input to the production and distribution sectors of the economy. Hence, in doing so, the study investigates freight transport demand by allowing the inter-modal competition between different modes (rail, highway, and waterway) of freight transport in a more comprehensive manner. To obtain the own-price and substitution elasticities, the study estimates transport demand functions derived from translog transport cost functions for three modes (railway, highway, and waterway) using maximum likelihood (ML) method of estimation. Annual aggregate time series data is used for the period 1945-1974. The study finds that initially both Canadian rail and trucking freight transport demand are less sensitive to their respective freight rates whereas such responsiveness increases over time albeit being inelastic. On the other hand, freight demand for waterway services is relatively more sensitive to its freight rate at the start and also remains stable over time. Regarding the elasticities of substitution, study also reveals that railway and waterway carriers are complementary till 1955 but become more competitive thereafter. Moreover, the relationship between railway and waterway carriers turns out to be highly competitive throughout the period of investigation.

Fitzsimmons (1981) employs an ad-hoc model to analyze competition between rail and barge transport for United States grain transport. The main variables of the study are rail volumes, barge and rail rates and use of domestic grain (output). The ordinary least square method is adopted for estimating log-linear model. Estimated output, own price (rail-rate) and cross-price (truck-rate) elasticities of rail grain transport are 0.740, -1.21 and 2.43, respectively.

Lewis and Widup (1982) follow an approach similar to Oum (1979) but within the U.S context. The study develops a derived transport demand model using translog transport cost function for motor carrier shipments of two modes (rail and road). An important feature of the study is that it incorporates eight 'quality of service' variables into the analysis and uses annual data for single commodity such as assembled automobiles from 1955 to 1975. Using different static and dynamic specifications, the estimated price elasticities of rail are larger than those of trucking in absolute value. In particular, the estimated price elasticity of trucking is between -

0.52 and -0.57, and that of rail is between -0.92 and -1.08. However, regarding quality of service variables, the study finds that transit time is the only significant variable while cross price elasticities for both modes such as trucking and rail reveals that they are competitive.

In a different study, Wilson et al. (1988) investigate the markets of rail and road transport for wheat shipments in the United States. For that, the authors built a model in which both supply and demand functions are treated as a system of behavioral equations. The results are obtained using three-stage-least-square (3SLS) method on monthly data from 1973:7 to 1983:6. The findings of the study suggest that rail rates are more strongly affected by the factors representing competition from trucks (such as availability of rail cars, technological improvement and fuel prices) than by the rail costs. Moreover, all price elasticities pertaining to rail transport are elastic, and those of trucking largely depends on the availability of rail cars.

Miljkovic et al. (2000) construct a model of rail freight and barge market to assess the factors having major impact on rail and barge rates for export-bound grain from Midwest Illinois to Mexican Gulf exporting ports. Their model consists of a system of four equations plus two identities, with first two equations being supply and demand for barge industry whereas second pair represents the supply and demand equations for rail industry. Three stage least square (3SLS) method is used on an annual data from 1980-1995 to estimate the model's parameters. The results based on demand equations show that both modes (rail and barge) are strong substitutes, and that no significant relationship exists between transport rates and export-related variables. Similarly, the direct relationship between price and quantity is significant only in the supply equation of rail. A major limitation of the study is that it fails to identify the single most important factor for transport (rail and barge) rates due to the interactive nature of demand and supply processes.

Mitchell (2010) analyzes the Australian inter-capital non-bulk freight demand based on three modes road, rail and air. For estimation, the study uses two different flexible functional forms such as (1) a generalized translog cost function and (2) an aggregate linear logit expenditure share system. The data for estimation covers a period of 1973-2001. The study adopts full information maximum likelihood estimation method (FIML) to derive model's parameters. However, the estimates derived from the above functional forms produce quite different results. In particular, the translog model not only violates the principle of concavity[8] but also reports, for many cases, the larger estimated short-run own and cross-price elasticities

[8] The principle of concavity implies that translog cost function is concave in input prices.

than their long-run values. On the other hand, linear logit model outperforms the translog model in both of these respects that not only estimated short-run own and cross-price elasticities are smaller than their long-run counterparts but also that concavity holds for linear logit model. Therefore, results derived from linear dynamic logit model suggests that in short-run, Australian non-bulk road freight demand is relatively inelastic across all corridors (short, medium and long-distance routes)[9], and also remains relatively inelastic in long-run for short and medium routes. The results regarding non-bulk rail freight demand are quite similar to non-bulk road freight demand except that the estimated elasticities, on average, are relatively larger for rail freight demand than road freight demand. Finally, non-bulk inter-capital sea freight is elastic and more responsive to medium and long-distance routes.

Babcock and Gayle (2014) examines the U.S (as well as the east and the west regions) railroad grain transportation demand for major commodities such as wheat, soybeans, and sorghum during 1980 to 2010. The authors adopt a two-region spatial equilibrium model, an approach developed by Yu and Fuller (2005). The main variables of study are grain transport (measured as thousands of tons) by rail, rail freight price (measured as rail revenue per ton), grain production (soybeans, corn, wheat and sorghum), barge rates (to represent cross price elasticity of railroad grain transport demand). The study incorporates two estimation methods. In addition to ordinary least squares (OLS), the generalized method of moments (GMM) principle is also adopted to take care of possible feed in effects from rail freight rate to railroad grain transportation. A formal statistical test suggests that rail freight price is endogenous variable. Three variables such as railroad diesel fuel price, railroad labor cost and number of covered hopper railcars are used as instruments for own price in regression. The findings based on generalized method of moments (GMM) imply that railroad grain transport demand is significantly determined by all the explanatory variables considered above. The own price, elasticity of grain output and cross-price elasticity of railroad grain transport are -1.23, 0.95 and 0.48, respectively.

Studies on freight demand tend to produce a wide range of price and output elasticities and hence make it difficult for researchers to generalize the results of different studies. In addition to the primary studies, some analysts also review the previous econometric studies on rail and road freight transport demand to have consensus on the possible range of elasticities

[9] The short-distance intercapital corridor consists of less than 1200 km while medium- distance is between 1200km to 1800km. Moreover, the long-distance route is greater than 1800 km.

(see, for example, Clark et al., 2005; Oum et al., 1990, 1992; Winston, 1983; Zlatoper and Austrian, 1989). In their review of road and rail freight market elasticities, Oum et al. (1990) examine 17 freight studies from Asia-pacific, UK and North America and report estimates pertaining to all major commodity groups and grains only. According to their survey, price elasticities regarding all commodities are in a range of -0.60 to -1.52, whereas those of grains are between -0.52 to -1.18. The analysts also provide the possible reasons for obtaining a wide range of elasticities in the existing literature. These are intensity of inter-modal competition between different modes, differences in geographic locations and time horizons, degree of aggregation in markets and use of different functional forms (Oum et al., 1992).

Rail freight transport demand studies, based on time series data, are generally aggregate in nature and incorporate few broad macroeconomic variables for estimation. Recent studies employ multivariate time series econometric methods such as co-integration and vector autoregressive models to analyze aggregate freight transport demand (Kulshreshtha et al., 2001; Ramanathan, 2001; Wijeweera et al., 2014). Ramanathan (2001) examines long-run association between the performance of Indian transport sector using two-step Engle-Granger co-integration and error correction model. An aggregate passenger (passenger-kilometers) and freight transport (ton-kilometers) activity of three modes road, rail and air is added together to develop a separate econometric model for both passenger and freight transport. Using annual data for the period 1956-1989, the study finds that long-run freight demand is determined by the industrial production and price index. The estimated long-run output and price elasticities of freight transport are 1.183 and -0.188 while their values in the short-run are 0.994 and 0.072, respectively. The error correction term shows that ton-kilometers adjust 40% in the first year to restore its long-run equilibrium.

A major limitation of Ramanathan's study is the presumption of existence of at most one co-integrating vector even for multi variables case and also does not treat the possible endogeneity of explanatory variables well. Kulshreshtha et al. (2001) recognize these issues in their analysis of freight transport demand for Indian railways. They employ the Johansen co-integration and error correction model on annual time series data for the period 1960-1995. The empirical results show that a unique long-run co-integration relationship exists among rail freight demand, freight-rate and GDP. The long-run output and price elasticities of rail freight demand are 0.86 and -0.20 while the short-run elasticities are smaller than their long-run values. Furthermore, the system corrects itself within 3 years from any short-run disequilibrium through the adjustments in GDP and freight transport demand while price variable (real freight rate) behaves weakly exogenous with respect to the system.

Wijeweera et al. (2014) apply the concept of Vector Autoregressive (VAR) model on an annual data for the period 1970-2011 to examine the effect of business cycle (GDP), freight rate and international trade (nominal exchange rate) on non-bulk Australian rail freight demand, treating all variables symmetrically (endogenous). The results derived from impulse response functions (IRF) and forecast error variance decompositions reveal that two most important determinants of rail freight demand are freight rate and variation in Australian dollar. In particular, a depreciation of Australian dollar promotes rail freight demand in Australia. Moreover, authors also find that, in the long-run, there exists negative and significant association between freight-rate and rail freight demand whereas the effect of GDP on Australian non-bulk rail freight demand is negative albeit insignificant.

Few studies employ several econometric methods for freight demand estimation and analyze the differences in the estimation results (Chung and Kang, 2015; Shen et al., 2009). Shen et al. (2009) utilize six econometric models to derive empirical estimates of output elasticities for both aggregate road plus rail freight transport as well as for different commodity groups and compare elasticities using different econometric techniques. These econometric models are traditional ordinary least square (OLS) regression model, partial adjustment model (PAM), reduced auto-regressive distributed lag model (ADLM), unrestricted vector auto-regressive (VAR) model, time varying parameter (TVP) model and structural time series (STS) model. The authors find some variation in resulting coefficients (elasticities) derived from various techniques. The estimated long-run output elasticities range from 0.720 to 1.485. The study also compares the forecasting performance of all models using Mean Absolute Prediction error (MAPE) criteria and finds that no single model outperforms others in all situations.

Andersson and Elger (2012) investigate empirical relationship between Swedish freight transport (aggregate as well as for each specific mode such as road, rail, and sea) and economic activity (GDP, industrial production, imports and exports) at three different time horizons (short-run, medium-run and long-run) using annual time series data for the period 1996 to 2007. The study adopts Engle (1974)'s band spectrum regression as a method of estimation. According to this model, each variable is first decomposed into different components (short, medium and long-run) and then a different model is estimated for each time horizon. The results indicate that all variation (volatility) in freight demand from short to medium-run is mainly driven by temporary changes in exports and imports while GDP remains insignificant. However, in long-run, GDP coupled with freight demand exert a significant positive impact on freight transport demand for all transport modes. The long-run income elasticities, for different transport modes, vary between 0.9 and 2.6.

Recently, European studies investigate the freight demand in a multimodal framework (Beuthe et al., 2001; Jensen et al., 2019; Jourquin, 2018; Rodrigues et al., 2015; SteadieSeifi et al., 2014), where different modes (road, rail, water, etc.) are well integrated to facilitate the freight movements (from origin to destination) in an optimal manner. Many studies use the network modelling to derive the multimodal freight demand elasticities. The model incorporates following characteristic; Predicting both mode and route choices simultaneously, the network model can choose many such combinations of mode-route choices over a network, for a given origin-destination pair. Then, optimal combination, the one with the minimum cost, can be obtained with the help of algorithm. So, multimodal transport network describes a process of handling transport chains such that moving a consignment from door to door involves the use of several interlink modes. For example, Beuthe et al. (2001) use the geographic information multimodal network model to compute the direct and cross elasticities of freight demand (tons and ton-kilometers) for three modes of freight transportation in Belgium such as road, rail and waterways. The model uses the knowledge of both origin-destination matrices for 10 different commodity groups and cost information of transport operations to minimize the generalized cost of corresponding transportation tasks through an optimal assignment (mode and route choice) of flows between modes, routes, type of vehicles. The freight demand elasticities of road, rail and waterways are derived with respect to the variations in total costs, travel costs and distance (short vs. long) scenarios. The results regarding direct elasticities, based on all or nothing assignment, show that aggregate elasticity of road freight transport is elastic (inelastic) when measured in ton-kilometers (tons) while those of rail and inland waterway demands are both elastic. The smaller elasticities of both water and rail are observed over long distance than for short distance. The cross-elasticities of aggregate demand imply that each transport mode is a substitute of other, in all cases. Moreover, the commodity specific direct elasticities indicate that road transport is more competitive or dominant for commodities (petroleum products) suitable for short distance movements than for those with movements over a long distance (solid fuel). Similarly, rail freight elasticity is more elastic for agricultural products and animals while the elasticity of inland waterways with respect to metallurgic products is the highest.

Using a combination of operational research and multinomial logit model, Jourquin (2018) employs a digitalized network model to derive the direct and cross elasticities of freight transport demand for Benelux countries, where three modes such as road, railway network and inland waterways are more competitive, and also for Europe. For that, the generalized cost (loading, unloading, travelling, fixed, etc.) of each transport mode on a network and each of 10 commodity groups is obtained from the origin-destination matrices. The conditional logit choice model is estimated (for each commodity group) with generalized cost is the only explanatory variable in the utility function. The direct and cross elasticities of freight demand with respect to variation in both generalized cost and travel time on a network are derived using a box-cox transformation. The model validation exercises are also done, and the results indicate a good match between observed flows and model outputs. For Europe, the elasticities of road, rail, and inland waterways, derived from a reduction in generalized cost scenario, are -0.36, -1.43 and -1.71, respectively while these same elasticities, for Benelux, are -0.39, -0.94 and -1.50, respectively. The study also makes comparison of cost elasticities to other multi-mode studies and observes some variation in elasticities, owing to various factors such as differences in methodology, data, spatial scope, zoning, and transport markets.

Jensen et al. (2019) analyze the dis-aggregate stochastic model of transport chain choice for Europe. The study uses two different survey data sets on commodity flows (Sweden, 2009 & France, 2004) at an individual shipment level. The data set consists of information regarding commodity type, volume, weight, mode information, value from the shipment and consistency, and origin-destination from the segment of transport chain. The commodity flows data is converted into different zones and segments of transport chains (only road, rail, Roll-on-Roll-off ferries, inland waterways, or any combinations of modes) to minimize the generalized transport costs. It further combines both data sets with the level of service (LOS) information, derived from European freight networks, to estimate the transport chain choice model. The model incorporates 9 different single and multi-mode chain alternatives such that three of them can be either container or non-containerized general cargo. The freight transport is divided into containers, general cargo, liquid bulk and dry bulk, which are further classified into 10 commodity groups. Different models, with different cost specifications and nesting structures, are estimated using multinomial nested logit model. Different elasticities such as travel time, transport cost, values of transport time and mode specific elasticities are computed through simulations. The results show that several factors such as transport time, transport costs, commodity type, direct access to rail & waterways and value density of goods matter for transport chain choice.

3.2.1.1 Previous Studies on Rail Freight Transport in Pakistan

Although some empirical freight transport studies exist for Pakistan, none of them have investigated the issue of demand for rail freight transport properly. For instance, Beenish et al. (2016) explore the nexus between railways freight performance (measured as goods transported) and economic growth (GNI growth-rate) in Pakistan for period 1980-2012. The study employs Johansen co-integration and error correction test based on Fully Modified Ordinary Least Square (FIML) to estimate the existence of stable long-run relationship between above stated variables. The results indicate that a stable long-run relationship exists between rail freight performance and economic growth and also that only economic growth (GNI growth-rate) responds to short-run deviations to re-establish long-run equilibrium relationship whereas freight performance remains weakly exogenous to the system. Moreover, Granger causality test indicates that weak uni-directional causality runs from economic growth to rail freight performance.

In a different perspective, Choudhary et al. (2009) treat road and rail transport activity as transport infrastructure and analyze freight transport infrastructure in Pakistan using Porter's (1980) framework for time series data from 1990-2008. The forecasting freight transport demand (road, rail and aggregate) until 2030 based on historical trend analysis reveals that road freight demand is likely to grow continuously at an annual growth rate of 6.2% to 7.2 % provided that the GDP growth rate remains 6% or above. According to the freight projections, the share of road freight transport will remain a major and dominant mode with a share of 95% in terms of freight movement while share of rail freight transport will continue to remain at 5% or less in future.

3.2.2 Literature Review of Rail Travel or Passenger Demand

Understanding the main drivers of rail passenger or travel demand is crucial in making various key policy decisions (travel demand management, frequency of rail operations, investment in rail infrastructures, etc.) in a more effective manner. Therefore, many past empirical studies have analyzed the factors affecting rail travel demand (Bekõ, 2004; Doi and Allen, 1986; Fitzroy and Smith, 1995; Fowkes et al., 1985; Jones and Nichols, 1983; McGeehan, 1984). For example, Jones and Nichols (1983) first investigate the UK inter-city rail travel demand using four week ticket sales data from London to 17 provincial centers during 1970-1976; the results based on ordinary least square (OLS) estimation show that average real rail-fare, rail travel time, (cyclical) economic activity and level of road services are the main determinants of inter-city rail travel in London. In a different study, Doi and Allen (1986) use monthly US ridership data to estimate the demand for rail ridership on a single urban rail rapid-transit-line with two functional forms such as linear and logarithmic. The fare elasticities of US rail ridership in logarithmic and linear models are -0.245 and -0.233, respectively. Later on, using quarterly and monthly data from 1992 to 2002, Bekõ (2004) examines the relationship between the demand for public railway passenger transport in Slovenia to different groups of explanatory variables like price, income, socio-economic and seasonal variables; The study finds that both income and fare effects are inelastic and are important determinants for railway passenger transport in Slovenia, which implies that passengers treat public railway transport in Slovenia as an essential normal good, and also that railway authorities can increase the rail passenger revenues by raising the rail fare.

A major problem associated with most of above cited rail travel studies is that they have estimated the demand model with contemporaneous relationships of variables, implicitly assuming that rail passengers quickly adjust their travelling behavior in response to a change in any one of the relevant factors in travel demand function (e-g. rail-fare, income, quality of rail services, prices & services of competing modes, etc.). However, later studies employ dynamic models to incorporate explicitly both short-run and long-run responses in rail travel demand analysis and conclude that responsiveness of travel demand is not instantaneous, and that short-run behavioral responses are quite different to those of long-run responses (Owen and Phillips, 1987; Voith, 1991). Moreover, ignoring such differences between short and long-run demand responses may also have serious implications for policymakers and planning agencies in making appropriate policy decisions. For instance, both Owen and Phillips (1987) and Voith (1991) find that short-run rail travel demand is inelastic while the long-run effects of fare change on rail travel are more elastic, which means that rail operators can generate additional passenger revenues by increasing the rail fares in the short-run. However, such policy would be counter-productive in the long-run because passengers' travel behavior may change over time in response to a rise in price level. Therefore, a considerable risk is involved in making policy decisions emanating from static travel demand studies without differentiating between short and long-run responses (Wijeweera et al., 2014).

The above time series rail travel studies can further be criticized for not considering the issue of non-stationarity. In most applications, time series data is non-stationary such that mean and variance are not constant over time. Therefore, ignoring non-stationarity of variables in a regression model may lead to spurious relations, which may result in biased co-efficient estimates and invalid statistical inferences (Granger and Newbold, 1974). Subsequent studies have considered these issues in their analysis and therefore utilize the time series econometric methods such as co-integration and error correction models to specify the rail travel demand relationships (Coto-Millán et al., 1997; Kulsreshtha and Nag, 2000; Rahman and Balijepalli, 2016; Wijeweera and Charles, 2013a, 2013b; Wijeweera et al., 2014).

Coto-Millán et al. (1997) first apply the Johansen multivariate co-integration and error correction model to investigate the determinants of Spanish inter-city passenger transport demand for different modes road, Talgo-rail (highest quality), long-distance rail (lowest quality) and air using quarterly data from 1980-1992. For Talgo-rail demand, the estimated long-run (short-run) fare, GDP, and cross price (fuel price) elasticities are -1.70 (-0.85), 1.18 (3.65) and 0.76 (0.73), respectively. However, the demand for long-distance rail transport is significantly related to fare and fuel price, with long-run estimates are -0.68 and 0.37 while the effect of fuel price, in the short-run, is only significant in long-distance rail demand equation with a value of 0.56. For a developing country, Kulsreshtha and Nag (2000) study the determinants of passenger demand for rail transport in India for three classes (lower, second and upper-class) and employ Johansen's co-integration method to estimate a separate demand model for each passenger-class. The results show that both price (fare) and income are important drivers of the demand for all three classes, with long-run price elasticities of three classes vary between -0.87 to -2.27 and those of income elasticities are in a range from 0.61 to 1.42.

In a recent study, Wijeweera et al. (2014) use single equation Engle-Granger co-integration technique to analyze the rail travel demand in four main Australian cities[10]. The study chooses to measure the impact of several explanatory variables such as rail-fare, per-capita income, fuel price index, city population, vehicle-price index, and also quality variables (annual rail kilometers run, rail fatalities) on the dependent variable e.g. boarding passengers in each city's rail travel demand equation. They show that fare, city population and rail kilometer runs are the key determinants of city's rail travel demand. Likewise, Rahman and Balijepalli (2016) estimate and compare the fare and other elasticities of rail travel demand in three Indian cities Kolkata, Chennai and Mumbai, segmenting further into five suburban

[10] The main cities are Adelaide, Melbourne, Perth and Sydney.

divisions Chennai, Mumbai (Central, Western), Kolkata (Eastern, South Eastern). Three econometric models such as static (OLS), dynamic (error correction model and partial adjustment model) and panel data models are applied on time series data to estimate the effects of several variables on the demand for each sub divisional rail transport. Moreover, they also adopt bootstrapping regression method to deal with small sample size. In general, the results indicate that overall rail travel demand is inelastic, as the fare elasticity is less than 1. Other variables e.g., petrol price and vehicle kilometers are also considered important for rail demand in most of the cities.

Some panel studies have also examined the cross-section or cross-country variations in rail travel demand. For example, Voith (1991) use dynamic panel data of SEPTA commuter rail system (129 stations) from 1978 to 1986 to study the impact of fares and service related variables on rail ridership in short and long-run. The estimation results show that long-run elasticities of ridership are two-times larger than short-run elasticities. In a different study, Asensio (2000) investigates the rail travel demand of 11 suburban areas of Spanish railways and finds that (fare) price and rail quality indicators play a significant role in determining rail travel demand. Chen (2007) estimate the demand for passenger rail transport in London to 46 origin stations during 1995-2002 and results from fixed effects model indicate that fare, employment and gross value added are important for rail transport demand, with estimated elasticities are -0.76, 2.26 and 0.89, respectively. Recently, Canavan et al. (2018) analyze the demand for urban metro rail transport of 32 world metro systems using panel data from 1996 to 2015. The study incorporates two different indicators (passenger-kilometers and passenger journeys) to represent rail passenger demand and regressors in both models are rail fare, income, quality variables of rail transport, rail network and population. The results show that all explanatory variables exert a significant and positive impact on both measures of rail travel demand except for the coefficient associated with fare, which is significant and negative. Moreover, for both passenger-kilometers and passenger journeys, the long-run income and price elasticities are less than one, which also offer important policy implications for urban metro rail organizations regarding the use of fares to increase passenger earnings.

3.2.2.1 Empirical Studies on Rail Travel Demand in Pakistan

An extensive empirical literature regarding rail travel demand is available for developed countries, which has almost reached to maturity. On the other hand, understanding of empirical rail travel demand in developing countries is relatively limited. In particular, only one empirical study of Hussain et al. (2016) have investigated the rail passenger demand in Pakistan. The study's main explanatory variables are average rail-fare, real per-capita GDP, fuel-price and population, which are expected to be important for rail passenger-kilometers' demand. The study's main result is that rail-fare and fuel-price (high-speed diesel) are statistically significant and negatively related to rail passenger-kilometers, while both real per-capita GDP and population exert significant positive impact on rail passenger-kilometers. A major limitation of the study is that since road is the main competitor of rail, its price or costs is not considered. One wonders about the exact role of fuel-price variable in rail travel or passenger demand analysis since, as a cost, it mainly affects the supply of rail transport. If it is used as an approximation of road's travel costs (as in many empirical studies), one would expect a positive influence on rail travel demand. All that is not clear and rather dubious, and one may question whether the estimated rail demand function is not just a descriptive relation rather than a demand function.

3.3 Methodological Framework and Data Related Issues

The next section provides details about econometric model of aggregate rail freight demand, followed by rail travel demand while econometric co-integration approach will be discussed thereafter. The data related issues will be explained after methodology.

3.3.1 Model of Rail Freight Transport Demand

Since freight transport is generally considered as an intermediate input to the production process of firms, its demand can be derived from production and distribution sectors of the economy. Therefore, demand function of freight transport, just like demand functions of many other inputs, can be derived from a typical representative firm's optimization problem (profit-maximization or cost-minimization). In their survey, Oum et al. (1992) explain the concepts of transport elasticities and provide an excellent discussion on the derivation of freight and passenger demand functions. So, for this section, we follow their study to derive a general form of freight demand function. Consider a production function $Q = Q(l, d, \varepsilon)$ of a representative profit maximizing firm, which maximizes profit with given output level and input prices. Where l, d and ε are the vectors of inputs, firm's observed characteristics and other unobserved variables, respectively. The optimal $l^*$and Q^* that maximizes firm's profits are the input demand and output supply functions of the firm and can be given by the following form,

$$l^* = l(P, w, d, \varepsilon) \tag{3.1}$$

$$Q^* = Q(P, w, d, \varepsilon) \tag{3.2}$$

Where P and w are the vectors of output and input prices, respectively. An important point regarding input demand function in (3.1) is that it does not contain firm's output as an argument, which is completely opposite to the input demand function, which is derived by minimizing firm's costs for a given level of output. The conditional input demand function, in that case, will be :

Min wl subject to $Q(l, d, \varepsilon) \geq Q_0$

$$l^* = l(Q, w, d, \varepsilon) \quad (3.3)$$

Since input demand function in eq. (3.3) is derived by keeping output fixed, the resulting elasticity of demand captures pure substitution effect due to price change. However, the elasticity of input demand related to equation (3.1) captures both substitution and output or scale effect due to a price change.

To measure the (ordinary) price elasticities of freight demand, equations (3.1) and (3.2) reveal that a demand system must be estimated simultaneously with output decisions of shippers. However, ignoring such output decisions by shippers is similar to the assumption that changes in freight-rates do not alter the output levels.

Generally, it is unclear as what type (conditional or ordinary) of input demand elasticities do most ad hoc freight demand models estimate? For a time series study, the resulting elasticities would be more appropriately treated as ordinary demand elasticities if shipper's output is not appeared in demand function. However, the elasticities would be considered as conditional demand elasticities when shippers' output appeared in demand function or equation (see, for example, Oum et al., 1992).

Since several decision-makers (such as shipper, carrier(s), freight forwarder, and receiver, etc.) are involved in moving freight from origins to destinations, it would not be easier to provide sound theoretical basis or model of rail freight transport demand at macro level. Therefore, we specify an aggregate model of demand for rail freight in the following form, which is generally consistent with previous empirical studies on aggregate demand for rail and/or road freight transport (Kulshreshtha et al., 2001; Ramanathan, 2001; Shen et al., 2009):

$$TKM = f(FR, IPI, TR, FP) \quad (3.4)$$

Or a more specific econometric model of rail freight demand in double log-form is specified as follows

$$lnTKM_t = \pi_0 + \pi_1 lnFR_t + \pi_2 lnIPI_t + \pi_3 lnTR_t + \pi_4 lnFP_t + u_t \quad (3.5)$$

Where 'TKM' is ton-kilometers, 'FR' is for freight-rate, 'IPI' represents the industrial production index, 'FP' is fuel-price, π's are the parameters or elasticities to be estimated and u is the error-term. Each of the variables in equation (3.5) is explained below:

Ton-kilometers (TKM): Our objective is to analyze the major determinants of rail freight demand using time series data. Different indicators can be used to represent rail freight demand such as (1) freight moved by its weight (measured in thousand or million tons) and (2) freight moved by both its weight and distance covered (measured by ton-kilometers). We measure rail freight demand by ton-kilometers, which is a more appropriate measure of freight demand. Many empirical rail freight studies have used ton-kilometer or ton-miles as a measure of rail freight transport demand (see, for example, Kulshreshtha et al., 2001; Rao, 1978; Wijeweera et al., 2014). We focus on the major factors affecting rail freight demand in Pakistan.

Freight Rate (FR): Rail freight demand, like demand for many other products, is a function of its own price, which is rail freight rate. Rail freight rate is the rate charged by rail authorities for moving freight (measured as ton-kilometers) from its origins to destinations. Since time series data on actual rail freight rate is not available for Pakistan, we use a proxy of rail freight rate as average-rate-charged-per-ton-per-kilometer. It can be derived by taking ratio of total annual rail freight earnings to total annual ton-kilometers performed by rail freight. The expected sign of the coefficient associated with freight rate is negative (as per law of demand) i.e., $\pi_1 < 0$.

Industrial Production (IPI): Since freight transport can also be perceived as an input or cost in production process, it can also be related to output or economic activity. An increase in aggregate output or production is likely to raise the rail freight demand. Therefore, the expected sign of π_2 is positive. There are number of indicators that can be used to represent aggregate economic activity. These are gross domestic product (GDP), industrial production and gross value added (GVA). All three indicators have been used in aggregate empirical freight transport studies for economic activity (Andersson and Elger, 2012; Kulshreshtha et al., 2001; Ramanathan, 2001; Shen et al., 2009). However, McKinnon (2007) and, Agnolucci and Bonilla (2009) are of the view that GDP is an incorrect indicator to use for economic activity because GDP measures the value of both goods and services. However, service activities are likely to produce less freight demand than production of goods. Therefore, a model with GDP as an indicator of output or economic activity may underestimate the income effect or elasticity. So, we use an index of large-scale manufacturing industries (LSMI) as an industrial production index (IPI) for production or economic activity, as it is more closely related to goods movements than GDP and can be a better measure of aggregate domestic production activities. For IPI, year 2005-06 is used as a base year.

International Trade Openness (TR): Trade (openness) variable is included in our model to capture the impact of goods movements with other trading countries on rail freight demand in Pakistan. Theoretically, an increase in trade with other countries is likely to increase aggregate freight demand in Pakistan, including rail freight. Therefore, the expected sign of π_3 is positive. Some of the existing aggregate empirical rail freight studies have also incorporated trade variable in their analysis (see, for example, Andersson and Elger, 2012; Wijeweera et al., 2014) We measure international trade as a ratio of GDP in Pakistan.

Fuel Price (FP): Trucking is the main competitor of rail freight in Pakistan. However, time series data regarding trucking rates are not available. Therefore, fuel price, particularly the price of high-speed diesel, is used as an approximation for trucking costs. So, fuel price is used to measure the cross-price elasticity of rail freight transport. The previous studies have estimated the cross-price elasticity of rail freight transport (FitzRoy & Smith, 1995; Oum, 1989). The expected sign of fuel price is positive because an increase in trucking costs will be associated with more demand for rail freight and vice-versa and is measured in rupees/liter.

In addition, many service quality indicators such as route coverage, frequency and reliability are also highly relevant to rail freight transport. However, the absence of long time series data on these variables limits their use in our analysis.

3.3.2 Economic Model of Rail Passenger or Travel Demand

As a derived demand, the passengers' demand for rail services are not acquired simply for its own sake of travelling, rather, they are demanded to satisfy some other objective (education, job, business, etc.) at the end of a trip. There are two basic economic approaches that can be used to derive the demand function of passenger transport such as maximization of a representative consumer's utility function subject to a given budget constraint or minimizing the expenditures or costs to achieve a given level of utility. In other words, the demand function which is obtained by maximizing the utility function is known as Marshallian or ordinary demand function while other one is termed as Hicksian or compensated demand function. Hicksian price elasticity captures only substitution effect if price change since utility level is kept fixed in Hicksian demand. However, Marshallian price elasticity measures both income and substitution effect of a given price change. Since Hicksian demand function also depends on utility, which is not directly observable, therefore, it is practically not estimable. So, passenger demand models, from all facets of transportation demand, are Marshallian demand functions and provide the associated elasticities. To analyze the inter-city travelling behavior in Spain, Coto-Millán et al. (1997) develop a theoretical model of passenger transport demand for three modes road, rail and air. We also follow their approach to derive a representative passenger's demand function of rail travel in the following way.

Modelling travel demand for a typical passenger having weakly separable preferences involves two stage budgeting process[11]. At first stage, the passenger assigns total spending among two broad groups namely passenger travel services and all other remaining goods and services. At second stage, passenger allocates his income to the goods and services included in each of these two groups. Therefore, the representative passenger's utility function can be written as:

$$U = U\left(x_1, x_2, \dots\dots, x_i, y_{i+1}, y_{i+2}, \dots\dots, y_j\right) \tag{3.6}$$

Where U is the passenger's utility function and we assume that certain properties such as continuity, differentiability, monotonicity and strict quasi-concavity hold for this utility function[12]. Where $x_g = (x_1, x_2, \dots\dots, x_i), g = 1,2, \dots\dots, i$ is the vector of passenger travel services while the other vector $y_h = \left(y_{i+1}, y_{i+2}, \dots\dots, y_j\right), h = i+1, i+2, \dots\dots, j$ is used to represent all goods and services other than passenger travel services. The passenger's optimization problem can be described as following:

$$\text{Max } U = U(x_g, y_h) \tag{3.7}$$

Subject to $p_g x_g + p_h y_h = Y$

Where $p_g = (p_1, p_2, \dots\dots, p_i)$ and $p_h = (p_{i+1}, p_{i+2}, \dots\dots, p_j)$ are the vectors of prices and Y is the passenger's income. Some other studies on passenger transport also adopt a similar

[11] Generally, both weakly and strong separable preferences are discussed in consumer's theory, which depend on the nature of relationship between different commodity groups. Strong separable preferences assume that each commodity belongs to a separate demand group, which implies that utility obtained from consuming a specific amount of commodity is independent of the consumption of all other commodities. This assumption is very restrictive and seems unrealistic. On the other hand, consumer's preferences are weakly separable if commodities can be further classified into sub-groups of commodities such that the marginal rate of substitution between any two goods in a particular group is unaffected by the consumption of commodities in any other group.
[12] Also see Mas-Colell et al. (1995) for a good discussion of these properties.

consumer optimization approach (see, for example, Bekõ, 2004; Coto-Millán, 2012; Oum et al., 1992).

The general solution of above optimization problem yields the first order conditions in the form of ordinary demand functions, which are as follows:

$$x_g = x_g(p_g, p_h, Y) \tag{3.8}$$

$$x_h = x_h(p_g, p_h, Y) \tag{3.9}$$

The above functions represent the demand function of passenger travel and demand function of all other goods and services except passenger travel, respectively. The first demand function in equation (3.8) is more relevant to us as we are dealing with rail passenger demand. The demand function is in generalized form, which can be used to analyze the rail travel demand in Pakistan. Therefore, a general economic model of rail travel demand using above demand function can be written as following:

$$PKM = f(RF, GDP, FPI, Route, POP) \tag{3.10}$$

The above rail travel demand model can be written in a more consistent econometric double log-form as following:

$$lnPKM_t = \lambda_0 + \lambda_1 lnRF_t + \lambda_2 lnGDP_t + \lambda_3 lnFPI_t + \lambda_4 lnRoute_t + \lambda_5 lnPOP_t + \vartheta_t \tag{3.11}$$

Where 'PKM' is used for passenger-kilometers, 'RF' stands for rail-fare, 'GDP' is real per-capita gross domestic product, 'FPI' represents the fuel-price index, 'Route' is route-density, 'POP' is population, and ϑ is the error-term. Equation (3.11) is specified in logarithmic-form and consistent with most of empirical literature on transport demand, because co-efficients λ's have direct interpretation in terms of elasticities of rail travel demand (see, for instance, Kulshreshtha et al., 2001; Rahman and Balijepalli, 2016; Ramanathan, 2001; Wijeweera et al., 2014). Each variable in above equation (3.11) can be explained as follows:

Passenger-kilometers (PKM): Rail travel demand is the focus of our analysis. Different indicators have been used to measure the demand for rail travel as the dependent variable. A significant amount of empirical rail demand studies have used passenger-kilometers (PKM) as the dependent variable for rail travel demand (See, for example, Coto-Millán et al., 1997; Kulsreshtha and Nag, 2000; McGeehan, 1984; Rahman and Balijepalli, 2016). However, some other studies have also employed total passengers or boarding passengers for rail travel demand

(Bekõ, 2004; Albert Wijeweera et al., 2014). Using 'PKM' as an indicator for rail travel demand is preferable because it measures both passengers and their travelling distance simultaneously. So, we use passenger-kilometers (PKM) as dependent variable for rail travel demand.

Rail-Fare (RF): Rail-fare is used to capture the own price effect in rail travel demand. Although rail ticket prices might seem more suitable for rail-fare, complexities associated with aggregating different ticket groups (student-fare, full-fare and off-peak fares) into a single value will result in serious complications (Albert Wijeweera et al., 2014). To avoid this, Kulsreshtha and Nag (2000) and Rahman and Balijepalli (2016) used average-revenue-per-passenger-kilometer as a proxy of rail fare while Jones and Nichols (1983) and Wijeweera et al. (2014) utilized average-revenue-per-kilometer as a proxy of rail fare. Since time series data on ticket prices is not available for rail transport in Pakistan, we adopt average-revenue-per-passenger-kilometer as a proxy of rail-fare and denoted by RF_t. The expected sign associated with the co-efficient of rail-fare is negative i.e. $\lambda_1 < 0$.

Real per-capita GDP (GDP): Income is an important determinant of rail travel demand. If the impact of income on rail travel demand is positive, then the rail travel can be treated as the normal good while it is an inferior good if the relationship between rail travel and income is negative. We use real GDP per-capita (at constant prices of 2005-06) as a proxy of rail passengers' income and expect a positive relationship between GDP per-capita and rail travel in Pakistan i.e., $\lambda_2 > 0$.

Fuel-Price Index (FPI): Since rail passenger transport faces a strong competition against road transport (from medium to long-distances), this variable is incorporated into the analysis for measuring the substitution effect or cross-price effect. However, A big chunk of road transport includes intra-city private transport that does not compete with rail. To this extent two modes are not comparable. As time series data on road travel costs are not available, we use fuel prices as a proxy or an approximation of road travel costs. So, an increase in fuel prices may likely to increase the cost of road travel and therefore may encourage the rail travel. Therefore, expected sign of λ_3 is positive. As in many other countries, road sector in Pakistan uses several types of fuels (high-speed diesel (D), gasoline (G), compressed natural gas (CNG), etc.). However, the share of gasoline and high-speed diesel is the most dominant. So, to analyze the total fuel consumption in a more appropriate manner, we transform both aggregate fuel prices into a fuel price index (FPI) with the help of following weighted average formula:

$$FPI = \frac{P_g \times Q_g + P_{hsd} \times Q_{hsd}}{Q_g + Q_{hsd}}$$

Where P_g, Q_g are price and quantity of gasoline while P_{hsd} and Q_{hsd} denotes the price and quantity of high-speed diesel. The quantities of gasoline and high-speed diesel consumption are used as weights. For compatibility, year 2005 is used as the base year for fuel-price index. The construction of index is consistent with the empirical studies (Chi, 2018; Odeck and Johansen, 2016).

Rail's route-density (Route): This variable is included to control the supply side variables. In general, it is defined as the ratio of total number of places (route-kilometers) offered or supplied by the Pakistan Railway to country's total land area (in square-kilometers) at a given point in time, which is directly associated with the frequency of rail services. Asensio (2000) also used a similar indicator as quality variable in his analysis of sub-urban railway in Spain. FitzRoy and Smith (1995) incorporated route-density as a potential determinant of rail transport demand in European countries. Similarly, Canavan et al. (2018) also analyzed the impact of rail's network-length on both passenger journeys and passenger-kilometers. So, the expected sign of λ_4 is positive.

Population (POP): Population is another important variable for rail travel demand. Generally, it may directly affect the demand for rail travel through land-use factors and market size. We expect a positive relationship between rai travel demand and population i.e., $\lambda_5 > 0$.

Although other quality variables such as rail travel time and frequency related indicators are important for rail travel demand, the lack of long time series data limit their use in our study.

For chapter 3, we use annual time series data from 1978 to 2018. Different sources have been used for data collection. For instance, data regarding rail passenger-kilometers, ton-kilometers, average passenger yield and average freight-rate are obtained from Pakistan Railway (Yearbook, various issues). The fuel price data is taken from Hydrocarbon Development Institute of Pakistan (Energy Yearbook, various issues). Population related data is gathered from Pakistan Economic Survey (various issues). The data on real per-capita gross domestic product (GDP) is obtained from State Bank of Pakistan (Handbook of Statistic on Pakistan Economy, 2015) and Pakistan Economic Survey (Various issues). The data related to international trade is used from World Bank database (WDI, 2019), and industrial production index is taken from the Handbook of Statistics on Pakistan Economy (2015) and Pakistan

Economic Survey (2018-19). All three indices industrial production index (IPI), fuel-price index (FPI) and gross domestic product (GDP) are used with a common base year (2005-06) for compatibility reason, and also because 2005-06 is observed as the normal year in terms of economic working of Pakistan.

3.3.3 Econometric Model

In this section we describe the econometric method to derive the parameters of rail travel demand equation. As we are using time series data for our analysis, it is important to first consider the time series properties of each variable prior to model estimation, which may further guide us to select an appropriate econometric method. The time series properties are related to the behavior of mean and variance of each variable in a given model. If mean(s) and variance (s) of a variable (s) of interest remains constant over time, then the variable is called stationary or follows mean reverting process, and estimating a regression model with stationary variables with traditional econometric technique (ordinary least square) and hypothesis testing provide unbiased co-efficient estimates and valid inferences. However, the variables are non-stationary or integrated processes when their means and variances are not constant or time independent, and running a regression with non-stationary variables, without considering their time series properties, may provide spurious relations, biased estimates and invalid inferences (Granger and Newbold, 1974). The non-stationarity or integration of variables can be removed through differencing of variables. The stationarity and non-stationarity of an individual economic time series can be checked through the application of unit-root tests. Although various unit-root tests have been developed in the literature, the two famous standard unit-root tests are augmented Dickey-Fuller (ADF) and Phillips Perron (PP) test, first proposed by Dickey and Fuller (1979) and Phillips and Perron (1988). The generalized form of ADF test including trend and intercept can be written as:

$$\Delta X_t = a_0 + \gamma X_{t-1} + a_2 t + \sum_{i=1}^{p} b_i \Delta X_{t-i} + \varepsilon_t \qquad (3.12)$$

Where X_t is a variable or series to be tested for unit-root and Δ represents the first difference operator. Others a_0, a_2, b_i and ε_t are drift, deterministic trend, lagged difference coefficients, and white-noise error term, respectively. The presence or absence of unit-root (non-stationarity) can be checked by testing the joint hypothesis about the estimated parameter γ associated with lagged variable along with drift a_0 and deterministic trend a_2. In particular, the null hypothesis of unit-root in X_t implies that $\gamma = 0$ with an alternate hypothesis of stationarity i.e., $\gamma < 0$, and then calculated F-values can be compared with appropriate critical values provided by Dickey and Fuller (1981) to make a decision about unit-root.

The stationarity of time series variables in a regression model is desirable property to estimate meaningful relationships. Although non-stationary variables can be made stationary by taking the difference of variables, the use of variables in difference form may result in loss of valuable long-run relationships (Shrestha and Bhatta, 2018). An alternative strategy, also known as co-integration approach, is more useful, in which even all relevant non-stationary variables can be used at levels to specify the relationships. The co-integration tests are first proposed by Engle and Granger (1987), Johansen (1988) and Johansen and Juselius (1990). They view that since non-stationary variables (with same order of integration) follow the same behavior over time, it is quite possible that their linear combination may turn out to be stationary. Both tests Engle-granger and Johansen's require each variable in a given model to be non-stationary at the same order of integration (mostly I(1)). Moreover, Engle-Granger is a two-step co-integration technique, which, in the first step estimate a regression model by treating one as dependent and others remaining as independent variables through ordinary least square regression while at second stage the stationarity of regression residuals obtained in step 1 can be tested through ADF test. The variables are said to be co-integrated if residuals are stationary. The Engle-Granger technique is often criticized for a number of reasons, particularly because it doesn't provide a systematic process of estimating multiple co-integrating vectors separately (Enders, 2015). Therefore, we adopt a dynamic multivariate Johansen co-integration method to analyze the rail freight and travel demand relationship.

3.3.3.1 The Co-integrated VAR model

The starting point of Johansen's co-integration method is the unrestricted vector autoregressive (VAR) model of the following form:

$$Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \mu + \Phi D_t + \varepsilon_t \quad (3.13)$$

Where Y_t is $n \times 1$ vector representing endogenous variables i.e., $[Y_t = TKM_t, FR_t, IPI_t, TR_t, FP_t]$ and $[Y_t = PKM_t, RF_t, GDP_t, FPI_t, Route_t, POP_t]$. Each A_i is a '$n \times n$' matrix of coefficients while μ represents vector of drift terms. The vector D_t is a vector of dummy variables to capture the short-run effect of shocks to system (for example, shortage of locomotives, fuel, rolling-stock, the terrorist attacks on PR), and ε_t is a vector of white-noise error terms. The above VAR system can be equivalently written in the form of error correction model as following:

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{p-1} \Delta Y_{t-(p-1)} + \Pi Y_{t-1} + \mu + \Phi D_t + \varepsilon_t \qquad (3.14)$$

In above system, $\Pi = -(I - A_1 - A_2 \ldots\ldots - A_p)$ and $\Gamma_i = -(A_{i+1} + A_{i+2} + \cdots + A_{i+p})$

An important characteristic of the above equation is the rank of Π matrix, which represents the number of co-integrating vectors. Three possibilities may exist regarding the existence and number of co-integrating vectors. First, if rank of Π matrix is 0 then it is a null matrix, which implies that all variables are integrated of order (1) but no co-integration exists. Therefore, above system (3.11) reduces to VAR in differenced form. Second, when the rank of Π is equal to n, then it has full rank. However, co-integration does not exist even for a case of full rank because n linear combinations of variables are independent and stationary. In that case, we have VAR system at levels as all variables are stationary. Third, an intermediate case when the rank of Π matrix falls between 0 and n, i.e., $0 < rank(\Pi) < n$, then co-integration exists, and co-integrating vectors are multiple. For instance, a rank (Π) = 1 witnesses the existence of a unique co-integrating vector. Therefore, Π matrix can be written as $\Pi = \alpha\beta'$, where α is the matrix showing speed of adjustment while β denote the long-run co-efficients. To obtain the number of co-integrating vectors, the Johansen's procedure provides the estimates of both Π matrix and associated characteristic roots. The two likelihood ratio tests *trace-statistic* and *maximum-eigenvalue-statistic* are proposed by Johansen to test the hypothesis about the rank of Π matrix with the help of estimated characteristic roots. Both tests can be explained as following:

$$\lambda_{Trace}(r) = -T \sum_{i=r+1}^{n} ln\left(1 - \hat{\lambda}_r\right) \qquad (3.15)$$

$$\lambda_{max}(r, r+1) = -Tln(1 - \hat{\lambda}_{r+1})$$

Where T is the total usable observations and λ_i represents the estimated characteristic roots of Π matrix in a descending order. The null hypothesis of *trace-statistic* claims that the numbers of co-integrating vectors are r while the numbers of co-integrating vectors are generally more than r in an alternative hypothesis. Similarly, there are r co-integrating vectors in null hypothesis of *maximum-eigenvalue-statistic* against a more specific $r + 1$ vectors in an alternative hypothesis.

If co-integration exists, then the system in equation (3.14) can be transformed in the form of vector error correction model as following:

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{p-1} \Delta Y_{t-(p-1)} + \alpha(\beta' Y_{t-1}) + \mu + \Phi D_t + \varepsilon_t \qquad (3.16)$$

Where $\beta' Y_{t-1}$ is the error correction term, which measures the movements away from equilibrium. The above equation explicitly captures the short-run adjustment mechanism towards long-run steady-state equilibrium. The term $\beta' Y_{t-1}$ equals to zero in the equilibrium. On the other hand, since it measures the distance of disequilibrium, $\beta' Y_{t-1}$ is not zero when the system is away from equilibrium. In such case, the value of α informs us about speed of adjustment of vector Y_t to any disequilibrium.

3.4 Results and Discussion

This section offers empirical results and discussions of the demand for both aggregate rail freight and passenger transport in the long- and short-run, respectively. So, we first discuss the results of rail freight demand, and the results of rail passenger demand will be explained thereafter.

3.4.1 The Demand for Rail Freight Transport

The pre-requisite of Johansen co-integration analysis is to first check for time series properties of each individual time series. To provide consistency to the results, we employ two unit root tests namely augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test on each individual series to determine its order of integration and results of estimating equation (3.12) are provided in Table 3.1.

Table 3.1: Unit root tests for the Demand for Rail Freight Transport

Variable	ADF		Phillips-Perron (pp)		Result
	Levels	First difference	Levels	First difference	
$lnTKM_t$	-2.13	-4.93***	-2.33	-4.54***	I[1]
$lnFR_t$	-1.47	-4.54***	-1.46	-4.47***	I[1]
$lnIPI_t$	-1.28	-3.82**	-1.72	-3.84**	I[1]
$lnTR_t$	-2.17	-6.77***	-2.41	-6.75***	I[1]
$lnFP_t$	-0.96	-5.14***	-0.93	-5.21***	I[1]

Notes: Both ADF and PP tests involve regression with intercept only. The lag lengths are decided on the basis of Schwarz information Criterion (SIC). ** and * Indicates rejection of null hypothesis of unit root at 5% and 1% level of significance.

As both tests performed on each variable, the null hypothesis of unit root at level cannot be rejected for all variables in rail freight demand since t-statistic is greater than critical values (10%, 5% and 1%). However, null hypothesis of unit root is clearly rejected when applied to the first difference of each series. Consequently, it can be concluded that all variables are integrated of order one e-g. I(1) processes.

Since all variables are integrated of order one, it is meaningful to consider the long-run co-integration relationship between them with the help of Johansen co-integration test. First, an unrestricted vector autoregressive model (VAR) is estimated by considering all variables (ton-kilometers, freight rate, industrial production, international trade and fuel price) as endogenous. Since rail freight transport has sharply declined for the period 2010 to 2013, an exogenous dummy variable is also included in Johansen co-integration test to capture the outliers associated with the period 2010-2013. We generate dummy variable by using a value of '1' in these four years from 2010 to 2013 and '0' in all remaining years. The optimal lags are selected by estimating an unrestricted vector autoregressive model. Ignoring an optimal lag length may result in non-Gaussian residuals which can further invalidate the inferences.

Table 3.2 provides the optimal lag selection criteria based on five different criterions. Majority of criterions suggest an optimal lag length of 2, except Schwarz criterion (SC) and Hannan-Quinn (HQ). So, we select an optimum lag length of 2, given that our data is on annual basis. Moreover, at lag 2, the residuals from unrestricted vector autoregressive model are free from problems of serial correlation, heteroscedasticity, and non-normality.

Table 3.2: Optimal Lag Selection Criteria Using Unrestricted VAR Model

Lag	LR	FPE	AIC	SC	HQ
0	NA	0.0034	8.511	8.718	8.587
1	636.10	2.41e-10	-7.967	-6.726*	-7.512*
2	38.98*	2.37e-10*	-8.034*	-5.759	-7.200
3	30.71	2.75e-10	-8.025	-4.715	-6.812

*Indicates lag order selected by the criterion

LR: sequential modified LR statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

After selecting an optimal lag, we have performed the Johansen multivariate co-integration test to determine the existence and number of co-integration relationships. The results of Johansen co-integration analysis, based on two likelihood-ratio tests such as Trace statistic (represented by λ_{trace}) and Maximum Eigen-value statistic (λ_{max} value) along with 95% critical values are provided in Table 3.3. In comparison, testing of no co-integration or $r = 0$ against at most one co-integrating vector, both values of λ_{trace} and λ_{max} are greater than their 5% critical values. However, further null hypothesis of one co-integrated vector against an alternative hypothesis of two or more co-integrated vectors cannot be rejected by both tests. Hence both tests provide evidence in favor of the existence of unique long-run co-integration relationship.

Table 3.3: Johansen Co-integration Using λ_{max} and λ_{Trace} Tests (intercept and no trend in CE)

Null Hypothesis	Alternative Hypothesis	Trace and Eigen-value Statistic		5% critical value	Prob.
λ_{Trace} Test		**Eigenvalue**	**λ_{Trace} Value**		
r = 0	r > 0	0.7101	93.4224	69.8188	0.0002***
r ≤ 1	r > 1	0.3794	42.6467	47.8561	0.1414
r ≤ 2	r > 2	0.2785	23.0807	29.7970	0.2421
r ≤ 3	r > 3	0.2092	9.6957	15.4947	0.3049
λ_{max} Test		**Eigenvalue**	**λ_{max} Value**		
r = 0	r = 1	0.7101	50.7757	33.8768	0.0002***
r = 1	r = 2	0.3794	19.5660	27.5843	0.3720
r = 2	r = 3	0.2785	13.3850	21.1316	0.4174
r = 3	r = 4	0.2092	9.6267	14.2646	0.2376

[a] Note: r denotes the number of co-integrating vectors or relationships

*** represents significance at 1% level.

To analyze the causal relationships between rail freight demand to its influencing factors, the long-run weak exogeneity test is employed to determine whether speed-of-adjustment co-efficients are significantly different from zero i.e. $\alpha_i = 0$ (Johansen and Juselius, 1992). A variable is said to be weakly exogenous to a system if it does not respond to deviations from long-run equilibrium. The results are reported in Table 3.4 below.

Table 3.4: Results Based on Testing Weak Exogeneity in Rail Freight Demand Model[a]

Variable	Weak exogeneity $H_0\!:\alpha_i = 0$	P-values
$lnTKM_t$	9.567	0.001*
$lnFR_t$	8.249	0.004*
$lnIPI_t$	0.089	0.765
$lnFP_t$	0.730	0.392
$lnTR_t$	0.0624	0.802

[a] Values represent likelihood-ratio test stat based on χ^2distribution.

* weak exogeneity is rejected at 5% LOS.

The results indicate that we cannot reject the null hypothesis of weak exogeneity for industrial production, fuel price and international trade variables while it is clearly rejected at 5% level for ton-kilometers and freight rate. It implies that industrial production, fuel price and international trade are driving variables in a system of rail freight demand, and changes in these weakly exogenous variables would, as a result, cause a change in rail's ton-kilometers and freight rate, but causal effects in reverse direction do not exist.

We now move to the discussion regarding long-run relationship or elasticities of rail freight demand after having established a single long-run relationship represented by single co-integrating vector (β) given in Table 3.5.

To interpret the long-run relationship, we need to reverse the sign of coefficients provided by the co-integrating vector[13]. The first determinant of rail freight demand is freight rate (FR), which has a significant negative relationship with rail freight demand, confirming the law of demand. The long-run elasticity of rail freight demand with respect to freight rate is -0.433, which is quite inelastic. It means that all else equal if rail authorities increase the freight rate by 10%, as a result, the demand for rail freight transport will decrease by 4.33%, which is less than the increase in average freight rate in percentage term. This relationship is statistically

[13] Johansen's test reports the long-run relationship in terms of co-integrating vector β. If we assume that a unique co-integration relationship exists, the long-run rail freight demand equation (2.5) can be written as: $lnTKM_t - \pi_0 - \pi_1 ln(\mathrm{FR}_t) - \pi_2 \ln(IPI_t) - \pi_3 \ln(TR_t) - \pi_4 \ln(FP_t) = u_t$ or in vector-form $\beta x_t = u_t$ where $\beta = [1, -\pi_0, -\pi_1, -\pi_2, -\pi_3, -\pi_4]$ is the long-run co-integrating vector normalized to ton-kilometers (1st variable) and $x_t = [\mathrm{TKM}_t, \mathrm{FR}_t, \mathrm{IPI}_t, \mathrm{TR}_t, \mathrm{FP}_t]'$ is the vector of variables. The left-side of above equation represents linear combination of non-stationary variables (ton-kilometers, freight-rate, industrial production, trade and fuel-price) that should be stationary for co-integration to exist. Since all long-run elasticities (δ_i's) in co-integrating vector β are estimated by using all exogenous variables on left-side of equation with opposite sign, their signs should be reversed to restore the long-run rail freight demand equation (2.5).

significant at 1% level. It implies that rail management can increase its freight revenues or earnings by increasing average freight rate without reducing much of its freight transport, due to the inelastic nature of price elasticity of rail freight demand. Some earlier empirical studies on aggregate rail freight demand have also estimated a significant but low freight price effect. For example, Kulshreshtha et al. (2001) analyze rail freight demand for Indian railways and find that own price (freight rate) elasticities are significant, with coefficient of elasticities are in a range of -0.099 to -0.287, for all samples used in the study. Wijeweera et al. (2014) estimate Australian non-bulk rail freight demand with the help of vector auto-regressive (VAR) model and the results show that freight rate exerts a negative significant effect on rail freight demand.

Table 3.5: Estimated Long-Run Rail Freight Demand Model

Variable	β	Std. Error
$lnTKM_t$	1.000	-
$lnFR_t$	0.433***	0.130
$lnIPI_t$	-0.878***	0.328
$lnTR_t$	0.765	0.521
$lnFP_t$	-0.408***	0.159
C	-8.503***	1.644

Since long-run rail freight demand equation (β) is normalized to rail freight in ton-kilometers, the co-efficients imply that rail freight demand is negatively related to freight-rate and international trade while it has a positive relationship with industrial production index (IPI) and fuel price.
*** represents significance at 1% level.

The effect of output or economic activity (measured as industrial production index (IPI)) on rail freight demand is positive and the relationship is also statistically significant at 1% level. The result, in terms of elasticity, can be interpreted as follows; a 10% increase in industrial production (IPI) will produce 8.78% increase in rail freight demand. The relationship between industrial production and rail freight demand is relatively more sensitive and elastic. Our results are, in general, similar to the existing empirical literature of aggregate rail freight transport that the relationship between rail freight demand and economic activity (different indicators) is positive and significant. For example, Kulshreshtha et al. (2001) observe a positive and significant effect of GDP on aggregate rail freight demand for India, with GDP elasticity varies between 0.83 and 0.91. Likewise, Ramanathan (2001) also find that the long-run elasticity of aggregate (air, rail, and road) freight transport in India with respect to industrial output is 1.18.

Similarly, Shen et al. (2009) use six econometric models to estimate the relationship between UK aggregate (road plus rail) freight transport demand and industrial production. The results indicate that long-run production elasticity of road plus rail freight, based on four econometric models, is greater than 1. We also find that long-run relationship between international trade and rail freight are negative. However, the observed relationship is not significant at conventional levels.

On the other hand, the cross-price elasticity of rail freight demand with respect to trucking cost (fuel price) is 0.40, which is statistically significant at 1% level. In particular, a 10% increase in trucking cost is associated with an increase in rail freight demand by 4%. The variation in rail freight demand with respect to trucking cost is quite inelastic. It implies that road and rail are substitutes in handling domestic inland freight transport. However, the effect of trucking cost (fuel price) on rail freight is less dominant because trucking provides relatively more reliable, certain, flexible and door-to-door services as compared to rail. Fitzroy and Smith (1995) also estimate the impact of trucking cost (diesel price) on the demand for rail freight transport of fifteen European countries. Their results show that rail freight elasticity of trucking cost is 0.93, which is statistically significant at 10% level of significance.

3.4.2 Error-Correction model (ECM) of Rail Freight Demand in Pakistan

After discussing the long-run empirical rail freight transport demand in Pakistan, we now consider the short-run error correction model of rail freight demand. To measure the long-run relationships, an optimal lag length of 2 is selected. Since all variables are used in differenced form to estimate the short-run parameters, the optimal lag 1 is used for error correction model. The results are reported in Table 3.6. All coefficients corresponding to the differenced variables in rail freight demand equation are treated as short-run elasticities.

All short-run co-efficients are lower than their long-run values. However, most of them are statistically insignificant. It means that short-run conditions are less effective in terms of determining the equilibrium of rail freight transport. The co-efficients associated with differenced freight-rate and industrial production are -0.29 and 0.75, respectively. Similarly, short-run impact of fuel-price on rail freight demand is positive but insignificant. It implies that an increase in cost of trucking, in the short-run, will not induce the road shippers to substitute rail for their shipments. This may happen due to several factors, such as uncertainty associated with rail operations, limited capacity (freight wagons and locomotives) and less flexibility (door to door services). On the other hand, previous year growth in rail freight transport at lag-1 has statistically significant and positive impact on current demand for rail freight and indicates 56% increment in the next year's rail freight transport. Short-run impact of rail market shocks on rail freight demand is captured through a dummy variable in VECM, which is negative and highly significant at 1% level. It implies that rail market shocks have substantially reduced the short-run demand for rail freight transport over 2010-2013.

Table 3.6: Estimation Results of Short-run VECM Model of Rail Freight Demand

Regressor	**Dependent variable** $\Delta lnTKM_t$	***T-statistic***	**Dependent variable** $\Delta lnFR_t$	***T-statistic***
$\Delta lnTKM_{t-1}$	0.561***	2.761	-0.463***	-4.516
$\Delta lnFR_{t-1}$	-0.294	-1.052	-0.289	-1.424
$\Delta lnIP_{t-1}$	0.751	1.449	0.444	1.227
$\Delta lnFP_{t-1}$	0.147	0.602	-0.123	-0.732
$\Delta lnTR_{t-1}$	0.643	1.498	-0.110	-0.365
DUM	-0.511***	-3.88	-	-
ECT_{t-1}	-0.885***	-7.678	0.369***	4.655
Diagnostic tests	**Statistic**	**p-value**	**Statistic**	**p-value**
Serial correlation LM-test	2.745	0.097	2.353	0.125
Heteroskedasticity test	11.345	0.414	10.287	0.504
ARCH test	0.156	0.692	0.069	0.791
Jarque-Bera test	0.947	0.624	1.164	0.558
Durbin-Watson	2.113		2.155	

*** denotes level of significance at 1%.

DUM is the dummy variable for shocks in rail freight system and is equal to one for period 2010-2013.

Breusch-Godfrey test is used for testing serial correlation in residuals and Breusch-Pagan test is used for testing heteroskedasticity.

An important feature of error-correction model is the error-correction term ECT_{t-1}, which matters for the stability of long-run model. Error-correction terms of both rail freight demand and freight-rate equations are -0.88 and 0.369, respectively, and are statistically significant. It shows that for any deviations in a system of rail freight demand from its long-run equilibrium, the error-correction simultaneously takes place through both rail freight demand and freight-rate to restore the long-run mean equilibrium. It implies that, for any last period deviations (errors) from long-run relationship, short-run adjustment in rail freight demand takes place in such a way that 88% of the deviations from long-run equilibrium are corrected in the following period to restore the long-run rail freight demand relationship. On the other hand, fuel price also increases by 37% in the current period due to any deviation from equilibrium to re-establish the long-run relationship.

In addition, several diagnostic tests are also performed which assist us to check the appropriateness of estimated short-run model of rail freight demand. The results are given in lower panel of Table 3.6. P-value of Breusch-Godfrey LM test implies that null of no residual serial correlation cannot be rejected at 5% or 1% level of significance. So, the residuals of ECM are free of serial correlation. For testing heteroscedasticity in residuals, we performed Breusch-Pagan test and observed that p-value is greater than 10% significance level, showing no sign of heteroscedasticity in model's residuals. Similarly, we also find that there is no autoregressive conditional heteroskedastic (ARCH) effect in the residuals. The reported value of Jarque-Bera test is low, which implies that residuals are normally distributed. Finally, Durbin-Watson statistic suggests that residuals of short-run rail freight demand are free from autocorrelation.

3.4.3 Estimation Results of Rail Travel Demand

The first step of Johansen co-integration test is to determine the order of integration of each individual variable in rail travel demand model. For that, we apply ADF and PP tests on each series by estimating equation (3.12) for each variable in rail travel demand such as passenger-kilometers, rail-fare, real per-capita GDP, fuel-price index, rail's route-density and population. The model is estimated with an intercept and results of both tests are reported in Table 3.7 below. The null hypothesis of unit root at level for each series is not rejected by both tests, implying that each variable is non-stationary at levels. However, when unit root tests are applied on the first difference of each series, the null hypothesis of unit root on first differenced of all variables is clearly rejected at 1% level of significance. Therefore, we can infer that each variable is non-stationary and is integrated of order one I(1). Since all variables are non-stationary and are also integrated of the same order, we can proceed for testing the co-integration relationships between rail travel demand variables.

Table 3.7: Unit Root Tests of Rail Travel Demand

Variable	ADF Test		PP Test		Result
	Level	1st Diff.	Level	1st Diff.	
	Test Stats	Test Statistic	Test Stats	Test Statistic	
$lnPKM_t$	-2.04	-4.16***	-1.74	-3.75**	I(1)
$lnRF_t$	-1.19	-5.92***	-1.23	-6.06***	I(1)
$lnGDP_t$	-1.20	-4.29***	-1.69	-4.28***	I(1)
$lnFPI_t$	-0.88	-4.81***	-0.85	-4.79***	I(1)
$lnRoute_t$	-1.05	-6.17***	-1.03	-6.07***	I(1)
$lnPOP_t$	-1.51	-4.04***	-1.53	-4.00***	I(1)

[a] The regression of unit root test involves an intercept only.
[***] and [**] Represents the rejection of null hypothesis at 1% and 5% level, respectively.

An unrestricted VAR model is estimated with different lags to determine the correct specification of VAR model and results are reported in Table 3.8. Most of the criteria have suggested an optimal lag 1 except AIC, for which optimal lag length is 3. Since too many lags may reduce the available degrees of freedom and two few of them may result in problems of residuals autocorrelation. So, we have estimated VAR model with 1-lag and checked the presence of serial correlation in residuals.

Table 3.8: Optimal Lag Selection Criteria using VAR Model

Lag	LR	FPE	AIC	SC	HQ
0	NA	2.44e-13	-12.014	-11.507	-11.830
1	376.66*	1.18e-17*	-21.985	-19.958*	-21.252*
2	40.88	1.72e-17	-21.757	-18.210	-20.475
3	50.81	1.23e-17	-22.498*	-17.431	-20.666

*Indicates lag order selected by the criterion

LR: sequential modified LR statistic (each test at 5% level)

FPE: Final prediction error   AIC: Akaike information criterion

SC: Schwarz information criterion   HQ: Hannan-Quinn information criterion

The results show that null hypothesis of no serial correlation in VAR model with one-lag is rejected at 10% level by the multivariate LM test ($\mathrm{LM-stat} = 48.66, \mathrm{p-value} = 0.07$). Therefore, we find that VAR model with 2 lags is appropriate because no serial correlation is found at lag 2 i.e., $\mathrm{LM-stat_{pkm}} = 34.06, \mathrm{p-value} = 0.56$. Since the numbers of terrorist attacks on PR also have substantially increased from 2010 to 2013, the passenger traffic of PR has also significantly decreased during the same period. So, we incorporate a dummy variable as a deterministic regressor in an unrestricted VAR model to account for terrorist incidents and other events during the above-mentioned period.

The Johansen co-integration test is applied on rail travel demand model and results based on Trace-statistic and Maximum-eigen-value statistic are reported in Table 3.9. For rail passenger-kilometers model in Table 3.9, the null hypothesis of no co-integration against the alternate of one unique co-integration relation is clearly rejected by both tests, as trace and max values are clearly greater than the 5% tabulated values.

Table 3.9: The Johansen Co-integration Test[a] (Dep. Variable: passenger-kilometers)

Null hypothesis	Alternative hypothesis	Eigen value	Trace statistic	5% Critical Value
r=0	*r >0*	0.6487	123.870*	103.84
r≤1	*r>1*	0.5748	79.923*	76.972
r≤2	*r>2*	0.3710	44.002	54.079
r≤3	*r>3*	0.2312	24.523	35.192
r≤4	*r>4*	0.1719	13.480	20.261
Null hypothesis	Alternative hypothesis	Eigen value	Max-Eigen statistic	5% Critical value
r=0	*r=1*	0.6487	43.947*	40.956
r=1	*r=2*	0.5748	35.921*	34.805
r=2	*r=3*	0.3710	19.478	28.588
r=3	*r=4*	0.2312	11.043	22.299
r=4	*r=5*	0.1719	7.924	15.892

[a] The test involves a regression with restricted constant and dummy but without deterministic trend.

*Represents rejecting the null hypothesis at 5% level of significance.

Similarly, further null hypothesis of one unique cointegrating vector is again rejected in favor of two or more co-integrating vectors. However, the null of two co-integrating vectors against 3 or more co-integrating vectors or relations is not rejected further because calculated value is less than the critical or tabulated values at 5% level of significance. So, two long-run co-integrating vectors or relationships are identified or found between rail travel demand (measured by passenger-kilometers) to its determinants.

To investigate the causal relationships among variables in a model of rail travel demand, the long-run weak exogeneity test is also conducted to find out whether speed-of-adjustment co-efficients are significantly different from zero i.e. $\alpha_i = 0$. The results of weak exogeneity test are given in Table 3.10. It indicates that rail-fares, income, and population are weakly exogenous to the system since we cannot reject the null of weak exogeneity at 5% level. However, the case of weak exogeneity is clearly rejected for passenger-kilometers and fuel-price at 5% significance level while weak exogeneity is marginally rejected for Route (rail density) at 10% level of significance. It implies that rail-fares, income, and population are forcing variables such that their movements would consequently bring change in rail passengers, fuel price and rail density while the opposite does not hold.

Table 3.10: Weak Exogeneity Results of Variables in Rail Travel Demand[a]

Variable	Weak exogeneity $H_0: \alpha_i = 0$, i=1, 2,…..6	P-values
$lnPKM_t$	15.920	0.00*
$lnRF_t$	2.331	0.31
$lnGDP_t$	1.522	0.46
$\ln FPI_t$	19.038	0.00*
$lnRoute_t$	5.0615	0.07**
$lnPOP_t$	1.158	0.56

[a] represents the likelihood-ratio test based on χ^2-Distribution.

* & ** represents the rejection of weak exogeneity at 5% and 1% level, respectively.

Since two co-integrating vectors or relations are established for rail passenger-kilometers' model by the maximum eigen-value statistic, the identification of two co-integrating relationships may lead to an over-identification problem because linear combination of two co-integration relations is stationary (Harris and Sollis, 2003). To deal with this problem, restrictions are imposed on first 2 eigen-vectors (β_1 and β_2) of six eigen-vectors co-integration vectors (β_j). As a result, we uniquely identified the co-integrating vectors. The over-identifying restrictions are not significantly rejected by the likelihood-ratio (LR) test i.e., LR-stat = 3.924, p-value = 0.140. Hence, both β_1 and β_2 are unique co-integrating vectors in Table 3.11. Since our main interest is to analyze the relationship between rail travel demand to its determinants, both co-integrating vectors are normalized to passenger-kilometers (dependent variable), which is a measure of rail travel demand. The 1st co-integrating vector (β_1) explains the long-run relationship of rail travel demand (measured in rail passenger-kilometers) with rail-fare, fuel-price, and rail density. Similarly, 2nd co-integrating vector shows relationship between passenger-kilometers, rail-fare, income, and population. We now discuss and interpret each relationship.

In a co-integrating vector, since all variables are treated on the same side of dependent variable, we need to reverse the sign of each co-efficient in co-integrating vector before interpretation. In 1st co-integrating vector, rail travel demand (PKM) is negatively related to rail-fare and has a positive relationship with fuel-price and rail-density. Similarly, 2nd co-integrating vector shows a negative relationship of passenger-kilometers with rail-fare and positive relationship with income and population. The co-efficient of rail-fare in 1st co-integrating vector is -0.337, while it is equals to -0.259 in 2nd co-integrating vector. Both co-efficients are the long-run elasticities of rail travel demand with respect to rail-fare and are statistically significant at 1% level. They can be interpreted as "all else equal a 1% increase in average rail-fare will lead to decrease the long-run rail passenger-kilometers in Pakistan by 0.26% to 0.34%. It shows that rail travel demand is relatively more inelastic to its price, which implies that a decision to increase the average rail-fare by the rail authorities in Pakistan will not lead to a significant decrease in long-run rail travel demand in Pakistan and vice-versa. However, it may increase the passenger earnings of Pakistan-railways. Our results are comparable and similar to Hussain et al. (2016) for Pakistan, who also find that long-run elasticity of rail passenger-kilometers with respect to average rail-fare is -0.288. Similarly, other previous empirical studies also have witnessed a relatively low own-price elasticity of rail travel demand (Doi and Allen, 1986; McGeehan, 1984; Wijeweera et al., 2014).

The 2nd important determinant of rail travel demand is income, which is measured by real per-capita GDP. The co-efficient associated with income is positive and equals to '1.02', which is significant at 1% level of significant. It shows that ceteris paribus the rail travel demand, in long-run, will increase by 1% if real per-capita GDP increases by 1%. A one to one relationship with real per-capita income implies that rail travel demand will increase as economic growth progresses. This result is also consistent with the long-run income elasticity (0.995) of rail travel demand in Hussain et al. (2016), and with Coto-Millán et al. (1997).

Fuel price index (FPI) is another potential determinant of rail travel demand, which is used to capture the cross-price effects in rail travel demand. Long-run cross-price elasticity of rail travel demand is 0.534, which shows that if cost of road travel goes up by 1%, it will increase the demand for public transport, such as rail travel, by 0.53%. This variable is also significant at 1% level. Since cross-price elasticity of rail travel demand with respect to road travel costs is positive and significant, road and rail are substitutes for passengers' travel. Our results are mainly in line with others (Coto-Millán et al., 1997; Delsaut, 2014; Rahman and Balijepalli, 2016; Wijeweera and Charles, 2013a), who show that long-run cross-price elasticity of rail travel demand with respect to road costs (fuel-price) is positive and statistically significant.

Rail's route-density (measured as a ratio of rail route-kilometers to per sq. km of country area) is used as a supply side variable in rail travel demand. Its long-run elasticity is 4.16, which is statistically significant at 1% level. It implies that all else fixed if rail's route-density is increased by 1%, rail travel demand (measured by PKM) will increase by 4.16%. It has an important implication that if PR offers a greater number of places to passengers in future through infrastructural investments in route-kilometers, it will significantly accelerate the rail's PKM growth. One possible reason for such high impact is that average rail-fares are generally lower than bus-fares, and also because rail's travel services are mostly opted by the lower income groups of population, who cannot afford to travel by roads. Since rail's travel tends to become more efficient and competitive to road's travel from medium to long-distances, an increase in route-density of rail will further attract passengers to rail travel. The results are generally consistent with previous studies. For example, Fitzroy and Smith (1995) analyze rail (passenger and freight) transport demand for European countries and show that route-density (route-kilometers per sq. km) has positive significant relationship with rail transport demand. Asensio (2000) uses a similar quality indicator (ratio of number of places (in km) offered by railways to total rail network) and finds that the impact of quality variables on suburban rail ridership is positive and statistically significant. Canavan et al. (2018) also find a significant positive impact of rail network length on urban metro rail travel demand (passenger journeys and passenger-kilometers) of world's 32 metro systems.

Finally, population also exerts a positive and statistically significant (10% level) impact on rail travel demand in Pakistan whereby a 1% increase in population will cause 0.69% increase in rail travel demand in the long-run. Hussain et al. (2016) also obtain a positive effect of population on rail travel demand in Pakistan, though long-run population elasticity in their study is much more elastic (greater than 3). Similarly, Wijeweera and Charles (2013a) also find a similar long-run population elasticity (0.56) of rail passenger demand in Melbourne, Australia.

Table 3.11: Estimated long-run rail travel demand model (Dependent variable: PKM)

Variables	β1	Std. Error	β2	Std. Error
$lnPKM_t$	1.000	-	1.000	-
$lnRF_t$	0.337***	0.101	0.259***	0.084
$lnGDP_t$	-	-	-1.022***	0.379
$lnFPI_t$	-0.534***	0.093	-	-
$lnRoute_t$	-4.165***	0.865	-	-
$lnPOP_t$	-		-0.694*	0.392
C	-9.563	0.277	2.780	2.577

Since long-run rail travel demand equation (β_1) is normalized to rail passenger-kilometers, the co-efficients imply that rail travel demand is negatively related to rail-fare and has a positive relationship with fuel price and route-kilometers while the 2nd co-integrating vector (β_2) is also normalized to passenger-kilometers, which shows a negative relationship with rail-fare and positive relationship with income and population.
* & *** Represents significance at 10% and 1% level, respectively.

3.4.4 Error Correction Model of Rail Travel Demand in Pakistan

To investigate the short-run dynamics of rail travel demand, we have estimated the error-correction model and results are provided in Table 3.12. The error correction model is specified for three variables such as passenger-kilometers, fuel-price and rail's route-density, because weak exogeneity is rejected for these variables and they respond to the deviations from long-run equilibrium. For rail travel demand (measured by PKM), co-efficients pertaining to all differenced rail-fare, income, fuel-price, route-density, and population variables at lag-1 can be treated as short-run elasticities. All short-run elasticities are lower than the long-run elasticities and most of them have expected signs. However, only income effect is statistically significant in the short-run at 10% level, with elasticities 0.926. It shows that income promotes rail travel demand in the short-run. The last year growth in rail's PKM has positive and statistically significant impact on current year's PKM and explains next year's increase in rail travel demand by 43.3%. In addition, the effect of various rail market shocks (such as shortage of fuel, rolling stock, locomotives, and number of terrorist activities) on rail travel demand has also been considered in our model. These shocks may significantly change the rail travel over the period of analysis. We have incorporated a dummy variable to account for such effects over

2010-2013. The co-efficient of dummy variable in rail passenger-kilometers model is -0.09 and is statistically significant at 5% level, which implies that shocks have considerably reduced the demand for rail passenger-kilometers during 2010 to 2013.

Table 3.12: Error-Correction Model of Rail Passenger-Kilometers Travel Demand

Regressor	Dependent Variable		
	$\Delta lnPKM_t$	$\Delta lnFPI_t$	$\Delta lnRoute_t$
$ECT_{t-1,1}$	-0.012	0.394***	0.031*
	[0.065]	[0.101]	[0.017]
$ECT_{t-1,2}$	-0.506***	0.261	-0.035
	[0.137]	[0.21]	[0.036]
$\Delta lnPKM_{t-1}$	0.433***	-0.164	-
	[0.170]	[0.265]	
$\Delta lnRF_{t-1}$	-0.021	-0.397	-0.044*
	[0.088]	[0.257]	[0.023]
$\Delta lnGDP_{t-1}$	0.926*	0.054**	0.567***
	[0.516]	[0.023]	[0.154]
$\Delta lnFPI_{t-1}$	0.076	0.032	-
	[0.097]	[0.022]	
$\Delta lnRoute_{t-1}$	-0.007	1.850**	-1.723*
	[0.572]	[0.891]	[0.887]
DUM[a]	-0.092**	-	-
	[0.045]		
Residuals diagnostic tests			
Jarque-Bera	0.203	1.606	15.78
	(0.90)	(0.44)	(0.01)
LM-test χ^2 (1)	0.813	0.126	5.429
	(0.36)	(0.72)	(0.067)
Heteroskedasticity χ^2 (1)	16.78	8.967	20.32
	(0.20)	(0.77)	(0.087)
ARCH Test χ^2 (1)	0.220	0.956	0.916
	(0.63)	(0.32)	(0.338)
Durbin-Watson	2.12	1.94	1.78

[a] Represents dummy variable to account for PR crisis (shortage of locomotives and rolling stock, terrorist attacks on PR, with a value of one during 2010-2013.
Values in square-brackets are standard errors and those in parentheses represent p-values.
*,** and *** represent significance at 10%, 5% and 1%, respectively.

An important characteristic of the short-run or error-correction model is the error-correction-term (ECT_{t-1}), which tells us about the convergence or divergence of rail travel demand following a typical shock to the system. Since we have identified two co-integrating vectors for rail travel demand, there must be two error-correction terms for each of three variables (PKM, FP, Route). For 1^{st} co-integrating vector, error is corrected in the equations of both fuel-price (FP) and rail-density (Route) since the coefficients of error-correction terms are significant in both equations. However, error-correction-term of 2^{nd} co-integrating vector is only significant (1% level) in PKM equation and equals to '-0.506', which indicates that for any deviations from long-run equilibrium, rail PKM adjusts about 51% in the current period to re-establish the long-run equilibrium relationship.

Finally, a number of diagnostic tests are also performed on residuals of estimated models to determine the reliability and robustness of short-run model. The results are reported in the bottom of Table 3.12 along with their p-values. These tests are Jarque-Bera test, Lagrange-Multiplier (LM-test), Heteroskedasticity (the Breusch-Pagan-Godfrey test) test and ARCH-test. The p-values of these tests are mostly greater than statistical significance levels (1%, 5% and 10%), which indicates that null hypothesis of these tests (normality of residuals, absence of auto-correlation, no heteroskedasticity, no ARCH-effects) cannot be rejected. So, the residuals of estimated error-correction models of rail travel demand are free of such problems.

3.5 Conclusion

Rail is a preferable mode of transport in terms of handling long haul freight and passenger movements, and because of less deteriorating impact on environmental quality. In this chapter, we have analyzed the empirical structural relationship between the demand for both aggregate rail freight and passenger transport in Pakistan and some of their determinants. A multivariate co-integration approach is employed to estimate the short- and long-run parameters of both models. The study offers some conclusions and important policy implications. Our findings are partially in line with some previous studies that also obtain lower fare (freight-rate) price and higher income (output) elasticities of rail travel (freight) demand in developing countries. Johansen's co-integration method witnesses a single unique co-integrating relationship of rail freight demand while two co-integrating relationships are uniquely identified for rail travel demand by imposing overidentifying restrictions.

Estimating stable and consistent price and income elasticities of rail transport demand are important for policymakers and planners in terms of making effective decisions regarding rail transport demand management and planning. A number of inferences can be drawn from our study as following. First, a stable demand function exists for rail freight transport in Pakistan over the long-run, while two stable long-run demand functions exist for rail travel demand in Pakistan during the estimation period. Second, error correction takes place in two of five equations of rail freight demand in co-integrating vector. Similarly, for rail travel demand, error is corrected in three of six equations of co-integrating vector. Third, the long-run own-price (freight-rate, rail-fare) elasticities of both rail freight and travel demand are statistically significant and substantially less than one (in absolute values), which offer important policy implications for rail authorities in Pakistan in terms of using both freight-rate and rail fares as policy tools to manage their rail transport operations. For example, since long-run demand for both rail freight and passenger transport is quite inelastic to its own price, all else constant an increase in average freight-rate and rail-fare by rail authorities will lead to increase the total freight and passenger revenues or earnings, without losing much of rail's freight and passenger traffic in the long-run. On the other hand, reducing average rail's freight-rate and rail-fare would not increase the total rail's freight and passenger revenues but can raise rail's freight and passenger transport to some extent. Therefore, rail authorities can choose anyone (which is relatively more important) of two objectives such as (1) increasing rail's total freight and passenger earnings, or (2) increasing rail's freight and passenger transport, and may set their policy tools (freight-rate and rail-fare) accordingly. Fourth, long-run elasticity of rail-freight demand with respect to industrial production, and long-run elasticity of rail travel demand with respect to real per-capita GDP are both approximately unitary, which indicate that demand for both rail's freight and passenger transport is expected to increase with the economic growth of the country. Fifth, the long-run impact of fuel-price (an approximation of road's transport costs) on the demand for both rail's freight and passenger transport is significant and positive, which implies that generally road transport is the substitute of rail transport. Moreover, it also provides a possible mechanism of a modal-split from road to rail transport by increasing the costs of road transport (trucking-rates, travel costs). Sixth, although we find a positive effect of population on rail travel demand in Pakistan in long-run, its co-efficient is considerably lower than one, and is also marginally significant at 10% level. Finally, rail's route-density is considered the most dominant variable for rail travel demand in the long-run, in which an increase in route-density, through investments in rail network infrastructure, will promote long-run rail's passengers demand by more than one-to-one. Therefore, the long-run rail travel demand is the most sensitive to the variations in rail's route-density.

CHAPTER 4

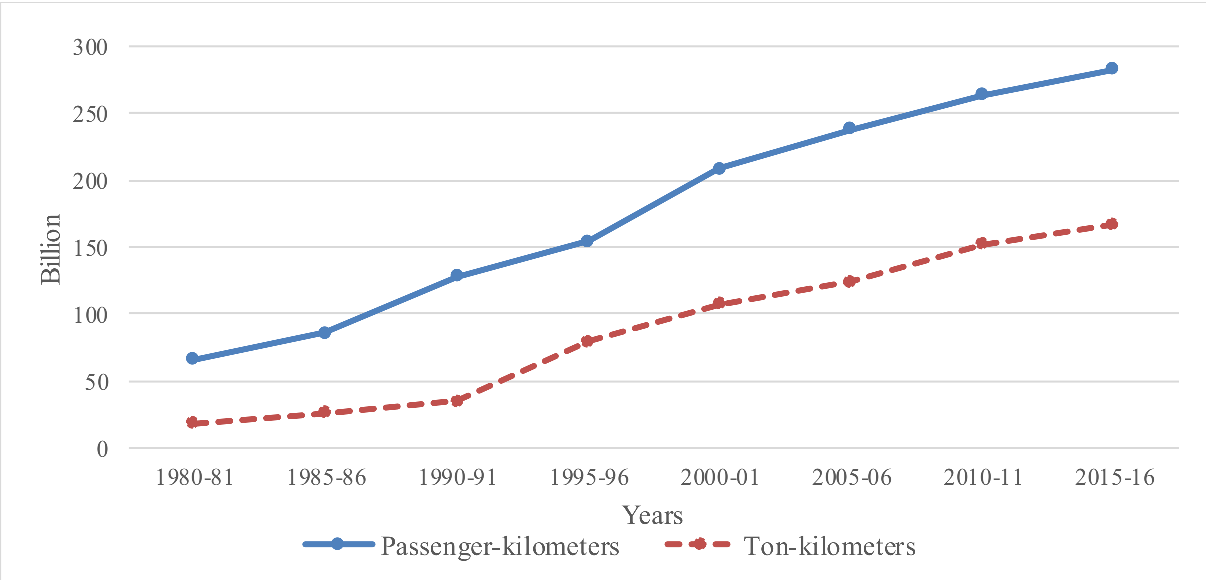
UNDERSTANDING THE DETERMINANTS OF ROAD TRANSPORT (FREIGHT AND PASSENGER) DEMAND IN PAKISTAN WITH ARDL CO-INTEGRATION APPROACH

4.1 Introduction

On international front, road transport facilitates around 70% of the demand for surface freight and 90% of passenger transport, respectively (IEA, 2017c). Over the last few decades or so, global road freight and passenger transport demand has significantly increased. For example, over the period 2000-2015, worldwide road's motorized passenger demand, measured in terms of passenger-kilometers (PKM), have increased from 27 trillion PKM to 41 trillion PKM. Similarly, world's road freight transport, measured by ton-kilometers (TKM), have also grown at an average rate of 7.6% per annum from 8 trillion TKM in 2000 to 24 trillion TKM in 2015 (Fulton and Eads, 2004; IEA, 2017b). If current trends in income and population continue, then it is projected by IEA (2017b) that the demand for road freight and passenger transport will increase to 85 trillion ton-kilometers and 72 trillion passenger-kilometers by 2050. Energy consumption is an important input to transport modes, especially road transport, for freight and passenger mobility, and road transport accounts for most of the final energy consumption in transport sector. World total final energy consumption (TFC) of road transport has also increased from 1418.71 million tons of oil equivalent (MTOE) in 2000 to 2034.22 million tons of oil equivalent (MTOE) in 2015 (IEA, 2002, 2017d), due to increasing road transport requirements. Since energy consumption of road transport mostly comes in petroleum products (which are directly related to environmental emissions and air pollutants), it is also considered as the one of the most important sources of CO_2 emissions. In 2015, world transport sector accounts for about 7737.8 million tons of CO_2 emissions or 24% of total CO_2 emissions from fuel combustion, while road transport alone emits about 5792 million tons of CO_2 emissions, which represents 75% of overall transport sector emissions (IEA, 2017a).

Road-based mode is the backbone of transport system in Pakistan, as it carries most of domestic freight and passenger traffic. In particular, it handles 92 percent of passenger and 96 percent of freight transport in Pakistan (Government of Pakistan, 2012). The demand for both road freight and passenger transport has significantly increased over the last few decades. For instance, data from Figure 4.1 shows that road's PKM demand has substantially increased by an annual average growth rate of 4.23%, from 66 billion PKM in 1980-81 to 282 billion PKM in 2016, while that of road's TKM demand has also grown from 18 billion TKM to 167 billion TKM during the same period, with average annual rate of 6.57%. The number of motor vehicles on road has increased rapidly in Pakistan due to an increase in freight and passenger transport demand. The number of road vehicles increased from 0.68 million in 1980 to 4.47 million in 2000 (more than 500%), and increased to 10.44 million in 2010. The number of vehicles increased further to 24.26 (mor than double) in 2018 (Government of Pakistan, Various issues).

Figure 4.1: Patterns of Road's Freight and Passenger Transport in Pakistan over 1980-2016



Data Sources: Pakistan Economic Survey (various issues); Pakistan Statistical Yearbook (various issues); Oil Companies' Advisory Committee (several years)

A rapid increase in the demand for both road freight and passenger transport has also posed several challenges or concerns for planners and policymakers in Pakistan such as higher energy consumption, environmental emissions, deteriorating urban air quality, road congestion, etc. For example, increasing reliance on road transport is not only over-burdening road systems, deteriorating roads quality, creating pollution and causing road-congestion, but also leads to higher transportation costs due to imported transport fuel (Planning Commission of Pakistan, 2018). Moreover, since road transport demand and energy-use or consumption are well-integrated, increasing the demand for road freight and passenger transport has also resulted in higher energy consumption, particularly the petroleum products, and associated CO_2 emissions. For instance, Pakistan's road sector consumed about 2.07 million-tons of oil equivalent energy and emitted around 6.40 million tons of CO_2 emissions in 1980 (IEA, 2007a, 2007b), which have increased to 15.65 million tons of oil equivalent energy and 44.90 million tons of CO_2 emissions in 2016, respectively (IEA, 2018a, 2018b). The demand for transport sector (especially road transport) is expected to increase further with population growth and economic development: urbanization, agricultural development and rapid industrialization together increase the demand for freight and passenger transport, and higher incomes expand the leisure-related travel (Ramanathan, 2001), which could lead to an unsustainable development of road transport. Therefore, an empirical analysis of road transport demand is important for an efficient planning of road transport.

To the best of our knowledge, this is the first empirical study that attempts to provide the empirical analysis of road transport (freight and passenger) demand in Pakistan. This chapter uses annual aggregate time series data for the period 1980-2016 and adopts the Auto-regressive distributed lag (ARDL) bounds testing approach of co-integration as an estimation method, proposed by Pesaran and Shin (1999) and Pesaran et al. (2001). Our analysis can provide answers to the following questions:

I. What are the main short-run and long-run determinants of road transport (both freight and passenger) demand in Pakistan?
II. How does the demand for freight and passenger transport respond to fuel price increases (decreases)?
III. Is the income of road travelers in Pakistan a more important determinant of road transport demand than fuel price?
IV. How effective are the demand management policies (such as fuel taxes) in reshaping the current trend of road transport demand in favor of other modes such as rail?

The estimation results show that long-run road transport demand, especially passenger transport, is relatively more inelastic, which indicates that policy instruments (such as fuel taxes) are relatively less effective in controlling the growth of road transport (especially passenger demand), and that a combination of other policy options (such as alternative fuels, conservation, etc.) are also important. Real per-capita GDP, rail-fare (cross-price), urban population and road-density are also important drivers of road passenger demand in the long-run, while industrial production index (IPI) and rail's freight-rate (cross-price effect) are identified as important determinants of the demand for long-run road freight transport.

The remaining sections of the chapter 4 are as follows: Section 4.2 will provide the empirical literature on road transport (freight and passenger) demand. Section 4.3 will explain the methodological framework and issues related to the variable construction and data sources. The empirical results will be discussed in section 4.4 and section 4.5 concludes the study with some policy implications.

4.2 Literature Review

The empirical literature on road transport can be divided into two equally important components of freight and passenger transport demand. The next section provides the analysis of empirical literature regarding freight and passenger transport, respectively.

4.2.1 Studies of Road Freight Transport Demand

Freight transport is an important component of road transport demand. Over the last few decades or so, the literature regarding freight transport modelling has improved significantly on both theoretical and methodological fronts. For example, survey papers by Winston (1983) and, Zlatoper and Austrian (1989) emphasize and differentiate between the two broad methods of modelling the freight transport demand, and are classified as aggregate or dis-aggregate models. The aggregate models are further classified as aggregate modal-split models or neo-classical aggregate models, based on the aggregate data available for a particular transport mode in an origin-destination pair. The estimation of aggregate models is usually done by using flexible functional forms such as translog functions. On the other hand, the dis-aggregate models are categorized into behavioral and inventory models, where the behavior of individual decision maker is incorporated into the analysis such as the individual shipper's choice about a particular transport mode for a given shipment size. The discrete choice models such as logit and probit models are used in dis-aggregated studies. These models have strong microeconomic foundations and reflect the choices of individual decision-makers more appropriately. However, the difficulty arises in obtaining such rich data at an individual level, which may limit their use for many cases. Earlier studies have used either of these approaches to estimate freight transport demand and produce a wide range of elasticities (see, for example, Baumol and Vinod, 1970; Daughety, 1979; Friedlaender and Spady, 1981a, 1981b; Lewis and Widup, 1982; Oum, 1979a; Sloss, 1971; Winston, 1981, among others), possibly due to level of aggregation, degree of inter-modal competition between transport modes in the study and use of functional forms (Oum et al., 1992).

Understanding the main drivers of road freight transport is important to shape the future growth of road freight transport in a more sustainable manner. Although various studies provide the empirical analysis of road freight demand, they are relatively scarce as compared to the studies on road passenger demand. In an early study, Bennathan et al. (1992) analyze freight transport demand (measured by ton-kilometers) for three modes (road, rail and waterways) by using cross-sectional data on 17 developed, 11 developing and 5 socialist countries. For road transport, the regression results show that road freight transport is mainly determined by gross domestic product (GDP). However, the long-run GDP elasticity of road freight transport is higher in developing countries (1.25) than developed countries (1.02). In a review article, De Jong et al. (2010) examine 36 empirical studies on road freight transport of European countries to investigate the price elasticities of different indicators such as ton-kilometers, vehicle-kilometers and fuel consumption, and explain that a considerable variation in price elasticities across studies can be attributed to various factors such as definitions of dependent and independent variables, research method, commodity type, distance-class (short, long), data type (time series, cross section, panel), geographic scope, etc. Later on, Dunkerley et al. (2014) review the empirical studies on both road freight and passenger transport and provide the possible range of fuel-price and income/output elasticities. According to study, fuel-price elasticity ranges from -0.1 to -0.5. On the other hand, income elasticity of road passenger transport is between 0.5 to 1.4, while the elasticity of freight transport with respect to economic activity is from 0.5 to 1.5 for an aggregate or overall commodity sector, but shows considerable variation across commodity sectors.

Due to developments in time series methods, the studies using aggregate time series data on regional or national commodity flows adopt time series econometric models to estimate the price and /or income elasticities of road freight demand (see, for insatnce, Agnolucci and Bonilla, 2009; Andersson and Elger, 2012; Bjørner, 1999; Ramanathan, 2001; Shen et al., 2009). Bjørner (1999) analyzes the demand for both road freight transport (measured in ton-kilometers) and freight traffic (vehicle kilometers driven) in Denmark; where freight traffic demand is derived from shippers' transport production function and that of freight transport is used as an input in firms' production of output. The Johansen co-integration model is used with quarterly time series data from 1980-1993 to derive the empirical results. The long-run price (measured as generalized cost of transport) and output elasticities of road freight transport are

-0.47 and 1.32 respectively, while the respective freight traffic elasticities of price and output are -0.81 and 0.92. For a developing country, Ramanathan (2001) analyzes the performance of Indian aggregate transport sector (road, rail and air) of freight and passenger using two-step Engle-Granger co-integration model and shows that aggregate freight transport (measured in terms of ton-kilometers) is more sensitive to the industrial production, with long-run elasticity equals to 1.183.

Shen et al. (2009) utilize six econometric models to estimate and forecast the UK aggregate (road plus rail) freight transport (measured in billion ton-kilometers) and dis-aggregate freight transport (seven commodity groups), using annual data from 1974 to 2006. The model is estimated with only two main explanatory variables economic activity (different proxies used are industrial production, gross domestic product and total output production plus imports) and price (road operating costs). The results indicate that the role of output, measured by industrial production, is the most dominant factor explaining UK road plus rail freight, and also that elasticity estimates of output vary across different models and also across various commodity sectors. Moreover, the forecasting performance of all models, based on mean-absolute-percentage-error (MAPE), suggest that no single model is considered best in all cases.

Similarly, Andersson and Elger (2012) examine the relationship between Swedish freight transport demand (measured as billion ton-kilometers for aggregate and separate modes) and economic activity (measured as gross domestic product, gross value added of commodity producing sectors) and trade variables (imports and exports are used separately) over different time horizons, defined as short-run, medium and long-run. The estimation results, based on band-pass filter, recommend that only trade variables are relevant for freight demand in the short-run while, in the medium-run, both trade and GDP are mutually important for explaining freight demand. However, in the long-run, only GDP is significant explanatory variable causing variations in freight demand, with estimated value of elasticity greater than one.

Winebrake et al. (2015) estimate the fuel price elasticities of combination truck vehicle-miles travel (VMT) and combination truck fuel-consumption (FC) in US from 1970 to 2012. The explanatory variables of the study are international trade (proxy of economic activity), fuel-prices (high-speed diesel), and interactive, and fixed effects of indicator variables to account for deregulation (regulatory environment is over the period 1970-1979, and 1980-2012 is deregulated environment) and shift in data collection methods. Due to non-stationarity of overall data, both models (trucking activity and fuel consumption) are estimated in first-differenced form, which also include a lagged-difference of dependent variable among explanatory variables. The empirical findings suggest that short-run fuel price elasticities of VMT and FC were -0.37 (37%) and -0.36 (36%) in regulated period (1970-1979) and reduced to zero over the deregulated environment (1980-2012). For both models, the long-run elasticities are derived by taking the ratios of short-run elasticities to one minus the co-efficient associated with lagged dependent variable, and the results indicate that long-run fuel-price elasticities, in both cases, are also zero.

For UK, Wadud (2016) studies the diesel demand for different road freight vehicles (light vs. heavy goods vehicles, Articulated vs. rigid trucks), and estimates income (GDP) and price elasticities. The study finds that, for both heavy and light goods vehicles, the income elasticity of diesel demand is closer to 0.80, while it is slightly lower to 0.56, in case of rigid trucks. On the other hand, diesel consumption of both light goods vehicles and articulated trucks is completely insensitive to diesel prices, while demand for diesel in rigid trucks decreases to some extent as a result of increase in diesel prices, but the response is small and diesel demand is inelastic. This implies that fuel-pricing may not be an effective policy option to reduce fuel consumption and associated carbon emissions in the UK freight sector.

Zou and Chau (2019) analyze the impact of fuel-prices on the freight transport (in tons) of various modes (road, rail, inland waterway, air) in Shanghai (China) by using monthly data from 2009 to 2016. The conventional first-differenced vector auto-regressive (VAR) model is estimated since presence of no-cointegration is identified by both Johansen and Phillips-Ouliaris co-integration tests. The co-efficients of first-differenced fuel-prices, in equations of road, rail and waterway freight transport, are statistically insignificant. It suggests that changes in fuel prices do not influence the short-run freight transport of various modes in Shanghai.

Gomez and Vassallo (2020) use panel data on 12 European countries from 1995 to 2015 to investigate the efficacy of heavy vehicle tolling in reducing the road freight transport and promoting a modal-split in favor of other competing modes (rail, inland waterways). For road freight transport (in million ton-kilometers) model, the study uses toll-rates of heavy vehicles, GDP of transport-intensive industries, international trade, and rail freight as explanatory variables. The estimation results from generalized method of moments (GMM) show that GDP intensive industries and international trade are important determinants of road freight transport with elasticities are 0.25 and 0.46, respectively, while the impact of toll-rates on road freight transport is very small (co-efficient closer to zero) and statistically insignificant. This indicates that charging system, other than mileage-based, is not effective in terms of decreasing road freight transport.

4.2.2 Empirical Literature on Road Passenger Transport Demand

The prime reason behind the estimation of road transport demand is to determine its major determinants. Road transport demand may respond to a number of monetary and non-monetary factors. Among them, the price and income are the two main determinants of road transport demand. The empirical studies produce a wide range of these empirical estimates of elasticities, owing to various factors such as the level of aggregation (data based on city or country), nature of data (time series, cross-section or panel data), functional form (linear, log-linear, and econometric method) and definitions of variables used in the study, etc. (Oum et al., 1992).

Road passenger transport demand is an important ingredient of transport planning and development. To that end, a significant amount of empirical studies, over the last few decades, have provided the empirical analysis of road passenger transport demand (see, for example, Acutt and Dodgson, 1995; Ajanovic and Haas, 2012; Clarket al., 2005; Elvik and Ramjerdi, 2014; Goodwin, 1992; Goodwin et al., 2004; Graham and Glaister, 2004; Hanly et al., 2002; Huang and Burris, 2015; Litman, 2013; Nolan, 2010; Odeck and Bråthen, 2008; Oum et al., 1992). For example, Oum et al. (1992) review the empirical literature of both freight and passenger demand of different transport modes and assess the nature of own price elasticities. After reviewing seven studies of automobile usage and twelve regarding urban transit, they find that the demand for both automobile usage and urban transit is price inelastic. In particular, own price elasticities of automobiles vary from -0.09 to -0.52 while the price elasticities of urban transit range from -0.01 to –0.78. Hanly et al. (2002) provide the survey of 69 studies on both road traffic and fuel consumption, and summarize the (fuel) price and income elasticities. Their results show that the elasticities of fuel consumption are greater than those of traffic elasticities. Moreover, Income elasticities are 1.5 to 3 times larger than fuel price elasticities and short-run elasticities are lower than long-run elasticities by a factor of 2 to 3.

Graham and Glaister (2004) review the available elasticity estimates of income and price within context of road's freight and passenger transport. Using a variety of indicators regarding passenger traffic demand such as fuel consumption, car-kilometers, car-trips and car-ownership, the results suggest that the effect of income is positive and crucial for explaining the variation in all kinds of indicators used for passenger traffic demand. The results related to the fuel price elasticities indicate that the effect of fuel price on fuel consumption is much stronger than other definitions of road traffic used. Moreover, the price elasticity of road freight transport demand ranges from -0.5 to -1.5. Nowak and Savage (2013) estimate the cross-elasticity of transit use (different modes such as city bus, city rail, sub-urban bus and commuter rail) with respect to gasoline price in Chicago. The estimated cross-price elasticities of city bus and sub-urban bus, when gasoline price is less than \$3/gallon, are 0.064 and 0.054, respectively. Also, the urban city and suburban bus elasticities significantly increased to 0.283 and 0.298 when gasoline price exceeded \$4/gallon later in the sample period. Elvik and Ramjerdi (2014) discuss the extent to which different economic policy instruments such as fuel prices, road congestion charging, toll schemes and reward systems are effective in promoting environmentally sustainable transport. The results, based on survey of price elasticities of transport demand, show that policy tools such as fuel prices, toll schemes and congestion charges are effective and can be used to control the traffic volume and associated emissions.

A number of studies analyze the road passenger or travel demand using fuel prices as a cost of travel (see, for example, Delsaut, 2014; Fujisaki et al., 2011; Gillingham, 2014; Musso et al., 2013), and investigate the sensitivity of road travel demand to changes in fuel prices and other control variables. For example, Fujisaki et al. (2011) use time series (both annual and quarterly) data to analyze the effects of gasoline price and income on various types of land transport (passenger-kilometers/capita) in Japan such as public transport (adding both rail and commercial bus transport), personal automobiles (aggregation of both registered non-commercial passenger cars and more than two-wheelers light cars) and surface transport (a total of personal automobiles and public transport). Both Multiple regression and partial adjustment models are employed in log-linear functional form to derive and differentiate between short and long-run (fuel) price and income elasticities. The estimated short-run real price and income elasticities of personal travel are -0.18 and 0.36 while those of long-run are -0.26 and 0.50, respectively. However, for public transport, both short and long-run price elasticities are lower than the elasticities of personal transport except that the impact of gasoline price on public transport is positive, which implies that an increase in cost of personal transport (fuel price) induces the consumers to switch from private to public transport. Moreover, the income effects of public transport are significantly larger than the income effects of private transport, both in the short-run as well as in the long-run.

In a similar study, Delsaut (2014) studies the impact of fuel price changes on the demand for road (vehicle-kilometers) and rail traffic, separately. The main explanatory variables of the road traffic model are fuel price, gross domestic product (GDP), road network. The estimation is done using partial adjustment model (PAM) on annual data from 1990-2010. The short-run and long-run own-price (fuel-price) effects are estimated as -0.13 and -0.27, respectively. Gillingham (2014) assesses the impact of gasoline prices on the demand for deriving in California, U.S.A, by making use of vehicle-level data, which consists of 5.8 million new registered vehicles from 2001 to 2003, and then this sample is used further for smog-test between 2006 to 2009. The travel demand by an individual vehicle, measured in vehicle-miles-traveled, is determined by the factors such as the price of gasoline facing by the owner, the attributes of the vehicle being driven, demographic effects and effects of economic conditions, etc. The study finds that the medium-run elasticity of driving with respect to gasoline price to be -0.22. Moreover, a considerable heterogeneity is observed in the elasticity values, due to variations in geography, buyers' type and demographic factors.

Souche (2010) examines the structural determinants of urban travel demand using cross-section data on transport systems of world's hundred cities in 1995. Different estimation strategies such as ordinary-least-squares (OLS), two-stage-least-squares (2SLS), 3-stage-least-squares (3SLS) and seemingly unrelated regression (SUR) methods are used to estimate the models of personal car travel and public transport. The study concludes that the user cost of car travel and urban density are important determinants of car travel, exerting negative effect on car travel. Moreover, the results also reveal that user cost of public transport exerts significant negative impact on its demand while urban density and user cost of car travel further encourage the demand for public transport. In a different study, Metz (2012) uses the time series data from National Travel Survey in Great Britain to analyze the behavior of personal daily travel over a period from 1970 to 2010. The analysis, based on trends, shows that demand for daily travel (measured as average distance travelled, trip-time (in hours) and trips) cease to grow with real household income. Therefore, the study proposes that demographic variables such as population growth and ageing of population will be main determinants of personal travel demand in the future.

Energy consumption is considered as an important component (input) of road transport and is also proportional to the transport demand, at least in the short-run. Therefore, a large pool of empirical studies analyze the transport demand using fuel consumption as a surrogate measure of transport demand (see, for example, Ajanovic et al., 2012; Birol and Guerer, 1993; Dahl, 2012; Dahl and Sterner, 1991; Hasanov, 2015; Omer, 2018; Romero et al., 2010; Sterner, 2006; Sterner and Dahl, 1992, among others). These studies investigate the transport fuel demand for countries with different background and derive the (fuel) price and income elasticities by using different econometric approaches. Then, based on price elasticities, they offer various energy policy proposals (using fuel price tax as environmental policy instrument) to curb the energy consumption of road transport and related CO_2 emissions. For instance, Birol and Guerer (1993) estimate both price and income elasticities of transport fuel (gasoline and diesel) demand for six developing countries, including Pakistan, using time series data for the period 1970-1990. The estimation results, based on partial adjustment model (PAM), suggest that the long-run income and price elasticities of gasoline demand in Pakistan are 1.49 and -0.07 respectively, while those of diesel demand are estimated as 1.91 and 0.22, respectively. In a more recent study for Pakistan, Omer (2018) examines income and price elasticities of three transport fuels (petrol, diesel and compressed natural gas (CNG)) using the technique of seemingly-unrelated-regression-equations (SURE). Models are estimated using monthly data from 2004 to 2015. The results show that fuels are substitutes and short-run elasticities are lower than long-run estimates. Moreover, the study only finds a positive income elasticity of petrol demand while income elasticities of both CNG and diesel demand are negative, implying that only petrol is normal good while the demand of other fuels is inferior one.

Although existing empirical literature, in general, indicate that the effect of income on road transport demand is positive, many studies pertaining to public (bus) transport demand offer a negative income elasticity of public transport demand (see for example, Bresson et al., 2003; Dargay and Hanly, 2002; Deb and Filippini, 2013; Frankena, 1978; Paulley et al., 2006, and many others), suggesting that the demand for public transport is an inferior good. The possible reason for such relationship is that most of these studies include both income and car-ownership, among others, as explanatory variables, while the car-ownership itself depends on the income. So, the multi-collinearity exists due to a strong correlation between income and car-ownership. Therefore, the effect of both these variables on the demand for public bus transport may not be separated and a careful analysis of the demand for public transport is required that can address these issues. For example, Crôtte et al. (2009), in their demand analysis of Mexico city metro, decompose the overall income effect into two uncorrelated components and observe that the demand for Mexico city metro is the normal good (a positive income elasticity) for minimum wage earners (who are not the potential car owners) while it is perceived as an inferior good for medium and/or high income groups. The literature on car-ownership model also suggests that income is one of the main determinants of car-ownership (see, for example, Button et al., 1993; Dargay and Gately, 1999; Ingram and Liu, 1999, among others). So, an increase in income is likely to be associated with more car-ownership and less use of public transport such as bus transit.

Recently, Sheng and Sharp (2019) use quarterly data (2001-2015) on road vehicle types (motorcycles, buses, diesel cars and petrol cars) in New Zealand to analyze the passenger transport demand for each mode of passenger travel. Transport demand (measured by vehicle-kilometers travelled) for each mode is expected to be determined by the income of road transport user of respective mode, own price of respective transport mode, price of complements/substitutes of respective transport mode, and demographic and socioeconomic factors. The study adopts seemingly-unrelated-regression (SUR) model to estimate the demand for each transport mode, as error-terms across demand equations for all transport modes are correlated. Own-price elasticities of both diesel cars and petrol cars are -0.11 and -0.08, and are statistically significant, which shows that the demand for both types of cars is inelastic. This implies that increasing fuel-prices through taxation would not lead to a significant reduction in vehicle-kilometer travel by cars. On the other hand, income elasticity of petrol cars is positive (0.51), while income elasticity of both buses and motorcycles is significantly negative, indicating that the demand for both buses and motorcycles falls as income rises.

Aggregate time series studies analyze the road passenger transport demand using co-integration and error correction models (Fouquet, 2012; Liddle, 2009; Odeck and Johansen, 2016; Ubaidilla, 2013). For example, Liddle (2009) investigates the relationship between vehicle-miles-per capita, GDP per capita, gasoline price and registered vehicles per-capita for United States within Johansen co-integration framework. The long-run price and income elasticities are estimated as -0.18 and 0.46, respectively. The results, based on short-run causality, suggest that only income exerts significant positive impact on vehicle-miles travel while other short-run effects of price and vehicle-ownership are irrelevant. Odeck and Johansen (2016) use two econometric methods dynamic ordinary least square (OLS) method and error correction model (ECM) to estimate and compare the fuel price and income elasticities of road traffic (vehicle-kilometers) and fuel demand (fuel consumption), and further derives the direct 'rebound effect' in Norwegian context. The short-run income and price elasticities of travel demand are 0.06 and -0.11, while the same long-run elasticities are 0.13 and -0.24, respectively. On the other hand, both short-run and long-run income elasticities of fuel demand are 0.06 and 0.09, respectively, whereas those of fuel demand with respect to fuel price, in the short and long-run, are -0.26 and -0.36, respectively. More recent studies provide the evidence of an asymmetric relationship between transport demand and fuel prices (See, for example, Chi, 2016, 2018; Kwon and Lee, 2014).

Traditionally, the possible solution to the problem of urban road congestion has been the expansion of existing road network, which reduces road congestion and generalized costs of travel (particularly travel time). However, decreasing costs of travel may encourage more demand for transport and could offset the initial capacity expansion effect, hence indirectly generating even more transport demand and road congestion. The behavioral response through which growth in road network further promotes more transport demand and congestion is known as 'induced demand'. A number of studies empirically investigate the road transport demand within induced demand context and provide strong empirical evidence that growth in road network further accelerates the transport demand and road congestion (see, for example, González and Marrero, 2012; Hymel, 2019; Litman, 2017; Noland, 2007; Tennøy et al., 2019).

4.3 Methodological Framework and Data

4.3.1 Theoretical Framework

Road transport demand is expected to be determined by a number of economic and demographic factors. Based on review of empirical literature, the following models are proposed to analyze the aggregate road passenger and freight transport demand, respectively (see, for insatance, Delsaut, 2014; Ramanathan, 2001; Ubaidilla, 2013, and others).

Model 1

$$PKM_t = e^{\alpha_0} {FPI_t}^{\alpha_1} {GDP_t}^{\alpha_2} RF^{\alpha_3} {UR_t}^{\alpha_4} {RD_t}^{\alpha_5} e^{\varepsilon_{1t}} \tag{4.1}$$

Model 2

$$TKM_t = e^{\beta_0} {FP_t}^{\beta_1} {IPI_t}^{\beta_2} FR^{\beta_3} {TR_t}^{\beta_4} e^{\varepsilon_{2t}} \tag{4.2}$$

Table 4.1: Symbols and Variable Names

Notation	Variable
PKM	*Passenger-kilometers*
FPI	*Fuel price index*
GDP	*Per-capita GDP*
RF	*Rail-fare*
UR	*Urbanization*
RD	*Road density*
TKM	*Ton-kilometers*
FP	*Fuel-price*
IPI	*Industrial production index*
FR	*Rail's freight-rate*
TR	*International trade*

The models given by the equations (4.1) and (4.2) are non-linear models in variables and therefore can be linearized by some logarithmic transformations in the following manner (see, for example, Hakim and Merkert, 2017; Rahman and Balijepalli, 2016; Wijeweera et al., 2014).

$$lnPKM_t = \alpha_0 + \alpha_1 lnFPI_t + \alpha_2 lnGDP_t + \alpha_3 lnRF_t + \alpha_4 lnUR_t + \alpha_5 lnRD_t + \varepsilon_{1t} \quad (4.3)$$

$$lnTKM_t = \beta_0 + \beta_1 lnFP_t + \beta_2 lnIPI_t + \beta_3 lnFR_t + \beta_4 lnTR_t + \varepsilon_{2t} \quad (4.4)$$

The dependent variable in equation (4.3) is the road travel demand, measured in terms of passenger-kilometers (PKM), is a function of cost of travel such as fuel price index (FPI), per-capita gross domestic product (GDP), rail-fare (RF), urbanization (UR) and road density (RD). The main advantage of using double-log model is that the parameters associated with explanatory variables can be directly interpreted as elasticities. For instance, all else equal, α_1 is the percentage change in passenger-kilometers due to a one percentage increase in the fuel price, and is called the (fuel) price elasticity of road travel demand.

The cost of travelling is an important determinant of road travel, for which different indicators such as generalized cost of transport (the costs related to vehicle ownership and maintenance, travel time, fuel taxes, safety, toll rates, etc.) or simply marginal cost (fuel price) of travel have been used in the literature. We use fuel prices as a cost of road travel, as no other cost related data is available for road travel (Delsaut, 2014; Dunkerley et al., 2014; Liddle, 2009; Ramanathan, 2001). From theory, the expected sign of α_1 is negative because people respond to an increase in cost of travel by reducing the amount of travel in the short-run while they may purchase more fuel-efficient vehicles in the long-run. Besides, the income of travelers is also important driver of passengers' transport demand. All else equal, an increase in income is likely to be associated with more travel demand by them. The gross domestic product (GDP) per-capita is used as the proxy of income. So, the expected sign of $\alpha_2 > 0$ is positive. The expected sign of α_3 is positive because road and rail are substitutes, which implies that all else equal an increase in rail-fare will lead to raise the demand for road travel. It is expected that the effect of urban population (measured as a percentage of total population) on the demand of road's passenger transport is positive, $\alpha_4 > 0$. The use of urban population is more relevant because most of road vehicles in Pakistan are concentrated in urban Pakistan. Others also use a similar indicator for analyzing the (aggregate) road passenger transport demand (see, for instance, Ramanathan, 2001; Ubaidilla, 2013). To capture the supply side effect, the road density, measured as a ratio of total road network to the total country's land area, is included as an explanatory variable in the model. The expected sign of α_4 is positive due to the reason that building more infrastructure, in the form of increasing road length, attracts more traffic.

On the other hand, road freight demand is measured in ton-kilometers, which also depends on trucking-rates, industrial production (IP), rail's freight-rate and international trade (TR). Since time series data on trucking-rates is not available, fuel-price (FP) such as high-speed diesel, is used as an approximation or of trucking costs (a proxy of trucking rates) (see, for example, Winebrake et al., 2015). The coefficient β_1 measures the impact of fuel price on road freight demand. The expected sign of β_1 is negative. Road freight demand, being an intermediate input to the production and distribution function of firms, also depends on the economic activity in the economy, for which different indicators such as gross domestic product (GDP), industrial production or gross value added (GVA) of commodity producing sectors have been used in the literature (see, for example, Agnolucci and Bonilla, 2009; Andersson and Elger, 2012; Bennathan et al., 1992; Ramanathan, 2001; Shen et al., 2009). However, we adopt the industrial production index (IPI) as a proxy of economic activity in road freight demand for consistency across rail and road freight demand models, as this indicator (IPI) is also used as an indicator for economic activity/output in rail freight demand. Moreover, it is argued that GDP may be an incorrect measure for economic activity, as it measures the value of both goods and services, while services sector is likely to produce less demand for freight transport. Therefore, GDP is likely to underestimate the income elasticity of freight demand (see, Agnolucci and Bonilla, 2009; McKinnon, 2007). The empirical transport literature on freight transport established that growth in economic activity promotes the demand of road freight transport. So, we presume that sign of β_2 will be positive. On the other hand, ceteris paribus an increase in the cost of rail freight (in terms of higher freight-rate) will be associated with a modal-split in favor of road freight transport. So, the expected sign of β_3 will be positive Similarly, it is also expected that the international trade also matters for road freight transport, as most of the country's exports and imports are carried by the road sector. So, an increase in international trade will likely to be associated with more freight transport on the roads (Productivity Commission, 2006; Winebrake et al., 2015). The expected sign of co-efficient associated with international trade is positive, $\beta_4 > 0$.

4.3.2 Econometric Method

Since the last few decades or so, continuous developments and improvements in time series models led the researchers to identify the problem of spurious relationships, associated with the use of single equation models (ordinary least square method), and devise more robust methods to deal with non-stationary variables or variables having stochastic trends.

We analyze the road transport demand using ARDL bounds testing approach of co-integration, first proposed by Pesaran and Shin (1999), and then Pesaran et al., (2001) provided further extensions. Subsequently, time series studies widely adopt ARDL approach to a variety of economic applications due to several advantages. First, ARDL co-integration technique offers some flexibility for researchers to estimate the demand relationships even when all the choice variables are first-difference stationary $\mathrm{I}(1)$, stationary at levels $\mathrm{I}(0)$ or mixture of both processes $\mathrm{I}(0)$ and $\mathrm{I}(1)$. Other standard tests of co-integration such as Engle and Granger (1987) does not offer such flexibility in its testing of co-integration. However, Johansen co-integration approach is equally good if all variables are I (1)[14]. Second, the ARDL bounds testing approach can simultaneously estimate both short-run and long-run parameters of the demand equation. Third, Narayan (2005) demonstrates that ARDL performs better, in small samples, than other Multivariate co-integration tests. Therefore, the ARDL model of Equations (4.3) and (4.4) is based on estimating unrestricted error correction models in the following forms.

[14] When all variables are integrated of order one I(1), then Johansen co-integration approach may have an additional advantage of testing multi-cointegration relationships among the choice variables.

$$\Delta lnPKM_t = \varphi_{10} + \sum_{i=1}^{b1}\gamma_{1i}\Delta lnPKM_{t-i} + \sum_{i=0}^{b2}\gamma_{2i}\Delta lnFPI_{t-i} + \sum_{i=0}^{b3}\gamma_{3i}\Delta lnGDP_{t-i} + \sum_{i=0}^{b4}\gamma_{4i}\Delta lnRF_{t-i} + \sum_{i=0}^{b5}\gamma_{5i}\Delta lnUR_{t-i} + \sum_{i=0}^{b6}\gamma_{6i}\Delta lnRD_{t-i} + \omega_1 lnPKM_{t-1} + \omega_2 lnFPI_{t-1} + \omega_3 ln\, GDP_{t-1} + \omega_4 lnRF_{t-i} + \omega_5 lnUR_{t-i} + \omega_6 lnRD_{t-i} + \vartheta_{1t} \quad (4.5)$$

$$\Delta lnTKM_t = \varphi_{20} + \sum_{i=1}^{c1}\theta_{1i}\Delta lnTKM_{t-i} + \sum_{i=0}^{c2}\theta_{2i}\Delta lnFP_{t-i} + \sum_{i=0}^{c3}\theta_{3i}\Delta lnIPI_{t-i} + \sum_{i=0}^{c4}\theta_{4i}\Delta lnFR_{t-i} + \sum_{i=0}^{c5}\theta_{5i}\Delta lnTR_{t-i} + \delta_1 lnTKM_{t-1} + \delta_2 lnFP_{t-1} + \delta_3 lnIPI_{t-1} + \delta_4 lnFR_{t-i} + \delta_5 lnTR_{t-i} + \vartheta_{2t} \quad (4.6)$$

Where φ_{10} and φ_{20} are drift terms, Δ is the first difference operator. The co-efficients ω_1 to ω_6 capture the long-run relationship between rail travel demand variables while the parameters δ_1 to δ_5 represent the long-run relationship between freight transport demand to its determinants. Others with summation signs such as from γ_1 to γ_6 and θ_1 to θ_5 capture the short-run effects. Symbols ϑ_{1t} and ϑ_{2t} are independent white-noise error-terms in above Equations (4.5) and (4.6). The ARDL bounds testing approach involves several steps. First, it estimates equations (4.5) and (4.6) independently by ordinary least square (OLS) method and then proceeds to determine whether co-integration exists or not by testing the joint significance of the parameters associated with the lag-level variables in above equations. The resulting null hypothesis of no co-integration against the alternate hypothesis of presence of co-integration in Equations (4.5) and (4.6) are given as follows:

Model 1

Null hypothesis $H_0: \omega_1 = \omega_2 = \omega_3 = \omega_4 = \omega_5 = 0 = \omega_6 = 0$

Alternative hypothesis H_1: At least one of the ω's is non-zero

Model 2

Null hypothesis $H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0 = \delta_5 = 0$

Alternative hypothesis H_1: At least one of the δ's is non-zero

The joint significance of these parameters is based on F-statistic, which follows non-standard asymptotic distribution under the null-hypothesis of no co-integration among the listed variables. Therefore, the computed value of F-statistic is compared with the two tabulated (critical) values provided by Pesaran et al. (2001), and Narayan (2005). These two critical values are known as upper and lower-bounds, and the critical values associated with upper-bounds are derived on the assumption that all choice variables in the model are I(1), while for lower-bound, it assumes that all relevant variables are I(0). Three possibilities may exist when making comparison of F-stat with the tabulated values. First, if value of F-statistic becomes larger than the value associated with upper-bound, then the null hypothesis of no co-integration will be rejected in favor of existence of co-integration among variables, without knowing their order of integration. Second, if the value of F-statistic falls short of lower-bound critical value, then null hypothesis cannot be rejected, which implies that co-integration does not exist among the variables of interest. Finally, if the F-computed value falls between upper and lower critical bound values, then the results would be inconclusive regarding co-integration and, in that case, the researcher may pursue the other tests of co-integration.

In case of co-integration, the long-run ARDL freight and passenger demand models are estimated in equations (4.3) and (4.4). The short-run parameters (elasticities) of passenger and freight demand can be estimated with the help of error correction model and is given by the following equations, respectively.

$$\Delta lnPKM_t = \gamma_0 + \sum_{i=1}^{b1} \gamma_{1i} \Delta lnPKM_{t-i} + \sum_{i=0}^{b2} \gamma_{2i} \Delta lnFPI_{t-i} + \sum_{i=0}^{b3} \gamma_{3i} \Delta lnGDP_{t-i} + \sum_{i=0}^{b4} \gamma_{4i} \Delta lnRF_{t-i} + \sum_{i=0}^{b5} \gamma_{5i} \Delta lnUR_{t-i} + \sum_{i=0}^{b6} \gamma_{6i} \Delta lnRD_{t-i} + \mu_1 \hat{\varepsilon}_{1,t-1} + \vartheta_{1t} \qquad (4.7)$$

$$\Delta lnTKM_t = \theta_0 + \sum_{i=1}^{c1} \theta_{1i} \Delta lnTKM_{t-i} + \sum_{i=0}^{c2} \theta_{2i} \Delta lnFP_{t-i} + \sum_{i=0}^{c3} \theta_{3i} \Delta lnIPI_{t-i} + \sum_{i=0}^{c4} \theta_{4i} \Delta lnFR_{t-i} + \sum_{i=0}^{c5} \theta_{5i} \Delta lnTR_{t-i} + \mu_2 \hat{\varepsilon}_{2,t-1} + \vartheta_{2t} \qquad (4.8)$$

The error correction terms in both equations (3.7) and (3.8) can be defined as follows.

$$\hat{\varepsilon}_{1,t-1} = lnPKM_{t-1} - (\alpha_0 + \alpha_1 lnFPI_{t-1} + \alpha_2 lnGDP_{t-1} + \alpha_3 lnRF_{t-i} + \alpha_3 lnUR_{t-1} + \alpha_4 lnRD_{t-1})$$

$$\hat{\varepsilon}_{2,t-1} = lnTKM_{t-1} - (\beta_0 + \beta_1 lnFP_{t-1} + \beta_2 lnIPI_{t-1} + \beta_3 lnFR_{t-i} + \beta_3 lnTR_{t-1})$$

Where the error correction terms $\hat{\varepsilon}_{1,t-1}$ and $\hat{\varepsilon}_{2,t-1}$ are the lagged error-terms obtained from the long-run Equations (4.3) and (4.4) of road passenger and freight demand, respectively. Similarly, $\mu_1$and μ_2 are the speed-of adjustment coefficients associated with error-correction terms in both Equations (4.7) and (4.8), and sign of both these coefficients are expected to be negative and statistically significant to ensure the stability of long-run transport demand relationships, and also to reinforce the long-run co-integration relationships in transport demand equations. The error correction models capture the short-run dynamics of the model and show convergence towards the long-run equilibrium.

We also conduct a battery of diagnostic tests to ensure the validity of estimated ARDL models. These tests include Breusch-Godfrey serial correlation LM test, Breusch-Pagan-Godfrey heteroskedasticity test, auto-regressive conditional heteroskedasticity (ARCH) test. Moreover, the stability of estimated parameters will also be tested with the help of cumulative (CUSUM) and cumulative sum of squares (CUSUMSQ) statistic, as suggested by Peseran and Peseran (1997).

4.3.3 Variable Formation and Data Sources

We use different sources for data collection. The data regarding road passenger-kilometers and ton-kilometers is from Pakistan Economic Survey (various issues), Pakistan Statistical Yearbook (various issues), Finance Division, Government of Pakistan (several issues). For further information regarding road PKM and TKM, see also Karandaaz Pakistan (2018). The road transport data regarding passenger and freight combines transport on all kind of roads, especially the National Highway and Motorway Network, which have a share of only 4.6% of total road network, carries 80% of Pakistan's total commercial traffic (Government of Pakistan, 2011). Most of the data used for the analysis of road passenger and freight transport is also previously used for rail freight and passenger transport and is already explained in chapter 3. For example, data related to rail-fare (RF) and freight-rate (FR), industrial production index (IPI), fuel-price (FP) and fuel-price index (FPI), real per-capita GDP and international trade (TR) is already explained in chapter 3. Remaining data related to total road network is collected from Pakistan Economic Survey (various issues) and that of urbanization is obtained from the World Development Indicators (WDI, 2019).

Some formation and definition of variables is worth mentioning. The road density is used as the ratio of total road network (both high and low-type), measured in kilometers, to total land area of Pakistan (square-kilometers). Urbanization is used as the percentage of total population living in urban areas.

4.4 Results and Discussion

A major advantage of using ARDL bounds approach of co-integration is that it can be applied even without knowing the order of integration of relevant variables (whether the variables of interest are integrated of order (0), (1) or mixture of the two (fractionally co-integrated). However, it is also well known that ARDL technique is not suitable (applicable) if any of the variables in a given model are integrated of order (2) or more. Therefore, we adopt two standard unit root tests such as augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) to ensure that none of variables in both road passenger and freight transport demand models are integrated of order (2). The results of both these tests are given in Table 4.2.

Table 4.2: Results of unit-root Tests

	ADF-test				**Phillip-Perron test**				**Result**
	level	1st diff.	level	1st diff.	level	1st diff.	level	1st diff.	
Variable	C		C&T		C		C&T		
lnPKM	-2.36	-7.02*	-0.94	-4.24*	-2.70**	-6.94*	-1.11	-8.72*	I (0)
lnFPI	-0.62	-3.63**	-1.71	-3.40**	-0.69	-3.82**	-1.80	-3.62**	I (1)
lnGDP	-1.51	-3.99*	-3.07	-4.82**	-1.29	-3.99*	-2.10	-4.09*	I (1)
lnRF	-0.24	-5.51*	-2.50	-5.42*	-0.14	-5.54*	-2.65	-5.44*	I (1)
lnUR	-2.13	-3.32**	-2.35	-5.75*	-4.84*	-3.53*	-0.95	-4.20**	I (0)
lnRD	-1.43	-5.11*	-1.23	-5.13*	-0.50	-5.02*	-0.32	-5.14*	I (1)
lnTKM	-1.54	-5.04*	-2.76	-6.26*	-3.63	-5.82*	-1.21	-6.75*	I (1)
lnFP	-0.37	-3.81*	-1.56	-5.60*	-0.41	-3.85*	-1.55	-5.61*	I(1)
lnIPI	-0.77	-4.05*	-2.97	-4.00*	-1.39	-4.13*	-2.27	-4.09*	I (1)
lnFR	-1.16	-3.70*	-3.16	-3.66*	-0.99	-3.46**	-2.21	-3.47**	I (1)
lnTR	-1.47	-6.09*	-2.61	-5.29*	-1.65	-6.15*	-2.11	-5.05*	I (1)

**and* represents significance at 5% and 1% level, respectively.

C&T represents constant and trend.

The results of both unit root tests indicate that most of variables in road passenger and freight demand models are integrated of order (1), as the null hypothesis of unit root at levels cannot be rejected for most of the variables whereas the null hypothesis of unit root at their first difference is clearly rejected by the significance of computed test statistic in Table 4.2. It implies that none of the variables are integrated of order (2), although some (PKM, UR) of them are integrated of order zero. Thus, one may proceed for testing the long-run relationships between road transport demand (freight and passenger) to their determinants using ARDL approach. Based on ordinary least square (OLS) method, both models of passenger and freight demand are estimated using Schwarz criteria (SC), such that the residuals of both models are not serially correlated. The selected optimal model for passenger demand is ARDL (1, 0, 0, 1, 0, 1) while the optimal model for freight demand is ARDL (1, 0, 0, 0, 0). The joint F-statistic of both passenger and freight models is computed to determine the possibility of long-run co-integration relationships between demand for road transport (freight and passenger) to their determinants. The results are given below in Table 4.3. A comparison of computed F-values to the critical values, provided by both Pesaran et al. (2001) and Narayan (2005), are given. It becomes clear that the calculated value of F-statistic in both models is significantly greater than the 5% critical upper bound values of both Pesaran et al. (2001) and Narayan (2005). Therefore, we reject the null hypothesis of no long-run co-integration relationships among road freight and passenger demand to their influencing factors and conclude that co-integration relationship exists.

Table 4.3: The results of ARDL Bounds test of Co-integration

Road Transport			Narayan (2005)				Pesaran et al. (2001)			
			5% critical bound		10% critical bound		5% critical bound		10% critical bound	
Model	k	F-stat	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
PKM[a]	5	5.99	2.80	4.01	2.33	3.41	2.39	3.38	2.08	3.00
TKM[b]	4	4.48	2.94	4.08	2.46	3.46	2.65	3.49	2.20	3.09

a represents passenger-kilometers.

b represents ton-kilometers.

Both critical bound values are obtained for case II with restricted intercept and no trend.

When co-integration is confirmed by the bounds tests, the next step in ARDL model is to estimate the long-run and short-run coefficients. The long-run estimates of both models along with some diagnostic tests are provided in Table 4.4 below.

All estimated long-run coefficients in both models have expected signs. All other variables except fuel price index/fuel-price are positively related to road travel/freight transport demand. For road travel demand, the impact of fuel price index is estimated as '-0.044' and is marginally significant at 10% level. This implies that road travel demand (measured in passenger-kilometers), in the long-run, will decrease by 0.044% in response to a 1% increase in fuel price. The less sensitivity of passenger demand to fuel prices show that road transport mainly depends on petroleum products for operations. Moreover, reducing road travel demand and associated externalities through fuel taxation will be less effective. However, the inelastic price effect also suggests that taxing fuel prices may also be an important source of government revenues. Unfortunately, we are unable to compare the results of this study with the previous studies on road transport in Pakistan due to the lack of such available empirical literature. However, many other international studies also report relatively low fuel price elasticities of road's passenger transport (see, for example, Boilard, 2010; Delsaut, 2014; Goodwin et al., 2004; Small and Van Dender, 2007).

The per-capita real income is another potential determinant of road travel demand. The co-efficient of per-capita income is'0.5416', implies that ceteris-paribus an increase in income of 1% is associated with an increase of road passenger-kilometers by 0.54%. It suggests that passengers treat road travel as a normal (necessity) good. Our results also support others such as Goodwin et al. (2004), Graham and Glaister (2004), Liddle (2009) and Litman (2013), who also observe that the relationship between road travel demand and income is positive and inelastic.

Table 4.4: Long-run Estimates Based on ARDL Model

Dependent variable: lnPKM			**Dependent variable: lnTKM**		
Regressor	Co-efficient	Standard Error	Regressor	Co-efficient	Standard Error
Constant	-10.5512	6.7182	Constant	5.4648	4.4276
$lnFP_t$	-0.0449*	0.0248	$lnFP_t$	-0.8847**	0.3423
$lnGDP_t$	0.5416**	0.2374	$lnIPI_t$	1.7332***	0.5448
$lnRF_t$	0.2045***	0.0567	$lnFR_t$	0.7705***	0.2324
$lnRD_t$	0.4083**	0.1842	$lnTR_t$	0.4894	1.2710
$lnUR_t$	5.2815**	2.2087	-	-	-
Diagnostic Tests		**p-values**	**Diagnostic Tests**		**p-values**
χ^2_{Serial}		0.1162	χ^2_{Serial}		0.0730
χ^2_{Hetero}		0.6414	χ^2_{Hetero}		0.2482
χ^2_{ARCH}		0.7733	χ^2_{ARCH}		0.1328

*, ** and *** represents the significance at 10%, 5% and 1%, respectively.

Next, we have also estimated the impact of rail-fares on road passenger-kilometers (PKM). The co-efficient is 0.2045, which indicates that 'all else equal if rail-fare (measured by average revenue per passenger-kilometer) increases by 1%, road's PKM will increase by 0.20%'. The co-efficient is statistically significant at 1% level of significance. A positive cross-price elasticity of road travel or passenger demand indicates that road and rail are substitutes for passengers.

The road density (RD) and urbanization (UR) are two additional important control variables in passenger demand model. The results show that the road density appears to be the one of the most statistically significant explanatory variables in road's travel demand equation. In particular, the impact of road density on passenger transport demand is estimated as '0.4083', states that a hypothetical 1% increase in road density will increase road's passenger-kilometers by 0.4083% in the long-run. The findings are in line with other previous empirical studies (see, for example, Chi, 2016; Hymel, 2019; Kwon and Lee, 2014; Noland, 2001), who support the stance that improvements in road network (building new roads or extension of existing roads) will lead to higher road passenger transport demand. Finally, the coefficient of UR is 5.2815, carries the impact of urbanization (proxied by urban population) on road travel demand in Pakistan. We can interpret it as '1% increase in urbanization will lead to 5.2815% rise in road passenger-kilometers in the long-run'. The variable is significant at 5% level and its impact on road passenger transport is the most dominant one as the coefficient associated with it is greater than 1. The positive coefficient offers a simple explanation that the demand for basic goods such as housing, jobs, education, and transport services increases as more people migrates from rural to urban areas. The empirical literature on the impact of urbanization on passenger transport demand is inconclusive. Studies such as Hymel et al. (2010) and Van Dender and Clever (2013) observe a significant and negative relationship of urban population and travel demand. On the other hand, Ramanathan (2001) witnesses a positive and relatively strong effect of urbanization on passenger transport demand for India. Similarly, Poumanyvong et al. (2012) obtains a significant and positive effect of urbanization on national transport and road energy use in case of low, middle and high-income countries.

On the other hand, the estimation results of road freight transport are also provided next to passenger transport in Table 4.4. The results reveal that most of the explanatory variables such as fuel price, industrial production and rail's freight-rate (measured in terms of average rate charged per ton-kilometer) exert statistically significant impact on road's freight demand except for the impact of international trade. In particular, the effect of fuel price on road freight transport is negative in the long-run, whereby a 1% increase in fuel price results in a decrease of road freight transport by 0.88%. It means that an increase of fuel price will increase the cost of road freight shipments and may induce the shippers to decrease the number of ton-kilometers shipped through road. In comparison, although the long-run fuel-price effects of both road freight and passenger demand are inelastic, the effect of fuel price on road freight is clearly more dominant than travel demand, which means that freight movers are relatively more sensitive to fuel prices than passengers. There are few empirical studies that have investigated the impact of fuel price on road freight transport demand. De Jong et al. (2010) provide the possible range of fuel price elasticities of road freight transport from -0.05 to -0.3. However, fuel price elasticities of road freight transport, in our case, are similar to Wang and Lu (2014), who find a similar fuel-price elasticity of road ton-kilometers for China .

The long-run estimate of road freight transport with respect to industrial production is 1.7332, means that an increase in industrial output by 1% causes road freight transport to increase by 1.74%. So, the observed impact of industrial output on road freight transport in the long-run is quite elastic. Our results are generally consistent with previous studies. For Example, Ramanathan (2001) finds that the long-run effect of industrial output on total freight transport (measured by ton-kilometers) in India is positive and elastic (greater than one). Shen et al. (2009) also observe that long-run elasticity of total (road plus rail) freight transport with respect to industrial production in four out of six econometric models is greater than 1.

We find a relatively strong and significant impact of rail's freight-rate (TR) on road freight transport in the long-run, whereby an increase in rail's freight-rate by 1% will likely increase the road freight transport by 0.77%. This implies that rail freight is a substitute of road freight. On the other hand, although the long-run impact of international trade (as percentage of GDP) on road's freight demand is positive as expected, its coefficient is not statistically significant at traditional levels.

The error correction model captures the short-run dynamics of both road (freight and passenger) transport demand models and the results of short-run models are reported in Table 4.5. From results, it can be observed that the estimated coefficients of both short-run models are of expected sign. Most of the short-run coefficients are, in general, statistically significant at 5% level of significance and are smaller in magnitude than their long-run estimates, which implies that the complete adjustment cannot take place in the short-run. An important aspect of the short-run models is the co-efficient associated with lagged error-terms $\hat{\varepsilon}_{1,t-1}$ and $\hat{\varepsilon}_{2,t-1}$, which measure the speed of adjustment towards equilibrium after a typical shock to the system in the short-run. For both models, the coefficients of lagged error-terms are provided in the last row of regressors in Table 4.5.

The coefficients of error correction terms in both models (passenger and freight) are negative and are statistically significant at 1% level, further reinforcing the already established long-run co-integration relationships.

Table 4.5: Short-run Estimates Based on ARDL Model

Dependent variable: $\Delta lnPKM$			**Dependent variable: $\Delta lnTKM$**		
Regressor	Coefficient	Standard Error	Regressor	Co-efficient	Standard Error
$\Delta lnFPI_t$	-0.0429	0.0577	$\Delta lnFP_t$	-0.1171**	0.0447
$\Delta lnGDP_t$	0.4922**	0.2246	$\Delta lnIPI_t$	0.2294**	0.1034
$\Delta lnRF_t$	0.0580	0.0607	$\Delta lnFR_t$	0.1019**	0.0433
$\Delta lnRD_t$	0.8252*	0.4841	$\Delta lnTR_t$	0.0647	0.1541
$\Delta lnUR_t$	4.8003**	2.1791	-	-	-
$\hat{\varepsilon}_{1,t-1}$	-0.9088***	0.1613	$\hat{\varepsilon}_{2,t-1}$	-0.1323**	0.0579
		Diagnostic Tests			
Adjusted R^2		0.9913	Adjusted R^2		0.9951
Durbin-Watson		2.2850	Durbin-Watson		1.8428
S.E of regression		0.0434	S.E of regression		0.0475
RSS		0.0446	RSS		0.0587

Notes:

$$\hat{\varepsilon}_{1,t-1} = lnPKM_{t-1} — (-0.0473 * lnFPI_{t-1} + 0.5416 * lnGDP_{t-1} + 0.2045 * lnRF_{t-1} + 0.4083 * lnRD_{t-1} + 5.2816 * lnUR_{t-1} - 10.5512)$$

$$\hat{\varepsilon}_{2,t-1} = lnTKM_{t-1} — (-0.8848 * lnFP_{t-1} + 1.7333 * IPI_{t-1} + 0.7706 * lnFR_{t-1} + 0.4894 * lnTR_{t-1} + 5.4746)$$

*, ** and *** represents the significance at 10%, 5% and 1%, respectively.

For road's travel demand, the coefficient of $\hat{\varepsilon}_{1,t-1}$ is -0.9088, suggests that for any short-run deviations from equilibrium, road's passenger demand adjusts towards long-run equilibrium by approximately 90% in the first year. Similarly, the estimated error correction co-efficient in road freight demand is -0.1323, indicating that short-run deviations in road freight demand are corrected in such a way that nearly 14% of disequilibria gap is corrected in first year to restore the long-run equilibrium.

At a final stage, we adopt several diagnostic tests to ensure that the selected ARDL models provide valid and reliable results. The results of all these tests are provided in lower panel of Table 4.4. For passengers' demand, the p-values associated with these tests are much higher than traditional significance levels, implying that there is no problem of serial correlation, heteroskedasticity and auto-regressive conditional heteroskedasticity (ARCH). On other hand, the results of diagnostic tests for road freight transport are also provided in Table 4.4, next to passenger transport results. The much higher p-values associated with these tests indicate the acceptance of null hypothesis that there is no evidence of problem of serial correlation, heteroskedasticity, ARCH effects in road's freight model. Moreover, the plot of cumulative sum of recursive residuals (CUSUM) and CUSUM of square (CUSUMSQ) statistic of both road passenger and freight demand models are provided by the Figures 4.2 and 4.3. The results indicate that the estimated parameters of the short-run models are stable and constant within the sample considered.

Figure 4.2 Graph of CUSUM and CUSUMSQ Tests of Road's Passenger-Demand

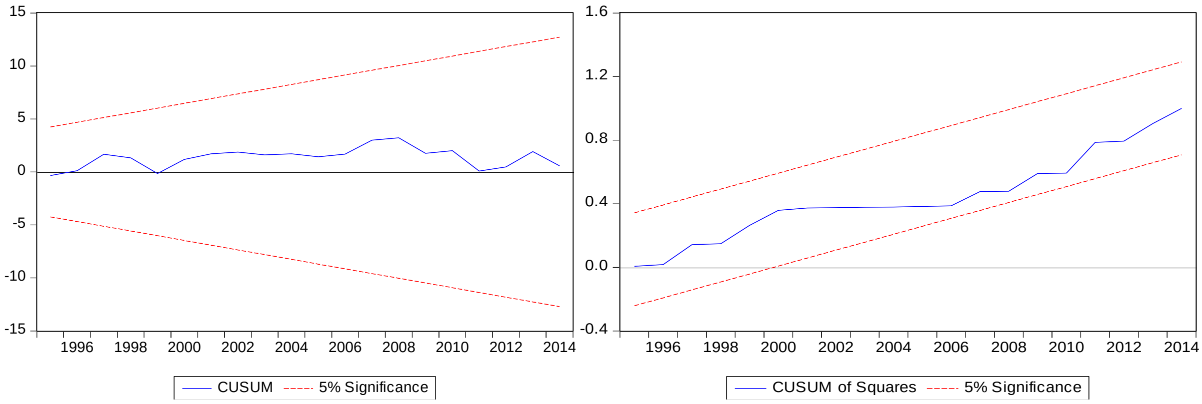
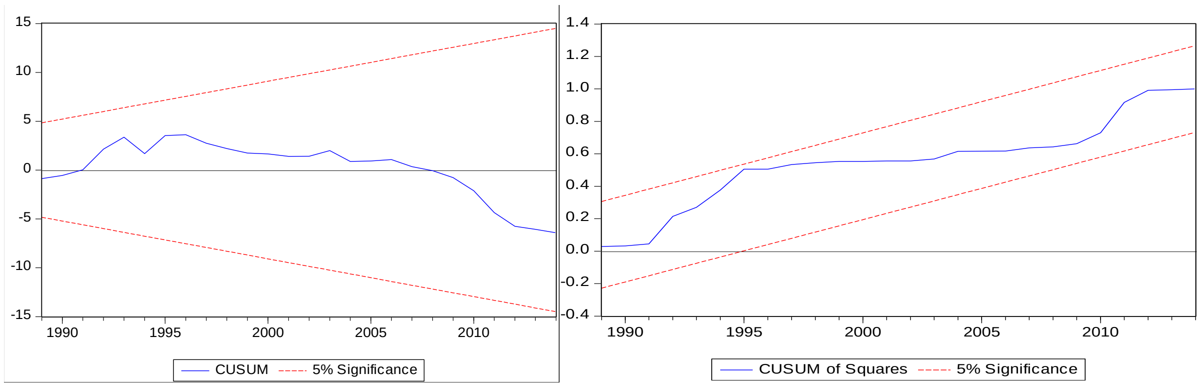


Figure 4.3: Graph of CUSUM and CUSUMSQ Tests of Road's Freight-Demand



4.5 Conclusion

Road sector, over the last few decades, has become the most dominant mode of handling inland passenger and freight transport in Pakistan. However, a rapid growth in road transport has also resulted in higher petroleum energy-use and associated emissions, road congestion, deterioration of urban air quality, etc. An accurate assessment of the demand for road transport is crucial for planning environmentally sustainable road transport in future. Therefore, this study provides an empirical analysis of road freight and passenger transport demand in Pakistan. Using ARDL bounds testing approach of co-integration, this study examines short and long-run responses of both road's passenger and freight demand to different economics and demographic factors including fuel prices, per-capita income, rail-fare, urbanization, road density, industrial output, rail's freight-rate and international trade.

A summary of empirical results and findings of the study can be explained as following. First, a stable demand function exists for both road's freight and passenger demand in Pakistan. Second, the fact that both road passenger and freight demand is less sensitive to fuel prices in the long-run is because long-run fuel price elasticities are less than 1 in absolute value. Motor fuel tax revenues, in Pakistan, are generally used in public investment projects such as transport infrastructure, education, health and energy. Our results indicate that increasing fuel taxes can generate more fuel tax revenues without decreasing road transport (freight and passenger) demand. These fuel tax revenues can further be used to augment the transport and other public infrastructural projects. However, since transport demand is less responsive to changes in fuel-prices in the long-run, especially the passenger's demand. Therefore, market policy instruments (such as higher fuel-prices) are less effective in reducing the growth of road's transport demand and associated emissions. Third, passenger's demand and per-capita GDP are positively related in the long-run, which implies that road's passenger demand is expected to increase with economic growth in the country. Fourth, urbanization has appeared as the most dominant variable for road passenger transport with a coefficient of 5, which implies that significant increase in road passenger transport demand is expected as urbanization in Pakistan progresses. If the current trends continue, the share of urban population in Pakistan will increase nearly to 60% by the 2025 (Government of Pakistan, 2014), which will further accelerate the demand for basic services including the demand for road transport. Fifth, empirical findings also show that an increase in road density also attracts more passenger demand or traffic, a phenomenon known as 'induced transport demand' in empirical literature. It implies that capacity expansion may not be an effective long-term policy option to stabilize or control the road's passenger growth. Similarly, the cross-price elasticity of the demand for road's passenger and freight transport with respect to rail's fare and freight-rate is positive and significant. This indicates that rail transport is a substitute of road transport for freight and passengers. Sixth, long-run elasticity of road freight transport with respect to industrial production index (IPI) is positive and greater than 1 implies that future road freight transport in Pakistan is likely to increase by almost 2% in response to a 1% increase in industrial output. So, the transport planners need to make alternative arrangements (such as incentives for modal-split, provide better and quality services of other modes) to make growth of future road transport more sustainable.

CHAPTER 5

ANALYZING THE (TECHNICAL) EFFICIENCY OF ROAD AND RAIL TRANSPORT IN PAKISTAN WITH DATA ENVELOPMENT ANALYSIS

5.1 Introduction

A reliable and an efficient transport system is one of the most important drivers of a country's economic growth and development. However, transport sector also consumes a great amount of social resources and poses serious challenges in terms of safety problems, higher energy consumption (mostly petroleum products) and related environmental emissions. Therefore, sustainable development of transport sector is considered as an important component of national transport policy and strategy in Pakistan, which aims to provide efficient, safe, sustainable, affordable and environment friendly means of transport ensuring reliable access to markets, education, jobs and other services for all (Planning Commission of Pakistan, 2018a). As a result, measuring and analyzing the efficiency of resource allocations in an integrated transport system is important to improve the performance of different transport modes and to enhance the coordinated development of various transport modes (Zhang and Du, 2017).

The literature on efficiency dates back to 1950s. In an earliest study, Koopmans (1951) provides the concept of efficiency, which is similar to the pareto-optimality condition. According to him, an input-output vector is efficient if and only if it is not possible to increase the net output of any one product or decrease the amount of any input without simultaneously decreasing the net output of any other product or increasing the amount of any other input. This approach measures the technical efficiency of a firm. In another important study, Debreu (1951) first offers a measure of the technical efficiency for the whole economy, which is known as 'coefficient of resource utilization'. Any deviation of this measure from one would lead to a deadweight loss for whole economy by not utilizing its resources efficiently. Later, Farrell (1957) explains that there are two components of firm's efficiency such as technical and allocative efficiency. Technical efficiency is related to the firm's ability to attain maximum output from a given level of inputs, while allocative efficiency deals with the firm's ability to utilize inputs in optimal proportions, given the level of production technology and respective inputs prices. A combination of both technical and allocative efficiencies would then offer a measure of an overall economic efficiency.

In present context, the efficiency of transport modes (road, rail, air, etc.) can be defined in terms of producing or facilitating maximum possible attainable outputs with given inputs level or minimizing inputs for given outputs level. Those transport modes are relatively more efficient, as compared to other transport modes in test group, if they produce a certain level of outputs or more while consuming a minimum possible level of inputs, or spending the same level or less amount of inputs to produce a given outputs level (Baran and Górecka, 2019). There are two broad approaches of measuring efficiency in transport sector, also known as parametric and non-parametric approaches (see, for exmple, Baran and Górecka, 2019; De Borger et al., 2002; Kerstens, 1996; Král' and Roháčová, 2013, etc.). The parametric approach is based on a specific parametric functional form while estimating the production frontier and is further divided into stochastic frontier analysis (SFA), thick frontier analysis (TFA) and distribution-free approach (DFA). However, non-parametric approach does not require any such specific functional form and statistical distribution assumptions. The data envelopment analysis (DEA) and free disposal hull (FDH) are most widely used non-parametric methods of frontier. According to Cooper et al. (2011), the DEA approach has certain characteristics or advantages. First, it can handle multiple inputs and outputs. Second, it does not assume any functional form for relating to outputs. Third, it does not require the same units of inputs and outputs. Forth, DEA permits efficiency estimations over time.

The data envelopment analysis has been widely used to measure the efficiency of various transport modes such as roads, railways, airports, seaports, etc. As such, a few DEA studies have also been conducted by researchers in Pakistan to measure the efficiency of transport sector. However, relative efficiency of different transport modes over time has not been estimated for Pakistan in prior studies. For example, Tahir (2013) uses DEA model to estimate and compare the earning, productive and financial efficiency of Chinese, Indian and Pakistan Railways. In a study relevant to ours, Alam (2017) evaluates the efficiency of Pakistan Railway over time from 1950 to 2014. In addition to CCR-DEA model[15] for measuring efficiency scores over time, the study also adopts Super-Efficiency DEA model, which may help to rank among the most efficient decision-making units (DMUs). The study uses five inputs such as total locomotives, freight wagons, coaching vehicles, track-kilometers and total

[15] CCR-DEA model stands for Charnes, Cooper and Rhodes (CCR) DEA model, also known as constant returns to scale, CRS-DEA model.

employment with two outputs such as total passengers (thousand numbers) and total freight (thousand tons) carried by rail. For air transport mode, Ennen and Batool (2018) employ DEA approach to calculate the cost and scale efficiencies of 12 major airports in Pakistan during 2012. Noor et al. (2018) estimate the efficiency of bus transport service on 15 selected routes in Lahore city, Pakistan over the period 2013-2014 via CCR-DEA and BCC-DEA models[16]. Moreover, they also utilize Malmquist productivity index to analyze the trends in productivity growth of bus routes over time from 2013 to 2014.

Although there are three basic modes of transport in Pakistan such as road, rail and air, road and rail are the two most dominant modes of facilitating domestic inland transport. Each mode can be used for two equally important types of transport e.g. freight and passenger transport, measured by two broad indicators, passenger-kilometers (PKM) and ton-kilometers (TKM), respectively. The output of each transport mode (PKM and TKM) requires several inputs such as labor, infrastructure, energy, and vehicles, etc. In the present study, we consider energy, employment (labor) and infrastructure as inputs to transport, as they are equally important inputs to transport. In many cases, data on most of the inputs such as labor, transport infrastructure (road or rail network) and energy consumption is not available exclusively for passenger or freight because same vehicle or locomotive can possibly be used either for passenger movements or materials or because both buses and trucks run on the same road network. For some inputs like energy, although one may estimate the energy efficiencies of both passenger and freight by making use of some standard norms regarding the allocation of energy consumption, the accuracy of efficiency estimates largely depends on those norms (Ramanathan, 2005). Therefore, we adopt a different approach, known as data envelopment analysis (DEA) that considers both freight and passenger transport simultaneously.

The objective of this chapter is to estimate and evaluate the own and relative efficiencies of two basic transport modes road and rail in Pakistan using DEA approach over the period 1980-2018. The efficiency of road and rail is measured by comparing two outputs (PKM and TKM) with three inputs (energy, employment, and network length). The air transport is dropped from the analysis, since output data regarding domestic air passenger-kilometers (PKM) and air freight ton-kilometers (TKM) are not available and because air transport accounts for only a small proportion of domestic passenger and freight traffic in comparison to rail and road. The organization of the study is as following: Section 5.2 discusses

[16] BCC-DEA model is after Banker, Cooper and Charnes (BCC) DEA model, and is also considered as variable returns to scale, VRS-DEA model.

the review of literature on DEA applications in transport sector's efficiency measurements. Section 5.3 offers methodological framework and data. Section 5.4 provides the efficiency results and discussion, and Section 5.5 concludes the study.

5.2 Literature Review

Charnes et al. (1978) first provided the concept of DEA as an effective tool of performance evaluation. It measures the relative efficiency of homogenous decision-making units (DMUs) by comparing the multiple inputs and outputs. Since the publication of Charnes et al. (1978), the DEA model has been extensively used in many applied research fields such as agriculture, banks, economy, education, health, government institutions, etc. (see, for example, Buleca and Mura, 2014; Deliktas and Günal, 2016; Henriques etal., 2018; Johnes, 2006; Stefko et al., 2018; Toma et al., 2015 and many others). In particular, the DEA method has also been applied in the context of various countries and regions for evaluating energy and environmental efficiencies (see, for example, Grigoroudis and Petridis, 2019; Lacko and Hajduová, 2018; Mardani et al., 2018; Rabar, 2017; Wang et al., 2019; Yan et al., 2018).

Empirical studies have widely used DEA approach to study the efficiency of transport sector. The DEA literature on transport sector is quite diverse and may further be classified on the basis of transport mode (road, rail, air, seaport, etc.), selection of outputs and inputs for analysis and type of DEA model used for efficiency measurements. For instance, Somogyi (2011) reviews 69 transport sector studies on all transport modes road, rail, air, ports, and public transport with DEA applications, especially focusing on the selection of inputs and outputs for analysis. Similarly, Cavaignac and Petiot (2017) conduct a more comprehensive review of previous DEA studies in transport sector by including 461 studies over the period 1989-2016 and use multiple correspondence analysis to describe the main research trends in transport sector. Since there exists an ample empirical literature on efficiency measurements of transportation using DEA approach, it is not practical to review all of them. So, we discuss few relevant studies on different transport modes. In one of the earliest studies, Odeck and Hjalmarsson (1996) use DEA model to measure the relative efficiency of Norwegian public trucks from 1983 to 1985, with four inputs wages, fuel consumption, costs related to rubber accessories and truck's maintenance costs, and one output as travelled-distance (in kilometers). In a different study, Sanchez (2009) analyzes both technical and scale efficiencies of public bus transport systems with BCC-DEA model in twenty four Spanish towns and further explore the determinants of technical efficiency via-Tobit regression analysis. Fancello et al. (2014)

use both CCR-DEA and BCC-DEA models to measure the relative (technical) efficiency of urban road networks in eight Italian cities. For a developing country, Singh and Jha (2017) employ DEA method to investigate the efficiency performance of 15 State Transport Undertakings in India during 2003-2014. Similarly, Fitzová et al. (2018) use a sample of 19 Urban Public Transport System in Chez Republic from 2010 to 2015 to find the determinants of public transport efficiency. First, DEA is used to estimate the efficiency scores of each system with three inputs energy, rolling-stock and labor and one output of passengers while estimated efficiency scores from DEA are further used in a Tobit regression analysis to determine the efficiency determinants of a system.

Many DEA efficiency studies are also available for other transport modes or sectors such as air, rail, and ports. The studies measuring efficiency in air transport can be further classified in two ways. First, some studies use commercial activities at airports to measure and compare the relative efficiency of selected airports with DEA analysis (Chow et al., 2008; Lai et al., 2015; lo Storto, 2018; Stichhauerova and Pelloneova, 2019; Wanke et al., 2016). Other studies incorporate the airlines (inputs, outputs) data to assess the relative efficiency of various airlines (Hu et al., 2017; Kottas and Madas, 2018; Lozano and Gutiérrez, 2014; Rai, 2013). A similar classification of DEA efficiency studies is also available for rail transport, in which studies either assess the performance of private or public rail transport companies (see, for example, Cantos et al., 1999; Kutlar et al., 2013; Li and Hilmola, 2019; Oum and Yu, 1994; Sharma et al., 2016; Tsai et al., 2015; Wanke and Azad, 2018) or measure the efficiency of railway stations (Duan et al., 2020; Jannah et al., 2020; Kim and Oh, 2009; Sancha et al., 2016; Sameni et al., 2016; Zhong et al., 2019). Many empirical studies have also explored the efficiency of ports using DEA approach (Cheon, 2008; González and Trujillo, 2009; Kutin et al., 2017; Roll and Hayuth, 1993; Zahran et al., 2017).

Some researchers investigate the energy efficiency of different transport modes. For example, Ramanathan (2000, 2005) estimates and compares the relative energy efficiencies of Indian road and rail transport using data envelopment analysis (DEA) from 1980-81 to 1993-94. The efficiency trends indicate that the relative efficiency of rail transport has increased over time such that rail is considered the most energy efficient transport mode in 1993-94, while the road's relative energy efficiency in 1993-94 is only about 63 percent in comparison to rail transport. Moreover, based on scenario analysis, the DEA results are further extended to estimate the future energy consumption of road and/or rail transport that would lead to a pre-specified DEA efficiency. The results show that huge reductions in energy consumption and related CO_2 emissions are possible if future modal split is promoted in favor of most energy efficient mode of rail transport. In a similar study, Lin et al. (2015) incorporate one input (energy consumption) and two outputs (passenger-kilometers and ton-kilometers) with DEA model to investigate the relative efficiencies of four transport modes road, rail, aviation and water transport in China from 1971 to 2011. The efficiency scores of both rail and water transport are both maximum (equal to one) in 2011, meaning that both modes are most energy efficient in 2011. However, others (road and aviation) are considered as energy inefficient modes in comparison to rail and water in 2011. Zhang and Du (2017), in a study relevant to ours, analyze the efficiency of four transport modes in China via-DEA model such as rail, road, air and water transport from 1985 to 2015, and they consider three inputs (transit mileage, fixed assets and employment) and two outputs (passenger-kilometers and ton-kilometers). The efficiency scores indicate that the efficiency of rail and road transport is relatively higher than other modes.

Since transport sector's energy consumption has direct implications for environmental problems, one should incorporate transport-related emissions into the analysis for true efficiency measurements. Therefore, some studies have also incorporated the undesirable outputs in their analysis of efficiency evaluation in transport sector via DEA model (see, Bi et al., 2014; Park et al., 2018; Zhou et al., 2014). In the same vein, Bi et al. (2014) adopt a non-radial DEA model with both desirable and undesirable outputs (transport value added, transport CO_2 emissions) along with inputs of energy, capital and labor to evaluate the energy and environmental efficiency of 30 provinces in China from 2006 to 2010, and they explain that non-radial DEA model may help to minimize both inputs and undesirable outputs simultaneously for a given level of input and outputs. With similar classification of inputs and outputs, Park et al. (2018) utilize slack-based DEA method to assess the environmental efficiency of transport sector in 50 states in U.S. over 2004-2012, and find that the environmental efficiency of U.S. transport sector is inefficient during the period of investigation, with an average efficiency score of U.S. states is less than 0.64. Later on, Feng and Wang (2018) investigate the performance and determinants of energy efficiency of China's transport sector at provincial level during 2006-2014. They use global meta-frontier Malmquist & meta-frontier DEA model to account for technological heterogeneities (due to differences in resource endowments, economic structure, uneven economic development) among provinces in their analysis of efficiency assessments, and further use meta-frontier Malmquist DEA model to examine the efficiency or productivity changes (trends) over time. The study shows that transport energy efficiencies first decreased between 2004 to 2010 due to poor management and growing regional disparities (gap) in technology and then increased thereafter as technology gap and management efficiency stabilized.

5.3 Methodological Framework and Data

5.3.1 Data Envelopment Analysis

The DEA model is widely used to measure the relative efficiency scores of homogenous productive units, also known as decision-making units (DMUs). The DEA model is more flexible in a sense that it incorporates multiple inputs and outputs to measure the efficiency of firms. For an efficient DMU, the maximum efficiency score produced by DEA model is 1, which means that DMU under investigation is 100% efficient within a test group.

The basic DEA model, also known as Charnes, Cooper, and Rhodes (CCR-DEA) model, is proposed by Charnes et al. (1978) , and can be explained as follows:

Suppose that there are n homogenous DMUs that consume r inputs and produce s outputs. In particular, let us assume that a specific DMU under consideration, say k-th DMU, uses $x_{ik}(i = 1,2, \ldots .r, k = 1,2, \ldots .n)$ inputs to produce $y_{kp}(p = 1,2, \ldots .s)$ outputs. The information regarding inputs and outputs can be written in the matrix form as following.

$$
\begin{aligned}
x_k &= (x_{1k}, x_{2k}, \ldots, x_{rk})^{\mathrm{T}},\ k = 1, 2 \ldots, n \\
y_k &= (y_{1k}, y_{2k}, \ldots, y_{sk})^{\mathrm{T}},\ k = 1, 2, \ldots, n \qquad (5.1) \\
\vartheta &= (\vartheta_1, \vartheta_2, \ldots, \vartheta_r)^{\mathrm{T}} \\
\mu &= (\mu_1, \mu_2, \ldots, \mu_s)^{\mathrm{T}}
\end{aligned}
$$

Where T is the transpose of a matrix, μ and ϑ are the vectors representing the weights assigned to outputs and inputs, respectively. In other words, these weights are known as the maximizing variables, because they will be chosen as such to maximize the efficiency.

The efficiency of a particular k_o-th ($1 \leq k_o \leq n$) DMU in CCR model can be obtained by maximizing the ratio of weighted sum of its outputs to the weighted sum of its inputs, subject to the constraint that efficiency score of each DMU is restricted between 0 and 1. Therefore, output oriented CCR DEA model can be written in a standard matrix form as following:

$$\text{Max} \quad \frac{\mu^{\mathrm{T}} \boldsymbol{y}_{k_O}}{\vartheta^{\mathrm{T}} \boldsymbol{x}_{k_O}}$$

$$\text{Subject to} \quad \frac{\mu^{\mathrm{T}} \boldsymbol{y}_{k}}{\vartheta^{\mathrm{T}} \boldsymbol{x}_{k}} \leq 1, \; k = 1, 2, \ldots\ldots, n \qquad (5.2)$$

$$\mu \geq 0, \vartheta \geq 0$$

Since DEA model in equation (5.2) is a linear fractional program which may lead to multiple solutions. Therefore, it can be converted into a linear program (LP) through CC (Charnes-Cooper) transformation. The linear program can be described as following:

$$\text{Max} \quad u^{\mathrm{T}} y_{k_0}$$

$$\text{Subject to} \quad v^{\mathrm{T}} x_k - u^{\mathrm{T}} y_k \geq 0, \; k = 1, 2, \ldots, n \qquad (5.3)$$

$$v^{\mathrm{T}} x_{k_0} = 1$$

$$u \geq 0, v \geq 0$$

Where u and v ($u = t\mu, v = t\vartheta$) are new vectors associated with output and input weights, respectively.

There are n DMUs in our general model. So, to calculate the efficiency of each DMU (a specific year) by DEA, the linear program in equation (4.3) can be solved n times. This will provide the efficiency scores of n DMUs (years).

5.3.2 Sources of Data

This study estimates and compares the efficiency of road and rail transport in Pakistan using DEA model, with two outputs PKM, TKM and three inputs namely energy, employment and network-length. For rail transport, the data on PKM, TKM, energy consumption, labor and rail-network (route-length) are obtained from Pakistan Railways (PR Yearbook, various issues). On the other hand, energy consumption data is not separately available for other specific transport modes e.g., road and air. However, energy consumption in overall transport sector is available from Hydrocarbon Development Institute of Pakistan (HDIP) (Energy Yearbook) by fuel-type e.g., aviation fuel, motor spirit, high-speed diesel, natural-gas, etc. So, we derived the approximate figures of road sector's energy consumption by subtracting the rail's energy consumption and others (aviation fuel, kerosene oil) from total energy consumption of transport sector. Therefore, the road's energy consumption is taken from HDIP

(Energy Yearbook, various issues). The data on road-network is obtained from Pakistan Economic Survey (various issues). The data regarding road sector's employment is not publicly available. However, some empirical studies have used total registered number of buses and trucks as a proxy of road sector's employment (see, for example, Lin and Ahmad, 2016; Lin and Raza, 2020). So, we also use total number of registered buses and trucks as a proxy of road's employment, and it is obtained from Pakistan Economic Survey (various issues). The remaining road's outputs data of PKM and TKM is used from different Government sources (Pakistan Economic Survey, several issues; Pakistan Statistical Yearbook, several issues; Oil Companies' Advisory Committee, several years), which is available till 2016. For further information regarding road passenger-kilometers and ton-kilometers, see also Karandaaz Pakistan (2018). Hence, for compatibility of results, the data for relative efficiency evaluation of rail and road transport range from 1980 to 2016.

5.4 Results and Discussion

First, we analyze the efficiency of rail transport, followed by the efficiency of road transport, and then relative efficiency of rail vs. road will be evaluated.

5.4.1 Efficiency Performance of Pakistan Railway (PR) during 1980-2018

The efficiency of PR is calculated from 1980-81 to 2017-18, such that each time period is used as an independent decision-making unit (DMU) for efficiency measurements. The time series data regarding outputs (PKM, TKM) and inputs (energy, labor, and rail infrastructure such as route-length) of PR is given in Table 5.1 below. The data regarding most of inputs such as energy consumption and employment reflects a clear declining trend. However, rail network figures show that number of places offered by Pakistan railway also has decreased over time, but not as continuously as other inputs have indicated. On the other hand, data on output such as TKM reveals a mixed pattern of ups and downs over the last four decades while PKM figures clearly indicate a positive growth for most of the time from 1980 to 2018.

Table 5.1: Physical Performance of PR during 1980-2018

years	PKM (Millions)	TKM (Millions)	Energy(toe)	Employment (numbers)	Rail network (Route-Km)
1980-81	16387	7918	430696	130297	8817
1985-86	16657	8270	376022	128047	8775
1990-91	19964	5709	241653	130884	8775
1995-96	18905	5077.4	180328	104281	8775
2000-01	19590	4520	140896	91454	7791
2005-06	25621	4971	150791	86096	7791
2010-11	20619	1758	104972	82424	7791
2015-16	21201	4774	141527	75242	7791
2017-18	24904	8081	158382	72078	7791

Toe stands for tons of oil equivalent

Source: PR Yearbook (various issues)

Next, we have estimated the efficiency of PR and efficiency scores of different years are given in Table 5.2. The data envelopment analysis (DEA) is conducted with the help of DEAP 2.1 software, written by Tim Coelli (1996). Two years (2011, 2012) are excluded from efficiency estimation of rail transport since rail operations during these two years are mostly suspended in Pakistan. Low values of both outputs and some of inputs (energy) in these two years could negatively affect the efficiency scores, as we obtained the maximum efficiency score in one of these two years when we initially included them in efficiency assessments of rail transport. Since the best efficiency performance in these years is not the genuine increase in efficiency, we exclude them from efficiency estimation of rail transport. Moreover, Oum et al. (1999) are also of the view that DEA efficiency ratios are very sensitive to measurement errors and outliers because they mostly depends on observed best practices in the sample.

The efficiency scores show that PR, in general, has experienced an increasing trend in efficiency. A possible justification of such improvements is due to shifting of PR from inefficient coal traction to more efficient diesel-traction. Five years 2006-07, 2008-09, 2010-11, 2013-14 and 2017-18 have been identified as the most efficient years for PR as compared to the remaining years, in which the efficiency values have reached to the maximum of one or 100 percent. This shows that PR better utilize its resources in these years as compared to the others.

Table 5.2: Efficiency Trends of Rail Transport in Pakistan Over 1980-2018

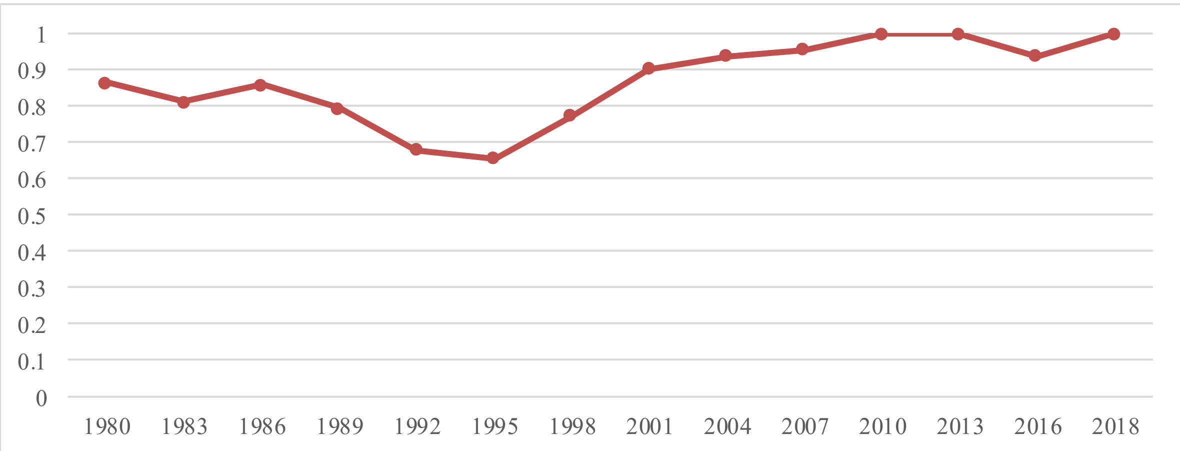
		Slacks (%)				
Years	**Efficiency (%)**	**PKM**	**TKM**	**Energy**	**Employment**	**Route network**
1980-81	87	49	0	51	32	0
1981-82	78	32	0	46	29	0
1982-83	81	25	0	45	29	0
1983-84	81	24	0	45	29	0
1984-85	79	25	0	43	28	0
1985-86	91	53	0	48	33	0
1986-87	86	42	0	36	33	0
1987-88	89	47	0	32	34	0
1988-89	92	31	0	30	36	0
1989-90	79	9	0	25	31	0
1990-91	70	0	0	19	24	0
1991-92	66	1	0	9	23	0
1992-93	68	12	0	7	22	0
1993-94	65	12	0	6	20	0
1994-95	74	18	0	5	21	0
1995-96	66	0	0	2	10	0
1996-97	69	0	0	0	5	0
1997-98	72	0	0	19	10	0
1998-99	77	0	0	0	9	0
1999-00	75	0	0	0	6	0
2000-01	82	0	0	0	11	0
2001-02	90	0	0	0	7	0
2002-03	98	0	0	0	10	0
2003-04	92	0	0	0	6	0
2004-05	94	0	0	0	1	0
2005-06	98	0	4	0	0	0
2006-07	100	0	0	0	0	0
2007-08	96	0	0	0	6	0
2008-09	100	0	0	0	0	0
2009-10	99	0	0	0	2	0
2010-11	100	0	0	0	0	0
2013-14	100	0	0	0	0	0
2014-15	91	0	0	0	0	7
2015-16	89	0	29	0	0	8
2016-17	94	0	34	0	0	6
2017-18	100	0	0	0	0	0

All remaining years are considered as inefficient. For example, the PR is only 87 percent efficient in 1980-81 as compared to its performance in most efficient years during 2006-07, 2008-09 and 2010-11, 2013-14 and 2017-18. This implies that PR uses 87% of its inputs to maximize its outputs, while 13% of them are wasted. The average efficiency score of PR is 85%.

Further sensitivity results are also provided in Table 5.2, which show how the performance of PR during less efficient years could have become efficient by reducing the consumption of inputs (energy, labor and track-length) and/or increasing the outputs such as passenger-kilometers and ton-kilometers. For inefficient years, the inputs slacks and outputs slacks represent an over-use of inputs and under-production of outputs, respectively. These slacks (in percentage) are computed as ratio of input or output slack to the actual input or output and are provided in Table 5.2. In 1980-81, the energy and employment slacks of PR was 51 and 32 percent, respectively, which implies that PR in 1980-81 could have been as efficient as its performance in relatively most efficient years if it had consumed 51 percent less energy and employed 32 percent less labor with same level of outputs of PKM and TKM. Similarly, the slack of PKM of PR was 49 percent in 1980-81. This means that to achieve the same efficiency performance of PR in 1980-81 as in five most efficient years, the PR should have increased the performance of PKM by 49 percent for the same performance of others (TKM, energy, employment, track-length).

The efficiency scores of PR are also shown in Figure 5.1 below. The patterns of efficiency indicate that generally the efficiency of PR has increased over time, with efficiency score in a most recent year (2018) is maximum (equals to one or hundred percent).

Figure 5.1: Efficiency Trends of Pakistan Railway Over 1980-2018



The efficiency improvements over time are mainly due to negative growth in all input resources such as energy, labor and infrastructure while registering a positive growth in outputs

(PKM and TKM). However, efficiency fluctuations in rail transport are obvious as average difference between maximum efficiency scores and inefficient scores is considerable.

5.4.2 Efficiency Evaluation of Road Transport in Pakistan from 1980 to 2016

In this section, we estimate and analyze the efficiency of road transport over the period from 1980-81 to 2015-16. The time series data regarding inputs (road energy consumption, employment, road-network) and outputs (PKM and TKM) are reported in Table 5.3 below.

Table 5.3: Physical Performance of Road Transport in Pakistan During 1980-2016

years	PKM (Millions)	TKM (Millions)	Energy(toe)*	Employment	Road network (km)
1980-81	65991	18207	2190449	108655	93960
1985-86	85952	26367	3114849	137729	126243
1990-91	128000	35211	4619771	189261	170823
1995-96	154566	79900	7074936	232690	217414
2000-01	208370	107085	8055234	302970	249972
2005-06	238077	124456	8762423	349738	259012
2010-11	263726	152154	11291230	414951	259463
2015-16	282457	167024	14666891	490753	264212

* toe refers to tons of oil equivalent.

Sources: Pakistan Economic Survey (several issues); Pakistan Statistical Yearbook (several issues); Oil Companies' Advisory Committee (several years); Pakistan Energy Yearbook (several issues)

The actual data on road transport in Table 5.3 clearly indicate that all road sector's inputs and outputs depict a significant growth over the period 1980-2016. This may be explained by the fact that since road sector facilitates most of the domestic inland passenger and freight transport in Pakistan, growing outputs (PKM, TKM) also require additional input resources such labor, energy and road infrastructure.

The efficiency values (in percent) of road transport in Pakistan are estimated by using the data from Table 5.3 and further results are reported in Table 5.4. The efficiency scores indicate that road sector is considered as the most efficient sector in fifteen out of thirty-five years considered, which implies that for these fifteen years, it has utilized its inputs, particularly energy, labor and road infrastructure (road length) in a relatively more efficient way to facilitate the PKM and TKM on roads.

Table 5.4: Efficiency of Road Transport Over 1980-2016

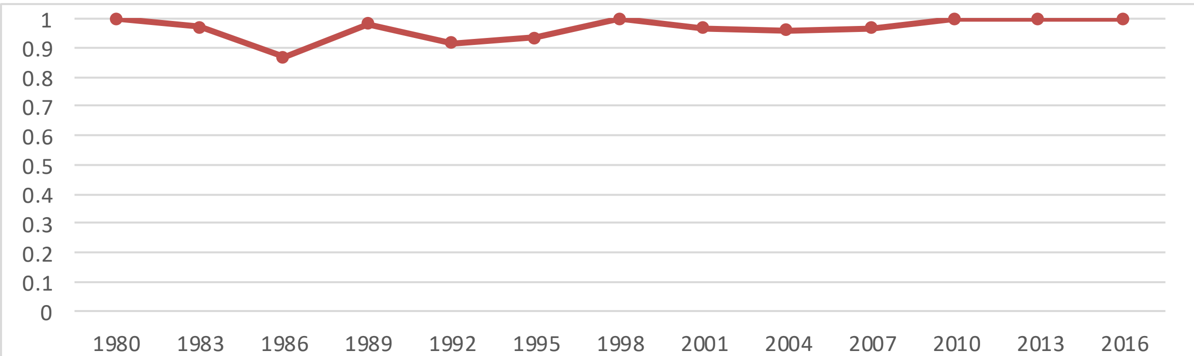
		Slacks (%)				
years	**Efficiency (%)**	**PKM**	**TKM**	**Energy**	**Employment**	**Road network**
1980-81	100	0	0	0	0	0
1981-82	99	0	2	0	0	1
1982-83	100	0	0	0	0	0
1983-84	97	0	0	0	0	6
1984-85	98	0	0	0	0	5
1985-86	96	0	0	0	0	6
1986-87	87	0	0	0	0	2
1987-88	100	0	3	0	0	0
1988-89	100	0	0	0	0	0
1989-90	98	0	4	0	0	0
1990-91	100	0	0	0	0	0
1991-92	94	0	61	0	0	24
1992-93	92	0	29	0	0	8
1993-94	91	0	0	0.18	0	0
1994-95	91	0	0	0	0	7
1995-96	93	0	0	2.5	0	0
1996-97	96	0.17	0	0.70	0	1
1997-98	98	0	0	0	0	5
1998-99	100	0	0	0	0	0
1999-00	95	0	0	0	0	6
2000-01	98	0	0	0	0	15
2001-02	97	0	0	0	0	9
2002-03	97	0	0	0	1	2
2003-04	95	0	0	0	0	1
2004-05	96	0	0	0	0	3
2005-06	100	0	0	0	0	0
2006-07	100	0	0	0	0	0
2007-08	97	0	0	3.22	0	0
2008-09	100	0	0	0	0	0
2009-10	100	4.1	0	0	0	2
2010-11	100	0	0	0	0	0
2011-12	100	0	0	0	0	0
2012-13	99	3.2	0	0	0	0
2013-14	100	0	0	0	0	0
2014-15	100	0	0	0	0	0
2015-16	100	0	0	0	0	0

The relative performance of road transport in remaining years is relatively less efficient, although efficiency scores in efficient and most of inefficient years are not very different. The average efficiency score in a particular year is 97 percent. The trend of road efficiency shows a mixed pattern of ups and down. In general, road efficiency has increased over time as it is maximum (one) in 2015. The efficiency fluctuations of road transport are relatively stable.

The sensitivity analysis for road transport is also conducted, and slacks are given in Table 5.4. Since the efficiency of road is maximum (100%) in 15 years, the slacks of both energy, PKM and TKM in these years are zero while at least one of those slacks (energy, employment, road length, TKM, PKM) may not be zero for inefficient years. For example, the efficiency of road transport in 1992-93 is 92 percent with slacks of road network and TKM are 8 and 29 percent, respectively. This means that if road transport in 1992-93 has to be as efficient as it is during relatively most efficient 15 years, then either it should have used 8 percent less road infrastructure (road network) with same levels of energy, employment, PKM and TKM or it should have realized 29 percent more TKM with same energy consumption, employment, road network and PKM.

Same efficiency patterns of road transport can be observed from Figure 5.2 below. It can be noticed that road sector has remained efficient throughout the period of analysis. Moreover, fluctuations in efficiency scores of road transport are not obvious and have remained stable.

Figure 5.2: Trend in Efficiency Scores of Road Transport Over 1980-2016



5.4.3 Relative Efficiency of Road vs. Rail Transport Over 1980-2016

Finally, the relative efficiency of rail and road transport is estimated, and results of efficiency scores are reported in Table 5.5 below. For compatibility, the relative efficiency of road vs rail transport is estimated for the period 1980-2016. The efficiency scores reveal that road sector remains relatively more efficient for most of the years than rail transport. Road sector's relative efficiency in terms of transforming inputs (energy, employment and network length) into outputs (PKM & TKM) is maximum (100%) in a more recent year (2016) while the relative efficiency of rail transport during the same year (2016) is less than maximum efficient (92%).

For inefficient years, the input and/or output slacks (%) of road and rail transport are also computed and are reported in Table 5.5. For example, relative efficiency of rail transport in 1980 was 95% as compared to maximum efficiency (100%). It indicates that performance of PR is relatively less efficient in the past. It contains positive slacks of PKM (3%) and energy (20%) during 1980, which implies that for PR to become as efficient as its performance in relatively most efficient years (1985, 1988, 2007, etc.), it could have increased PKM by 3% or could have reduced energy consumption by 20%.

Table 5.5: Relative Efficiency Trends of Rail vs. Road Transport in Pakistan from 1980 to 2016

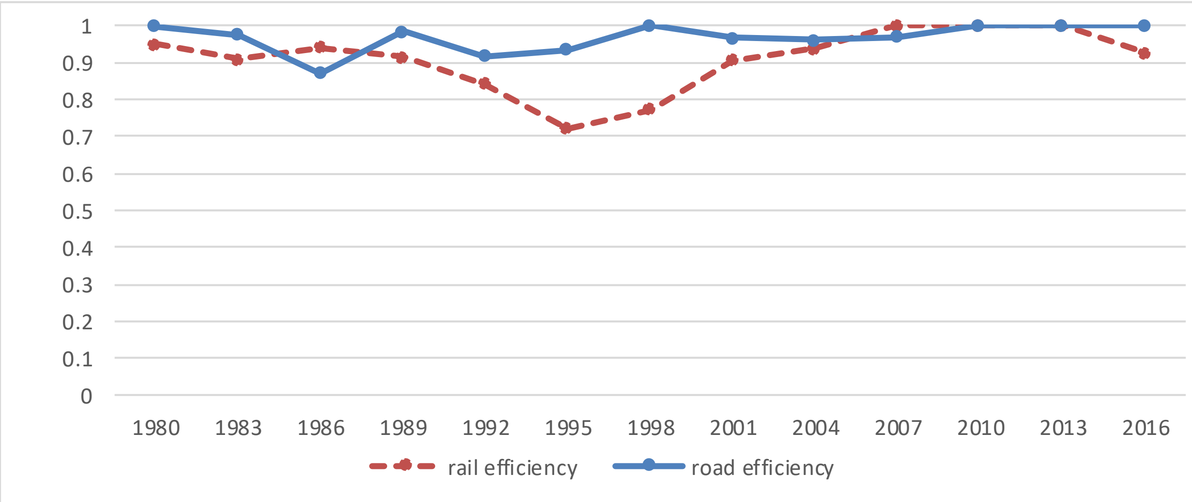
	Road Efficiency and Slacks (%)						Rail Efficiency and Slacks (%)					
Years	Efficiency (%)	PKM	TKM	Energy	Employment	Road Network	Efficiency (%)	PKM	TKM	Energy	Employment	Route network
1980-81	100	0	4	0	0	7	95	3	0	20	0	0
1981-82	99	0	2	0	0	1	85	0	0	32	0	0
1982-83	100	0	0	0	0	0	89	0	0	32	0	0
1983-84	97	0	0	0	0	6	91	0	0	31	0	0
1984-85	98	0	0	0	0	5	89	0	0	29	0	0
1985-86	96	0	0	0	0	6	100	0	0	0	0	0
1986-87	87	0	0	0	0	2	94	3	0	0	0	0
1987-88	100	0	3	0	0	0	97	11	0	0	0	0
1988-89	100	0	0	0	0	0	100	0	0	0	0	0
1989-90	98	0	5	0	0	0	91	0	0	9	8	0
1990-91	100	0	0	0	0	0	78	0	0	14	14	0
1991-92	94	0	61	0	0	25	80	10	0	0	9	0
1992-93	92	0	29	0	0	8	84	27	0	0	9	0
1993-94	91	0	0	1	0	0	81	29	0	0	7	0
1994-95	91	0	0	0	0	7	93	40	0	0	8	0
1995-96	93	0	0	3	0	0	72	4	0	0	3	0
1996-97	96	0.17	0	1	0	1	71	0	0	0	4	4
1997-98	98	0	0	0	0	6	74	0	0	20	8	0

Table 5.5: Relative Efficiency Trends of Rail vs. Road Transport in Pakistan from 1980 to 2016

	Road Efficiency and Slacks (%)						Rail Efficiency and Slacks (%)					
years	Efficiency (%)	PKM	TKM	Energy	Employment	Road Network	Efficiency (%)	PKM	TKM	Energy	Employment	Route network
1998-99	100	0	0	0	0	0	77	0	0	0	9	1
1999-00	95	0	0	0	0	6	75	0	0	0	6	0
2000-01	98	0	0	0	0	15	82	0	0	0	11	6
2001-02	97	0	0	0	0	9	91	0	0	0	8	9
2002-03	96	0	0	0	0	3	98	0	0	0	11	10
2003-04	95	0	0	0	0	2	92	0	0	0	6	0
2004-05	96	0	0	0	0	3	94	0	0	0	1	0
2005-06	100	0	0	0	0	0	98	0	4	0	0	0.27
2006-07	100	0	0	0	0	0	100	0	0	0	0	0
2007-08	97	0	0	3	0	0	100	0	0	0	0	0
2008-09	100	0	0	0	0	0	100	0	0	0	0	0
2009-10	100	4	0	0	0	2	99	0	0	0	3	4
2010-11	100	0	0	0	0	0	100	0	0	0	0	0
2011-12	100	0	0	0	0	0	100	0	0	0	0	0
2012-13	99	3	0	0	0	0	91	0	0	0	0	7
2013-14	100	0	0	0	0	0	92	0	0	0	0	9
2014-15	100	0	0	0	0	0	95	3	0	20	0	0
2015-16	100	0	0	0	0	0	85	0	0	32	0	0

The relative efficiency scores of road and rail transport are plotted in Figure 5.3 below. Relative efficiency patterns clearly indicate that road transport has remained relatively more efficient for most of the time than rail transport. For road transport, efficiency scores have remained smooth and closer to the maximum possible efficiency score (1 or 100%) and fluctuated within a narrow band of 0.9 to 1. One potential reason for road's higher efficiency could be attributed to the fact that National Logistics Cell (NLC) was formed in 1978, which had diverted freight business from rail to road, and passengers were forcefully diverted by some Mega transporters.

Figure 5.3: Relative Efficiency of Rail vs. Road Transport in Pakistan During 1980-2016



On the other hand, rail's transport efficiency initially decreased for more than a decade after 1980. A possible explanation of such decline can be attributed to different factors such as contraction in physical and operational performance of PR as a result of under investment, closure of various branch-lines and minor-stations due to decreasing passengers and financial health of PR, etc. (see, for instance, X. Li et al., 2018). The efficiency of PR improves thereafter due to the development projects implemented by PR to improve its performance (see, for example, section 2.3.2). In comparison, efficiency fluctuations of rail transport are relatively more pronounced and less stable than road sector.

5.5 Conclusion

Different transport modes require varying use of inputs to facilitate freight and passenger transport and an efficient use of those inputs is important in terms of promoting sustainable freight and passenger transport. Moreover, understanding the efficiency of transport modes is important for whole economy and for planning agencies allocating funds for infrastructure development of these transport modes. Two transport modes such as rail and road are the most dominant in terms of carrying domestic freight and passenger transport in Pakistan. Therefore, present study estimates and evaluates the efficiency of rail and road transport in Pakistan. Three inputs such as energy consumption, employment (labor) and network-length (infrastructure), and two outputs such as Passenger-kilometers and ton-kilometers are adopted for measuring efficiencies. A non-parametric approach, known as CCR-DEA model, is used to derive and compare efficiency scores of two transport modes rail and road over time.

The results implied that efficiency of both rail and road transport has generally increased over time when compared to their own performance in the past. However, efficiency of road transport is higher than rail transport as fluctuations in efficiency scores of road transport are not so obvious and are relatively stable as compared to the rail transport. Moreover, road transport has also remained relatively more efficient and consistent for most of the period of investigation when a direct comparison is allowed between rail and road transport. However, relative efficiency of rail transport is lower as compared to the road transport.

A balanced and coordinated development of different transport modes is an important component of transport policy in Pakistan for promoting well integrated transport system, which is lacking. Therefore, the efficiency improvements of less efficient transport modes (such as rail) are important to enhance the productivity of various modes of transport in an integrated system.

Although we have tried to estimate and evaluate the efficiency of rail and road transport in Pakistan, limitations still exist. For example, since transport modes also generate certain negative externalities (environmental emissions, accidents, air pollution, etc.), one should also consider such externalities, especially environmental emissions, for accurate efficiency measurements and sustainable development of respective modes. Moreover, we have used CCR-DEA model for efficiency measurements which has a limitation that all inputs or outputs of inefficient firms or DMUs tend to increase uniformly. Therefore, further research may also consider non-radial DEA models to evaluate efficiencies of transport modes.

CHAPTER 6

SUMMARY, POLICY IMPLICATIONS AND FURTHER DIRECTIONS OF RESEARCH

6.1 Summary and Conclusion

Currently, there are three basic transport modes (air, road and rail) in Pakistan to facilitate both passenger and freight movements. However, road and rail are the two major transport modes for handling inland transport. Rail was considered the most dominant mode of transport in Pakistan till 1970s, but its performance has decreased over time due to diversion of resources from rail infrastructural development to road's development. Consequently, a relatively strong growth has been observed for road's freight and passenger traffic over the last few decades, while rail's freight and passenger transport has witnessed a little growth or remained stagnant. Road carries 93 % of passengers and 97% of total inland freight transport in Pakistan as of 2015-16. This imbalance modal-split in favor of road is not only over-burdening road systems, deteriorating roads quality, creating pollution and causing road-congestion, but also leads to higher transportation costs due to imported transport fuel (Planning Commission of Pakistan, 2018). Moreover, growing road freight and passenger transport has also resulted in higher energy consumption (mostly petroleum products) and associated environmental emissions, hence making the future growth of road transport less sustainable. In a recent past, government of Pakistan, in its vision 2020, has also planned to increase the share of rail transport from 4% to 20% over the period 2015-2025. It is well established that transport demand analysis plays an important role in terms of transport planning and management.

The present study analyzes transport demand and evaluates the technical efficiency of different transport modes in Pakistan using two main objectives. The first objective deals with the estimation of the aggregate demand functions for both freight and passenger transport of rail and road modes. For rail's freight demand, variables such as freight-rate, industrial production, trucking-rates and international trade are used as regressors, while rail-fare, real per-capita GDP, road's travel costs, rail's route-density and population are incorporated as explanatory variables in rail travel demand equation. The Johansen's multivariate co-integration approach is adopted to estimate the demand functions of rail's freight and passenger transport. Similar economic models are considered for road freight and passenger demand within Auto-regressive distributed lag (ARDL) model of co-integration. Since required data on trucking-rates and road travel costs are not available, fuel-price (high-speed diesel) is used as an approximation of trucking costs, and fuel-price index (using two fuels gasoline and high-speed diesel) is considered as an approximation of road travel costs.

The second objective is to estimate the technical efficiency of two transport modes rail and road in Pakistan and trace out the relative efficiency patterns of both over time. The efficiency evaluation of these transport modes is important because they receive a significant share of public sector funds for infrastructural development (or maintenance of existing). The analysis is conducted with a non-parametric approach, known as data envelopment analysis (DEA). Efficiency of a transport mode, in a particular year, is derived by making a comparison of its outputs (passenger-kilometers, ton-kilometers) to its inputs (energy consumption, employment and infrastructure).

To address the above listed objectives, this dissertation uses annual time series data on several economic and demographic variables (listed above) from 1978 to 2018 for rail transport and over 1980-2016 for road transport. A summary of main results of the study is provided below:

- Estimations results show that generally real per-capita GDP (industrial production) and own-prices, among other factors, are important determinants of the demands for passenger (freight) transport of rail and road transport in the long-run, while they are less important or effective in determining the short-run transport demand for rail and road.
- Regarding magnitudes, estimated own-price elasticities of long-run freight (passenger) demand of rail and road are -0.43 (-0.26 to -0.34) and -0.88 (-0.04), respectively. Similarly, long-run income (output) elasticities of rail and road passenger (freight) transport demand are 1.02 (0.87) and 0.54 (1.73), respectively.
- In particular, the long-run demand for both rail freight and passenger transport is relatively more inelastic with respect to its own price (average freight-rate and rail fare), which implies that Pakistan-railway's total revenues would increase if it decides to raise its average prices of freight and passenger transport without losing most of its traffic, and vice-versa.
- Own-price elasticities of road transport demand are lower than one (in absolute value), particularly the demand for road passenger transport. It means that market policy

instruments such as fuel-prices may not be very effective in terms of reducing the growth of road transport.

- In general, both components (freight/passenger) of rail and road transport demand are relatively more sensitive to industrial production/per-capita GDP, which shows that demand for transport would increase with country's economic growth, particularly the demand for both road freight and rail travel.
- The cross-price elasticities of both rail freight and travel demand with respect to fuel-price (a proxy of trucking-rates and road travel costs) are statistically significant and positive in the long-run. Similarly, the impact of both rail freight-rate on road freight demand and rail-fare on road travel demand are also significantly positive. It indicates that road and rail transport modes are substitutes of each other.
- The impact of rail/road transport infrastructure on its passenger demand is captured through rail's route-density/road's network density and found that transport infrastructure development is important in promoting rail/road passenger demand growth. However, route-density exerts a much more powerful and strong effect on rail passenger demand than the impact of road density on its passenger demand.
- Although total population/urban population are positively related with rail/road passenger demand in the long-run, the relationship between urban population and road passenger demand is more dominant and sensitive than that of total population with rail demand for passenger transport.
- From short-run models of rail transport demand, it is found that the error-correction mechanism in rail freight demand works through two (ton-kilometers and freight-rate) of the five equations in a co-integrating vector, while three equations (passenger-kilometers, fuel-price and route-density) adjust for rail travel demand to restore the long-run equilibrium relationship.
- A comparison of speed of adjustment co-efficients across rail and road, based on error-correction models, indicate that road travel demand adjusts at a relatively faster rate (91%) than rail travel demand (51%) to re-establish the long-run equilibrium. However, the reverse is true for freight demand adjustment, in which deviations of rail freight demand from its equilibrium are more quickly corrected (88%) than road freight demand (14%).

- It is also found that the various market shocks (fuel-shortage, lack of locomotives, rolling-stock, terrorist attacks, etc.) have significant and negative short-run impact on the demand for rail freight and passenger transport in Pakistan from 2010 to 2013.
- The efficiency assessment results show that the (technical) efficiency of rail transport, in general, has increased over time when compared to its own past performance. The efficiency improvements are observed as it has moved from fuel-inefficient coal-traction to more efficient diesel-traction. Similarly, efficiency scores of road transport also reveal a stable efficiency (close to maximum achievable of one) performance of road sector.
- Finally, relative efficiency of both rail and road transport is evaluated by incorporating the actual performance of both transport modes in each year as an independent decision-making unit (DMU). The results indicate that relative efficiency of road sector is higher than rail, and that efficiency fluctuations of road transport are not so obvious and remains relatively stable throughout the period of investigation.

6.2 Policy Implications in a Broader Perspective

A number of policy implications are drawn from this dissertation. First, it is found from our analysis that the overall rail transport demand for both freight and passenger is relatively more price inelastic, which can be served as an important policy parameter to manage rail operations. It implies that all else equal if rail authorities in Pakistan are more concerned to increase total revenues, then raising the average rail-fare and freight-rate would be the appropriate strategy to adopt, without significantly reducing the rail traffic. On the other hand, if their foremost objective is to encourage or promote rail traffic then decreasing fare and freight-rate would lead to raise the rail freight and passenger traffic to some extent but would not result in more revenues. Therefore, it offers rail authorities a choice to set fare and freight-rate according to what is more important: (i) an increase in rail's overall traffic, or (ii) an increase in rail's total revenues.

We also have observed low price elasticities of road transport demand, particularly the road passenger demand, which signify that adjusting the fuel prices alone may not be an effective policy option for controlling the future growth of road transport. Therefore, other policy options such as alternative fuels, conservation, etc. are important.

It is also identified that investments in transport infrastructure of road and rail network (in terms of increasing their densities) further accelerate or enhance the passenger demand of respective transport modes. However, priority should be given to invest in rail infrastructure development (particularly in rail network) to increase its route density, because a strong growth in rail passengers is expected as route-density of rail increases. On the other hand, growth of road transport is found relatively less sustainable due to various factors such as higher energy use (mostly petroleum products) and associated environmental emissions, road congestion in major cities, deteriorating urban air-quality, etc. Therefore, rail transport should be made more attractive, particularly for long-haul journeys, and its competitiveness should be improved on several aspects such as continuity and improvements in rail network, service reliability, quantity and quality of rail infrastructure, etc.

6.3 Further Directions of Research

Although we have conducted transport demand analysis of road and rail at an aggregate level, further research can be conducted on different aspects. For example, demand analysis at dis-aggregate level for different rail passenger-classes (air-condition, first-class, second-class, economy-class, etc.) and for different commodity groups handles by road and rail would lead to more convincing analysis. Similarly, the role or importance of various service quality indicators (such as frequency, reliability, route-coverage, travel time, safety, etc.) can also be considered in determining transport demand, especially for rail transport. The analysis of transport demand can also be extended on methodological front to investigate the asymmetric response of transport users to price and income, as recent empirical literature on transport demand provides strong evidence in favor of asymmetric behavior.

REFERENCES

Acutt, M. Z., & Dodgson, J. S. (1995). Cross-elasticities of demand for travel. *Transport Policy*, *2*(4), 271–277.

Agnolucci, P., & Bonilla, D. (2009). UK freight demand: elasticities and decoupling. *Journal of Transport Economics and Policy (JTEP)*, *43*(3), 317–344.

Ahern, A., & Anandarajah, G. (2006). Influence of price and income on rail travel in Ireland. *Proceedings of the Institution of Civil Engineers-Transport*, *159*(4), 177–181.

Ahmed, A., & Fujiwara, A. (2010). Land transport sector in Bangladesh: an analysis towards motivating GHG emission reduction strategies. 国際協力研究誌, *16*(2), 55–68.

Ajanovic, A., Dahl, C., & Schipper, L. (2012). Modelling transport (energy) demand and policies—An introduction. *Energy Policy*, *41*, 3–16.

Ajanovic, A., & Haas, R. (2012). The role of efficiency improvements vs. price effects for modeling passenger car transport demand and energy demand—Lessons from European countries. *Energy Policy*, *41*, 36–46.

Alam, K. M. (2017). Efficiency Evaluation of Pakistan Railways Using Data Envelopment Analysis. *Civil and Environmental Research*, *9*(4), 1–6.

Andersson, F. N. G., & Elger, T. (2012). Swedish freight demand: short, medium, and long-term elasticities. *Journal of Transport Economics and Policy (JTEP)*, *46*(1), 79–97.

Aschauer, D. A. (1989). Is public expenditure productive? *Journal of Monetary Economics*, *23*(2), 177–200.

Asensio, J. (2000). The success story of Spanish suburban railways: determinants of demand and policy implications. *Transport Policy*, *7*(4), 295–302.

Asian Development Bank. (2010). *Sector Assessment (Summary): Transport (Road Transport[NonUrban])*. https://www.adb.org/sites/default/files/linked-documents/48402-001-ssa.pdf

Asian Development Bank. (2015). *Sector Assessment: Transport*. https://www.adb.org/sites/default/files/linked-documents/2-SRI-Sector-Assessment-Transport.pdf

Babcock, M. W., & Gayle, P. G. (2014). Specifying and Estimating a Regional Agricultural Railroad Demand Model. *Journal of the Transportation Research Forum*, *53*(1), 35–48.

Baran, J., & Górecka, A. K. (2019). Economic and environmental aspects of inland transport in EU countries. *Economic Research-Ekonomska Istraživanja*, *32*(1), 1037–1059.

Baumol, W. J., & Vinod, H. D. (1970). An inventory theoretic model of freight transport demand. *Management Science*, *16*(7), 413–421.

Beenish, H., Mehmood, B., Yousaf, U. S., & Sattar, M. Y. (2016). Nexus between economic growth and railways in Pakistan: Cointegration estimation with multiple structural break test and causality analysis. *Science International*, *28*(3), 2743–2746.

Bekõ, J. (2004). Some evidence on elasticities of demand for services of public railway passenger transportation in Slovenia. *Eastern European Economics*, *42*(2), 63–85.

Ben-Akiva, M., Meersman, H., & Van de Voorde, E. (2013). *Freight Transport Modelling*. Emerald group publishing limited.

Bennathan, E., Fraser, J., & Thompson, L. S. (1992). What determines demand for freight transport? In *Policy, Research working papers; no. WPS 998. Transport*. The World Bank.

Beuthe, M., Jourquin, B., Geerts, J.-F., & à Ndjang'Ha, C. K. (2001). Freight transportation demand elasticities: a geographic multimodal transportation network analysis. *Transportation Research Part E: Logistics and Transportation Review*, *37*(4), 253–266.

Bhattacharyya, S. C. (2019). *Energy economics: concepts, issues, markets and governance*. Springer Nature.

Bi, G., Wang, P., Yang, F., & Liang, L. (2014). Energy and environmental efficiency of China's transportation sector: a multidirectional analysis approach. *Mathematical Problems in Engineering*, *2014*.

Birol, F., & Guerer, N. (1993). Modelling the transport sector fuel demand for developng economies. *Energy Policy*, *21*(12), 1163–1172.

Bjørner, T. B. (1999). Environmental benefits from better freight transport management: freight traffic in a VAR model. *Transportation Research Part D: Transport and Environment*, *4*(1), 45–64.

Boilard, F. (2010). Gasoline demand in Canada: parameter stability analysis. *EnerInfo*, *15*(3).

Bresson, G., Dargay, J., Madre, J.-L., & Pirotte, A. (2003). The main determinants of the demand for public transport: a comparative analysis of England and France using shrinkage estimators. *Transportation Research Part A: Policy and Practice*, *37*(7), 605–627.

Buleca, J., & Mura, L. (2014). Quantification of the efficiency of public administration by data envelopment analysis. *Procedia Economics and Finance*, *15*, 162–168.

Button, K., Ngoe, N., & Hine, J. (1993). Modelling Vehicle Ownership and Use in Low Income Countries. *Journal of Transport Economics and Policy*, 51–67.

Canavan, S., Graham, D. J., Anderson, R. J., & Barron, A. (2018). Urban Metro Rail Demand: Evidence from Dynamic Generalized Method of Moments Estimates using Panel Data. *Transportation Research Record*, *2672*(8), 288–296.

Cantos, P., Pastor, J. M., & Serrano, L. (1999). Productivity, efficiency and technical change in the European railways: a non-parametric approach. *Transportation*, *26*(4), 337–357.

Cavaignac, L., & Petiot, R. (2017). A quarter century of Data Envelopment Analysis applied to the transport sector: A bibliometric analysis. *Socio-Economic Planning Sciences*, *57*, 84–96.

Chapman, L. (2007). Transport and climate change: a review. *Journal of Transport Geography*, *15*(5), 354–367.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444.

Chen, N. (2007). Modelling demand for rail transport with dynamic econometric approaches. *International Review of Business Research Papers*, *3*(2), 85–96.

Cheon, S. (2008). Productive efficiency of world container ports: a global perspective. *Transportation Research Record*, *2062*(1), 10–18.

Chi, J. (2016). Long-and short-run asymmetric responses of motor-vehicle travel to fuel price variations: New evidence from a nonlinear ARDL approach. *Transport Policy*, *50*, 126–134.

Chi, J. (2018). Imperfect reversibility of fuel demand for road transport: Asymmetric and hysteretic effects of income and price changes in Korea. *Transport Policy*, *71*, 116–125.

Choudhary, M. A., Khan, N., Arshad, M., & Abbas, A. (2009). Analyzing Pakistan's Freight Transportation Infrastructure Using Porter's Framework and Forecasting Future Freight Demand Using Time Series Models. *2nd, WSEAS International Conference on Urban Planning and Transportation; Recent Advances in Urban Planning and Transportation; 2009*, 70–77.

Chow, J. Y. J., Yang, C. H., & Regan, A. C. (2010). State-of-the art of freight forecast modeling: lessons learned and the road ahead. *Transportation*, *37*(6), 1011–1030.

Chu, Z. (2012). Logistics and economic growth: a panel data approach. *The Annals of Regional Science*, *49*(1), 87–102.

Chung, S. H., & Kang, K. W. (2015). A Comparative Study on the Forecasting Accuracy of Econometric Models: Domestic Total Freight Volume in South Korea. *Journal of Korean Society of Transportation*, *33*(1), 61–69.

Clark, C., Naughton, H. T., Proulx, B., & Thoma, P. (2005). A survey of the freight transportation demand literature and a comparison of elasticity estimates. *Institute for Water Resources US Army Corps of Engineers Alexandria, Virginia*.

Coelli, T. (1996). A guide to DEAP version 2.1: a data envelopment analysis (computer) program. In *Centre for Efficiency and Productivity Analysis, University of New England, Australia*.

Cooper, W. W., Seiford, L. M., & Zhu, J. (2011). Data envelopment analysis: History, models, and interpretations. In *Handbook on data envelopment analysis* (pp. 1–39). Springer.

Coto-Millán, P. (2012). *Utility and Production: Theory and Applications*. Springer Science & Business Media.

Coto-Millán, P., Agüeros, M., Casares-Hontañón, P., & Pesquera, M. Á. (2013). Impact of logistics performance on world economic growth (2007–2012). *World Review of Intermodal Transportation Research*, *4*(4), 300–310.

Coto-Millán, P., Baños-Pino, J., & Inglada, V. (1997). Marshallian demands of intercity passenger transport in Spain: 1980–1992. An economic analysis. *Transportation*

Research Part E: Logistics and Transportation Review, *33*(2), 79–96.

Crôtte, A., Noland, R. B., & Graham, D. J. (2009). Is the Mexico City metro an inferior good? *Transport Policy*, *16*(1), 40–45.

D'Aleo, V., & Sergi, B. S. (2017). Does logistics influence economic growth? The European experience. *Management Decision*.

Dahl, C. A. (2012). Measuring global gasoline and diesel price and income elasticities. *Energy Policy*, *41*, 2–13.

Dahl, C., & Sterner, T. (1991). Analysing gasoline demand elasticities: a survey. *Energy Economics*, *13*(3), 203–210.

Dargay, J., & Gately, D. (1999). Income's effect on car and vehicle ownership, worldwide: 1960–2015. *Transportation Research Part A: Policy and Practice*, *33*(2), 101–138.

Dargay, J. M., & Hanly, M. (2002). The demand for local bus services in England. *Journal of Transport Economics and Policy (JTEP)*, *36*(1), 73–91.

Daughety, A. F. (1979). Freight transport demand revisited: A microeconomic view of multimodal, multicharacteristic service uncertainty and the demand for freight transport. *Transportation Research Part B: Methodological*, *13*(4), 281–288.

De Borger, B., Kerstens, K., & Costa, A. (2002). Public transit performance: what does one learn from frontier studies? *Transport Reviews*, *22*(1), 1–38.

De Jong, G. C., Schroten, A., van Essen, H., Otten, M., & Bucci, P. (2010). The price sensitivity of road freight transport: A review of elasticities. *Applied Transport Economics, a Management and Policy Perspective, De Boeck, Antwerp*.

De Jong, G., Gunn, H., & Walker, W. (2004). National and international freight transport models: an overview and ideas for future development. *Transport Reviews*, *24*(1), 103–124.

Deb, K., & Filippini, M. (2013). Public bus transport demand elasticities in India. *Journal of Transport Economics and Policy (JTEP)*, *47*(3), 419–436.

Debreu, G. (1951). The coefficient of resource utilization. *Econometrica: Journal of the Econometric Society*, 273–292.

Deliktas, E., & Günal, G. G. (2016). Economic growth and input use efficiency in low, Upper-Middle and high incomed countries (1991-2011): a data envelopment analysis. *Procedia Economics and Finance*, *38*, 308–317.

Delsaut, M. (2014). The effect of fuel price on demands for road and rail travel: an application to the French case. *Transportation Research Procedia*, *1*(1), 177–187.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427–431.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: Journal of the Econometric Society*, 1057–1072.

Doi, M., & Allen, W. B. (1986). A time series analysis of monthly ridership for an urban rail rapid transit line. *Transportation*, *13*(3), 257–269.

Duan, Y.-Q., Fan, X.-Y., Liu, J.-C., & Hou, Q.-H. (2020). Operating efficiency-based data mining on intensive land use in smart city. *IEEE Access*, *8*, 17253–17262.

Dunkerley, F., Rohr, C., & Daly, A. (2014). *Road traffic demand elasticities: A rapid evidence assessment*. RAND Corporation.

Elvik, R., & Ramjerdi, F. (2014). A comparative analysis of the effects of economic policy instruments in promoting environmentally sustainable transport. *Transport Policy*, *33*, 89–95.

Enders, W. (2015). *Applied Econometric Time Series Fourth Edition*. Wiley.

Engle, R. (1974). Band Spectrum Regression. *International Economic Review*, *15*(1), 1–11.

Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: Journal of the Econometric Society*, *55*, 251–276.

Ennen, D., & Batool, I. (2018). Airport efficiency in Pakistan-A Data Envelopment Analysis with weight restrictions. *Journal of Air Transport Management*, *69*, 205–212.

EU Statistical Pocketbook. (2017). EU transport in figures. In *Luxembourg: Publications Office of the European Union*.

European Commission. (2010). *Illustrated Glossary for Transport Statistics*. OECD, Eurostat, UNECE (United Nations Economic Commission for Europe).

European Environment Agency. (2019). *Passenger and freight transport demand in Europe — European Environment Agency*. https://www.eea.europa.eu/data-and-maps/indicators/passenger-and-freight-transport-demand/assessment-1

Evans, A. W. (1969). Intercity travel and the London Midland electrification. *Journal of Transport Economics and Policy*, 69–95.

Fancello, G., Uccheddu, B., & Fadda, P. (2014). Data Envelopment Analysis (DEA) for urban road system performance assessment. *Procedia-Social and Behavioral Sciences*, *111*, 780–789.

Farhadi, M. (2015). Transport infrastructure and long-run economic growth in OECD countries. *Transportation Research Part A: Policy and Practice*, *74*, 73–90.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, *120*(3), 253–281.

Feng, C., & Wang, M. (2018). Analysis of energy efficiency in China's transportation sector. *Renewable and Sustainable Energy Reviews*, *94*, 565–575.

Fitzová, H., Matulová, M., & Tomeš, Z. (2018). Determinants of urban public transport efficiency: case study of the Czech Republic. *European Transport Research Review*, *10*(2), 42.

FitzRoy, F., & Smith, I. (1995). The demand for rail transport in European countries. *Transport Policy*, *2*(3), 153–158.

Fitzsimmons, E. L. (1981). A statistical sketch of the demand for rail transport of grain and soybeans. *Transportation Journal*, *20*, 59–65.

Fouquet, R. (2012). Trends in income and price elasticities of transport demand (1850–2010). *Energy Policy*, *50*, 62–71.

Fowkes, A. S., Nash, C. A., & Whiteing, A. E. (1985). Understanding trends in inter-city rail traffic in Great Britain. *Transportation Planning and Technology*, *10*(1), 65–80.

Frankena, M. W. (1978). The demand for urban bus transit in Canada. *Journal of Transport*

Economics and Policy, 280–303.

Friedlaender, A. F., & Spady, R. H. (1981). *Freight transport regulation: equity, efficiency and competition in the rail and trucking industries*. Cambridge, Mass: MIT Press.

Fujisaki, K., Morichi, S., & Ito, M. (2011). Effect of Fluctuation of Gasoline Prices on Transport Behavior-An Empirical Analysis Using Transport Statistics in Japan. *Journal of the Eastern Asia Society for Transportation Studies*, *9*, 354–369.

Fulton, L., & Eads, G. (2004). IEA/SMP model documentation and reference case projection. In *WBCSD/IEA*.

Garcia Sanchez, I. M. (2009). Technical and scale efficiency in Spanish urban transport: estimating with data envelopment analysis. *Advances in Operations Research*, *2009*.

Gillingham, K. (2014). Identifying the elasticity of driving: Evidence from a gasoline price shock in California. *Regional Science and Urban Economics*, *47*, 13–24.

Givoni, M., Brand, C., & Watkiss, P. (2009). Are railways climate friendly? *Built Environment*, *35*(1), 70–86.

Goetz, A. R. (2011). The global economic crisis, investment in transport infrastructure, and economic development. *Transportation and Economic Development Challenges*, *53*.

Gomez, J., & Vassallo, J. M. (2020). Has heavy vehicle tolling in Europe been effective in reducing road freight transport and promoting modal shift? *Transportation*, *47*(2), 865–892.

González, M. M., & Trujillo, L. (2009). Efficiency measurement in the port industry: a survey of the empirical evidence. *Journal of Transport Economics and Policy (JTEP)*, *43*(2), 157–192.

González, R. M., & Marrero, G. A. (2012). Induced road traffic in Spanish regions: A dynamic panel data model. *Transportation Research Part A: Policy and Practice*, *46*(3), 435–445.

Goodwin, P. B. (1992). A Review of New Demand Elasticities with Special Reference to Short and Long run Effects of Price Changes. *Journal of Transport Economics and Policy*, *26*(2), 155–169.

Goodwin, P., Dargay, J., & Hanly, M. (2004). Elasticities of Road Traffic and Fuel

Consumption with Respect to Price and Income: A Review. *Transport Reviews*, *24*(3), 275–292.

Goverment of Pakistan. (2011). *Pakistan Economic Survey*. https://doi.org/10.5040/9781350989931.ch-006

Government of Pakistan. (1990). *Pakistan economic survey*. Finance Division, Economic Adviser's Wing.

Government of Pakistan. (2008). *Transport and Communications*. http://www.finance.gov.pk/survey/chapters/14-Transport final08.pdf

Government of Pakistan. (2009). *Pakistan Economic Survey*. http://www.finance.gov.pk/survey/chapter_10/14_Transport.pdf

Government of Pakistan. (2012). *Pakistan Economic Survey*. http://www.finance.gov.pk/survey/chapters_13/13-Transport final.pdf

Government of Pakistan. (2013). *Transport and Communications*. http://www.finance.gov.pk/survey/chapters_14/13_Transport_and_coms.pdf

Government of Pakistan. (2014a). *Pakistan Economic Survey*. http://www.finance.gov.pk/survey_1415.html

Government of Pakistan. (2014b). *Pakistan Vision 2025 One Nation-One Vision*. https://fics.seecs.edu.pk/Vision/Vision-2025/Pakistan-Vision-2025.pdf

Government of Pakistan. (2018). *Pakistan Economic Survey*. http://www.finance.gov.pk/survey/chapters_19/Economic_Survey_2018_19.pdf

Government of Pakistan. (2019). *Pakistan Economic Survey*. http://www.finance.gov.pk/survey_1819.html

Graham, D. J., & Glaister, S. (2004). Road Traffic Demand Elasticity Estimates: A Review. *Transport Reviews*, *24*(3), 261–274.

Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, *2*(2), 111–120.

Grigoroudis, E., & Petridis, K. (2019). Evaluation of National Environmental Efficiency Under

Uncertainty Using Data Envelopment Analysis. In *Understanding Risks and Uncertainties in Energy and Climate Policy* (pp. 161–181). Springer.

Hakim, M. M., & Merkert, R. (2017). Econometric evidence on the determinants of air transport in South Asian countries. *Transport Policy*.

Hanly, M., Dargay, J., & Goodwin, P. (2002). Review of Income and Price Elasticities in the Demand for Road Traffic. In *(London: ESRC Transport Studies Unit, University College London)*.

Hasanov, M. (2015). The demand for transport fuels in Turkey. *Energy Economics*, *51*, 125–134.

Henriques, I. C., Sobreiro, V. A., Kimura, H., & Mariano, E. B. (2018). Efficiency in the Brazilian banking system using data envelopment analysis. *Future Business Journal*, *4*(2), 157–178.

Hu, J.-L., Li, Y., & Tung, H.-J. (2017). Operational efficiency of ASEAN airlines: Based on DEA and bootstrapping approaches. *Management Decision*, *55*(5), 957–986.

Huang, C., & Burris, M. W. (2015). The short-run impact of gas prices fluctuations on toll road use. *Case Studies on Transport Policy*, *3*(2), 137–150.

Hussain, A., Raza, S., & Shafi, M. (2016). An Empirical Analysis of Passenger Rail Demand in Pakistan. *Research Journal Social Sciences*, *5*(1), 77–102.

Hymel, K. (2019). If you build it, they will drive: Measuring induced demand for vehicle travel in urban areas. *Transport Policy*, *76*, 57–66.

Hymel, K. M., Small, K. A., & Van Dender, K. (2010). Induced demand and rebound effects in road transport. *Transportation Research Part B: Methodological*, *44*(10), 1220–1241.

IEA. (2002). *Energy Balances of Non-OECD Countries 1999-2000*. Organisation for Economic Co-operation and Development.

IEA. (2007a). *CO2 Emissions from Fuel Combustion*. OECD Publishing.

IEA. (2007b). *Energy Balances of Non-OECD Member Countries-Extended Balances*. Organization for Economic.

IEA. (2017a). CO2 emissions from fuel combustion–highlights. In *IEA Statistics*.

IEA. (2017b). Energy technology perspectives 2017. In *Catalysing Energy Technology Transformations*. IEA/OECD Paris.

IEA. (2017c). *Tracking clean energy progress 2017*. International Energy Agency Paris, France.

IEA. (2017d). *World Energy Balances 2017*. OECD.

IEA. (2018a). *CO2 emissions from fuel combustion highlights: 2018 edition*.

IEA. (2018b). *World energy balances*.

Ingram, G. K., & Liu, Z. (1999). *Determinants of motorization and road provision*. The World Bank.

Jannah, A. N., Muthohar, I., & Parikesit, D. (2020). Efficiency Analysis of Commuter Line Stations (Case study: Tebet Station to Cilebut Station, Indonesia). *2nd International Symposium on Transportation Studies in Developing Countries (ISTSDC 2019)*, 131–135.

Japan International Cooperation Agency. (2004). *Diesel Electric Locomotives Rehabilitation Project (1) and Diesel Electric Locomotives Production Project (2).* https://www.jica.go.jp/english/our_work/evaluation/oda_loan/post/2005/pdf/2-30_full.pdf

Jensen, A. F., Thorhauge, M., de Jong, G., Rich, J., Dekker, T., Johnson, D., Cabral, M. O., Bates, J., & Nielsen, O. A. (2019). A disaggregate freight transport chain choice model for Europe. *Transportation Research Part E: Logistics and Transportation Review*, *121*, 43–62.

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

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, *52*(2), 169–210.

Johansen, S., & Juselius, K. (1992). ÅTesting Structural Hypotheses in a Multivariate Cointegration Analysis of the PPP and the UIP for the UK. *Journal of Econometrics*, *53*(12), 211–244.

Johnes, J. (2006). Data envelopment analysis and its application to the measurement of efficiency in higher education. *Economics of Education Review*, *25*(3), 273–288.

Jones, I. S., & Nichols, A. J. (1983). The demand for inter-city rail travel in the United Kingdom: some evidence. *Journal of Transport Economics and Policy*, *17*(2), 133–153.

Jourquin, B. (2018). Estimating elasticities for freight transport using a network model: an applied methodological framework. *Journal of Transportation Technologies*, *9*(01), 1.

Karandaaz Pakistan. (2018). *Bankability of the Transport Sector*.

Kenneth A. Lewis and David Paul Widup. (1982). Deregulation and rail-truck competition: evidence from a translog transport demand model for assembled automobiles. *Journal of Transport Economics and Policy*, *16*, 139–149.

Kerstens, K. (1996). Technical efficiency measurement and explanation of French urban transit companies. *Transportation Research Part A*, *6*(30), 431–452.

Kim, S.-H., & Oh, S.-M. (2009). Evaluating the performance of freight railway stations using data envelopment analysis. *Journal of the Korean Society for Railway*, *12*(2), 315–320.

Kong Wing Chow, C., Ka Yiu Fung, M., Law, J. S., & Van Hui, Y. (2008). Measuring the Efficiency of Ariports in China with the DEA and Endogenous-Weight TFP Methods. *International Journal of Transport Economics*, *35*(1), 1000–1029.

Koopmans, T. C. (1951). Activity analysis of production and allocation. In *Activity Analysis of Production and Allocation*. John Wiley, Inc.

Kottas, A. T., & Madas, M. A. (2018). Comparative efficiency analysis of major international airlines using Data Envelopment Analysis: Exploring effects of alliance membership and other operational efficiency determinants. *Journal of Air Transport Management*, *70*, 1–17.

Kráľ, P., & Roháčová, V. (2013). Measuring the efficiency of public road transport companies in the Slovak Republic using DEA and SFA. *Statistika*, *93*(2), 76–85.

Kulshreshtha, M., Nag, B., & Kulshrestha, M. (2001). A multivariate cointegrating vector auto regressive model of freight transport demand: Evidence from Indian railways.

Transportation Research Part A: Policy and Practice, *35*(1), 29–45. https://doi.org/10.1016/S0965-8564(99)00046-4

Kulsreshtha, M., & Nag, B. (2000). Structure and dynamics of non-suburban passenger travel demand in Indian railways. *Transportation*, *27*(2), 221–241.

Kupfer, F., Meersman, H., Onghena, E., & Van de Voorde, E. (2017). The underlying drivers and future development of air cargo. *Journal of Air Transport Management*, *61*, 6–14.

Kutin, N., Nguyen, T. T., & Vallée, T. (2017). Relative efficiencies of ASEAN container ports based on data envelopment analysis. *The Asian Journal of Shipping and Logistics*, *33*(2), 67–77.

Kutlar, A., Kabasakal, A., & Sarikaya, M. (2013). Determination of the efficiency of the world railway companies by method of DEA and comparison of their efficiency by Tobit analysis. *Quality & Quantity*, *47*(6), 3575–3602.

Kwon, Y., & Lee, J. (2014). Asymmetric responses of highway travel demand to changes in fuel price: An explanation via fuel price uncertainty. *Transportation Research Part A: Policy and Practice*, *63*, 56–66.

Lacko, R., & Hajduová, Z. (2018). Determinants of environmental efficiency of the EU countries using two-step DEA approach. *Sustainability*, *10*(10), 3525.

Lai, P., Potter, A., Beynon, M., & Beresford, A. (2015). Evaluating the efficiency performance of airports using an integrated AHP/DEA-AR technique. *Transport Policy*, *42*, 75–85.

Lean, H. H., Huang, W., & Hong, J. (2014). Logistics and economic development: Experience from China. *Transport Policy*, *32*, 96–104.

Li, W., & Hilmola, O.-P. (2019). Belt and Road Initiative and Railway Sector Efficiency—Application of Networked Benchmarking Analysis. *Sustainability*, *11*(7), 2070.

Li, X., Alam, K. M., & Wang, S. (2018). Trend analysis of pakistan railways based on industry life cycle theory. *Journal of Advanced Transportation*, *2018*.

Liddle, B. (2009). Long-run relationship among transport demand, income, and gasoline price for the US. *Transportation Research Part D: Transport and Environment*, *14*(2), 73–82.

Lin, B., & Ahmad, I. (2016). Energy substitution effect on transport sector of Pakistan based on trans-log production function. *Renewable and Sustainable Energy Reviews*, *56*, 1182–1193.

Lin, B., & Raza, M. Y. (2020). Energy substitution effect on transport sector of Pakistan: A trans-log production function approach. *Journal of Cleaner Production*, *251*, 119606.

Lin, W., Chen, B., Xie, L., & Pan, H. (2015). Estimating energy consumption of transport modes in China using DEA. *Sustainability*, *7*(4), 4225–4239.

Litman, T. (2013). *Understanding transport demands and elasticities: How prices and other factors affect travel behavior*.

Litman, T. (2017). *Generated traffic and induced travel*. Victoria Transport Policy Institute.

lo Storto, C. (2018). The analysis of the cost-revenue production cycle efficiency of the Italian airports: A NSBM DEA approach. *Journal of Air Transport Management*, *72*, 77–85.

Looney, R. E. (1998). The growth and decline of Pakistan's rail system. *International Journal of Transport Economics/Rivista Internazionale Di Economia Dei Trasporti*, 353–378.

Lozano, S., & Gutiérrez, E. (2014). A slacks-based network DEA efficiency analysis of European airlines. *Transportation Planning and Technology*, *37*(7), 623–637.

Marcos, C. B., & Martos, L. P. (2012). Estimating the demand for freight transport: the private versus public trade-off in Andalusian food industry. *Available at: Encuentros. Alde. Es/Anteriores/Vieea/Autores/B/36. Doc (Accessed 5 March 2018)*.

Mardani, A., Streimikiene, D., Balezentis, T., Saman, M. Z. M., Nor, K. M., & Khoshnava, S. M. (2018). Data envelopment analysis in energy and environmental economics: An overview of the state-of-the-art and recent development trends. *Energies*, *11*(8), 2002.

Markovits-Somogyi, R. (2011). Measuring efficiency in transport: the state of the art of applying data envelopment analysis. *Transport*, *26*(1), 11–19.

Mas-Colell, A., Whinston, M. D., & Green, J. R. (1995). *Microeconomic theory* (Vol. 1). Oxford university press New York.

McGeehan, H. (1984). Forecasting the demand for inter-urban railway travel in the Republic of Ireland. *Journal of Transport Economics and Policy*, *18*(3), 275–291.

McKinnon, A. C. (2007). Decoupling of road freight transport and economic growth trends in the UK: An exploratory analysis. *Transport Reviews*, *27*(1), 37–64.

Melo, P. C., Sobreira, N., & Goulart, P. (2019). Estimating the long-run metro demand elasticities for Lisbon: A time-varying approach. *Transportation Research Part A: Policy and Practice*, *126*, 360–376.

Metz, D. (2012). Demographic determinants of daily travel demand. *Transport Policy*, *21*, 20–25.

Milioti, C. P., & Karlaftis, M. G. (2014). Estimating multimodal public transport mode shares in Athens, Greece. *Journal of Transport Geography*, *34*, 88–95.

Miljkovic, D., Price, G. K., Hauser, R. J., & Algozin, K. A. (2000). The barge and rail freight market for export-bound grain movement from midwest to Mexican Gulf: An econometric analysis. *Transportation Research Part E: Logistics and Transportation Review*, *36*(2), 127–137. https://doi.org/10.1016/S1366-5545(99)00025-3

Mitchell, D. (2010). Australian intercapital freight demand: an econometric analysis. *33rd Australasian Transport Research Forum (ATRF) 2010 Proceedings, 29 September-1 October*.

Mohmand, Y. T., Wang, A., & Saeed, A. (2017). The impact of transportation infrastructure on economic growth: empirical evidence from Pakistan. *Transportation Letters*, *9*(2), 63–69.

Morton, A. L. (1969). A statistical sketch of intercity freight demand. *Highway Research Record*, *296*.

Munnell, A. H. (1990). Why has productivity growth declined? Productivity and public investment. *New England Economic Review*, *Jan*, 3–22.

Musso, A., Piccioni, C., Tozzi, M., Godard, G., Lapeyre, A., & Papandreou, K. (2013). Road transport elasticity: how fuel price changes can affect traffic demand on a toll motorway. *Procedia-Social and Behavioral Sciences*, *87*, 85–102.

Narayan, P. K. (2005). The saving and investment nexus for China: evidence from cointegration tests. *Applied Economics*, *37*(17), 1979–1990.

Nelldal, B.-L., & Andersson, E. (2012). Mode shift as a measure to reduce greenhouse gas emissions. *Procedia-Social and Behavioral Sciences*, *48*, 3187–3197.

Nolan, A. (2010). A dynamic analysis of household car ownership. *Transportation Research Part A: Policy and Practice*, *44*(6), 446–455.

Noland, R. B. (2001). Relationships between highway capacity and induced vehicle travel. *Transportation Research Part A: Policy and Practice*, *35*(1), 47–72.

Noland, R. B. (2007). Transport planning and environmental assessment: implications of induced travel effects. *International Journal of Sustainable Transportation*, *1*(1), 1–28.

Noor, N., Mehmood, B., & Wasif, M. (2018). Efficiency Analysis of Public Transport in Lahore, Pakistan. *Pakistan Journal of Applied Economics*, *Special Issue*, 357–376.

Nowak, W. P., & Savage, I. (2013). The cross elasticity between gasoline prices and transit use: Evidence from Chicago. *Transport Policy*, *29*, 38–45.

NTRC and JICA. (2006). *Pakistan Transport Plan Study in the Islamic Republic of Pakistan*. http://open_jicareport.jica.go.jp/pdf/11821907_02.pdf

Nuzzolo, A., Coppola, P., & Comi, A. (2013). Freight transport modeling: review and future challenges. *International Journal of Transport Economics/Rivista Internazionale Di Economia Dei Trasporti*, 151–181.

Odeck, J., & Bråthen, S. (2008). Travel demand elasticities and users attitudes: A case study of Norwegian toll projects. *Transportation Research Part A: Policy and Practice*, *42*(1), 77–94.

Odeck, J., & Hjalmarsson, L. (1996). The performance of trucks—an evaluation using data envelopment analysis. *Transportation Planning and Technology*, *20*(1), 49–66.

Odeck, J., & Johansen, K. (2016). Elasticities of fuel and traffic demand and the direct rebound effects: An econometric estimation in the case of Norway. *Transportation Research Part A: Policy and Practice*, *83*, 1–13.

Omer, M. (2018). *Estimating Elasticity of Transport Fuel Demand in Pakistan*. State Bank of Pakistan, Research Department.

Oum, T. H. (1979a). A cross sectional study of freight transport demand and rail-truck competition in Canada. *The Bell Journal of Economics*, *10*, 463–482.

Oum, T. H. (1979b). Derived demand for freight transport and inter-modal competition in Canada. *Journal of Transport Economics and Policy*, *13*, 149–168.

Oum, T. H. (1989). Alternative Demand Models and Their Elasticity Estimates. *Journal of Transport Economics and Policy*, *23*(2), 163–187.

Oum, T. H., Waters, W. G., & Yong, J.-S. (1990). *A Survey of Recent Estimates of Price Elasticities of Demand for Transport* (No. 359; Infrastructure and Urban Development Department).

Oum, T. H., Waters, W. G., & Yong, J.-S. (1992). Concepts of Price Elasticities of Transport Demand and Recent Empirical Estimates: An Interpretative Survey. *Journal of Transport Economics and Policy*, *26*(2), 139–154.

Oum, T. H., Waters, W. G., & Yu, C. (1999). A survey of productivity and efficiency measurement in rail transport. *Journal of Transport Economics and Policy*, 9–42.

Oum, T. H., & Yu, C. (1994). Economic efficiency of railways and implications for public policy: a comparative study of the OECD countries' railways. *Journal of Transport Economics and Policy*, 121–138.

Owen, A. D., & Phillips, G. D. A. (1987). The characteristics of railway passenger demand. An econometric investigation. *Journal of Transport Economics and Policy*, *21*(3), 231–253.

Pakistan Railway. (2018). *The Success story 2013-18.* https://www.pakrail.gov.pk/images/downloads/TheSuccessStory2013_2018.pdf

Pakistan Railways. (2017). *Year book (2016-2017) available at http://pakrail. com/yearbook. php*. February.

Pakistan Statistical Yearbook. (2018). Federal bureau of statistics. In *Statistics Division, Government of Pakistan*.

Park, Y. S., Lim, S. H., Egilmez, G., & Szmerekovsky, J. (2018). Environmental efficiency assessment of US transport sector: A slack-based data envelopment analysis approach. *Transportation Research Part D: Transport and Environment*, *61*, 152–164.

Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., Preston, J., Wardman, M., Shires, J., & White, P. (2006). The demand for public transport: The effects of fares, quality of service, income and car ownership. *Transport Policy*, *13*(4), 295–306.

Pesaran, M. H., & Pesaran, B. (1997). *Working with Microfit 4: Interactive Econometric Analysis*. Oxford University Press, Oxford.

Pesaran, M. H., & Shin, Y. (1999). An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis. In S. Strom (Ed.), *Econometrics and Economic Theory in the 20th Century* (pp. 371–413). Cambridge University Press. https://doi.org/10.1017/CCOL521633230.011

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289–326. https://doi.org/10.1002/jae.616

Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335–346.

Planning Commission. (2014). Pakistan vision 2025. In *Ministry of Planning*.

Planning Commission. (2018). *Planning commission Report, Ministry of Planning Development & Reform Government of Pakistan*. https://www.pc.gov.pk/uploads/vision2025/Pakistan-Vision-2025.pdf

Planning Commission of Pakistan. (2018). *Transport and Logistics in 11th Five Year Plan 2013-2018*.

Porter, M. E. (1980). *Competitive strategy: techniques for analyzing industries and competitors*. New York: Free Press.

Poumanyvong, P., Kaneko, S., & Dhakal, S. (2012). Impacts of urbanization on national transport and road energy use: Evidence from low, middle and high income countries. *Energy Policy*, *46*, 268–277.

Productivity Commission. (2006). Road and rail freight infrastructure pricing. In *Inquiry Reports*. Productivity Commission, Government of Australia. https://doi.org/10.2139/ssrn.1018886

Profillidis, V. (2016). *Transport Economics* (Fifth). Papasotiriou, Athens.

Rabar, D. (2017). An overview of data envelopment analysis application in studies on the socio-economic performance of OECD countries. *Economic Research-Ekonomska Istraživanja*, *30*(1), 1770–1784.

Rahman, S., & Balijepalli, C. (2016). Understanding the determinants of demand for public transport: Evidence from suburban rail operations in five divisions of Indian Railways. *Transport Policy*, *48*, 13–22.

Rai, A. (2013). Measurement of efficiency in the airline industry using data envelopment analysis. *Investment Management and Financial Innovations*, *10*(1), 38–45.

Ramanathan, R. (2000). A holistic approach to compare energy efficiencies of different transport modes. *Energy Policy*, *28*(11), 743–747.

Ramanathan, R. (2001). The long-run behaviour of transport performance in India: A cointegration approach. *Transportation Research Part A: Policy and Practice*, *35*(4), 309–320. https://doi.org/10.1016/S0965-8564(99)00060-9

Ramanathan, R. (2005). Estimating energy consumption of transport modes in India using DEA and application to energy and environmental policy. *Journal of the Operational Research Society*, *56*(6), 732–737.

Ramli, A. R., & Graham, D. J. (2014). The demand for road transport diesel fuel in the UK: Empirical evidence from static and dynamic cointegration techniques. *Transportation Research Part D: Transport and Environment*, *26*, 60–66.

Rao, P. S. (1978). Forecasting the demand for railway freight services. *Journal of Transport Economics and Policy*, 7–26. http://www.jstor.org/stable/10.2307/20052487

Regan, A. C., & Garrido, R. A. (2001). *Modelling Freight Demand and Shipper Behaviour: State of the Art, Future Directions*. In: Hensher D, editor. Travel Behaviour Research. Pergamon-Elsevier Science.

Rodrigue, J.-P. (2016). *The geography of transport systems*. Taylor & Francis.

Rodrigues, V. S., Pettit, S., Harris, I., Beresford, A., Piecyk, M., Yang, Z., & Ng, A. (2015). UK supply chain carbon mitigation strategies using alternative ports and multimodal freight transport operations. *Transportation Research Part E: Logistics and Transportation Review*, *78*, 40–56.

Roll, Y., & Hayuth, Y. (1993). Port performance comparison applying data envelopment analysis (DEA). *Maritime Policy and Management*, *20*(2), 153–161.

Román-De la Sancha, A., Mayoral, J. M., & Román, L. I. (2016). Modeling urban transfer stations efficiency. *Procedia Computer Science*, *83*, 18–25.

Romero-Jordán, D., Del Rio, P., Jorge-García, M., & Burguillo, M. (2010). Price and income elasticities of demand for passenger transport fuels in Spain. Implications for public policies. *Energy Policy*, *38*(8), 3898–3909.

Saidi, S., Shahbaz, M., & Akhtar, P. (2018). The long-run relationships between transport energy consumption, transport infrastructure, and economic growth in MENA countries. *Transportation Research Part A: Policy and Practice*, *111*, 78–95.

Sameni, M. K., Preston, J., & Sameni, M. K. (2016). Evaluating efficiency of passenger railway stations: A DEA approach. *Research in Transportation Business & Management*, *20*, 33–38.

Sezer, S., & Abasiz, T. (2017). The impact of logistics industry on economic growth: An application in OECD countries. *Eurasian Journal of Social Sciences*, *5*(1), 11–23.

Sharma, M. G., Debnath, R. M., Oloruntoba, R., & Sharma, S. M. (2016). Benchmarking of rail transport service performance through DEA for Indian railways. *The International Journal of Logistics Management*.

Shen, S., Fowkes, T., Whiteing, T., & Johnson, D. (2009). Econometric modelling and forecasting of freight transport demand in Great Britain. *Proceedings of European Transport Conference, 5-7 October*.

Sheng, M., & Sharp, B. (2019). Aggregate road passenger travel demand in New Zealand: A seemingly unrelated regression approach. *Transportation Research Part A: Policy and Practice*, *124*, 55–68.

Shrestha, M. B., & Bhatta, G. R. (2018). Selecting appropriate methodological framework for time series data analysis. *The Journal of Finance and Data Science*, *4*(2), 71–89.

Singh, S. K., & Jha, A. P. (2017). Efficiency and effectiveness of state transport undertakings in India: A DEA approach. *Theoretical Economics Letters*, *7*(06), 1646.

Sloss, J. (1971). The demand for intercity motor freight transport: A macroeconomic analysis. *The Journal of Business*, *44*(1), 62–68.

Small, K. A., & Van Dender, K. (2007). *Long-run trends in transport demand, fuel price elasticities and implications of the oil outlook for transport policy*. OECD.

Souche, S. (2010). Measuring the structural determinants of urban travel demand. *Transport Policy*, *17*(3), 127–134.

South Asia Terrorism Portal. (2018). *Terrorist attacks on Railways in Pakistan*. https://www.satp.org/satporgtp/countries/pakistan/database/railwayattack.htm

SteadieSeifi, M., Dellaert, N. P., Nuijten, W., Van Woensel, T., & Raoufi, R. (2014). Multimodal freight transportation planning: A literature review. *European Journal of Operational Research*, *233*(1), 1–15.

Stefko, R., Gavurova, B., & Kocisova, K. (2018). Healthcare efficiency assessment using DEA analysis in the Slovak Republic. *Health Economics Review*, *8*(1), 6.

Sterner, T. (2006). Survey of transport fuel demand elasticities. In *Report*. Naturvårdsverket.

Sterner, T., & Dahl, C. A. (1992). Modelling transport fuel demand. In *International energy economics* (pp. 65–79). Springer.

Stichhauerova, E., & Pelloneova, N. (2019). An Efficiency Assessment of Selected German Airports Using the DEA Model. *Journal of Competitiveness*, *11*(1), 135–151.

Tahir, N. (2013). Efficiency analysis of Pakistan Railway in comparison with China and India. *International Journal of Transport Economics/Rivista Internazionale Di Economia Dei Trasporti*, 71–98.

Tang, C. F., & Abosedra, S. (2019). Logistics performance, exports, and growth: Evidence from Asian economies. *Research in Transportation Economics*, *78*, 100743.

Tavasszy, L., & De Jong, G. (2013). *Modelling freight transport*. Elsevier.

Tennøy, A., Tønnesen, A., & Gundersen, F. (2019). Effects of urban road capacity expansion–

Experiences from two Norwegian cases. *Transportation Research Part D: Transport and Environment*, *69*, 90–106.

Tiwari, P., & Gulati, M. (2013). An analysis of trends in passenger and freight transport energy consumption in India. *Research in Transportation Economics*, *38*(1), 84–90.

Toma, E., Dobre, C., Dona, I., & Cofas, E. (2015). DEA applicability in assessment of agriculture efficiency on areas with similar geographically patterns. *Agriculture and Agricultural Science Procedia*, *6*, 704–711.

Tong, T., & Yu, T. E. (2018). Transportation and economic growth in China: A heterogeneous panel cointegration and causality analysis. *Journal of Transport Geography*, *73*, 120–130.

Tsai, C.-H. P., Mulley, C., & Merkert, R. (2015). Measuring the cost efficiency of urban rail systems an international comparison using DEA and tobit models. *Journal of Transport Economics and Policy (JTEP)*, *49*(1), 17–34.

Tyler, J., & Hassard, R. (1971). Development of Traffic Generation/Distribution Models in British Rail and their Application to Forward Planning. *PTRC: Models of Traffic Outside Towns. London*.

Ubaidilla, N. Z. (2013). An econometric analysis of road transport demand in Malaysia. *International Journal of Business Tourism and Applied Sciences Vol. 1 No*, *1*(1).

Uddin, W., Khan, B., Shaukat, N., Majid, M., Mujtaba, G., Mehmood, A., Ali, S. M., Younas, U., Anwar, M., & Almeshal, A. M. (2016). Biogas potential for electric power generation in Pakistan: A survey. *Renewable and Sustainable Energy Reviews*, *54*, 25–33.

Van Dender, K., & Clever, M. (2013). *Recent trends in car usage in advanced economies: slower growth ahead?; summary and conclusions*.

Vlahinić Lenz, N., Pavlić Skender, H., & Mirković, P. A. (2018). The macroeconomic effects of transport infrastructure on economic growth: the case of Central and Eastern EU member states. *Economic Research-Ekonomska Istraživanja*, *31*(1), 1953–1964.

Voith, R. (1991). The long-run elasticity of demand for commuter rail transportation. *Journal of Urban Economics*, *30*(3), 360–372.

Wadud, Z. (2016). Diesel demand in the road freight sector in the UK: Estimates for different vehicle types. *Applied Energy*, *165*, 849–857.

Wang, L.-W., Le, K.-D., & Nguyen, T.-D. (2019). Assessment of the Energy Efficiency Improvement of Twenty-Five Countries: A DEA Approach. *Energies*, *12*(8), 1535.

Wang, T., & Lin, B. (2019). Fuel consumption in road transport: A comparative study of China and OECD countries. *Journal of Cleaner Production*, *206*, 156–170.

Wang, Z., & Lu, M. (2014). An empirical study of direct rebound effect for road freight transport in China. *Applied Energy*, *133*, 274–281.

Wanke, P., Barros, C. P., & Nwaogbe, O. R. (2016). Assessing productive efficiency in Nigerian airports using Fuzzy-DEA. *Transport Policy*, *49*, 9–19.

Wanke, P., & Kalam Azad, M. A. (2018). Efficiency in Asian railways: a comparison between data envelopment analysis approaches. *Transportation Planning and Technology*, *41*(6), 573–599.

WDI. (2019). *World Development Indicators (WDI) | Data Catalog*. https://datacatalog.worldbank.org/dataset/world-development-indicators

Wijeweera, A., & Charles, M. (2013a). An empirical analysis of the determinants of passenger rail demand in Melbourne, Australia. *Economic Analysis and Policy*, *43*(3), 249–264.

Wijeweera, A., & Charles, M. B. (2013b). Determinants of passenger rail demand in Perth Australia: a time series analysis. *Applied Econometrics and International Development*, *13*(2), 217–230.

Wijeweera, A., To, H., & Charles, M. (2014). An empirical analysis of Australian freight rail demand. *Economic Analysis and Policy*, *44*(1), 21–29. https://doi.org/10.1016/j.eap.2014.01.001

Wijeweera, A., To, H., Charles, M. B., & Sloan, K. (2014). A time series analysis of passenger rail demand in major Australian cities. *Economic Analysis and Policy*, *44*(3), 301–309.

William W. Wilson, W. W. W. and W. W. K. (1988). Modal competition in grain transport. *Journal of Transport Economics and Policy*, *22*, 319–337.

Winebrake, J. J., Green, E. H., Comer, B., Li, C., Froman, S., & Shelby, M. (2015). Fuel price elasticities in the US combination trucking sector. *Transportation Research Part D:*

Transport and Environment, *38*, 166–177.

Winston, C. (1981). A disaggregate model of the demand for intercity freight transportation. *Econometrica: Journal of the Econometric Society*, 981–1006.

Winston, C. (1983). The demand for freight transportation: models and applications. *Transportation Research Part A: General*, *17*(6), 419–427.

World Bank. (2006). *Transport Competitiveness in Pakistan, An Analytical Underpinning for National Trade Corridor Improvement Program*. http://documents1.worldbank.org/curated/en/961511468289228268/pdf/36523.pdf

World Bank. (2014). *Cleaning Pakistan's air: policy options to address the cost of outdoor air pollution*. The World Bank.

World Health Organization. (2018). *Global status report on road safety 2018*.

World Health Organization. (2020). *Road traffic injuries*. https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries

Yan, Q., Wang, X., Baležentis, T., & Streimikiene, D. (2018). Energy–economy–environmental (3E) performance of Chinese regions based on the data envelopment analysis model with mixed assumptions on disposability. *Energy & Environment*, *29*(5), 664–684.

Yu, T.-H., & Fuller, S. W. (2005). The measurement of grain barge demand on inland waterways: a study of the Mississippi River. *Journal of the Transportation Research Forum*, *44*(1), 27–39.

Zahran, S. Z., Alam, J. Bin, Al-Zahrani, A. H., Smirlis, Y., Papadimitriou, S., & Tsioumas, V. (2017). Analysis of port authority efficiency using data envelopment analysis. *Maritime Economics & Logistics*, *19*(3), 518–537.

Zhang, Z., & Du, L. (2017). Research on Evaluation of resource allocation efficiency of transportation system based on DEA. *IOP Conference Series: Materials Science and Engineering*, *207*(1), 12056.

Zhong, Y., Chen, J., & Liu, X. (2019). Evaluation Model of Transfer Efficiency in Rail Transit Station. *2019 12th International Conference on Intelligent Computation Technology and*

Automation (ICICTA), 492–495.

Zhou, G., Chung, W., & Zhang, Y. (2014). Measuring energy efficiency performance of China's transport sector: A data envelopment analysis approach. *Expert Systems with Applications*, *41*(2), 709–722.

Zlatoper, T. J., & Austrian, Z. (1989). Freight transportation demand: a survey of recent econometric studies. *Transportation*, *16*(1), 27–46.

Zou, G., & Chau, K. W. (2019). Long-and Short-Run Effects of Fuel Prices on Freight Transportation Volumes in Shanghai. *Sustainability*, *11*(18), 5017.