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THE IMPACT OF FUEL PRICE ON THE COST OF PUBLIC TRANSPORT IN SOUTH AFRICA

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ABSTRACT

This study investigates the impact of fuel prices on public transport costs in South Africa from 1994 to 2022. With 80% of the population relying on public transport and over 80,000 buses transporting 850 million people annually, rising fuel prices significantly affect operational costs, often leading to fare hikes. This study investigates the long-term determinants of the cost of public transport (CPT) in South Africa, utilizing an Autoregressive Distributed Lag (ARDL) model for time series analysis over the period from 1993 to 2022. The results from the ARDL (4, 4, 4, 4, 4) model indicate a significant long-run relationship between fuel prices (FP), inflation (INF), GDP (LGDP), income levels (LINC), and the cost of public transport (CPT). Specifically, the coefficient for fuel prices (FP) is 0.0178, indicating that a R1.00 increase in fuel prices leads to a R0.0178 increase in the cost of public transport, reflecting the direct impact of fuel price fluctuations on transport costs. Similarly, inflation (INF) shows a positive relationship with CPT, with a coefficient of 0.0654, suggesting that a rise in inflation contributes to higher transport costs. The coefficient for GDP (LGDP) is 4.9516, implying that higher levels of economic output are associated with an increase in public transport costs, possibly due to rising demand and operational costs in a growing economy. On the other hand, income levels (LINC) exhibit a negative relationship with CPT, with a coefficient of -6.0052, indicating that higher income levels reduce the cost of public transport, which is likely due to increased demand for more efficient services. These findings suggest that public transport costs in South Africa are influenced by a mix of macroeconomic variables, with fuel prices and inflation being the most significant drivers. The study underscores the need for policy interventions to manage fuel price volatility and mitigate its effects on public transport affordability. The study also explores mitigation strategies like government subsidies and alternative energy sources to stabilize public transport costs. Results show a significant positive impact of fuel prices, inflation, and GDP on transport costs.

Keywords: Fuel price, cost of public transport, Income, South Africa

DECLARATION

I, Mhlantlalala Aphelele, solemnly declare that the dissertation titled "The impact of fuel price on cost of public transport in South Africa" submitted in fulfilment of the requirements for the degree of Master of Commerce (Economics) at the University of Fort Hare is my own work. This study has not been submitted and will not be presented at any University in a similar or any award of degree.

Signature:

Date: : 12/04/2025

PLAGIARISM

I, Mhlantlalala Aphelele , the undersigned, hereby declare that this dissertation is my own original work that has not been taken or stolen somewhere else, and that it complies with the University of Fort Hare plagiarism policy rules.

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RESEARCH ETHICS CLEARANCE

I, Mhlantlalala Aphelele with student number 201801237, confirm that I am familiar with the University of Fort Hare's research ethics policy and have made sure to adhere to the rules. I have received approval from the Research Ethics Committee at the University of Fort Hare, and my reference number is HOM021SMHL01.

Signature :

Date : 12/04/2025

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Above all GOD IS ABLE.

DEDICATION

This thesis is devoted to my deceased father, Thembikile Benjamin Mhlantlalala, who was not just an amazing father but also my closest companion. Your wisdom, affection, and constant support have been a beacon in my life. Although you are gone, I am still inspired by your memory daily. This accomplishment belongs to both of us equally, and I aim to make you proud as you have always had faith in me. Dad, I appreciate all that you do. This is meant for you, keep on resting forever.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
ARDL	Autoregressive Distributed Lag
BFP	Basic Fuel Price
CEF	Central Energy Fund

CNG	Costs and Natural Gas
CPI	Consumer Price Index
CPT	Cost of Public Transport
CUSUM	Cumulative Sum of Recursive Residuals
CUSUMQ	Cumulative Sum of Squares of Recursive
CV	Critical Value
DME	Department of Minerals and Energy
EC	Eastern Cape
ECM	Error Correction Model
FP	Fuel Price
FS	Free State
GDP	Gross Domestic Product
GFL	General Fuel Levy
GP	Gauteng Province
HQC	Hannan-Quinn Criterion
IBLC	Inbound Landed Cost
INC	Income
INF	Inflation
KZN	Kwazulu-Natal
LCPT	Log of Cost Of Public Transport
LGDP	Log of Gross Domestic Product
LINC	Log of Income
LP	Limpopo Province

LPG	Liquefied Petroleum Gas
MP	Mpumalanga
NC	Northern Cape
NHTS	National Household Travel Survey
NW	Northwest
OLS	Ordinary least Square
PP	Phillips- Perron
RAF	Road Accident Fund
SARB	South Africa Reserve Bank
SBC	Schwarz Bayesian Criterion
TPB	Theory of Planned Behavior
TRA	Theory of Reason Action
USD	Dollars
WC	Western Cape
ZAR	Rand

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CHAPTER 1: Introduction and Background

1.1 Introduction And Background Of Study

Fuel availability has long been recognised as an economic driver, covering several government fiscal shortfalls, while facilitating the worldwide movement of motorists and enterprises. The entire fuel price is determined by each nation's fuel-pricing system (Naape and Matebula, 2022). Public transport is becoming increasingly important in the South African economy. The transport sector had an essential impact on South Africa's economic growth by providing transport to millions of people who relied on public transport and manufacturing jobs. Bronkhorst (2019) postulates that 80% of South Africa's population relies on public transport, with more than 80,000 buses transporting 850 million people annually. These buses are valued at R25 billion, and the bus business employs approximately 30,000 people. This highlights the critical role of the public transport sector in supporting both the economy and the livelihoods of many South Africans, underscoring the importance of maintaining an efficient and affordable transport system (Naape and Matebula, 20220.

Adeniran (2016) highlights that public transport costs refer to the expenditure customers incur for their travel fares. In simple terms, these expenses are borne by individuals when utilising public transportation services. They represent agreed-upon prices for transporting passengers from specific starting points to designated destinations. Public transport companies must reveal this information to ensure transparent transactions, thus making fare rates routinely accessible to customers.

Conversely, Thiel (2022) argues that public transport costs can fluctuate depending on the chosen mode of transportation, which may include buses, trains, taxis, or the more costly Uber. Additionally, cost can also be influenced by one's place of residence. However, in most cases, public transportation is a more economical option than private transportation.

Gebremeskel et al. (2023) contended that urban residents must have access to inexpensive, sustainable public transportation because it provides a means of escaping social and economic hardships. Additionally, it is a vital link between obtaining resources for living and social assistance. In terms of travel expenses, accessible public transportation can also impact a person's assets, including financial assets. Official transportation services are inaccessible to most lowincome people, due to expensive charges. In other cases, the availability of expensive transportation choices might cause additional stress owing to the length of the trip and the uncomfortably long travel distance. Conversely, it should be noted that fuel price is one of the factors that affect the cost of public transport.

Bujeti (2023) argues that rising fuel prices increase the cost of public transport, which raises the cost of going to work, education, or other vital locations. This particularly burdens lowincome people, who have difficulty making ends meet. The financial problems suffered by vulnerable groups are worsened by the rising cost of fuel, as 40% of people in developing nations live in extreme poverty. However, a paper published by TMMBS (2023) claims that a drop in the price of fuel immediately results in lower costs for public transport. Consumers and companies stand to gain from this decrease in fuel price. Customers benefit from reduced daily commuting expenses, while companies see a decrease in transportation expenditure, resulting in lower prices for goods and services. Because firms have more money to invest in other areas, lower public transport expenses can stimulate the economy.

The fuel prices in South Africa pose a severe threat to public transportation. Affordable fuel availability is a critical transportation component that is extremely sensitive to political issues. Typically, fuel costs comprise 10%-40% of the total operating costs for public transport (Saferspaces, 2023). Fuel costs are affected by volatility and variations, as South Africa imports fuel. South Africa experienced a drastic rise in petrol price between July 2012 and July 2019, growing by 46.1% or 7.7% annually on average. The 22.9% increase in petrol prices since the start of 2018 is a significant issue (Hassan & Meyer, 2020).

Fuel prices increased by 7.6% in both August and September of 2023, marking the second consecutive month of increases. During September, the cost of offshore 95-octane fuel increased by R1.71, reaching a 13-month high of R24.54. This increase in fuel prices had a significant impact on the transport industry, contributing significantly to the monthly inflation rate. Furthermore, the consumer price index (CPI) rose by 0.6% in the month, with transportation accounting for 0.4% of the rise (Statistics South Africa, 2023).

1.2 Problem statement

As fuel is a substantial cost for public transportation firms in South Africa, the transportation industry is concerned about rising fuel prices. Fuel price increases in 2022 are the result of a variety of causes, such as the Ukrainian war and fundamental challenges in the economy. South Africans depend significantly on roads for travel. According to Taylor (2022), over 80% of public transport users rely on taxis to get to work, while 16% use buses. Separately, 34.1% of the overall working population commute by private car, highlighting the diverse but road-dependent nature of transportation in the country.

High fuel prices have contributed to significant increases in public transport costs in South Africa, placing additional financial pressure on low-income households and daily commuters.The few bus services that operate primarily travel great distances between cities, while metro rail services have ceased operations. This has resulted in a spike in the consumption of minibus taxis, which have become the primary means of transportation. With no oversight, these taxis virtually have a stranglehold on the public transportation the marketplace. Rising fuel prices have raised the cost of public transportation, notably minibus taxis. Despite this, passengers continue to rely extensively on them for transit to and within towns, as they are the primary mode of transportation. However, the government has minimal involvement in developing rules to control and monitor public transportation provision in these locations, limiting the government's influence over the sector's administration and planning (Mbara, 2021).

According to eNCA (2022), taxis are the most popular mode of transportation for South Africans traveling to work and are typically the most cost-effective alternative for many. Consequently, rising fuel prices have a significant impact on the cost of public transport in South Africa. Transport industry owners are obliged to raise their fares, which has a severe impact on customers. In 2022, 93 octane petrol costs R23,94 cents per liter, while 95 octane petrol will cost R26,46 more per litre. Gavin (2022) indicated that diesel for transporters rose by R1,42 for 500ppm and R1,43 for 50ppm in 2022. Prices hiked to R25,49 and R35,75, respectively. The Central Energy Fund blamed the price increase for growing foreign fuel costs and a weak Rand. Diesel prices have more than doubled since December 2021. This led to greater public transit expenditure. Similarly, Creamer Media (2022) observes that rising diesel prices encountered by public transportation firms are passed on to the public via higher fuel taxes. This has had a significant influence in South Africa.

Simelane (2020) emphasizes that people who lack the financial means to use public transportation may encounter difficulties in reaching necessary societal services like public housing, schools, and clinics. In South Africa, this problem is a major challenge because South Africans spend around 20% of their earnings on public transportation expenses. According to his findings indicate that for public transportation to be truly affordable, passengers should aim to allocate 10% or under of their earnings on transportation costs. The expense of traveling is connected to the overall expense of residing. Maintaining affordable fuel prices is essential to ensure people can stay mobile while staying within their budget.

Furthermore, Simelane (2020) emphasizes that metrorail trains and municipal buses often benefit from subsidies, significantly reducing travel costs during off-peak hours. However, prices tend to surge notably during rush hour. In comparison, paratransit options are cost-effective in South Africa, although in many instances trains or buses prove to be more economical than minibus taxis. Since most public transportation users in South Africa come from poor backgrounds, affordability remains a paramount concern. As a result, ongoing efforts are necessary to ensure that public transportation fares remain within reach of the populace. To this end, this study investigated the impact of fuel prices on the cost of public transport.

1.3 Research Objectives

The primary objective of this study is to investigate the impact of fuel prices on the cost of public transport in South Africa from 1994 to 2022 using yearly data. The specific aims include:

- To review the trends of fuel price and cost of public transport in South Africa
- To econometrically investigate the impact of fuel price on the cost of public transport in South Africa
- To provide policy recommendations for South Africa based on the results.

1.4 Hypothesis

H0 Fuel price does not have a significant impact on the cost of public transport in South Africa.

H1 Fuel price has a significant impact on the cost of public transport in South Africa.

1.5 Significance of the study

Since an increase in fuel price leads to an increase in the cost of public transport, a study by Xinhua (2022) argues that the cost of living rises due to higher public transport costs, which lowers the overall quality of life. It should be noted that many people use public transport at least once a day; hence, this issue is urgent. Nevertheless, few studies have been conducted on the fuel price and cost of public transport globally (Nkuah & Berko, 2015; Mayburov & Leontyeva, 2017; Aljoufie, 2019; Ajayi, Ogundele, Adebayo, Aworemi, & Babalola, 2019; Gebremeskel, Woldeamanuel & Woldetensae, 2023).

On that note, a study by Mayburov and Leontyeva (2017) concluded that regular increases in fuel prices progressively discourage people living in cities from using public transportation. In contrast, Ajayi (2019) revealed that when fuel prices rise, people choose to use public transportation instead of driving their vehicles because it is less costly. This is supported by Zhang and Burke (2020), who suggest that when fuel prices rise, people are more likely to use public transportation. In contrast, Gebremeskel et al. (2023) discovered that low- and middle-income people had more travel issues than those with higher incomes, notably in terms of total trip time and the proportion of cash spent on transportation. Aljoufie (2019) stated that increased public transportation costs, caused by higher fuel prices, have a detrimental impact on travel behavior. As a result, the research presents diverse perspectives on how fuel prices affect public transportation costs.

Furthermore, it should be noted that studies conducted in South Africa did not focus on fuel price and the cost of public transport, but rather on fuel price and other elements of the cost of public transport (Rangasamy, 2017; Ncanywa & Mgwangqa, 2018; Leshoro & Maluleke, 2020; Ntshingila, 2022). Therefore, to the best of the author's knowledge, no research has been conducted in South Africa as in the current study. Therefore, this study investigated the impact of fuel prices on the cost of public transportation in South Africa. This analysis clarifies to South African policymakers that precautions must be taken to prevent excessive fuel price increases, as this might affect the public. This study also assists public transport businesses in developing a sound plan and technique to permanently address the fuel price increase problems. This study benefits the public, allowing them to know that whenever there is a fuel price increase in a country, public transport costs tend to increase. This study adds to the body of current literature on this topic and is used as a resource for academics and students seeking to pursue additional research in a similar field.

1.6 Organization of the study

The thesis is divided into six chapters. The first chapter offers an outline of the study's background, while the second chapter investigates South African fuel prices and public transportation cost patterns. Chapter 3 examines theoretical and empirical literature. Chapter 4 describes the econometric methodologies employed, while Chapter 5 gives the analysis and interpretation of the findings. Finally, Chapter 6 summarizes the important results and makes policy suggestions based on them.

CHAPTER 2: Overview of Trends In Fuel Price and Cost Public Transport In South Africa

2.1 Introduction

Public transportation is critical for guaranteeing mobility and connectivity within communities, serving as a lifeline for millions of people worldwide. With its diverse landscapes and sprawling cities, public transportation is more than a convenience for many South Africans; it is a need. Understanding the cost structure of public transportation is critical for policymakers, commuters, and stakeholders since it encompasses a variety of elements that affect the overall affordability and accessibility of these services (Walker, 2008).

The cost of public transport in South Africa is a multifaceted concept, comprising several components that collectively determine the affordability and efficiency of transportation systems across the country. These components encompass both monetary and non-monetary factors, ranging from ticket prices and subsidies to infrastructure investments and operational expenses (Mules & Dwyer, 2005).

At the forefront of the cost structure are ticket prices, which directly impact commuters' budgets and decision-making processes. In South Africa, ticket fares vary widely depending on the mode of transportation, distance traveled, and the region in which the service operates (Branda, Marozzo & Talia, 2020). For instance, urban areas typically have more extensive public transportation networks, offering options such as buses, trains, and taxis, each with their own fare structure. Meanwhile, in rural and underserved areas, where public transport options may be limited, the cost of accessing transportation can be disproportionately high, further exacerbating socioeconomic disparities.

Subsidies play a pivotal role in mitigating the financial burden on commuters and ensuring the affordability of public transport services. Government subsidies are allocated to transportation authorities and operators to offset operational costs and keep ticket prices at manageable levels. (Jennings, 2015). However, the allocation and distribution of subsidies can be a contentious issue, as competing priorities and budget constraints often influence funding decisions. Moreover, the effectiveness of subsidies in achieving equitable access to transportation services remains a subject of debate, particularly in marginalized communities where transportation infrastructure is inadequate or nonexistent.

Infrastructure investments constitute another significant component of the cost of public transport in South Africa. The construction and maintenance of transportation infrastructure, including roads, bridges, railway lines, and terminals, require substantial financial resources. These investments not only facilitate the efficient movement of people and goods but also contribute to economic development and social integration. However, inadequate infrastructure investment, coupled with rapid urbanization and population growth, can lead to congestion, delays, and service disruptions, affecting the overall quality and affordability of public transport (Fedderke, Perkins & Luiz, 2006).

Operational expenses, encompassing fuel, labor, maintenance, and administrative costs, constitute a substantial portion of the cost of providing public transport services. Operators must balance the need to cover these expenses with the imperative to keep ticket prices affordable for commuters. Factors such as fluctuating fuel prices, wage demands, and regulatory compliance further complicate cost management efforts, requiring operators to adopt innovative strategies to improve efficiency and sustainability (Daraio, Diana, Di Costa, Leporelli, Matteucci & Nastasi, 2016).

2.2 Overview Of Cost Of Public Transport In South Africa

The importance of transportation in fostering social and economic development is undeniable, especially in developing nations where mobility is often limited due to inadequate transport services. Rapid urbanization, driven by economic growth and rural-urban migration, has led to sprawling cities like Johannesburg, exacerbating the need for efficient public transport (Loh & Brieger, 2013; World Population Review, 2018). However, private cars dominate commuter transport in Johannesburg, contributing to congestion in a city already facing high population growth rates (Gauteng Province Roads and Transport, 2016; Luke, 2018; TomTom, 2017).

The transportation system in Johannesburg suffers from chronic underinvestment, resulting in congestion, pollution, accidents, and declining public transport (Pojani & Stead, 2015). These issues are compounded by the legacy of apartheid, which enforced racial segregation and forced many non-White residents to commute long distances for work, leading to fragmented urban spaces and ongoing social exclusion (Kani, 2018; Thomas, 2016). This situation highlights the urgent need for investment in sustainable transportation infrastructure to address congestion and promote inclusivity in urban mobility.

According to Statistics South Africa's National Household Travel Survey (NHTS 2021), Gauteng (34.2%), KwaZulu-Natal (15.6%), and the Western Cape (14.4%) account for the majority of the country's workforce. According to the study, 62% of workers nationally work five days a week, 24.1% work six or more days, and 13.8% work one to four days per week (Kgwedi, 2022), shedding light on regional labor distribution and work patterns.

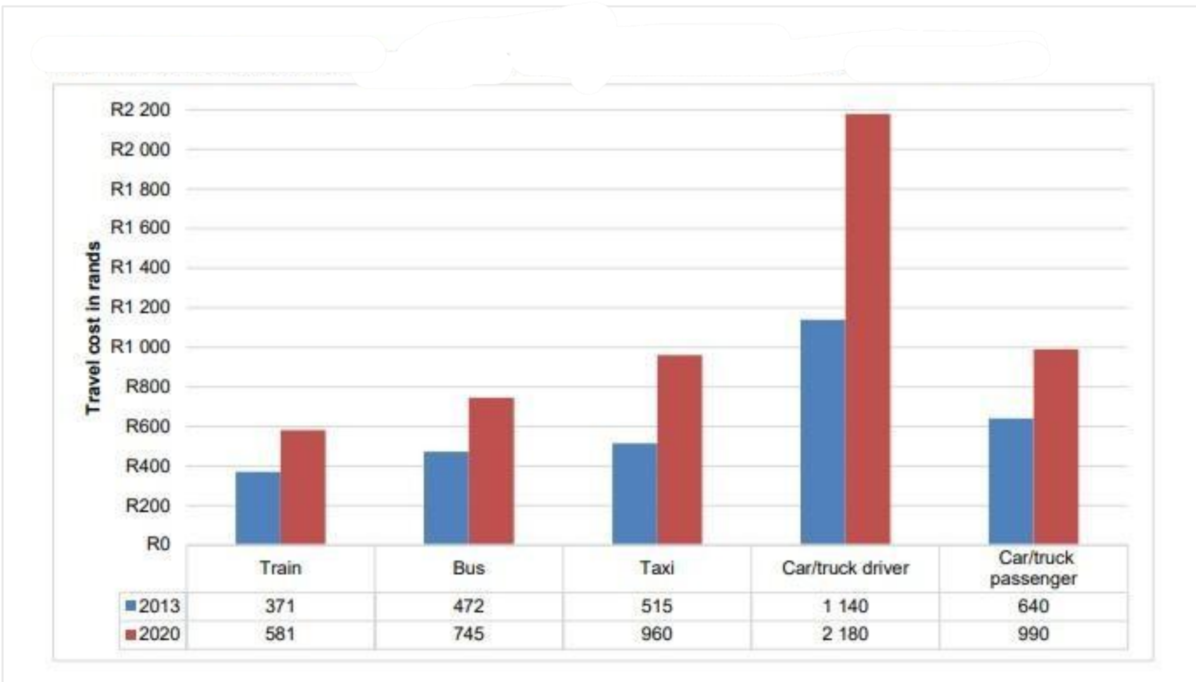


Figure 2.1: Monthly cost of transport to by main mode transport from 2013 to 2020 ***(Source: NHS,2020).***

The findings show that individuals commuting by vehicle, bakkie, or truck had the highest average travel expenditures, at R2,180, compared to R960 for taxi users, R990 for passengers in automobiles, bakkies, or trucks, and R745 for bus users. Train travel was the least costly, costing an average of R581. From 2013 to 2020, travel expenditures rose across all means of transportation, with vehicle drivers seeing the greatest increase. Taxis were the most expensive public transportation alternative, costing R960.

2.2.1 Waiting Time on Public Transport Costs.

According to BusinessTech (2023), South African workers' commute patterns differ greatly. Most workers, 29.8%, begin their commute between 07:00 and 07:59, with the biggest numbers seen in the Eastern Cape (44%), Free State (38.8%), and Northern Cape (36.4%) at this time. Approximately 24.5% of workers begin their journey before 06:00, with the largest rates in Mpumalanga (33.4%), Gauteng (27.6%), and Northwest (26.4%). In contrast, the Eastern Cape has the fewest early commuters, with just 17.1% departing before 06:00. Approximately 18% of workers begin their journey between 06:30 and 06:59, with Limpopo, Northern Cape, and Free State having the highest rates (23% each) and KwaZulu-Natal at 18.9%. Approximately 10% of workers begin commuting at or after 08:00, with significantly higher rates in Gauteng (12.4%) and KwaZulu-Natal (11.4%).

Table 2.1 Waiting Time on Public Transport Cost by each province.

Province	Number of persons who completed the question ('000)	Time workers leave (percentage of workers within province)					
		Before 06:00	06:00 to 06:29	06:30 to 06:59	07:00 to 07:59	08:00 or later	Total
Western Cape	2 008	18,3	19,2	17,4	34,9	10,2	**100,0**
Eastern Cape	982	17,1	11,6	17,9	44,0	9,4	**100,0**
Northern Cape	291	19,3	14,8	23,0	36,4	6,5	**100,0**
Free State	628	17,9	14,0	22,5	38,8	6,8	**100,0**
KwaZulu-Natal	2 008	25,2	18,0	18,9	26,5	11,4	**100,0**
North West	773	26,4	13,8	17,2	34,0	8,6	**100,0**
Gauteng	4 639	27,6	18,9	16,0	25,2	12,4	**100,0**
Mpumalanga	954	33,4	15,5	18,3	26,4	6,4	**100,0**
Limpopo	1 068	23,9	18,7	23,2	26,5	7,7	**100,0**
RSA	**13 352**	**24,5**	**17,4**	**18,0**	**29,8**	**10,3**	**100,0**
Geographic location							
Urban	10 320	23,2	17,6	17,2	31,0	11,0	**100,0**
Rural	3 032	28,7	16,6	20,9	26,0	7,8	**100,0**

(*Source, Businesstech, 2021).*

2.2.2 Inefficiencies of public transport

Efficient public transportation is essential for urban dwellers, enabling timely and convenient access to work, education, and numerous services. However, waiting time at transit stops significantly affects commuters' overall experience and can incur hidden costs. This study explores the implications of waiting time on public transport costs, drawing comparisons between Johannesburg and Cape Town based on recent data (Simelane, 2020). Waiting for transportation entails more than just idle time, it incurs opportunity costs and affects commuters' productivity and well-being. Long waiting times lead to frustration and can result in decreased job satisfaction and lower economic productivity.

In Johannesburg, where train commuters and 70% of taxi users experience waiting times under 3 minutes, the perceived efficiency contrasts sharply with bus commuters' experiences. With over 35% of bus users waiting between 19-21 minutes, the hidden costs of waiting accumulate. Longer waiting times may necessitate earlier departure from home, potentially leading to increased childcare or other pre-commute costs.

Conversely, in Cape Town, train commuters face the longest waiting times, with 20% waiting 25 minutes or more. This extended waiting period can disrupt daily schedules, leading to increased stress and reduced leisure time. Minibus taxi users, constituting almost 30% of passengers, experience waiting times between 7 and 10 minutes, adding to the overall cost of transportation.

The inconsistency between the two cities' data highlights the complexity of urban transportation systems and the need for tailored solutions. While bus commuters endure the longest waits in Johannesburg, the situation reverses in Cape Town. Such disparities underscore the importance of context-specific interventions to address waiting time issues effectively.

The economic impact of prolonged waiting times extends beyond individual commuters. Businesses may experience decreased productivity due to employee tardiness or absenteeism resulting from unreliable public transport. Moreover, excessive waiting times can deter potential ridership, affecting revenue streams for transit agencies and potentially leading to fare increases to offset operational costs.

Table 2.2: Total time traveled to place of employment by major mode and province in 2020

Main mode of travel and total time in minutes	PROVINCE									
	WC	EC	NC	FS	KZN	NW	GP	MP	LP	RSA

TRAIN										
Mean (minutes)	105	95	*	*	110	*	107	*	*	107
1-30	0,2	*	*	*	4,5	*	4,5	*	*	3,1
31-60	23,5	17,6	*	*	6,0	*	14,5	*	*	15,9
61*	76,4	82,4	*	*	89,5	*	81,0	*	*	81,0
Total	**100,0**	**100,0**	*	*	**100,0**	*	**100,0**	*	*	**100,0**
BUS										
Mean(minutes)	87	67	52	79	74	89	93	92	75	84
1-30	3,6	13,7	40,6	10,2	9,7	16,0	6,5	8,2	15,4	9,2
31-60	39,0	48,3	31,6	24,7	35,3	24,9	22,6	28,1	32,3	30,7
61*	57,3	38,0	27,8	65,1	55,0	59,1	70,8	63,7	52,3	30,1
Total	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**
Taxi										
Mean(minutes)	66	48	45	45	61	54	70	51	54	63
1-30	20,5	34,8	37,6	40,4	19,5	30,0	14,7	37,9	31,4	21,4
31-60	33,2	47,4	49,6	44,1	43,1	45,8	39,1	41,2	42,6	40,6
61*	46,3	17,8	12,8	15,5	37,4	24,2	46,2	20,8	26,0	38,0
Total	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**
Car Driver										
Mean(minutes)	42	37	30	36	44	31	51	44	40	63
1-30	47,2	57,4	73,5	63,1	45,4	66,4	37,3	54,4	58,7	21,4
31-60	34,1	29,8	17,6	25,0	36,4	26,3	39,1	30,9	26,3	40,6
61*	18,7	12,9	8,8	11,8	18,2	7,2	23,7	14,7	14,9	38,0
Total	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**
Car Passenger										
Mean(minutes)	48	42	39	40	47	38	53	67	50	49
1-30	37,6	48,7	58,8	58,6	48,2	51,5	31,6	28,4	40,0	40,4
31-60	45,1	34,5	19,7	25,5	29,7	38,7	40,5	30,1	38,0	36,8
61*	17,3	16,8	21,5	15,8	22,1	9,8	27,9	41,5	21,6	22,8
Total	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**

Walk all the way										
Mean(minutes)	23	27	26	29	34	28	35	37	32	31
1-30	83,6	74,1	76,4	73,2	65,5	72,7	62,2	60,0	69,3	69,3
31-60	12,3	12,3	17,3	20,2	23,8	19,7	24,1	28,4	22,3	21,4
61*	4,1	4,1	6,2	6,7	10,6	7,7	13,8	11,6	8,4	9,3
Total	**100**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100,0**	**100.0**	**100,0**

(Source, Businesstech, 2021)

- **Cells with unweighted numbers of 3 or fewer offer unreliable estimations. Totals do not include undefined cases.**

Most train commuters spend over an hour traveling to work, while taxi users typically take between 30 to 60 minutes. On the other hand, most individuals who walk or use a car travel for about 30 minutes. O'Neill (2010) highlighted how urban transportation issues hinder mobility and accessibility, particularly affecting the economically disadvantaged. Petterson (2016) emphasized the importance of public transportation for fostering competitive economies, poverty alleviation, and environmental conservation. Initial policies such as the White Paper on National Transport Policy (Department of Transport, 1996) targeted an 80:20 division between public and private transportation. Later approaches focused on sustainable transport choices to lessen environmental harm and advance social inclusivity (National Planning Commission, 2011; Department of Transport, 2015; Department: Roads and Transport, Gauteng Province, 2012).

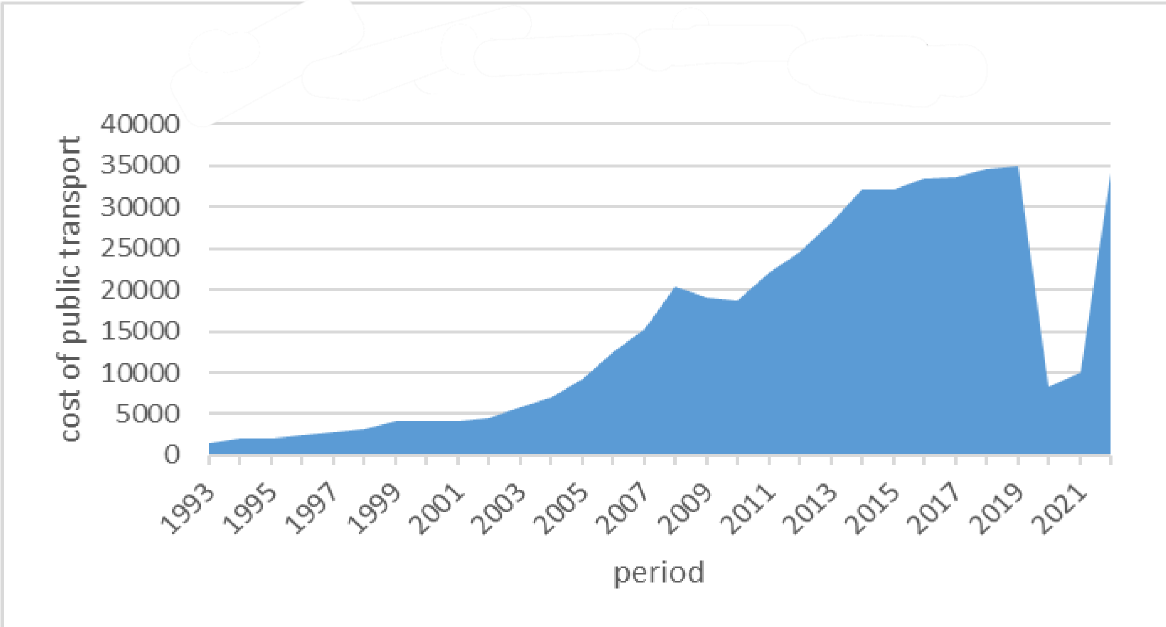


Figure 2.2 Trend for cost of public transport in South Africa Source: Own graph with data acquired from South African Reserve Bank 2022

From 1993 to 1999, the cost of public transport in South Africa displayed a trend of increasing at a decreasing rate, influenced by the lingering effects of historically unjust laws on transport and the efforts to address fragmented spaces through various public transport solutions. The end of apartheid in 1994 marked a period of political and economic transformation, with investments in infrastructure and subsidies aimed at improving public transport networks, initially resulting in stable or decreasing costs for commuters. However, challenges such as inefficient service delivery, inadequate infrastructure, and urban population growth led to inconsistencies in service quality and reliability, pushing some commuters towards informal and costlier transportation modes, exacerbating inequalities in access and affordability (National Planning Commission, 2011).

Subsequently, from 2001 to 2008, public transport costs in South Africa experienced a period of sharp increases driven primarily by inflation and the global financial crises of 2008. Economic slowdown, rising unemployment, and inflationary pressures influenced the cost of public transportation, with fare adjustments made to account for inflationary pressures and rising operational costs such as wages, maintenance, and fuel (Petterson, 2016).

Moreover, from 2011 to 2020, there was a significant rise in public transport costs in South Africa, attributed to investments in new infrastructure aimed at expanding public transit networks, upgrading vehicles, and implementing technological improvements. While these investments aimed to enhance service quality and efficiency, they also led to increased costs, necessitating fare adjustments to cover associated capital and maintenance expenses. Additionally, changes in demand for public transportation services influenced by factors like population growth, urbanization, economic conditions, and cultural shifts, played a role in fare pricing dynamics, with higher demand potentially allowing transportation providers to spread costs across a larger rider base, thus mitigating the need for fare hikes.

The COVID-19 pandemic caused interruptions and modifications, which contributed to the cost rise. The pandemic, which began in 2020, had a significant impact on public transportation networks across the world, including South Africa (van Ryneveld, 2020). Measures such as lockdowns, social distancing protocols, and travel bans curtailed the demand for public transit, resulting in revenue downturns for operators and financial stress on the sector. To mitigate the situation, authorities implemented temporary fare cuts, service modifications, and hygiene protocols to ensure passenger and staff safety. Despite these efforts, the financial blow from reduced ridership persisted, prompting fare hikes in certain instances to offset operational expenses and sustain service provision. Additionally, the pandemic brought to light the underlying vulnerabilities and inequalities in South Africa's public transport network, disproportionately affecting marginalized communities with service disruptions, and limited alternative transportation options.

Following the pandemic, the rise in public transport costs eased off due to post-COVID-19 measures introduced by the government, particularly towards Sustainable and Inclusive Mobility. The trajectory of public transport costs in South Africa from 1994 to 2022, (Cartenì, Di Francesco, Henke, Marino and Falanga 2021), demonstrates a multifaceted interaction of economic, social, and environmental influences. While transitions, growth phases, and crises have all contributed to fluctuations in transport affordability, the COVID-19 pandemic emphasized the necessity for resilience and adaptability in confronting unforeseen challenges.

2.2.3 Public transport costs continue to drive higher inflation.

Yearly consumer price inflation accelerated from 5.7% in February to 5.9% in March, falling just short of the monetary policy goal range set by the South African Reserve Bank, which has a maximum of 6%. Food and non-alcoholic drinks, housing and utilities, and transportation were the main contributions, with transportation accounting for 2.1 percentage points of the yearly rate. (Businesstech, 2022).

Figure 2.3 South African annual consumer price inflation from 2015 to 2022

Source : (Consumer Price Index, 2022)

According to recent statistics issued by Statistics South Africa (Stats SA, 2022), taxis play the most important role in South Africa's public transportation network. According to data, taxis are the preferred mode of transportation for more than half (51.0%) of families that use public transit, beating out buses (18.1%) and trains (7.6%). This finding stems from the Measuring Household Expenditure on Public Transport technical research, which gives insight on the complicated dynamics of transportation preferences across the country. The results show a considerable monthly jump in the consumer price index (CPI), with a 1.0% increase in March, up from 0.6% in February. This third CPI update includes updated weights and a new basket of goods and services, using December 2021 as the rebased reference point (Stats SA, 2022). Despite the CPI's ascent, South Africans face mounting transportation expenses exacerbated by surging fuel prices. Between February and March alone, fuel prices skyrocketed by 7.2%, catapulting inland 95-octane petrol to a record high of R21.60 per liter—an unprecedented spike of R1.46 per liter.

Over the twelve months leading to March, fuel prices soared by a staggering 33.2%, with petrol and diesel experiencing respective hikes of 32.6% and 35.1%.

The transport index for March further reflects this economic strain, propelled by escalations in toll fees, air transport fares, and bus tariffs. Notably, the burden of transportation expenses falls disproportionately on households, particularly impacting those in the lowest income quintile. Figure 2.2 clearly shows the financial strain, with higher income households (R404) having much higher average monthly travel costs than lower income households (R136). Despite price variations, taxis remain the most costly method of transportation, averaging R254 per person per month, followed by trains at R248 and buses at R231. Surprisingly, households in the lowest income quintile devote a greater proportion of their money to public transportation, with almost two-thirds (66.6%) spending more than 20% of their monthly household budget on transportation. In comparison, just 2.9% of households in the top income quintile encounter comparable financial challenges (Loewald, Makrelov, & Pirozhkova, 2022).This disparity underscores the urgent need for targeted interventions to alleviate the economic strain on vulnerable households and foster equitable access to transportation services across all income brackets. As fuel prices and transportation costs continue to surge, policymakers must address these socioeconomic disparities to ensure inclusive and sustainable mobility for all South Africans.

According to Stats SA (2022), roughly 3.7 million students commute mostly by public transportation. Taxis are the most popular mode of transportation among students, followed by buses and trains. Interestingly, students in the highest income quantity devote a larger share of their budget to transportation than their peers in the lowest income quartile. In terms of cost analysis, trains are the most costly method of transportation, with an average monthly cost of R422, followed by buses at R393 and taxis at R375. Students in the lowest income quintile are particularly affected, with many spending more than 20% of their monthly household income on public transit. Additionally, 39.1% of workers rely on public transportation to go to work. Taxis are the most popular mode of transportation among these commuters, accounting for 26.5%, followed by buses (7.6%) and trains (5.0%). Aside from public transportation, many employees use private automobiles, walk, or carpool. Notably, workers from higher-income households often have higher commuting costs than those from lower-income households.

Breaking down costs per mode of transport, taxis emerge as the most expensive option, with an average per capita monthly cost of R561, followed by buses at R502, and trains at R402.

Notably, workers from the lowest income quantity are disproportionately impacted, with a massive portion spending over 20% of their monthly household income per capita on public transportation. These findings underscore the disproportionate burden of transportation costs on lower-income households, highlighting the need for targeted interventions to alleviate this financial strain. (StatsSA, 2022; Mtembu, 2020).

2.3 Forms of public transport in South Africa

Transportation infrastructure in Africa and other developing countries frequently lacks proper planning, efficiency, and operating capability. The issues have been exacerbated by urbanization trends, which have overburdened transportation infrastructure owing to rising populations (Walters, 2013; Jennings, 2015). Municipal buses and Metrorail trains are the primary modes of official transportation in South Africa. Nonetheless, these services operate independently in terms of structure, administration, and financial support, resulting in a lack of cohesiveness in the public transportation system and ongoing instability (Walters, 2014).

2.3.1 Buses

Public transport services were implemented in South Africa in the 1930s to improve the country's chaotic public transportation system (Sey, 2008). Buses have played a crucial role in providing transportation services to the population of South Africa, particularly for Black individuals commuting between homelands and cities since the early days. During apartheid, segregation led to communities of color being situated far from employment, leisure, and commercial centres, emphasizing the necessity of a subsidized bus service for impoverished areas (Walters, 2014; Weakley & Bickford, 2015).

As per certain commuters, commuter buses have drawbacks like lengthy travel durations and exorbitant transportation costs, which can make bus journeys unenjoyable for individuals dependent on public transit (Mitizi, 2017; Hitge, 2015). A study of passenger behavior in South African commuter transport systems discovered dissatisfaction, particularly concerning safety issues like bus stop and transportation safety. Additionally, the research discovered discontent regarding the frequency of off-peak buses, with the lack of amenities at bus stops being highlighted as the top unsatisfactory aspect of buses (Lombard et al., 2007).

Access to legal means of public transit in South Africa pales in contrast to the availability of informal minibus taxi services. According to the NHTS 2013 report, around 17% of households lacked access to taxi services, while a shocking 50% lacked access to official bus services. This stark disparity highlights the critical issue of accessibility in the country's public transportation infrastructure, where a large section of the population relies on informal taxis due to shortcomings in formal services.

While bus travel has its inconveniences, it is usually regarded as one of the safest modes of public transportation. This safety reputation stems from their dependable functioning and slower speeds, which improve security but can also result in longer travel times and higher expenses (Mtizi, 2017). According to the NHTS 2013 study, buses were chosen over trains in numerous South African cities owing to their perceived safety and accessibility. Despite this preference, buses remain substantially less popular in certain areas than minibus taxis.

2.3.2 Trains

Public train services are currently the least used form of public transportation due to ongoing problems with Metrorail and the rail system. Based on household surveys conducted in South Africa, it was found that 81% of households do not have access to train services since trains mainly run in major cities like Gauteng, Cape Town, Durban, East London, and Port Elizabeth (NHTS, 2013; Kerr, 2017).

Despite being a crucial means of commuting for many South Africans, train services in the country have consistently faced numerous challenges, rendering them unreliable (Thomas, 2016). Key issues include punctuality, overcrowding, distance from stations, and train security (NHTS, 2014). Overcrowding remains a significant problem for Metrorail, to the extent that passengers are often compelled to occupy spaces between carriages, posing risks to their safety (Mthimkhulu, 2017).

The lack of reliability in train services is a major disadvantage of using this form of public transportation. Trains in South Africa are commonly viewed as the most unreliable choice, with a considerable number arriving late or not showing up at all (NHTS, 2014). According to research utilizing NHTS 2014 data, commuters' main complaints were availability, overcrowding, timeliness, and dependability, demonstrating widespread dissatisfaction with rail service (Heyns & Luke, 2018). Inadequate infrastructure and limited access to schedules worsen the issue, making it difficult for the service to stick to its timetable despite having schedules posted on their website. Studies have shown that 37.8% of individuals who use trains often experience instances where the service is not available (Walter, 2008; NHTS, 2014).

A review of rail infrastructure difficulties in Cape Town identified delayed response times as a major concern in meeting maintenance and repair demands. Response times were shown to be influenced by factors such as event time, location, nature of the problem, and availability of maintenance professionals. The research advocated using a decision support model designed for this purpose, which might not only shorten reaction times but also help managers quickly pinpoint event sites and find underlying issues. (Conradie et al., 2019).

Trains in some parts of Cape Town have a criminal aspect to them since they are not effectively regulated. The safety of passengers on and around the train and its stop is a critical issue that requires more attention. According to a survey conducted by NHTS in 2013, women are the least probable to utilize trains in comparison to other available modes of transportation. This is mainly due to safety issues and the significant distances to walk at train stations, which can make it harder for them to access the rail system.

2.3.3 Taxis

In South Africa and other Southern African cities, informal transportation systems, notably minibus taxis, are commonly used for getting to work and education (Schalekamp, 2015). Minibus taxis have formed the backbone of the public transportation system, serving a big section of the population (Woolf and Joubert, 2013; Van Zyl, 2009). Paratransit choices such as minibus taxis account for a considerable proportion of public transportation journeys in Sub-Saharan Africa, ranging from 50% to 98% (Behrens et al., 2016). In Gauteng, for example, minibus taxis account for over 70% of all public transportation trips, outnumbering private automobiles for a variety of reasons (DoT, 2007; Golub, 2003). This growth emphasizes the critical role that minibus taxis play in the region's transportation system, demonstrating their transformation from a modest paratransit alternative to a major business.

Minibus taxis and other informal transportation services often emerge spontaneously rather than being intentionally designed. This is due to inadequate planning and funding for transportation systems, compounded by growing urban populations and sprawl that strain existing infrastructure. These informal services fill gaps left by the formal transit sector, catering to passengers who are typically overlooked.

Minibus taxis provide a specific demand that is often fulfilled by the transit service business. Paratransit services in Global South cities frequently adapt to local circumstances due to weak institutional frameworks and geographical barriers to the expansion of big bus networks

(Forray & Figueroa, 2011). In many African cities, minibus taxis are the principal mode of public transit. Buses currently account for 65% of public transportation customers in South Africa and are well-known for their efficiency (van Zyl, 2009).

During the apartheid era, minibus taxis performed a significant role in transporting African workers from townships to metropolitan centers, efficiently filling gaps caused by the shortcomings of established transportation networks. Their presence on South African roads is not only ubiquitous but also emblematic of the country's transportation infrastructure. Without minibus taxis, it is challenging to envision a functional South African transportation system, given their indispensable role in meeting the diverse needs and demands of commuters (Sebola, 2014).

2.4 Social factors influence work-related public transportation travel.

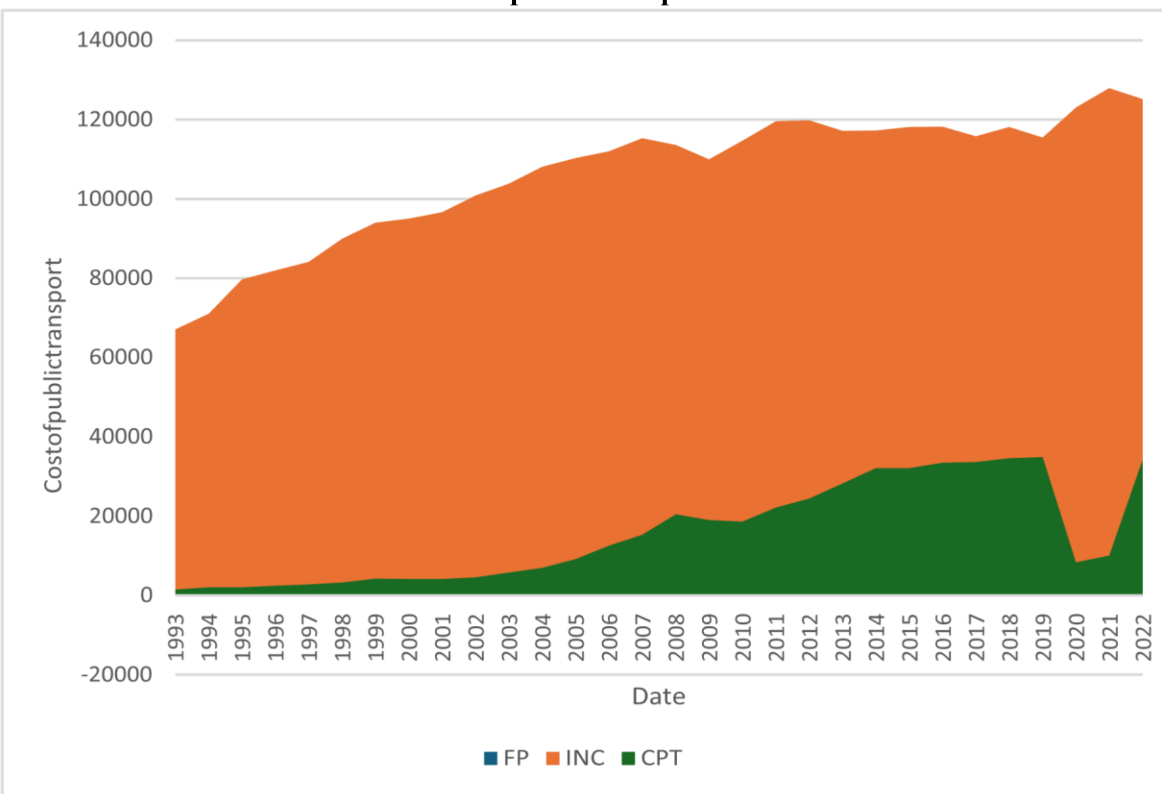


Figure 2.4 Relationship between Cost of transport, fuel price and income

Source:Own graph with data acquired from South African Reserve Bank 2022

Sociodemographic and socioeconomic characteristics have a significant impact on workrelated public transportation use. Certain demographic groups frequently have limited access to various public transportation alternatives during various times of the day (Martinez et al., 2018).

Gender disparities influence travel patterns and distances, as women often have distinct household duties. This causes families to make extra journeys for home duties like food shopping and dropping off children at different locations (Levinson, 1999; Mauch & Taylor, 1997). According to research, while men and women make the same number of journeys on weekdays, women travel around 8 kilometers less than men. However, during weekends, this disparity is reduced to only 2 kilometers (Aguilera et al., 2011). A person's socioeconomic level influences their capacity to acquire an automobile and pick their location of residence, with wealthier individuals having more possibilities. The South African population's socio-economic advancement depends on having safe, accessible, and affordable public transport infrastructure (Thomas, 2016).

2.4 Overview of Fuel prices in South Africa

Following an extensive examination in 2002, the BFP was put into effect in 2003 by the former Department of Minerals and Energy (DME). The IBLC formula was replaced by the BFP, consisting of 'spot,' and 'posted' elements - with spot prices representing current oil buying/selling prices and posted prices being fixed prices for purchase/sale over time, unaffected by market changes.

Table 2.3 Fuel Price in Africa

Country	Last	Previous	Reference	Unit
Egypt	0.24	0.37	Mar/24	USD/Liter
Nigeria	0.38	0.69	Feb/24	USD/Liter
Ghana	1.02	1.04	Mar/24	USD/Liter
Sudan	1.05	1.05	Mar/24	USD/Liter
Tanzania	1.24	1.2	Mar/24	USD/Liter
South Africa	1.29	1.21	Mar/24	USD/Liter
Kenya	1.41	1.28	Feb/24	USD/Liter
Zimbabwe	1.68	1.64	Mar/24	USD/Liter

(Source: Stats Sa, 2022).

The recent escalation in fuel prices in South Africa, particularly for diesel inland and coastal regions, reflects a complex interplay of global market dynamics. Diesel prices surged between 88 to 94 cents per liter at the coast, while petrol experienced a modest decrease of 12 cents per liter on May 4, 2022. This pricing volatility stems primarily from a notable shortage in diesel supply, attributable to reduced exports from Russia, a key global exporter of distillate fuel. Despite efforts by the National Treasury to mitigate the impact through a reduction in the general fuel levy (GFL) by over R1 per liter, the relief provided remains constrained. The intricacies of the fuel market reveal that governmental interventions, such as the reduction in the GFL, offer limited scope for substantial alleviation.

The determination of South Africa's fuel prices is influenced by two key factors: international oil prices and the exchange rate between the Rand and the US Dollar. Notably, the recent strength of the Rand against the Dollar has acted as a mitigating factor, preventing further exorbitant price increases.

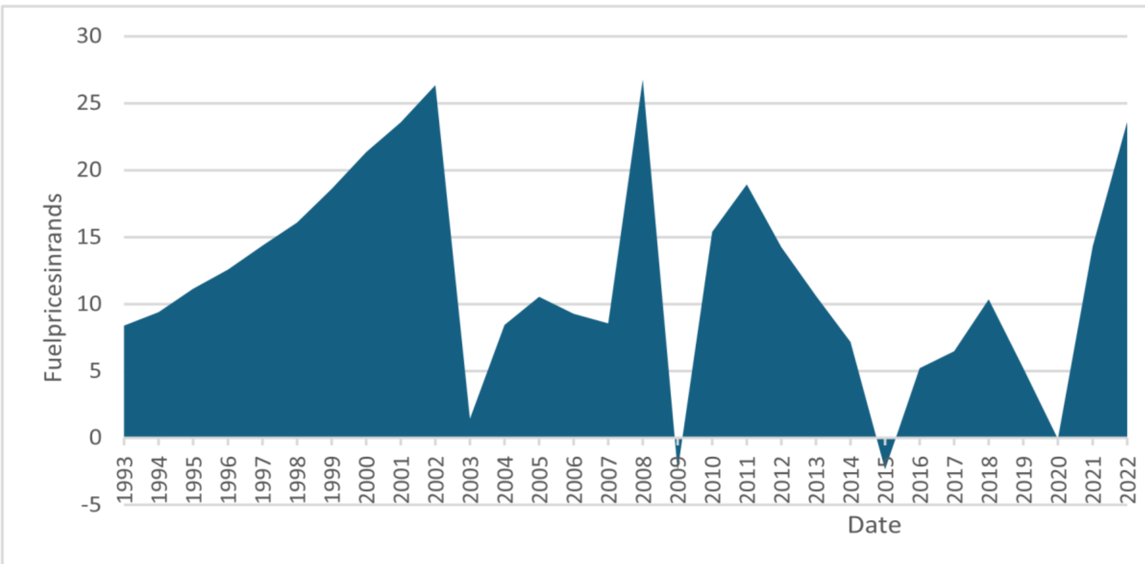


Figure 2.5: Fuel prices in South Africa

Source: Own graph with data acquired from South African Reserve Bank 2022

Since the 1950s, South African fuel prices have been decided using the import parity pricing theory, which links the local price to the cost of importing the commodity (Competition Tribunal 2006). The IBLC equation was used to determine petrol's import parity price. This method was introduced in the 1950s and was used to calculate the retail price of gasoline until

April 2003. It distinguished between two groups of elements that influenced the gasoline price. Initially, those that demonstrated the effects of global events and, subsequently, various internal factors. The calculation of the international price factor in the equation considered the current oil prices worldwide and the expenses related to shipping these goods to South Africa.Firstly, petrol prices tracked non-petrol price movements quite closely during the period 1975 to the end of the 1980s and between 2000 and 2005. Since 2005, petrol prices have increased greatly, but there has been a noticeable decrease in recent times. In Figure 2a, the breakdown of factors influencing the price of petrol in cents per liter from both domestic and international sources is shown. This shows that although both factors contributed more to the domestic fuel price, the impact of international factors, as shown by the BFP, became increasingly predominant over time. From 1990 onwards, the proportion of international factors (BFP) affecting petrol prices ranged from 35 to 40 percent, using data available from 1986. The analysis focuses on this period and utilizes the Hodrik-Prescott filter to identify trends.

By the end of 2013, global influences had influenced around 60% of fuel prices. However, when global fuel prices fell, the contribution reduced to around 50 percent by the end of 2015. Furthermore, the strong relationship between South African fuel prices and the BFP during the early 2000s emphasises the role of global variables in affecting local petrol price volatility. This relationship, discovered by a continuous computation beginning in January 1986, became notably clear when the BFP's portion of the petrol price increased significantly (Figure 2c).

International influences have two primary effects on local gasoline prices: they affect product pricing and costs, as well as contributing to exchange rate volatility. Figure 3 shows how exchange rate changes affect the Basic Fuel Price (BFP), with figures in both rand (ZAR) and dollar (USD). Since 2000, the growth in the BFP has been predominantly driven by growing global product prices and costs, as seen by parallel changes in the ZAR and USD BFPs. Notably, in the mid-to-late 2000s, the rand's strengthening greatly reduced domestic price rises.

The recent weakening of the rand has resulted in a significant increase in domestic fuel costs. Between January 2011 and January 2014, the rand lost 57% of its value, while foreign product prices in terms of the Basic Fuel Price (BFP) fell by around 18%. If the rand had held its value from January 2011, South African fuel costs would have been almost 40% cheaper in rand terms. With persistent worries about the impact of adverse global financial market circumstances on developing-market currencies, especially the rand, the exchange rate is projected to play a key influence in future petrol price changes.

2.5 Understanding the Composition of Fuel Prices in South Africa

Fuel prices are a critical economic indicator, influencing not only the cost of transportation but also impacting various sectors of the economy. In South Africa, the fuel price is a multifaceted construct, comprising four main elements that collectively determine the purchase price at the pump.

Primarily, the Basic Fuel Price (BFP) forms the foundation of the fuel price structure, encompassing approximately 42% of the total cost. The BFP is influenced by two primary factors: The Rand/US Dollar exchange rate and international petroleum prices. Fluctuations in these variables directly affect the purchase price of fuel, which is denominated in US dollars. Moreover, additional costs such as freight, insurance, storage, and financing are integrated into the BFP, reflecting the comprehensive nature of this component.

The second component encompasses wholesale and retail margins, distribution, and transport costs, collectively constituting around 22% of the total fuel price. These costs are associated with the logistical processes involved in transporting fuel from refineries to retail outlets, including storage, transportation, and customs duties. Furthermore, retail margins allocated to fuel station owners contribute to this segment, reflecting the operational expenses and profit margins within the retail sector of the fuel industry.

A massive portion of the fuel price, approximately 23%, is attributed to the General Fuel Levy (GFL). This levy is directed towards the National Treasury, providing the government with discretionary funds that can be allocated to various sectors according to national priorities. Unlike the BFP and transport-related costs, which are influenced by market dynamics, the GFL represents a deliberate fiscal policy tool through which the government can generate revenue and address socio-economic objectives.

Lastly, the Road Accident Fund (RAF) Levy constitutes approximately 13% of the fuel price. This levy is specifically designated for financing road accident claims, emphasizing the government's commitment to addressing the societal impacts of road accidents. By allocating a portion of the fuel price to the RAF Levy, the government ensures a dedicated stream of funding to support victims and mitigate the financial burden associated with road accidents.

Anticipated oil shortage due to geopolitical tensions and potential oil sanctions on Russia has led to a rise in the price of Brent Crude Oil. The graph below illustrates the relationship between Brent Crude and the South African fuel price.

2.5 The correlation between Brent Crude and the South African fuel price

Figure 2.6 Brent Crude and the South African Fuel Price

(Source: Bloomberg, FNB Wealth and Investments, 2022)

2.6 The Ripple Effects of Higher Fuel Prices on South African Consumers

In South Africa, the economic landscape is intricately tied to the price of fuel. When fuel prices surge, the repercussions are far-reaching, extending beyond the pump and seeping into various facets of everyday life. This essay delves into the knock-on effects of escalating fuel prices on South African consumers, illuminating the interconnected web of impacts that reverberate throughout the economy.

One of the most immediate and palpable effects of soaring fuel prices is felt by vehicle owners. As the cost per liter climbs, motorists find themselves shelling out more at petrol stations to keep their vehicles fueled. This surge in motor vehicle running costs creates a direct dent in the pockets of South African consumers. Commuters, already grappling with tight budgets, are forced to allocate a larger portion of their income to cover the essential expense of fuel. For many, this translates to skimping on other necessities or tightening their belts in other areas of expenditure.

Beyond individual vehicle owners, the ripple effect extends to the realm of public transportation. With higher fuel prices, operating costs soar for companies providing bus and taxi services. These enterprises, often operating on thin profit margins, are left with little choice but to pass on the burden to consumers in the form of increased fares. Consequently, commuters reliant on public transportation endure most of this additional cost, compounding the financial strain on already cash-strapped households. The domino effect is palpable, as elevated transport costs further squeeze disposable income, limiting spending power and curbing economic activity.

The impact of escalating fuel prices extends its tentacles into the realm of consumer goods, amplifying the cost of living for South African households. As transportation costs surge, the logistical framework supporting the movement of goods across the country becomes costlier to maintain. This uptick in logistical expenses inevitably trickles down to the end consumer, manifesting as inflated prices on a diverse array of consumer products. From groceries to electronics, the price tags attached to everyday essentials witness an upward trajectory, eroding the purchasing power of consumers. The consequence is a palpable strain on household budgets, as families grapple with the burden of steeper costs for goods and services.

The surge in fuel prices sets off a chain reaction that reverberates throughout the South African economy, casting a shadow of financial strain over consumers at every turn. From inflated motor vehicle running costs to elevated transport fares and soaring prices of consumer goods, the knock-on effects are unmistakable. As South African households navigate the challenging terrain of heightened living expenses, the impact of escalating fuel prices serves as a stark reminder of the intricate interplay between economic forces and everyday livelihoods.

2.7 The Impact of Crude Oil Prices on Public Transport Costs in South Africa

Crude oil prices have a significant impact on public transportation expenditures in South Africa, as several forms of transportation are essential for economic and social activity. Fluctuations in global oil prices have a considerable impact on the pricing and availability of public transportation services. This study investigates the complex link between crude oil prices and public transportation costs in South Africa (Henseler and Maisonnave, 2018).

Form the 2.7 below, it is essential to acknowledge that crude oil serves as a fundamental input in the production and operation of various modes of public transportation, including buses, taxis, trains, and to extent, even aviation. The direct correlation between crude oil prices and fuel costs is unmistakable. As oil prices surge, the expenses associated with fuel procurement and distribution escalate, compelling transport operators to adjust their pricing structures to mitigate rising operational costs.

In South Africa, where a considerable portion of the population relies on public transport for daily commuting and essential travel, any increase in fuel prices directly translates into higher fares for passengers. For instance, minibus taxis, a prevalent mode of transportation catering to millions of commuters, heavily rely on diesel fuel. As the cost of diesel rises due to escalating crude oil prices, taxi associations are compelled to raise fares to maintain profitability and cover operating expenses, including fuel, maintenance, and regulatory compliance (Sauti, 2006).

Moreover, the impact of crude oil prices extends beyond direct fuel costs to encompass various indirect expenses associated with transportation. For example, higher oil prices contribute to inflationary pressures across the economy, affecting the prices of goods and services, including vehicle maintenance, spare parts, and insurance premiums. These secondary cost escalations further strain the financial viability of public transport operators, necessitating fare adjustments to remain sustainable in a challenging operating environment.

Furthermore, the interplay between crude oil prices and macroeconomic factors, such as currency exchange rates and government policies, amplifies the complexity of public transport cost dynamics in South Africa. The depreciation of the South African rand against major currencies amidst rising oil prices exacerbates the financial burden on transport operators, as imported fuel becomes more expensive in local currency terms. Additionally, government interventions, such as fuel subsidies or taxation policies, can either alleviate or exacerbate the cost implications of fluctuating oil prices on public transport, depending on their design and implementation (Arku, Kallah-Dagadu & Klogo, 2021).

2.8 Impact of Crude Oil Prices on Public Transport Costs in South Africa from 2020 to 2024

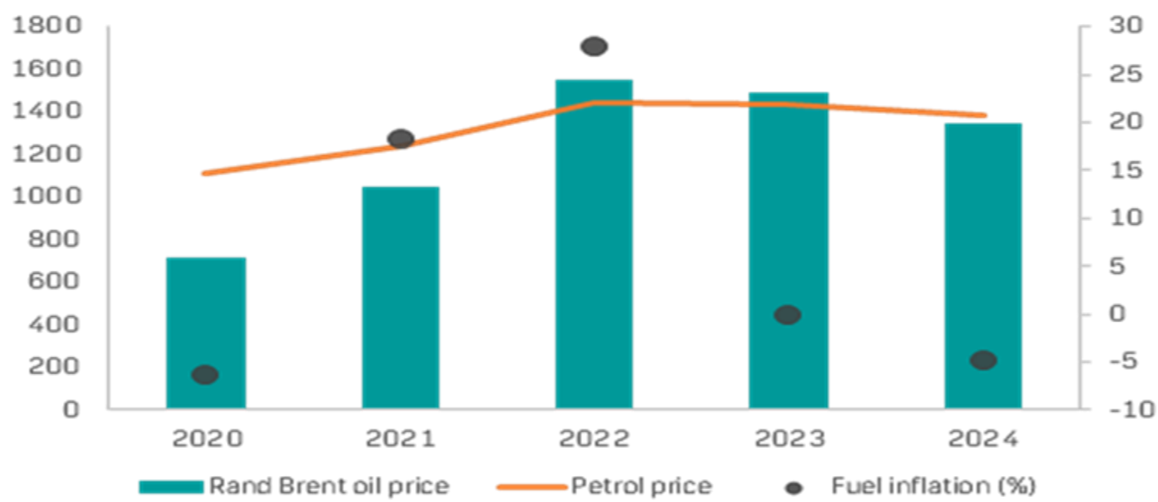


Figure 2.7 Crude Oil Prices on Public Transport Costs

(Source: FNB Economics, FNB Wealth and Investments).

2.9 Oil industry in South Africa

The oil industry is divided into two major categories: upstream and downstream activities. Upstream activities include the search for and extraction of natural gas and crude oil. Downstream refers to the processing, distribution, and advertising of consumer goods. South Africa relies entirely on imports of crude oil, primarily from the Middle East and Africa, because the country lacks its own reserves. In South Africa, the key petroleum products for sale include gasoline, diesel, aviation fuel, lamp oil, heavy oil, asphalt, and liquefied petroleum gas (LPG). Petrol and diesel are the primary liquid fuels utilized in South Africa.

The government has entire control over the retail price of fuel price, allowing for reasonable profits across the petroleum value chain, including taxes and tariffs that benefit the government. South Africa's fuel prices are established by the Basic Fuel Price, a formula that reflects the actual costs of importing a sizeable portion of the country's liquid fuel needs from abroad refining centres capable of meeting quality and supply standards. This implies that the local price is influenced by worldwide market demand and supply for oil goods, as well as the rand's exchange rate versus the dollar.

2.10 Conclusion

In conclusion, the fluctuations in fuel prices significantly affect the cost of public transport in South Africa, placing a considerable burden on households reliant on daily commuting. As fuel prices rise, so do transportation fares, disproportionately impacting low-income individuals and families who heavily rely on public transit. This exacerbates financial strain and reduces accessibility to essential services and opportunities. Addressing this issue requires comprehensive strategies that prioritize affordability, efficiency, and sustainability in public transportation, ensuring equitable access for all members of society while mitigating the economic hardships faced by households.

CHAPTER 3: LITERATURE REVIEW

3.1 Introduction

The objective of this chapter is to go over the theoretical and empirical literature for this study. This evaluation focuses on the areas listed below. Theoretical literature demonstrates how fuel costs affect the cost of public transit. The empirical literature review focuses on research from developing and developed nations, as well as South Africa. The last portion addresses the review of literature and the conclusion.

3.2 Theoretical Literature

The following theories are discussed in relation to how fuel price affects the cost of public transport:

3.2.1 Theory of Demand

Charles Davenant (1656-1714) first suggested the well-known demand theory in his book Probable Methods of Making People Gainers in the Balance of Trade (1699). In 1890, economist Alfred Marshall introduced a pictorial illustration of the Law of Demand. Marshall's book Principles of Economics (1890) combined demand and supply into one analytical framework. According to Webster and Bly (1981), the law of demand asserts that when the price of a product or service rises, the amount demanded decreases, and when the price falls, the amount demanded rises. If fuel costs rise, so do operational expenditures for public transit providers. To sustain profitability, or at least cover expenditures, operators may need to raise rates. As a result, travellers may choose alternate forms of transportation or restrict their use of public transit altogether. The principle of demand does not necessarily apply in every scenario. There are several exceptions to traditional economic behavior, such as war, economic downturn, the demonstration effect, the Giffen paradox, speculation, the ignorance effect, and survival necessities. For example, in the event of a probable conflict, individuals will acquire and store necessary products despite of price rises. This behavior deviates from the conventional demand rule, as demand for these commodities stays strong even as prices rise owing to the urgency caused by the war.

Demand theory is a fundamental concept in economics that explains the relationship between the price of a good or service and the quantity demanded by consumers. However, like any theory, it has its own set of limitations. There are some key limitations of the theory of demand that was promoted by Lancaster (1957): Assumption of Ceteris Paribus, which often relies on the ceteris paribus assumption, which means that all other factors remain constant. It is challenging to isolate the effect of price changes on demand when numerous other factors, such as income, tastes and preferences, prices of related goods, and consumer expectations, are constantly changing. Ignoring Interdependencies: The theory of demand assumes that goods and services are independent. However, in the real world, many products are complements or substitutes for each other, and changes in the demand for one product can affect that for another. This interdependency is often overlooked in basic demand theory. Incomplete Information: Consumers do not always have perfect information about the prices, quality, or availability of goods and services (Smith, 2018).

Therefore, their demand decisions may not always align with the theoretical predictions. Additionally, asymmetrical information between buyers and sellers can lead to market inefficiencies and demand distortions. Long-Term Effects: The theory of demand focuses primarily on short-term changes in demand due to price fluctuations. However, in the long term, consumers may adjust their preferences, habits, and income levels, leading to shifts in demand that the theory does not fully account for. The theory of demand assumes that consumers are rational decisionmakers who always seek to maximise their utility given their budget constraints. However, human behaviour is often influenced by psychological factors, emotions, and social pressures, leading to decisions that may not align with rational economic models (Allain, 2009).

Furthermore, Lancaster indicated the last limitation of Aggregate Demand versus Individual Demand. While the theory of demand provides insights into individual consumer behaviour, aggregating individual demand to derive market demand curves assumes that all consumers are identical, which may not be the case. Heterogeneity among consumers can lead to variations in demand patterns that are not captured by aggregate demand models. The theory of demand is static in nature and does not account for dynamic market conditions, such as technological advancements, changes in regulations, or unexpected events, such as natural disasters or pandemics, which can significantly impact demand patterns (Louviere, Hensher, & Swait, 2000).

Tijjani, Saad, and Bernard (2022) assert that in the demand theory, the demand for products is influenced by variables, including price, income, taste, population, and the cost of comparable items. All other things being equal, when any of these changes, the need for these items varies. The literature examines how much the transportation sector requires, which might rely on the price of petrol, and how much money those who need transport have. This concept best explains the problems associated with fuel pricing. It has also been said that demand aims to satisfy the requirements of the client or business. Therefore, demand and utility cannot be separated economically.

Tijjani et al. (2022) further stated that the most significant factor influencing how much people desire something is its utility. Therefore, businesses that want to make the most money will attempt to boost output by employing more input, while customers will strive to get the most out of the products they purchase. These items may be constrained by finance, costs, and other factors. As a result, the demand function for a good demonstrates the relationship between the amount of good that people desire and the variables that influence it. In other words, a person's desire for a thing is primarily influenced by price and financial situation. This applies to this study because the demand for public transport might change owing to the cost of public transport.

3.2.2 The Cross Price Elasticity of Demand Theory

A concept of cross-price elasticity of demand originated in economics. It quantifies how the quantity required for one commodity reacts to a change in the price of another (Regmi & Seale, 2010). The idea has been modified and built on by numerous economists over time, but Alfred Marshall, a major economist in the late nineteenth and early twentieth century, was a significant contributor to its development. Marshall's work provided much of the groundwork for current microeconomics, particularly the idea of elasticity. He released his main work, "Principles of Economics," in 1890. However, this idea has its drawbacks. The cross-price elasticity of demand examines how the amount sought for one commodity varies in response to a change in the price of another. While it is a useful notion when analysing market dynamics, it does have certain drawbacks. Cross-price elasticity posits a linear connection between two products. However, demand connections can be nonlinear, especially when comparing complimentary or replacement items. For example, the link between fuel costs and vehicle demand may not be precisely linear. Cross-price elasticity might fluctuate over time. In the near term, customers may have few options for switching between items; nevertheless, eventually, they may discover replacements or alternatives. Thus, short-term elasticity may not correctly reflect long-term elasticity. Brown et al (2023) indicated limitation of cross-price-elasticity demand as Complexity of Markets. In realworld markets, goods often have multiple substitutes and complements, making it challenging to measure the cross-price elasticity for each relationship precisely. Moreover, the presence of complementary goods can complicate the interpretation of the cross-price elasticity. For instance, if the price of fuel decreases, it may increase the demand for public transport, which is a complement; however, this relationship might not be captured effectively by cross-price elasticity alone. Assumption of rational behaviour: Cross-price elasticity assumes that consumers make rational decisions based solely on prices and utility maximisation. Consumer behaviour is influenced by various psychological, social, and cultural factors that may not be captured by economic models alone.

Studies have been done that estimated the long-run relationship of public transportation (Mattson, 2008; Chi, 2022). There are also studies that have estimated the cross-price elasticity between different modes of transportation (Currie & Phung, 2007; Lane, 2010). Most studies that have been done have examined cross-price elasticity in the short run. The consensus is that the cross-price elasticity between fuel price and public transportation is inelastic, with a cross-price elasticity of around 0.2 in the USA for the short run (Mattson, 2008; Lane, 2010; Chi, 2022; Currie & Phung, 2007).

Bergman (2023) found a difference in cross-price elasticity in the short and long run. He argues that this is because consumers need time to adjust to price changes. Taylor and Flink (2003) also reached a similar conclusion and attributed this long- and short-run difference to adjustment time. If fuel prices, for example, decrease, a consumer might maximise its utility by switching to car usage. If this is the case, then a car must be acquired which can take time because it is expensive, and a consumer may have to save up capital to adjust the mode of transportation. The same can be said if fuel prices increase, some consumers may not have access to any form of public transportation and may therefore cope in the short run by using bicycles instead of cars. However, consumers might maximise their utility by moving to an area with access to public transportation eventually. Therefore, consumers will eventually be incentivised to move to places with better public transportation. This enormous difference in short- and long-run cross-price elasticity was also found by Chi (2019) in Chicago, where the long-run cross-price elasticity was around 0.2, and the short-run elasticity was around 0.09 in a linear autoregressive distributed lag model.

Other findings do not regard different modes of transportation or long- and short-run elasticities, which are beneficial for understanding cross-price elasticity in general. The cross-price elasticity between public transportation in Chicago is non-linear, both in the short and long run (Chi, 2022; Savage & Nowak, 2013). This means that elasticity may increase at higher fuel price levels and decrease at lower levels. Another reason for this is that consumers start to care more about their transportation mode when a larger share of their disposable income goes towards it (Cowie & Ison, 2020).

There also seems to be a substantial difference in the cross-price elasticity for various levels of urbanised areas. The elasticity was the highest in small, urbanised cities and was lower in rural areas and highly urbanised cities (Belloc, Giménez-Nadal, & Molina, 2022). In rural areas, the supply of public transportation is quite scarce; therefore, it is not a viable substitute. Other modes such as carpooling are more widely used. However, in highly urbanised areas, there are already many citizens who use these services, so the change is small, possibly because other types of modes may be more relevant there, such as walking or biking. Therefore, caution should be exercised when applying the results of studies outside the area of interest.

Substitution Effect: When the price of one good rises, consumers may substitute it with a cheaper alternative, if all else remains constant. In the context of public transport, if the cost of using buses or trains increases owing to higher fuel prices, some consumers may switch to other modes of transportation, such as private cars, cycling, or walking, if feasible. Alternatively, they may choose to carpool or utilise ride-sharing services (CSIR. 2014). Income Effect: Changes in the price of goods or services can also impact consumers' purchasing power and overall spending patterns. If public transport fares increase due to rising fuel prices, households may have less disposable income available for other goods and services, potentially leading to adjustments in spending habits or lifestyle choices.

3.2.3 Planned behaviour theory

Icek Ajzen (1985) proposed the Theory of Planned Behaviour (TPB) in his chapter "From intentions to actions: A theory of planned behavior." The TPB was developed from the Theory of Reason Action (TRA), which was first proposed in 1980 by Martin Fishbein and Ajzen. According to the theory, intentions influence actions, which are determined by three critical factors: attitudes, subjective norms, and perceived behavioral control (Sansom, 2023).

Attitudes refer to an individual's evaluation of a behaviour influenced by beliefs about its outcomes. In the context of public transport costs, attitudes toward using public transport may be shaped by perceptions of convenience, affordability, and environmental impact. When fuel prices rise, individuals may perceive public transport as a more cost-effective and sustainable alternative to driving, leading to more positive attitudes toward its use. Conversely, if the public transport fare increases in response to higher fuel prices, attitudes may become more negative as individuals perceive it as less affordable (Creamer & Media, 2022).

Subjective norms capture the influence of social pressures and norms on behaviour. In the case of public transport costs, subjective norms may arise from societal attitudes toward environmental conservation, traffic congestion, and economic efficiency. If societal norms prioritise the use of public transport to alleviate traffic congestion and reduce carbon emissions, individuals may feel compelled to use it, regardless of fluctuations in fuel prices. However, if the cost of public transport increases disproportionately in response to fuel price increases, subjective norms may weaken, leading to greater resistance to its use in cities (Belloc et al., 2022).

Furthermore, perceived behavioural control reflects an individual's belief in their ability to perform a behaviour, considering internal and external factors. In the context of public transport costs, perceived behavioural control may be influenced by factors such as accessibility, reliability, and affordability. Higher fuel prices may lead individuals to perceive public transport as a more viable option if they believe it offers greater control over transportation costs than driving. However, if public transport fares escalate beyond what individuals perceive as manageable, their perceived behavioural control may diminish, leading them to seek alternative modes of transportation or modify their travel behaviour. Bosnjak et al (2020). The interaction between attitudes, subjective norms, and perceived behavioural control shapes individuals' intentions regarding the use of public transport in response to fuel price fluctuations. Positive attitudes toward public transport, reinforced by supportive subjective norms and perceived behavioural control, may lead individuals to choose public transport, even when fuel prices are high, provided that the cost remains reasonable and competitive. Conversely, negative attitudes, weakened subjective norms, and a perceived lack of control over rising public transport costs may drive individuals back to private vehicle use despite higher fuel prices, undermining efforts to promote sustainable transportation alternatives.

Bosnjak et al (2020) indicated strengths, weakness, and limitations of planned behaviour theory. The theory includes a broader range of contributing components than other motivation theories, such as the locus of control theory, which considers only one of the three factors addressed in the theory of planned behaviour. However, this theory may not always be accurate for predicting conduct. This is especially true when unexpected occurrences or elements arise in a situation that does not fall within the theory's three categories. Furthermore, the theory is supported by a substantial amount of empirical research demonstrating its usefulness, applicability, and capacity to withstand thorough examinations. However, the theory fails to include subconscious elements that may influence decision making. They tend to concentrate on conscious decisionmaking processes. This focus on the aware mind might not accurately depict the intricacies of human behavior. It assumes that an individual has the necessary means and chances to successfully perform the intended action, regardless of their initial plans. Other factors like fear, danger, mood, and experience are not factored into account when it comes to influencing behavioral intention and motivation. The TPB has proven to be more useful in public health than the Health Belief Model, but it still has constraints in not considering environmental and economic factors. In recent years, researchers have incorporated elements of TPB and incorporated additional components from behavioral theory to create a more comprehensive model. This is a reaction to certain shortcomings of TPB when it comes to tackling public health issues Bosnjak et al (2020).

The idea of planned conduct is a widespread behavioural paradigm that helps us to understand how people's behaviour might change. This concept assumes that conduct is a product of purposeful planning (attitudes). For example, increased fuel prices may result in more favourable opinions about public transportation owing to their cost-effectiveness. Furthermore, according to this paradigm, behavioural beliefs have either positive or negative consequences for a specific behaviour, normative beliefs generate perceived social pressure or subjective norms, and control beliefs trigger the perception of behavioural control. The more robust an individual's positive attitude, subjective norm, and perceived control, the more likely they are to engage in the desired behaviour (Arafat & Ibrahim, 2018). The idea of planned behaviour is particularly pertinent to public transportation because it believes that individuals analyse the costs and advantages of numerous transportation alternatives when determining travel.

Planned behaviour theory offers a valuable framework for understanding how fuel price fluactuations influence public transport costs and usage patterns. Policymakers and transportation authorities can design interventions to mitigate the impact of fuel price fluctuations on public transport affordability and promote sustainable mobility choices by considering attitudes, subjective norms, and perceived behavioural control. Strategies such as fare subsidies, service enhancements, and public awareness campaigns can help align individual intentions with societal goals, fostering a more resilient and equitable transportation system in the face of evolving fuelprice trends.

3.3 Empirical reviews

This section analyses empirical studies conducted in developing and developed countries, as well as South Africa. This is explained below.

3.3.1 Developing countries.

Nkuah and Berko (2015) examined how rising fuel prices affected the public transport industry in Ghana’s WA Municipality. This investigation used both quantitative and qualitative approaches. Of the 80 questionnaires sent, 76 were returned. SPSS and Microsoft Excel were used to assist in the data analysis. The findings show that rising fuel prices increase the cost of public transportation, thereby negatively affecting the public. However, these findings contradict those of Ajayi (2019), who revealed that when fuel prices rise, people choose to utilise public transportation instead of driving their vehicles because it is less costly.

Ajayi (2019) investigated the impact of fuel price increases on the choice between public and private transportation in Osun State, Nigeria. A total of 120 passengers were randomly chosen from two local government areas in Osun State, using an incidental random sample. The results showed that even though a fuel shortage leads to a shortage of public transport and higher fares, which discourages travellers from travelling, people prefer to utilise public transport when fuel prices increase because they are thought to be less expensive than using private vehicles. These findings are supported by Zhang and Burke (2020), who suggested that when petrol prices are higher, individuals are more willing to use public transportation.

Fuje (2020) examined the effects of fuel subsidy reforms on the cost of public transport in Ethiopia from 1996 to 2013. Ethiopia decided to eliminate its subsidy in October 2008, resulting in a 39% increase in diesel prices. This price increase led to a notable upsurge in public transportation costs, which negatively affected those who used public transport. Similarly, Mayburov and Leontyeva (2017) concluded that frequent fuel price hikes have negative effects on people; hence, the increase in fuel prices gradually persuades the urban population to avoid using public transport.

Gebremeskel, Woldeamanuel, and Woldetensae (2023), assessed the trip costs of transportation passengers, which they labeled as travel "budgets," considering both time and money spent. This study involved surveying 457 individuals who use public transportation in Ethiopia. The research employed proportions, percentages, and cross-tabulation of important characteristics, along with statistical methods like one-way analysis of variance (ANOVA), to evaluate the susceptibility of transit passengers. The findings indicate that individuals with lower and middle incomes experience more challenges with travel compared to those with higher incomes, in terms of both total travel time and the amount of money spent on transportation. 88% of low-income households allocate over 20% of their income to transportation costs. Nonetheless, for individuals with higher earnings, it represents less than 15% of their family income, showing reduced financial challenges.

3.3.2 Developed countries

Mayburov and Leontyeva's (2017) study emphasized the importance of public transportation fares. This illustrates the importance of a holistic strategy for constructing modern public transportation systems. According to the report, the key objective of the plan should be to reduce the number of private automobiles in urban areas while increasing public transit usage. It has been established that the cost per trip is an important consideration for transportation service users when deciding whether to travel by car or public transit. It has been established that the cost of public transportation in Russia has risen faster than the overall increase in the price of all goods and services, including automobiles, gasoline, and lubricants. The cost increase resulted in a 3.6fold decline in the demand for public transportation services throughout the 15 years studied. During the same period, the number of privately owned vehicles increased by 120%. The result is that repeated price increases have progressively influenced the urban population to avoid public transportation. This increased demand for cars subsequently drove the expansion of car usage. Higher public transportation costs have resulted in a decreased demand for public transportation services. In contrast, Ajayi (2019) revealed that people prefer to use public transport when fuel prices increase because they are thought to be less expensive than using private vehicles.

Travel behaviours are affected by public transport costs; therefore, to add to the empirical literature, Aljoufie (2019) investigated the impact of rising fuel prices on changes in travel behaviour in Jeddah, the second-largest city in Saudi Arabia. A household survey was conducted to collect information on the travel habits of the Jeddah City population before and after the fuel price increased. The results indicate an increase in fuel prices has significantly influenced travel habits in Jeddah due to the higher transportation expenses. Travel behaviors are impacted when the cost of public transportation goes up due to an increase in fuel prices. Rohani and Pahazri (2018) also support this idea, stating that changes in fuel prices caused a shift in the travel behaviors of transportation users.

Bergman (2023) examined how gasoline costs impact public transportation in a research study on Chicago. He used an ARDL model to analyse the long-term coefficients of gasoline prices in relation to the use of trains and buses, along with the short-term coefficients. This model displays no cointegration between the two modes. The cross-price elasticity was higher in the short term for buses, but more significant initially for rail usage. During this period, the cross-price elasticity was lower than in previous studies, indicating a decrease. The causes of this remain unknown, but it is possible that the shifts are due to the presence of new alternatives or the drop in gasoline prices in recent times according to theory. Therefore, this thesis recommends further investigation into the impact of rail usage on bus usage in urban areas, as well as how one mode of public transportation may affect the usage of another.

Recent studies from developed countries offer critical insights into the link between fuel prices and public transport costs, highlighting how rising energy prices shape transport affordability and accessibility. For example, in Germany, the introduction of a highly subsidized €9 public transport ticket in 2022 aimed to offset the pressure of rising fuel prices and reduce car dependency. This initiative led to a significant increase in public transport ridership and a measurable decline in car usage (Wolff et al., 2023). However, the effect was temporary, with researchers concluding that while fare reductions can provide short-term relief, long-term behavioral change requires sustained investment in infrastructure and service quality (Wolff et al., 2023). This illustrates how fuel price volatility can prompt immediate government responses but also underscores the need for durable strategies in public transport policy.

In the United Kingdom, policy responses have taken a different direction. The government extended a 5p fuel duty cut intended to ease fuel price pressures, but critics argue the measure disproportionately benefits wealthier individuals who drive more frequently. The Institute for Fiscal Studies (2024) found that the policy is regressive and fails to address structural challenges in public transport affordability and access. Similarly, in Australia, the Australian Automobile Association (2024) reported that transport costs rose by 10.5% in a single year, outpacing inflation, with fuel and insurance being primary drivers. These studies reflect the broader international consensus that while fuel subsidies and fare relief programs can cushion short-term impacts, sustainable affordability in public transport requires integrated approaches that address pricing, infrastructure, and long-term resilience. Lessons from these countries provide a valuable comparative lens for understanding and improving transport cost dynamics in South Africa.

3.3.3 South African studies

Understanding the drivers of public transport costs is essential for designing effective and inclusive transport policies in South Africa. Although few studies in South Africa have explored public transport expenses, they have not focused exclusively on the impact of fuel prices. For instance, Rangasamy (2017), Ncanywa and Mgwangqa (2018), Leshoro and Maluleke (2020), and

Ntshingila (2022) considered a range of factors influencing transport costs, such as operational efficiency, infrastructure, and fare regulation. However, to the best of our knowledge, no study has specifically examined the direct relationship between fuel prices and public transport expenses in South Africa. Addressing this gap will not only enrich academic discourse but also provide valuable insights for policymakers seeking to mitigate the impact of fuel price volatility on transport affordability.

3.4 Assessment of Literature Review

The relationship between fuel prices and public transport costs is complex, influenced by various economic and behavioral theories. The theory of demand explains how price changes affect demand, though it assumes all other factors remain constant, limiting its applicability. Crossprice elasticity of demand highlights the interdependence of goods but struggles with accurately capturing demand shifts. The theory of planned behavior emphasizes how attitudes, norms, and perceived control shape transport choices. Empirical studies show mixed results: fuel price fluctuations sometimes raise costs and lower usage, while in other cases, public transport remains popular due to cost-effectiveness. Research in South Africa is limited, necessitating further study to understand local impacts. A multidisciplinary approach is essential to address the interplay between economic, social, and psychological factors in transport economics.

Furthermore, in assessing the existing literature on public transport costs, it is evident that previous studies have made notable methodological contributions, particularly through the application of time series econometric techniques. Several studies have employed methods such as Vector Autoregression (VAR), Cointegration analysis, and more recently, the Autoregressive Distributed Lag (ARDL) model to investigate relationships among macroeconomic variables (Pesaran et al., 2001; Baghery & Zare, 2020). The ARDL approach has gained prominence due to its flexibility in handling variables with mixed orders of integration (I(0) and I(1)) and its ability to simultaneously estimate both short-run and long-run dynamics (Pesaran & Shin, 1999). This methodological advancement has enhanced the robustness of empirical findings, especially in transport and energy economics (Alam & Uddin, 2017). However, despite these gains, there remains limited application of the ARDL model in the context of analyzing fuel price effects on public transport costs in South Africa. This study seeks to contribute to the literature by applying the ARDL framework to fill this methodological and empirical gap.

3.5 Conclusion

In conclusion, a comprehensive review of the theoretical and empirical literature sheds light on the intricate relationship between fuel prices and public transport costs. The theoretical framework, comprising the theory of demand, the cross-price elasticity of demand theory, and the theory of planned behaviour, provides valuable insights into the economic, social, and psychological factors influencing consumer behaviour and decision-making processes in response to fuel price fluctuations. Empirical studies from various countries, including developing nations such as Ghana, Nigeria, and Ethiopia as well as developed countries such as Russia and the United States, offer diverse perspectives on the impact of fuel price dynamics on public transportation costs and usage patterns. While some studies suggest a direct correlation between rising fuel prices and increased public transport costs, others highlight the complexities of consumer behaviour, indicating a mixed impact on mode choice and travel behaviour. Furthermore, the scarcity of research addressing the relationship between fuel prices and public transportation costs in South Africa underscores the need for further investigation in this area. By bridging this knowledge gap, policymakers and transportation authorities can develop targeted interventions to mitigate the impact of fuel price fluctuations, promote sustainable mobility solutions, and ensure equitable access to transportation services. The blend of theoretical insights and empirical findings underscores the multifaceted nature of the relationship between fuel prices and public transport costs, emphasising the importance of considering diverse perspectives and interdisciplinary approaches in addressing the challenges and opportunities posed by fuel price dynamics in the public transport sector.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 Introduction

This section outlines the methods that have been followed in the study. It is broken into many sections. The research approach is presented first, followed by the study design in the second section. The third part, model specification, describes the model used in this investigation. This is followed by the fourth component, which defines variables and a priori expectations. Sections 5 and 6 provide data sources and estimate procedures, and conclusion.

4.2 Research Approach

This study's empirical research is conducted using quantitative techniques. Quantitative research examines occurrences using numerical data, which is then evaluated using mathematical procedures, usually statistics. More broadly, it refers to an empirical study in which variables are predicted and examined numerically and statistically (Ndlovu, 2021). The justification for using this method is that researchers collect data in real time, allowing for fast statistical analysis. Furthermore, quantitative research emphasizes objective facts and statistics, reducing prejudice and saving time (Miller, 2020).

4.3 Research design

Quantitative research designs are classified into four categories: descriptive, correlational, causal-comparative/quasi-experimental, and experimental. This study used a causalcomparative/quasi-experimental design to investigate how explanatory factors influence a dependent variable. The study seeks to investigate the cause-and-effect link between gasoline prices and public transportation expenses.

4.4 Model Specification

The study is grounded in the theory of demand, which effectively explains the impact of fuel prices on the transportation sector. As the literature highlights, fuel price fluctuations influence both the costs faced by public transport operators and the affordability for consumers. When fuel prices rise, transportation providers often pass these increased costs onto passengers through higher ticket prices. This affects demand, as individuals may adjust their use of public transport based on their ability to afford the higher fares, leading to a direct link between fuel prices, transport costs, and consumer demand. The model is adopted and modified from the work of Rangasamy(2017).

The model is specified as follows:

$$Infl_t = \beta_0 + \beta_1 Gap_t + \beta_2 Petrol_t + \varepsilon_t \text{ ………………} \mathbf{4.1}$$

where *Infl* - headline inflation, β_0 - constant, *Gap* -output gap, *Petrol* - petrol inflation, ε - white noise error term.

This current study modified the model and is written as function form:

$$CPT = f\ (FP, GDP, INC, INF) \text{ ……………………………} \mathbf{4.2}$$

The equation is presented in regression format as**:**

$$CPTt = \beta 0 + \beta 1\ FPt + \beta 2\ GDPt + \beta 3\ INCt + \beta 4 INFt + \varepsilon t \ldots\ldots\ldots\ldots\ldots \mathbf{4.3}$$

Where CPT is cost of public transport, FP is fuel price, GDP is gross domestic product, INC is income, INF is inflation, ε is the error term, β_0 is constant and β_1 to β_4 are coefficients of explanatory variables.

4.5 Definition of variables and priori expectations

The cost of public transportation (**CPT**) is what consumers pay for transportation; in other words, it is the expense absorbed by a person who uses public transportation (Adeniran, 2016). The Cost of Public Transport variable in this study is not a formal composite index of all public transport modes. Instead, it was constructed using annual average fare data primarily from minibus taxis, which are the dominant mode of public transport in South Africa, serving over 80% of commuters (Department of Transport, 2022). Additional data from buses and commuter rail were reviewed to ensure the trend reflects general transport cost movements. However, due to data limitations and the dominant use of taxis, minibus taxi fare trends were used as a proxy to represent national public transport costs. This method provides a realistic and policy-relevant approximation of CPT over time.The cost of public transportation is the dependent variable.

Fuel Prices (**FP**): Fuel price is the monetary value assigned to any sort of fuel, and a fuel is defined as a substance that reacts exothermically with oxygen. When the fuel burns, the energy contained inside it is released. Fuel is one of the most important materials on our planet. Without fuels, the globe would seem radically different (BBC, 2023). Fuel prices are projected to be positively correlated with the cost of public transportation.

Gross domestic product (**GDP**) is the monetary worth of a country's final products and services over a given period (such as a quarter or a year). It refers to all production that occurs within a country's borders. GDP is composed of commodities and services produced for market sale as well as nonmarket output, such as government-provided defense or educational services (Callen, 2023). The two variables are expected to have a negative relationship.

Income (**INC**) is the money received by a person or company in exchange for labour, the production of an item or service, or the use of capital. Individuals are often paid a wage, whereas companies earn by selling goods or services at a profit greater than their manufacturing costs (Indeed, 2023). Income and transportation costs are projected to be negatively correlated.

Inflation (**INF**) is a steady increase in the general price of goods and services. It is estimated using the consumer price index, which represents the periodic percentage change in the average cost a customer would pay for a basket of products and services that may fluctuate at predefined intervals (Nsiah, Yusuf, Tweneboah, Agyei and Baidoo, 2021). Inflation is projected to be positively correlated with the cost of public transportation.

4.6 Data Sources

The study collected data from the South African Reserve Bank (SARB) and Quantec's official websites. The information is provided annually and includes the years from 1994 to 2022. The investigation timeframe was deliberately selected to cover events in South Africa both before and after gaining independence, enabling a broad range of comparative analysis and a more precise evaluation of lasting relationships. The computation was carried out using E-Views 11 software.

Cautionary Note:

It is important to note that the number of observations used in this study is below the conventional threshold of 30.

4.7 Estimation Technique

To estimate the connection between variables, ARDL approach were applied. To make sure the series is stationary and reliable regression findings is produced, this research first performed the unit root test. This test was performed as time series data is typically non-stationary, as with other economic estimations (Lesho & Maluleke, 2020). The ARDL technique, which eliminates the pre-testing issues related to traditional cointegration and does not need the classification of variables as I (1) or I (0), was used in this study. The ARDL is used when variables have mixed order of integration. Furthermore, unlike VAR models, ARDL is more reliable for identifying cointegrating connections in small samples (Pahlavani, Wilson & Worthington, 2005). It should be noted that other empirical studies that are demand oriented (Sheefeni, 2013; Ndaguba & Hlotywa, 2021) also used the ARDL technique; hence, it becomes appropriate to use it in the case of this study. Lastly, the study conducted diagnostics tests, namely normality tests, serial correlation tests and heteroskedasticity tests, to verify the reliability of the ARDL model.

4.7.1 Stationarity/Unit root testing

Like prior time series studies, this investigation starts with an evaluation of unit roots. Since many variables in their level form are non-stationary, forecasting without understanding their stationarity can lead to inaccurate outcomes (Godza, 2013). Both formal and informal methods are utilized to test for stationarity and unit roots. Informal testing includes the use of correlograms, which visually represent the data, while formal unit root testing involves the Augmented DickeyFuller (ADF) and Phillips-Perron (PP) tests.

4.7.2 Informal Unit roots

Examining the time series by looking at shifts in the average, spread, self-correlation, and seasonal patterns can help with simple informal checks for stationarity. Their study solely depends on randomly inspecting graphs and correlograms. Nonetheless, they do offer hints on the existence of stationarity (Mtolo, 2015). Additionally, autocorrelation should be used to analyse the system's informal techniques. This is achievable by using visual tools that allow for comparing the data with other factors. Brooks (2008) mentioned that utilizing visual aids when analysing structural variables assists in pinpointing structural weaknesses.

4.7.3 Formal Unit roots

Formal statistical tests are used to assess stationarity. Formal tests differ in their rigidity of criteria and the hypotheses they use. Economists rely on formal statistical tests to ensure their accuracy (Mtolo, 2015). To examine the variables' time series characteristics, both the PhillipsPerron and the Augmented Dickey-Fuller tests were used. As a result, this research will use these two sophisticated approaches to identify the variable integration order.

4.7.3.1 Augmented Dickey Fuller (ADF)

Dickey-Fuller test determines if a time series has a unit root, which indicates that the series is non-stationary under the null hypothesis. This test needs a special approach to be effective. In contrast, the Augmented Dickey-Fuller (ADF) test presumes that the error component is correlated rather than uncorrelated (Mtolo, 2015). The primary purpose of the ADF test is to determine if an autoregressive model has a unit root, which might lead to statistical discrepancies. The ADF test is distinguished by the following characteristics:

$$\Delta Yt = \beta_1 + \beta_{2t} + \delta Yt_{-1} + \mu t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; 4.4$$

- **ΔY_t**: The first difference of the variable Y at time t, calculated as $Y_t - Y_{t-1}$. This helps in transforming a non-stationary series into a stationary one.

- **β_1**: The intercept or constant term in the regression.

- **$\beta_2 t$**: A deterministic time trend, where t represents time and β_2 is its coefficient. This is included if the data show a linear trend over time.

- δY_{t-1}: The lag of the level of Y multiplied by a coefficient δ. The coefficient δ is key in testing whether there is a unit root.

- μ_t: The error term or residual, capturing random shocks or unexplained variation in the model.

The Augmented Dickey-Fuller (ADF) test, like the Dickey-Fuller test, determines the presence of a unit root in time-series data. According to Gujarati and Porter (2009), this test has applications in quantitative analysis, econometrics, data mining, and a variety of numerical methodologies. The ADF test is distinguished by its capacity to handle more complicated time series patterns over longer durations. In this case, the null hypothesis of the ADF test is represented by a zero coefficient, a negative integer that indicates the presence of a unit root. A positive ADF test result indicates that the null hypothesis of a unit root may be rejected (Gujarati & Porter, 2009).

4.7.3.2 Phillips-Perron test (PP)

The Phillips-Perron (PP) tests are remarkably like the Augmented Dickey-Fuller (ADF) tests and can produce equivalent findings on some instances. The primary variation between the two is that the PP test automatically accounts for autocorrelated residuals (Gujarati and Porter, 2009). Mathematician Peter C. B. Phillips devised the PP test in 1988. The summary is formatted as follows:

$$\Delta Y_{t-1} = \alpha_0 + \Upsilon y_{t-1} + \mu_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; 4.5$$

- ΔY_{t-1}: The first difference of the variable Y at time t−1, i.e., $Y_{t-1}-Y_{t-2}$. This helps test for stationarity by removing trends or seasonality.
- α_0: The intercept or constant term, capturing the mean level of the differenced series.
- ΥY_{t-1}: The lagged level of the original series Y at time t−1, multiplied by the coefficient ϒ. This is the key term for testing unit roots. If ϒ=0, the series has a unit root and is nonstationary
- μ_t: The error term or white noise, accounting for random shocks or residual variations in the model.

4.7.4 Autoregressive Distributed Lag (ARDL)

Pesaran et al. (2001) introduced the Autoregressive Distributed Lag (ARDL) co-integration approach. Unlike previous methodologies, the ARDL cointegration method does not need unit root pre-testing. The ARDL cointegration approach is particularly advantageous when working with small sample sizes, as it does not require the variables to be of the same order of integration. It can accommodate a mix of I(0) and I(1) variables, making it ideal for datasets where variables exhibit different integration properties (Pesaran et al., 2001). Unlike other cointegration techniques that require all variables to be integrated of the same order, ARDL is robust and efficient in small samples, providing reliable estimates even when the sample size is limited. Moreover, it simultaneously estimates short-run and long-run relationships, making it a versatile method for studying dynamic interactions, such as those between fuel prices and public transport costs, while preserving the integrity of the model in small datasets.

The F-statistic is used to assess the overall relationship of the regression model (Wald test). Using this approach, the F-statistic surpasses the threshold value range, suggesting a long-term correlation in the series. The key advantage of this method is its capacity to discover cointegrating vectors even when several cointegrations exist (Nkoro & Uko, 2016).

The Johansen cointegration test cannot be employed when the variables have varying levels of correlation or if all variables are not stationary, because it requires all variables to be of order I. (1). For time series data with a non-stationary and mixed order of integration, an autoregressive distributed lag (ARDL) model based on ordinary least squares (OLS) can be utilized (Shrestha & Bhatta, 2018). This model has enough delays to accurately describe the process of creating data in a specific-to-general modeling technique. ARDL has the potential to become a dynamic error correcting model by incorporating a simple linear transformation known as ECM. The ECM corrects inaccurate connections in non-stationary time series data by combining short-term changes with long-term balance, while keeping the long-term data unchanged (Shrestha & Bhatta, 2018).
The basic model described below can be used to teach the ARDL approach:

$$Yt = \alpha + \beta xt + \sigma zt + \varepsilon t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.6$$

- $\mathbf{Y}_t$: The dependent variable at time t, representing the outcome you're trying to explain or predict.
- α (alpha): The interception term. This is the expected value of Y_t when both X_t and Z_t are equal to zero.
- βX_t: This is the coefficient (β) multiplied by the independent variable X_t. It represents the effect of a one-unit change in X_t on Y_t, holding Z_t constant.

- σZ_t: Similar to the previous term, σ is the coefficient for the independent variable Z_t, showing its effect on Y_t when X_t is held constant.
- ε_t (epsilon): The error term or residual, capturing all other influences on Y_t that are not explained by X_t or Z_t.

4.7.4.1 Steps of the ARDL cointegration technique

Step 1: Establishing Whether the Variables Have a Long-Term Relationship

The bound F-statistic is determined at the start of the study to determine whether there is a long-term link between the variables under study. In this procedure, each variable is viewed as endogenous, whereas all other variables are considered exogenous (Nkoro & Uko, 2016).

Step 2: Estimating the Long Run Estimates of the Selected ARDL Model and Choosing the Appropriate Lag Length for the ARDL Model

The ARDL technique to cointegration is effective when the regression model shows a consistent link, making it hard to rule out the possibility of long-term correlations between variables in different models. As a result, we seek for random error terms that follow a normal distribution and are devoid of non-normality, autocorrelation, and heteroskedasticity. Setting the proper lag time for each variable in the ARDL model is critical. The ideal lag length (k) can be calculated by using model selection criteria such as the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), or Hannan-Quinn Criterion (HQC) to discover the best model for the long-term equation (Nkoro & Uko, 2016).

4.7.4.2 Error Correction Model (ECM)

The Error Correction Model (ECM) is a powerful econometric tool used to analyze both the short-run dynamics and long-run equilibrium relationships among time series variables. It is especially useful when the variables in question are non-stationary but cointegrated, meaning they share a stable long-term relationship despite short-term fluctuations. In the context of the ARDL (Autoregressive Distributed Lag) framework, once a long-run relationship is established through bounds testing, the ECM is derived to examine how quickly variables return to equilibrium after a shock.

According to Nemushungwa (2013), achieving co-integration is necessary to obtain longterm estimates in the ARDL model. Furthermore, the existence of co-integration indicates the presence of an error correction term, which shows how quickly a short-term disturbance reverts to long-term equilibrium. Once a co-integration test vector is identified, the ARDL model for the cointegrating vector is re-parameterized using the ECM. Details on the short-term changes and longterm connectivity. The cointegration models' coefficients are calculated from the term EC_t, representing the speed of adjustment parameter or feedback effect, and standardized on X_t and Y_t in the equation. The EC_t shows the extent to which past period imbalances are being corrected in y_t, or the amount of imbalance being rectified. Positive coefficient indicates divergence, while negative number signifies convergence. If the estimated EC_t is equal to 1, then the entire adjustment of 100% takes place immediately and completely within the period. If the estimated EC_t is 50%, then adjustments of 50% are made each period or year. Claiming there is a long-term link when $EC_t = 0$ is not reasonable, indicating a lack of adjustment as shown by Nkoro & Uko in 2016.

4.7.5 Diagnostic tests

Analyzing the performance of each model is critical for determining how much confidence can be placed in the expected results. The main diagnostic tests utilized in this investigation are described below. These tests contribute to the dependability and accuracy of the model's conclusions.

4.7.5.1 Serial correlation

In this work, the LM test was employed to analyse serial correlation and detect autocorrelation, as indicated by Gujarati and Porter (2009). Autocorrelation is widespread in time series data and can be caused by faulty model parameters, repetitive measurement errors, or omitting important variables from the model (Godza, 2013). The LM test ensures that these errors are detected and addressed throughout the study.

4.7.5.2 Whites Heteroscedasticity Test

According to Brooks (2008), the term "heteroskedasticity" is derived from Greek and refers to variability in data point distributions. In layman's words, it refers to a condition in which data does not have a consistent amount of fluctuation, which is known as homoscedasticity. In regression models, it is accepted that the error components have consistent variance or are homoscedastic. When this constant variance does not exist, heteroskedasticity arises. The White test is a typical way to screen for homoscedasticity. While White's null hypothesis presupposes that the error terms are homoscedastic, Brooks proposes an alternative hypothesis, implying that the error terms may be heteroskedastic.

4.7.5.3 Normality Test

The normality test was used to determine if the random variables followed a normal distribution, which is crucial to the residuals generated by a linear regression model. If the error term does not follow a normal distribution, it should not be used in tests based on normal distribution assumptions, such as Z-tests, F-tests, and Chi-square tests. The Jarque-Bera (JB) test is used to determine the normality of residuals by looking at the asymmetry (skewness) and weakness (kurtosis) of time-series data. Brooks (2008) defines a normal distribution as having a zero sum of skewness and kurtosis. If the JB statistics remain good, it will rise higher. According to Gujarati and Porter (2010), the null hypothesis of normality should be rejected if the JB statistic exceeds the critical value for two degrees of freedom, implying that the distribution is not normal.

4.7.5.4 Stability of the co-integration relation

A stability test is necessary to assess the accuracy and reliability of the autoregressive distributed lag (ARDL) model and its parameters, among other factors. The CUSUM and CUSUMQ plots are used to assess the correctness of the model variables, as stated by Srinivasan and Kalaivani in 2013.

The method entails adding the squares of the differences determined incrementally from smaller groups of the data. When testing for coefficient stability under the null hypothesis, data that falls within the critical values at the 5% significance level indicates that the model is stable and supports the null hypothesis. CUSUM tests are used to evaluate the stability of coefficients in a multiple linear regression model $Y = X\beta + \varepsilon$. This advice is based on aggregating a series of mistakes or squared deviations determined sequentially from several data segments. If the data match the crucial values at the 5% significance level for coefficient stability under the null hypothesis, we may infer that the model is stable and accept the null hypothesis (Gujarati and Porter, 2010).

4.8 Conclusion

This section outlines the variables used in the study, explains their relevance, and describes the methods used to attain the research objectives. Several research methodologies are addressed, including stationarity testing, cointegration analysis, and diagnostic procedures. The Augmented Dickey-Fuller and Phillips-Perron tests are used in this work to measure stationarity. To guarantee the accuracy of the results, these tests are utilized. Despite both tests functioning in an equivalent manner, the outcomes of the PP test are favored over the ADF test because PP is considered more advanced. The ARDL method is favored over Johansen cointegration due to its benefits. The bounds test helps ascertain the level of integration between variables. These were included as diagnostic tests need to be done before understanding variable estimations. E-views 11 is used for conducting all testing procedures. The upcoming chapter presents and evaluates the findings achieved by utilizing the ARDL method on the dataset.

CHAPTER 5

PRESENTATION AND INTERPRETATION OF THE RESULTS

5.1 Introduction

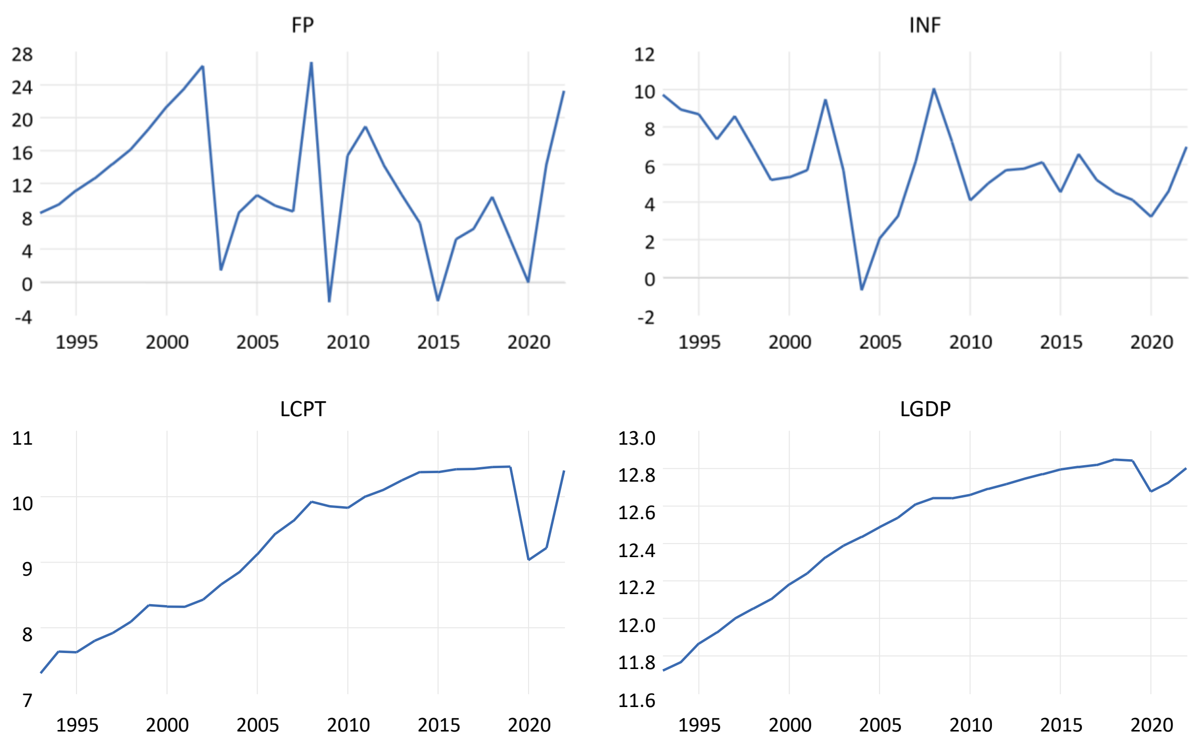
Chapter 4 outlines the model specifications and methodologies applied in this research, along with the empirical findings aimed at achieving the study's objectives by identifying factors that affect public transport costs. The primary aim of this chapter is to employ econometric techniques to evaluate how fuel prices influence public transport costs in South Africa. The analysis draws on data from the South African Reserve Bank (SARB) and Quantec, covering the period from 1994 to 2022.

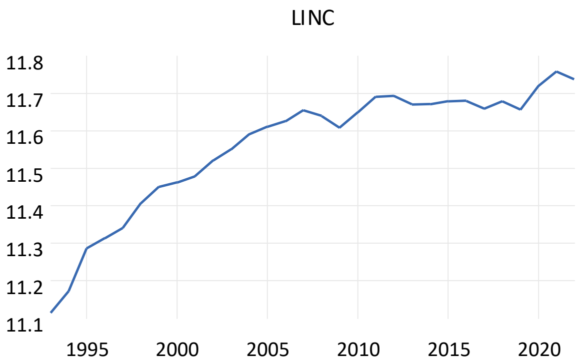
This chapter is divided into many sections. Section 5.2 goes over the statistical data utilized in the analysis, and Section 5.3 shows the correlation matrix for the variables. Sections 5.4 and 5.5 present the findings of both informal and rigorous testing for stationarity and unit roots. Section 5.6 uses the ARDL approach to investigate the long-term and short-term connections between the variables. Finally, Sections 5.7 and 5.8 explain diagnostic and stability tests were out on the ARDL model.

5.2. Unit Root Test Results

Prior to estimating the ARDL model, the data series must be validated for stationarity. Using non-stationary data for model estimate might produce misleading results. Ensuring that the data is stationary is critical to avoiding erroneous regression outputs and obtaining trustworthy conclusions, as stationarity is a key criterion for time series analysis. Data stationarity is often analyzed using a variety of methodologies, including graphical analysis and formal tests like the Augmented Dickey-Fuller (ADF) and Phillips-Perron tests.

Figure 5.1 displays the raw data for LGDP (Log of GDP), LCPT (Log of Cost of Public Transportation), LINC (Log of Income), INF (Inflation), and FP (Fuel Prices) in their original form. While FP and INF have intrinsic stationarity, implying steady statistical features over time, LGDP, LCPT, and LINC show patterns indicating non-stationarity. This suggests that without differencing, these variables may result in erroneous model estimates. The collection of data, which spans the years 1994 to 2022, gives a complete picture of South Africa's economic indicators across three decades, allowing for an extensive investigation of long-term patterns and correlations. The nonstationarity of LGDP, LCPT, and LINC indicates that these variables should be modified to prevent false correlations in the study. Differing these variables ensures that the model accurately reflects the underlying relationships while avoiding distortions caused by trends in raw data.

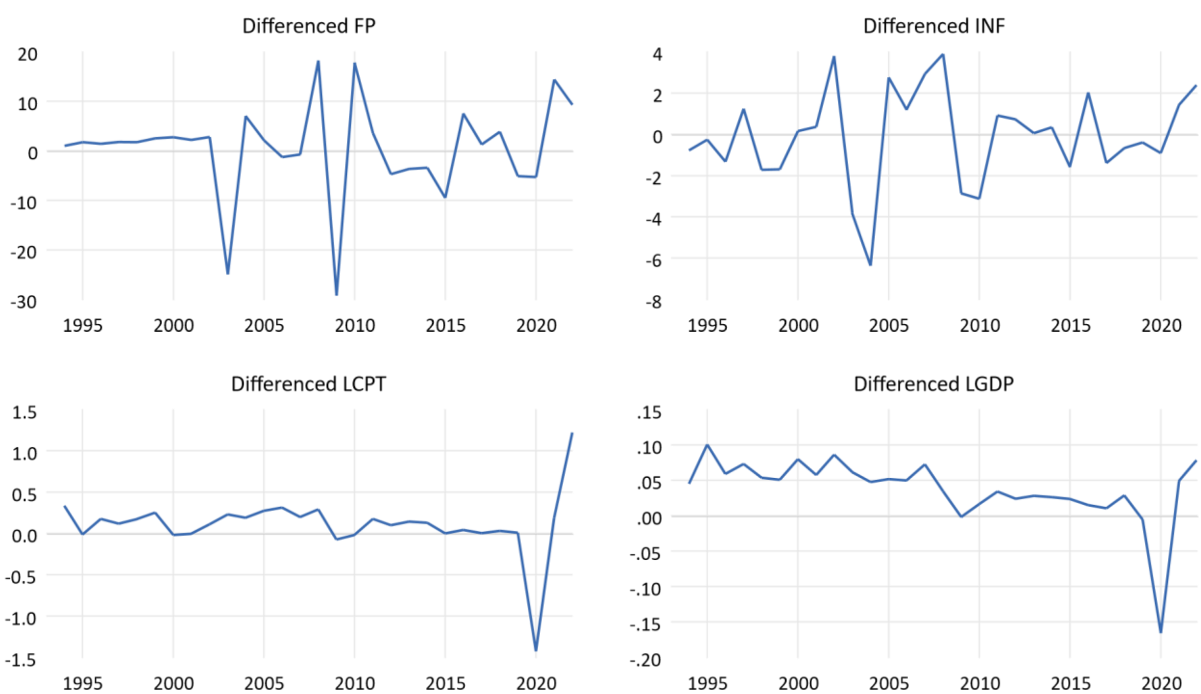


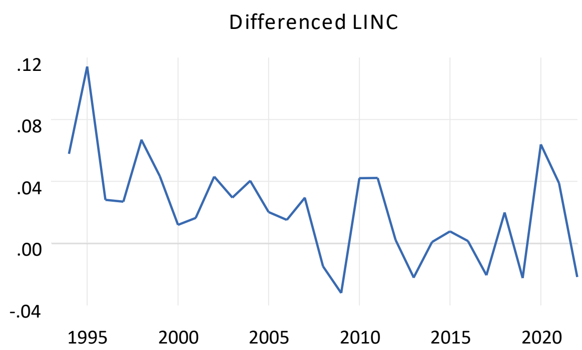


Source: Authors own graph using EViews 11

Figure 5.1 Informal unit root test at level

Figure 5.2 illustrates the variables after being differenced. Following the first difference, all variables exhibit stationarity. To mitigate the risk of spurious outcomes, only stationary variables after the first difference is used in the study. Also demonstrates the clear transformation of the variables after differencing, showing consistency with stationarity conditions. By ensuring all variables are stationary, the study improves the reliability of the regression results, reducing the likelihood of misleading or biased findings. The use of differenced variables aligns with best practices in time series analysis, reinforcing the validity of the study's conclusions. These graphical representations are provided below.





Source: Authors own graph using EViews 11

Figure 5.2 Informal unit root test: Differenced

Table 5.1: Formal unit root test at level

	AUGMENTED DICK-FULLER			**PHILLIPS-PERON**		
Variables	**constant**	**Trend and Constant**	**None**	**constant**	**Trend and Constant**	**None**
FP	**-4.0950*****	**-4.2619****	**-1.6459***	**-4.0877*****	**-4.2143****	**1.3507**
LGDP	**-3.3430****	**1.2850**	**4.1445**	**-4.1063*****	**-0.3175**	**3.2664**
LINC	**-4.4671*****	**-2.9512**	**3.4722**	**-11.5551*****	**-4.2621****	**2.8782**
INF	**-3.8673*****	**-4.0135**	**-1.4223**	**-3.1323****	**-2.6463**	**-1.1793**
LCPT	**-1.9392**	**0.4675**	**1.7204**	**-1.5647**	**-2.1422**	**1.9403**

(1) Null hypothesis, H0 = unit root exists on variables.

*(2) Stationary variables at 1%, 5% and 10% are represented by ***, ** and * respectively. These critical variables are obtained from McKinnon (1996).*

(3) CV stands for critical values.

(4) Akaike information criterion was used for lag length selection and E- views selected lags automatically

The table 5.1 shows a table of formal unit root at level under Augmented Dick Fuller and Phillips.

Most of the variables are stationery except LGDP, LINC, INF and LCPT.

Table 5.2: Formal unit root at first difference

	AUGMENTED DICKEY-FUCLLER			PHILLIPS-PERON		
Variables	**constant**	**Trend and Constant**	**None**	**constant**	**Trend and Constant**	**None**
FP	**-7.8938*** **	**-7.7568*** **	**-8.0213** **	**-9.5749*** **	**-8.9164*** **	**-9.8083*** **
LGDP	**-3.7041*** **	**-5.5749*** **	**-1.2935* **	**-3.7088*** **	**-9.2369*** **	**-2.5327** **
LINC	**-3.8522*** **	**-4.7820*** **	**-3.2380*** **	**-3.7971*** **	**-4.7674*** **	**-3.1533*** **
INF	**-5.3694*** **	**-5.5440*** **	**-5.3238*** **	**-6.9736*** **	**-9.2839*** **	**-6.9559*** **
LCPT	**-4.9221*** **	**-5.5433*** **	**-1.7307* **	**-3.1518** **	**-2.1061* **	**-3.2810*** **

(1) Null hypothesis, $H0$ = unit root exists on variables.

*(2) Stationary variables at 1%, 5% and 10% are represented by ***, ** and * respectively. These critical variables are obtained from McKinnon (1996).*

(3) CV stands for critical values.

(4) Akaike information criterion was used for lag length selection and E- views selected lags automatically

Table 5.2 presents the results of the formal unit root tests following the initial adjustments, revealing that all previously non-stationary variables, such as FP (Fuel Price), LGDP, LINC, INF, and LCPT, became stationary at different levels. The ADF and Phillips-Perron tests indicate that FP is stationary, with test statistics of -7.8938, -7.7568, and -8.0213 across different conditions, all significant at the 1% level. Similarly, INF also exhibits stationarity, with test statistics of -5.3694, -5.5440, and -5.3238, all significant at the 1% level. These results suggest that the fuel price and inflation variables do not exhibit long-term trends and are stable over time after differencing. Following the normalization for the initial difference, all variables showed stationarity at the 1% significance level in both tests, which confirms their integration at the first difference (I(1)).

Since all variables demonstrated significance at the first difference, the formal unit root findings align with the informal graphical analysis, indicating that the variables are integrated of order 1. This consistency supports the use of the ARDL (Autoregressive Distributed Lag) model for assessing cointegration between these variables. The ARDL model is particularly suitable for variables with different integration orders, and it allows for the examination of both short-run and long-run relationships between them. The details of this cointegration analysis will be discussed in the next section.

5.3 Estimation of the ARDL Technique

As described in the previous chapter, the ARDL technique used in this work consists of numerous processes in addition to identifying the parameters' integration order. These procedures involve determining the right lag length, running bound tests to assess the long-term connection, and calculating the long-term coefficients and short-term dynamics of the ARDL model.

5.4 Selection of the Lag Length

The AIC and SIC criteria are used to identify the ideal lag duration for a model, with the general rule being that the criterion with the lowest value is the best fit (Brooks 2002; Nemushungwa 2013). Given that the data for this study is gathered quarterly, a maximum of eight delays can be allowed. The Akaike Information Criterion (AIC) and the appropriate lag duration for our model are shown in Table 5.3. As described in the appendix, the lag order for the ARDL model is chosen based on the minimal AIC value of 7.876, which determines the lag structure for the ARDL (4, 4, 4, 4, 4) model.

5.5 Bound Testing for the long-run link

The bound testing approach determined a long-term relationship between fuel prices and the various independent variables that affect them. The Akaike Information Criterion (AIC) is used to calculate the optimal lag time for assessing the variables' integrated order. Table 5.3 shows the outcomes of this investigation.

Null Hypothesis: No long-run relationships exist.

Table 5.3 : Bound Test for co-integration relationship

Test statistics	value	K
F -statistics	29.01501	4
Critical value bounds		
Significance level	Lower critical Bound I (0)	Upper critical bound I (1)
10%	2.2	3.09
5%	2.56	3.49
1%	4.28	5.84

Source: Author's Own Creation Using EViews 11

The F-statistics of 29.01501, as shown in Table 5.3, surpasses the upper threshold value of 3.49 at the 5% significance level, allowing us to reject the null hypothesis of no cointegration. This indicates the presence of a stable long-term relationship between the cost of public transportation (CPT), the dependent variable, and its explanatory factors, confirming that the variables are cointegrated. The ARDL (4, 4, 4, 4, 4) model, chosen using the Akaike Information Criterion (AIC), was employed to estimate both the short-run and long-run dynamics of the variables. The ARDL approach is particularly useful in small samples and for variables with mixed integration orders (I(0) and I(1)) (Pesaran et al., 2001). The long-run results reveal significant relationships between fuel prices, income levels, public transport subsidies, and inflation in determining the cost of public transportation in South Africa. These findings align with Demand Theory, which posits that the quantity demanded for a good, such as public transportation, is inversely related to its price and is influenced by consumer income levels (Mankiw, 2016). Thus, higher fuel prices lead to increased transport costs, potentially reducing demand for public transport, particularly among low-income households.

Additionally, the Cross Price Elasticity of Demand Theory provides further insights into the relationship between fuel prices and public transport costs. According to this theory, fuel and public transport are complementary goods, meaning that an increase in the price of fuel leads to an increase in the cost of public transport, reducing its demand (Varian, 2010). This negative crossprice elasticity highlights the sensitivity of public transport demand to fuel price fluctuations. Moreover, the significant role of government subsidies in offsetting these cost increases is consistent with the theory, which suggests that subsidies can make public transport more affordable, thus increasing demand even in the face of rising fuel prices. These results underscore the need for policy interventions, such as subsidies or price stabilization measures, to protect consumers, particularly in urban areas where public transportation is essential for daily commuting.

5.6. Estimation of the Long-run Co-efficient.

After validating the presence of a long-term co-integration connection between the variables, the long-term coefficients were computed using the ARDL (4, 4, 4, 4, 4) model. This model was chosen based on the Akaike Information Criterion (AIC). Table 5.4 shows the outcomes of this estimation.

Table 5.4: Estimated Long Term Coefficients Utilizing ARDL (4,4,4,4,4) Model

Dependent Variable: D(LCPT)		**Sample adjusted 1993 to 2022.**		
Method ARDL		**Selected Model: ARDL (4, 4, 4 , 4, 4)**		
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
FP	**0.017806**	**0.001001**	**17.79076**	**0.0357**
INF	**0.065419**	**0.001919**	**34.09110**	**0.0187**
LGDP	**4.951576**	**0.093373**	**53.03015**	**0.0120**
LINC	**-6.005237**	**0.172813**	**-34.74999**	**0.0183**
C	**16.78647**	**1.014156**	**16.55216**	**0.0384**

Source: Author's Own Creation Using EViews 11

$EC = LCPT - (0.0178*FP + 0.0654*INF + 4.9516*LGDP -6.0052*LINC +16.7865)$

The long-run ARDL results show a positive relationship between fuel prices and the cost of public transport in South Africa at the 5 percent significance level. This implies that a R1.00 change in fuel prices will lead to a significant increase in the cost of public transport by R0.017.

This finding confirms the prior expectation of the BBC (2023), which stated that fuel is one of the most important materials on our planet. Without fuel, the globe would appear radically different (BBC, 2023). Additionally, the empirical findings of Aljoufie (2019) show that a rise in fuel prices has a considerable impact on travel behavior in Jeddah, primarily due to an increase in transport costs.

When there is a rise in the cost of public transport due to a rise in fuel prices, travel behaviours are affected. This is also supported by Rohani and Pahazri (2018), who argued that following the increase in fuel prices, the travel habits of those who used transportation had shifted.

The table 5.4 also illustrate a positive relationship between the inflation and cost of public transport in South Africa. Ceteris paribus, a unit change in inflation will increase the cost of public transport by 0.065419. The relationship is also statistically significant at 5% level, thus confirming the strong nexus. This confirms also with the prior expectation of Nsiah, Yusuf, Tweneboah, Agyei and Baidoo (2021) who estimated using the consumer price index, which represents the periodic percentage change in the average cost a customer would pay for a basket of products and services that may fluctuate at predefined intervals.

Long-term ARDL data show that there is a positive and substantial association between South Africa's GDP and public transport expenses. Specifically, a 1% increase in GDP leads to a 4.9% increase in public transportation expenses. GDP growth often results in more disposable incomes and increased demand for products and services, including public transportation. This increasing demand may result in greater operating costs, which are caused by variables such as rising fuel prices, higher salary demands, and increased maintenance requirements. Furthermore, economic expansion might cause inflationary pressures, affecting the total cost structure.

In South Africa, the requirement to improve and extend transportation infrastructure to service expanding urban populations needs considerable expenditures, which raises prices (Stats SA, 2022). This conclusion contradicts Callen's (2023) prior predictions, which held that GDP is made up of products and services generated for market sale, as well as non-market outputs such as government-provided defense or education services. Callen predicted a negative association between these two factors.

Finally, it is worth noting that income is negatively related to public transportation expenditures in South Africa. The long-term ARDL results show that a 1% increase in income leads to a 6% decrease in public transportation expenses, which is statistically significant at the 5% level. Income (INC) is the money earned by people or businesses in exchange for labor, products, services, or capital. Individuals normally earn wages, but businesses profit by selling goods or services at prices greater than their production costs (Indeed, 2023). The presented negative relationship between income and transportation costs can be attributed to income inequality. Lower-income people rely more heavily on public transit, therefore when their income declines, the burden of transportation expenditures grows in proportion to their income. In contrast, higherincome people are more likely to utilize private transportation, reducing their reliance on public transit and its related expenditures (Ramudzuli, 2019).

5.7 Error correction model (ECM)

Following the examination of integrating correlation over the long term, the next step involves conducting Error Correction Model (ECM) analysis to assess cointegration in the short run. The estimated ECM, depicted in table 5.5 below, serves this purpose.

Table 5.5 ECM Regression

Variable	Dependent Variable: D(LCPT)			
	Coefficient	Std. Error	t-Statistic	Prob.
D(LCPT (-1))	14.12262	0.427351	33.04691	0.0193
D(LCPT (-2))	12.60025	0.401007	31.42153	0.0203
D(LCPT (-3))	0.271107	0.034769	7.797412	0.0812
D(FP)	0.057066	0.001841	30.99748	0.0205
D(FP (-1))	-0.179034	0.005320	-33.65551	0.0189
D(FP (-2))	-0.178907	0.005328	-33.58048	0.0190
D(FP (-3))	-0.063738	0.001742	-36.59074	0.0174
D(INF)	0.341177	0.010944	31.17509	0.0204
D(INF (-1))	-0.239739	0.007774	-30.84025	0.0206
D(INF (-2))	-0.157036	0.005952	-26.38383	0.0241
D(INF (-3))	-0.347736	0.010872	-31.98512	0.0199
D(LGDP)	5.946073	0.117192	50.73798	0.0125
D(LGDP (-1))	-77.34879	2.377047	-32.53986	0.0196
D(LGDP (-2))	-66.89791	2.002579	-33.40588	0.0191
D(LGDP (-3))	-31.44596	0.978289	-32.14382	0.0198

D(LINC)	-39.78344	1.112431	-35.76260	0.0178
D(LINC (-1))	22.69086	0.578676	39.21166	0.0162
D(LINC (-2))	1.122976	0.201929	5.561242	0.1133
D(LINC (-3))	-6.469514	0.380445	-17.00511	0.0374
CointEq (-1)*	-12.74297	0.394283	-32.31935	0.0197

Source: Author's own compilation from data extracted from EViews 11

In the table above error correction model yielded a coefficient of -12.74297 with a probability of 0.0197, indicating significance below the customary 5% level.

The findings indicate that following a recession, the variables in the model will eventually revert to their long-term equilibrium, correcting short-term imbalances at 12,74% annual rate. In addition, the error correction model shows that inflation, GDP, and fuel prices all have a positive and significant impact on short-term public transportation costs. In contrast, levels of income have a negative short-term relationship with public transportation costs in South Africa.

The primary objective of this study was to examine the long-term relationship between fuel prices and public transportation costs in South Africa, as well as to determine whether there is a short-term link between these variables. The F-bound test established the long-term relationship between fuel prices and cost of public transport. Furthermore, the error correction model indicated how rapidly the economy regains equilibrium following economic shocks. The results indicate that after a disturbance, the variables will return to their long-term equilibrium (see Appendix). As Manete (2017) pointed out, a critical criterion for the error correction model is that the coefficient be negative and statistically significant.

5.8 Diagnostic check results

Gujarati (2004) emphasizes the need of doing suitable diagnostic tests to ensure that the variables are statistically significant, the coefficients have the expected signs, and the findings are accurate. In this study, the author used these diagnostic tests to prevent generating inaccurate or inaccurate outcomes.

Table 5.6. Summary of diagnostic result

Test statistic	**Statistics**	**Probability**

Normality test:	Jarque-Bera	0.184341	0.911950
Serial correlation	Breusch-Pagan-Godfrey	1.372245	0.5035
Ramsey Reset specification test	Likelihood ratio	1.662282	0.1973
Heteroskedasticity	Breusch-Pagan-Godfrey	25.73417	0.3668
	White test	25.98851	0.3537

Source: Author's own creation using E-views 11

A Jarque-Bera test was used to determine the normality of the model's residuals, as shown in Table 5.5. The findings indicated a Jarque-Bera statistic of 0.184341 and a probability of 0.911950, both of which above the 5% significance threshold. As a result, we do not reject the null hypothesis, which suggests that the residuals are normally distributed. This conclusion shows that the residuals in this study follow a normal distribution.

Using the Breusch-Pagan-Godfrey approach, the LM test was used to determine serial correlation. The final F-statistic was 1.372245, with a chi-squared probability of 0.5035. Both results above the 5% significance level, implying that the residuals are not sequentially correlated. To analyse heteroskedasticity in the residuals, the Breusch-Pagan-Godfrey and White tests were used. The findings revealed a Chi-square probability of 0.3668 and a Breusch-Pagan-Godfrey Fstatistic of 25.73417. Furthermore, the White Test yielded an F-statistic of 25.98851 and a Chisquared probability of 0.3537. Importantly, both tests produced probabilities that exceeded the 5% significance threshold, showing that the residuals in this sample are not heteroskedastic. To check that the model was correctly stated, the Ramsey Reset test was run, providing a probability of 0.1973 and a likelihood ratio of 1.66228. The probability value is more than 5%, indicating that the model's specification is correct.

5.9 Stability of the ARDL Model

Srinivasan and Kalaivani (2013) demonstrated how to use the Cumulative Sum of Recursive Residuals (CUSUM) and Cumulative Sum of Squares of Recursive Residuals (CUSUMQ) plots to evaluate the long-term coefficient stability and short-term dynamics of the ARDL model. In this context, Figure 5.3 depicts the CUSUM plot, whereas Figure 5.4 shows the

CUSUMQ plot for the ARDL model proposed in this work. The goal of these stability tests is to see if the regression coefficients stay stable over time. They are regarded legitimate if both the CUSUM and CUSUMQ plots fall inside the crucial bounds at the 5% significance level. The results of these stability tests are shown in Figures 5.3 and 5.4.

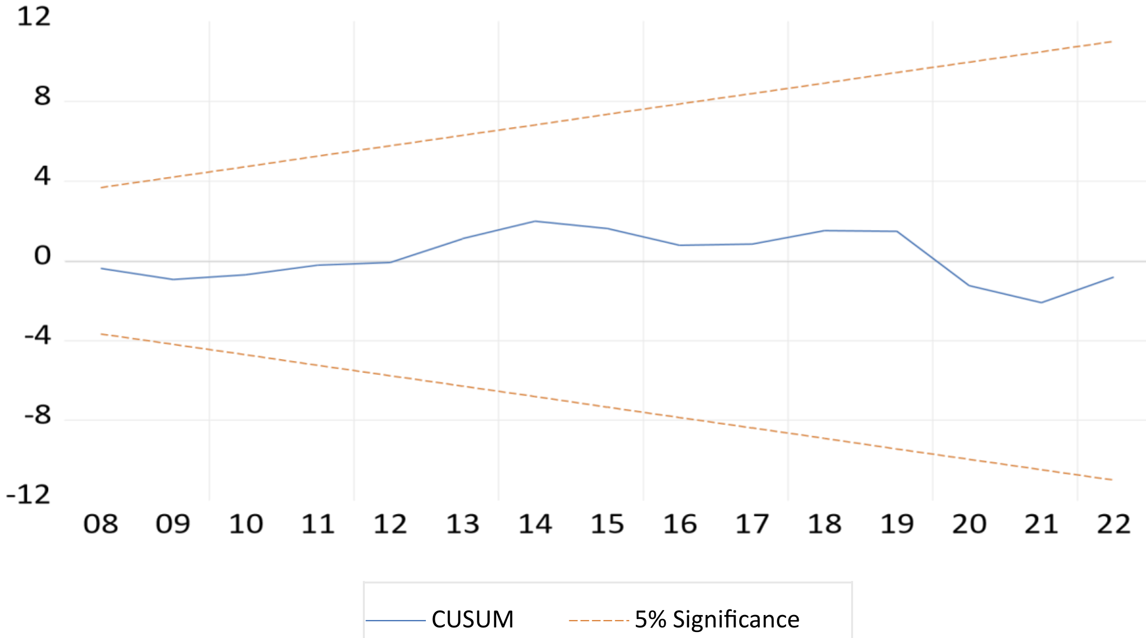


Figure 5.3: Stability Test Results of CUSUM test **(*Source: E-views 11)***

The cusum of squares study, together with the cusum test, verifies the null hypothesis regarding the model's stability. This conclusion is reinforced by the cusum of squares plot, which remains within the limitations defined by the 5% critical value lines (Figure 5.4).

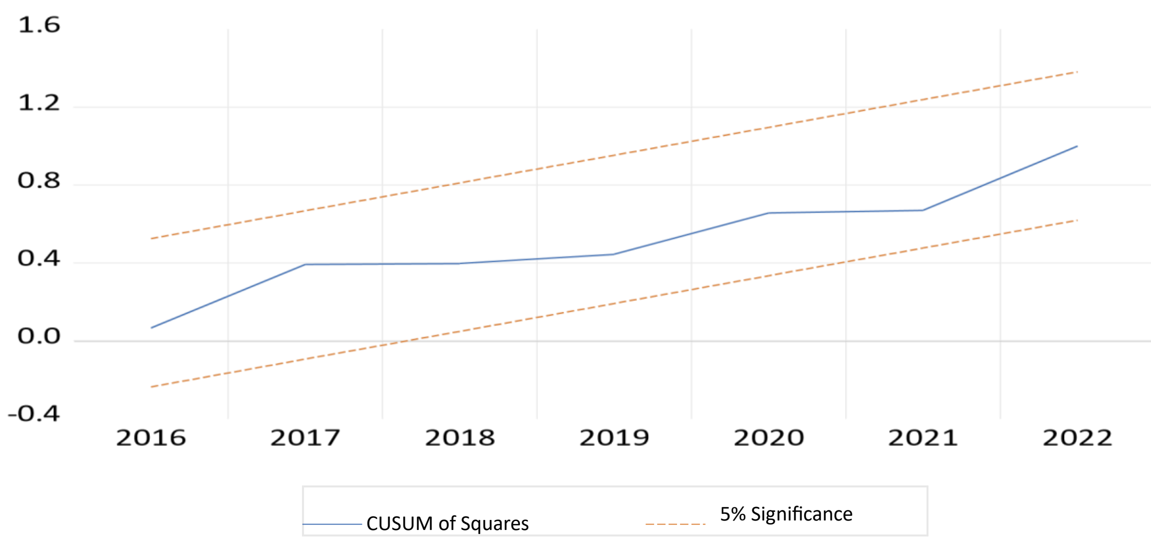
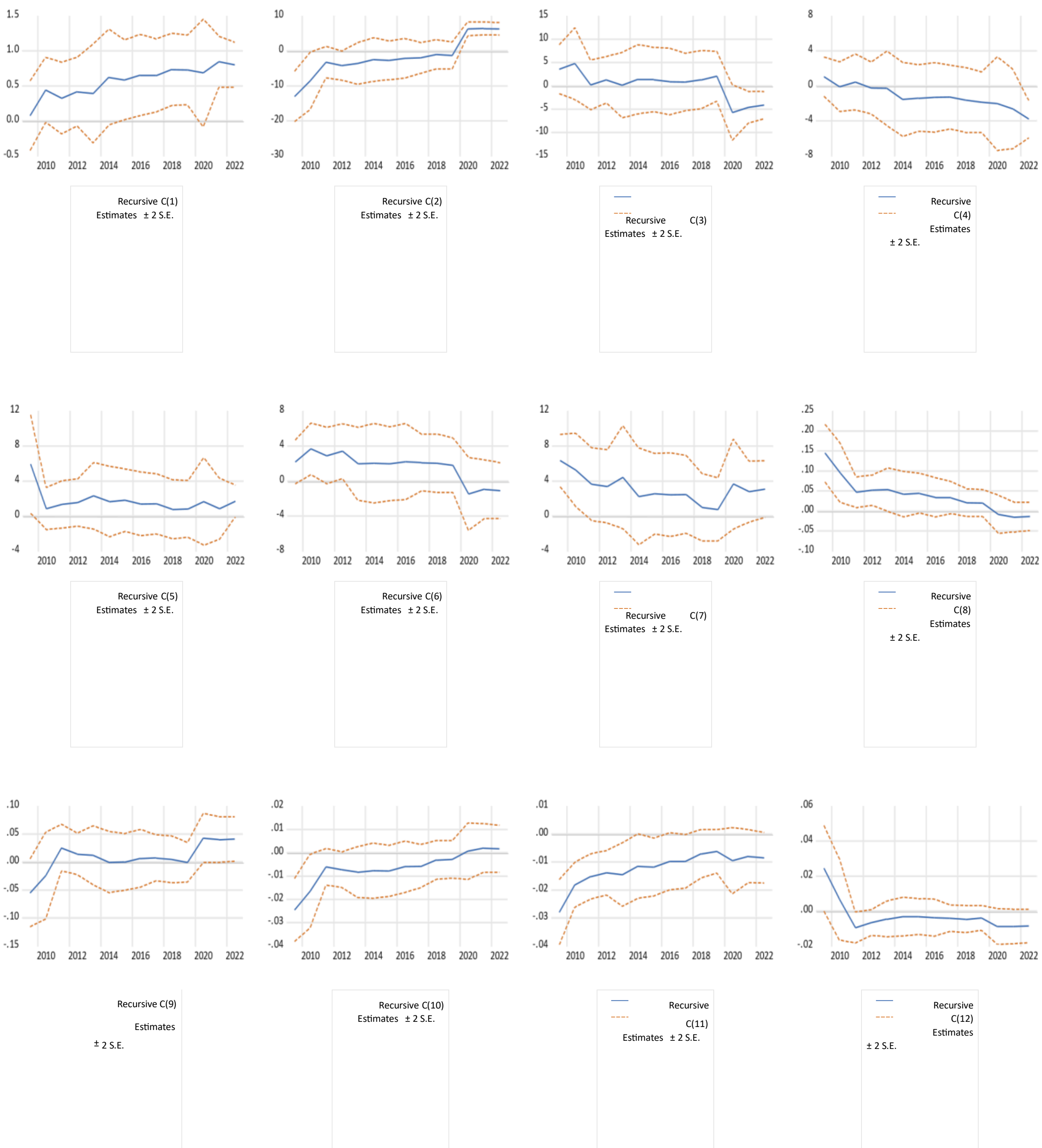


Figure 5.4: Stability test results of CUSUMQ test ***Source: Author's own EViews 11***

5.10 Recursive coefficient of ARDL

Figure 5.5 depicts the results of the recursive coefficient test, which proved the stability of all coefficients examined in the study. The 2SE modulus was used to verify the model's stability in the ARDL long-term framework, and the coefficients were found to be statistically significant.



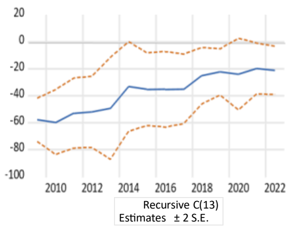


Figure 5.5. Recursive coefficient of ARDL (*Source: Author's own EViews 11)*

Figure 5.5 displays the results of the recursive coefficient test, which show that all the coefficients examined in this study are stable. The model's stability inside the ARDL long-term framework was evaluated using the 2SE modulus, and the findings revealed that the coefficients are statistically significant.

5.11 The actual, fitted, residual graph of the ARDL

Figure 5.6 shows how closely the long-term model, and the error correction model match the data from the endogenous dynamic model, while there are some notable differences. Major irregularities developed between 1996 and 2000, owing mostly to turmoil in politics in South Africa, which impacted public transit prices. Furthermore, there were significant fluctuations in the statistics throughout the 1994–1996 period of apartheid to democracy.

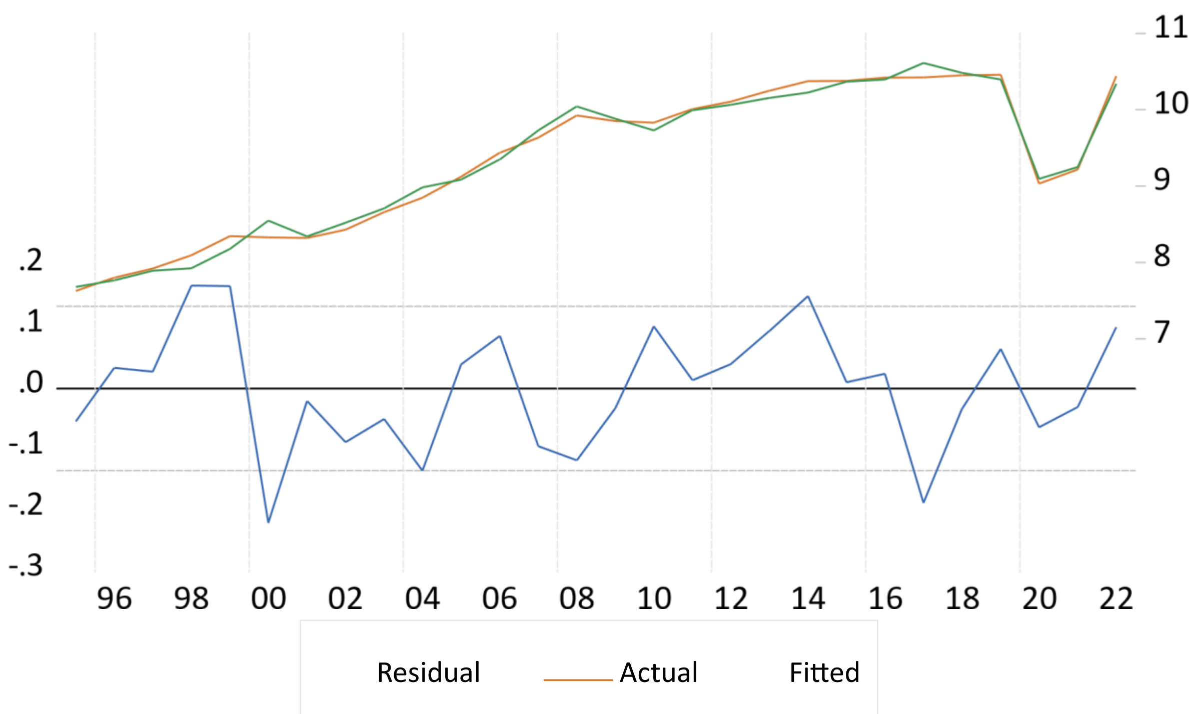


Figure 5.6. The actual, fitted, residual graph of the ARDL

Source: Author's own EViews 11

5.12 Conclusion

This chapter provides empirical data to support the analysis in Chapter 4. The study discovered a long-term link between fuel prices and public transportation costs in South Africa. The ARDL bound test findings show that the F-statistic surpasses the crucial upper bound at a 5% significance level, albeit the probability is lower than the needed 5% threshold. In the near run, the two variables show a positive association. Diagnostic tests were performed, including initial evaluations for variable robustness prior to generating the regression model, as well as stability tests to measure model resilience. The findings state that the data is consistent with the study's model and may be implemented in actual economic scenarios. The next chapter will summarize the findings and make policy suggestions.

CHAPTER 6

SUMMARY, CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

The study's last chapter summarizes the data reported in Chapter Five and recommends potential legislative reforms to reduce the impact of fuel prices on public transportation costs. Additionally, it proposes topics for future research and addresses the study's shortcomings.

6.2 Summary of the study

The study examined the impact of gasoline prices on public transportation expenses in South Africa from 1994 to 2022. The study used the Autoregressive Distributed Lag (ARDL) bounds test to investigate long-term repercussions, while the Error Correction Model (ECM) was used to assess short-term variations. Previous research on the link between gasoline prices and public transportation expenses found negative relationships.

Chapter One set the stage for the study by explaining the research problem. It emphasized the scarcity of information on the influence of gasoline prices on public transportation expenditures, citing contradictory findings from a variety of research, including those by Naape and Matebula, Gebremeskel, Woldeamanuel, Woldetensae, and Hassan and Meyer. The basic goal of the study was to evaluate how changes in gasoline prices affect public transportation expenses in South Africa, as well as numerous particular objectives.

The second chapter successfully met its second goal of examining the trends in fuel prices and the cost of public transport. The variations in fuel costs have a notable impact on the costs of public transportation in South Africa, showing a direct correlation between fuel prices and public transport costs where an increase in fuel prices leads to an increase in public transport costs. Thus, the research carried on and conducted the econometric tests in chapter 5.

Chapter 3 examined current theoretical and empirical literature. This thorough examination of both theoretical frameworks and empirical investigations provides light on the complex link between fuel prices and public transportation costs. The theoretical framework comprises the Theory of Demand, Cross Price Elasticity of Demand Theory, and the Theory of Planned Behavior. Together, these ideas shed light on the economic, social, and psychological variables that influence consumer behavior and decision-making in reaction to changes in gasoline costs. The empirical studies from various countries, including developing nations like Ghana, Nigeria, and Ethiopia, as well as developed countries like Russia and the United States, offer diverse perspectives on the impact of fuel price dynamics on public transportation costs and usage patterns. While some studies suggest a direct correlation between rising fuel prices and increased public transport costs, others highlight the complexities of consumer behaviour, indicating a mixed impact on mode choice and travel behaviour. Furthermore, the scarcity of research specifically addressing the relationship between fuel prices and public transportation costs in South Africa underscores the need for further investigation in this area.

Chapter 4 describes the ARDL model used in this work, which follows a thorough examination of the available literature. The dataset underwent stationarity testing using both informal and formal approaches. The casual technique included visual inspections, while the formal tests used were the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. First, a regression analysis was performed, followed by the ARDL approach to investigate the long-term association between variables. The short-term dynamics were investigated using the Error Correction Model (ECM). To assure the model's dependability, many diagnostic tests were performed. The Serial Correlation test determined if there was serial correlation in the residuals, whereas the Breusch-Godfrey test checked for heteroscedasticity. A normality test determined if the residuals followed a normal distribution, while the Ramsey Reset test assessed the ARDL model's specification correctness. Finally, stability was evaluated using CUSUM and CUSUMQ graphs to ensure the model's credibility and dependability.

Chapter 5 presents the research findings, which show a long-term relationship between fuel prices and public transportation costs in South Africa. The study employs the ARDL (Autoregressive Distributed Lag) bound test, which shows that the F-statistic is greater than the critical upper limit at the 5% significance level, despite the fact that the probability value is slightly lower. In addition, there is a short-term positive correlation between fuel prices and transportation costs. Before estimating the regression model, several diagnostic tests were performed to ensure that the variables were robust. Stability tests were also conducted to determine the model's overall dependability. The findings indicate that the data closely matches the model proposed in the study, making it applicable to real-world economic scenarios.

6.3 The Implications of the Study

The findings imply that rising fuel prices can directly affect public transport costs, but consumer behavior and travel patterns may vary based on economic and social factors. The mixed impacts across different countries suggest that fuel price fluctuations do not uniformly influence public transport cost. The lack of focused research on South Africa highlights the need for localized studies to better understand the specific effects in that region.

The methodology outlined in Chapter 4 emphasizes the ARDL model as a robust tool for analyzing both long-term relationships and short-term dynamics among the variables. The comprehensive checks for stationarity, along with diagnostic and stability tests, significantly enhance the reliability and credibility of the results. This rigorous approach ensures that the model accurately reflects the underlying data patterns, providing well-supported findings. The ARDL model, in this case, effectively captures the interdependencies between fuel prices and public transport costs, offering valuable insights for policy-making and economic analysis.

The findings suggest that fuel price fluctuations have both a significant long-term and shortterm impact on public transport costs in South Africa. The long-term relationship indicates that fuel price changes have a lasting effect on transport costs, underscoring the importance of policy interventions that address these long-term impacts. In the short term, the positive relationship between fuel prices and transport costs implies that immediate adjustments occur in response to fuel price changes, potentially influencing consumer behavior and transportation choices. The results from the ECM model further confirm that the short-term dynamics are driven by the speed of adjustment towards the long-term equilibrium. The model's robustness, validated by diagnostic and stability tests, ensures that the results are reliable and applicable to real-world scenarios, supporting its use in formulating effective policies and economic strategies.

6.4 Policy Recommendations

The study findings suggest that a direct correlation between rising fuel prices and increased public transport costs, others highlight the complexities of consumer behaviour, indicating a mixed impact on mode choice and travel behaviour. By addressing this knowledge gap, policymakers and transportation authorities can create targeted strategies to lessen the effects of fuel price fluctuations, promote sustainable mobility options, and ensure fair access to transportation services. The combination of theoretical insights and empirical findings highlights the complex relationship between fuel prices and public transport costs. It emphasizes the need to consider various perspectives and interdisciplinary approaches when tackling the challenges and opportunities related to fuel price changes in the public transport sector. Furthermore, an increase in GDP typically results in higher disposable incomes and a greater demand for goods and services, including public transport. This increased demand can raise operational costs, driven by factors such as higher fuel prices, wage demands, and maintenance expenses.

Moreover, economic growth can lead to inflationary pressures, impacting the overall cost structure. In South Africa, the upgrading and expansion of transport infrastructure to accommodate growing urban populations also require substantial investments, further pushing up costs. Businesses can better manage operating expenses despite variations in fuel prices by encouraging the use of alternative fuels for public transportation vehicles, such as compressed natural gas (CNG) or biofuel. This change can assist to lower fuel costs and lessen dependency on traditional petroleum-based fuels. Furthermore, income has a negative association with public transportation expenses in South Africa, implying that as income rises, the cost of public transportation falls. Income and transportation costs are projected to be negatively correlated. South Africa's financial gap explains the negative link between income and public transportation cost.

Individuals with less disposable income spend a greater proportion of their wages on transportation, whereas those with higher incomes suffer a reduced cost regarding this. Lowerincome individuals typically rely more on public transport, so as income decreases, the burden of transportation costs increases relative to income. By implementing government subsidies or fare reductions for public transportation services could indeed alleviate the burden of rising fuel prices on commuters in South Africa. This measure could make public transport more accessible and affordable for citizens, particularly those with lower incomes who heavily rely on it for their daily commute. The findings from the ECM model reveal that fuel price fluctuations have both short-term and long-term effects on public transport costs in South Africa. In the short run, fuel price changes lead to immediate adjustments in transport costs, which can significantly impact consumer behavior and travel patterns. To mitigate these short-term effects, policymakers should consider implementing temporary fare subsidies or price adjustments during periods of rising fuel prices. Additionally, the negative relationship between income and public transport expenses suggests that lower-income groups are more vulnerable to fuel price increases. As such, targeted subsidies or fare reductions for low-income commuters would help alleviate the financial burden and ensure that public transport remains accessible for those who depend on it most.

In the long term, the ECM model shows that fuel price changes lead to a gradual return to equilibrium, implying the need for more sustainable and long-term interventions. Investing in renewable energy sources, such as electric buses and solar-powered trains, can reduce operating costs and make the public transport system more resilient to fuel price shocks. Encouraging the use of alternative fuels, such as compressed natural gas (CNG) or biofuels, could also reduce dependency on volatile petroleum-based fuels. Furthermore, public awareness campaigns and incentive programs could promote sustainable travel behaviors like carpooling and telecommuting, which would reduce overall fuel consumption. These long-term strategies, in combination with short-term interventions, would help manage the impact of fuel price fluctuations on public transport costs while supporting the transition to a more sustainable and equitable transportation system.

Furthermore, investing in renewable energy sources for public transportation, such as solarpowered buses or electric trains, can reduce operating costs while strengthening the system's resilience to fuel price swings. In addition, encouraging the use of public transit can assist to relieve traffic congestion and give environmental advantages by reducing the number of automobiles on the road. However, it is critical to execute these subsidies properly and sustainably to guarantee that they fulfil their intended goals without putting long-term demand on government coffers. Furthermore, investing in renewable energy sources for public transportation, such as solarpowered buses or electric trains, can reduce operating costs while strengthening the system's resilience to fuel price swings. Furthermore, conducting public awareness campaigns and reward programs can stimulate behavioral changes like carpooling, telecommuting, and adopting more fuel-efficient driving practices. These techniques can assist reduce total fuel use while mitigating the impact of rising fuel prices on public transportation expenditures. Furthermore, conducting public awareness campaigns and reward programs can stimulate behavioral changes like carpooling, telecommuting, and adopting more fuel-efficient driving practices. These techniques can assist reduce total fuel use while mitigating the impact of rising fuel prices on public transportation expenditures.

6.5 Limitations of the study

There is empirical data quality and availability: there might be incomplete or inconsistent data on fuel prices and public transport costs across different regions and time periods. It is difficult to collect data for fuel prices because fuel prices vary depending on the internal or external factors for example Russia and Ukraine war impacted fuel price of South Africa, so it was difficult to capture data yearly because it does not capture data on a yearly basics. Lack of previous studies; a death of previous studies on the same topic in South Africa may hinder the contextualization of findings, as I am the first person in South Africa doing this study it was difficult to compare result or to validate the methodologies. Regional Variations: there is heterogeneity in transport system since South Africa is diverse urban and rural transport system might experience varying impacts of fuel prices changes, complicating a unified analysis. Furthermore, there is also economic disparities as result of different regions that have varying economic conditions affecting how fuel price changes impact public transport costs. Lastly, External factors due to government policies on subsidies, taxes, and public transport funding can influence the costs independently of fuel prices.

REFERENCES

Adeniran, A. O. (2016). Effects of fuel subsidy on transport costs and transport rates in Nigeria. J. Energy Technol. Policy, 6(11), 1-9.

Aivinhenyo, I., Zuidgeest, M., & van Ryneveld, M. (2016). Measuring destination accessibility by public transport incorporating user affordability: A case of Cape Town, South Africa. In XIV World Conference on Transport Research. Shanghai.

Alam, M. S., & Uddin, G. S. (2017). Impact of fuel prices on transportation costs in developing economies: An ARDL approach. Energy Economics, 66, 235-243.

Aljoufie, M. (2019). Analyzing the effect of fuel prices increase on travel behavior. Resourceedings, 2(1), 77-86.

Australian Automobile Association. (2024). *Transport Affordability Index: Q1 2024 Report*.

Baghery, F., & Zare, M. (2020). Cointegration and ARDL approach in economic modelling: An overview and application. Journal of Economic Dynamics, 55(3), 379-390.

BBC, (2023). Fuels. Available at: https://www.bbc.co.uk/bitesize/guides/z8yj6sg/revision/1

Bergman, M. (2023). Gasoline prices effect on public transportation: A study of Chicago: A study of the cross-price elasticity between gasoline prices and public transportation in a metropolitan setting.

Branda, F., Marozzo, F., & Talia, D. (2020). Ticket sales prediction and dynamic pricing strategies in public transport. *Big data and cognitive computing*, *4*(4), 36.

Bronkhorst, L. (2019). Identifying the challenges faced by a private bus operator (Doctoral dissertation, North-West University (South Africa)).

Brooks, C. (2008). Introductory econometrics for finance. 2nd edition. Chemistry & https://doi.org/10.1111/1468-0297.13911

Brown, R. M. (2007). *The pricing of commodity raw materials to the South African gold mining industry*. University of Pretoria (South Africa).

Bujeti (2023). Fuel Price Increase in Nigeria: Available at:
https://bujeti.medium.com/fuelpriceincrease-in-nigeria-what-it-means-for-your-business-and-why-

now-is-the-time-to-use-14d34d2e2761#:~:text=Impact%20on%20the%20General%20Population,struggling%20to%20make%20ends%20meet.

Businesstech, (2023. How much it costs South Africans to get to work. https://businesstech.co.za/news/industry-news/.

Callen, T. (2023). Gross Domestic Product. Available at: https://www.imf.org/en/Publications/fandd/issues/Series/Back-to-Basics/gross-domestic-product-GDP

Carruthers, R, Dick M, Saurkar A, (2005). Affordability of public transport in developing countries, Transport Papers TP-3, The World Bank, Washington S.C, January.

Cartenì, A., Di Francesco, L., Henke, I., Marino, T. V., & Falanga, A. (2021). The role of public transport during the second COVID-19 wave in Italy. *Sustainability*, *13*(21), 11905.

Clague, C. (2000). Capital Utilisation. Available at: https://www.researchgate.net/publication/227388557_Capital_Utilization

Creamer Media, (2022). Fuel price hikes will drive up costs across all supply chains. Available at: https://www.engineeringnews.co.za/article/fuel-price-hike-will-drive-up-costs-across-virtuallyallsupply-chains-2022-06-24

CSIR. (2014). State of logistics survey for South Africa. Available at: https://www.csir.co.za/sites/default/files/Documents/10th_SoL_Bold_Steps_Forward_web.pdf

Currie, G., & Phung, J. (2006). Exploring the impacts of fuel price increases on public transport use in Melbourne.

Daraio, C., Diana, M., Di Costa, F., Leporelli, C., Matteucci, G., & Nastasi, A. (2016). Efficiency and effectiveness in the urban public transport sector: A critical review with directions for future research. *European Journal of Operational Research*, *248*(1), 1-20.

Fedderke, J. W., Perkins, P., & Luiz, J. M. (2006). Infrastructural investment in long-run economic growth: South Africa 1875–2001. *World development*, *34*(6), 1037-1059.

Fuje, H. (2020). Transportation cost, fuel subsidies, and commodity prices. *World Trade Review*, *19*(S1), s88-s97.

Gebremeskel, E., Woldeamanuel, M., & Woldetensae, B. (2023). Transport vulnerability: Measuring travel time and expenditure budget in Addis Ababa. Research in Transportation Economics, 100, 101247.

Godza, P. (2013). Financial structure and economic growth nexus: comparisons of banks, financial markets, and economic growth in South Africa (Doctoral dissertation, University of Fort Hare).

Gujarati, D. N., & Porter, D. C. (2009). Basic Econometrics (5th ed.). Basic Econometrics

Hassan, A. S., & Meyer, D. F. (2020). Analysis of the non-linear effect of petrol price changes on inflation in South Africa. International Journal of Social Sciences and Humanity Studies, 12(1), 34-49.

Henseler, M., & Maisonnave, H. (2018). Low world oil prices: A chance to reform fuel subsidies and promote public transport? A case study for South Africa. *Transportation Research Part A: Policy and Practice*, *108*, 45-62.

Indeed, (2023). What Are the 3 Types of Income? Definition and Importance. Available at: https://www.indeed.com/career-advice/career-development/types-of-income

Institute for Fiscal Studies. (2024). *Distributional Effects of Fuel Duty Cuts in the UK*.

Jennings, G. (2015). Public transport interventions and transport justice in South Africa: a literature and policy review. Southern African Transport Conference.

Kgwedi, M. R. (2022). *The economic and time impact of poor access to public transport in South African metropolitan areas* (Doctoral dissertation, Stellenbosch: Stellenbosch University).

Leshoro, T. L., & Maluleke, G. (2020). Direct vs. indirect impact of fuel price on wages in South Africa: an analysis using the impulse-response function. Southern African Business Review, 24, 20-pages.

Loewald, C., Makrelov, K., & Pirozhkova, E. (2022). *The short-term costs of reducing trend inflation in South Africa*. Economic Research and Statistics Department, South African Reserve Bank.

Loh, L. C., & Brieger, W. B. (2014). Suburban sprawl in the developing world: Duplicating past mistakes? the case of kuala lumpur, Malaysia. *International quarterly of community health education*, *34*(2), 199-211.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). Stated choice methods: analysis and applications. Cambridge university press.

Luke, R., & Heyns, G. J. (2020). An analysis of the quality of public transport in Johannesburg, South Africa using an adapted SERVQUAL model. *Transportation Research Procedia*, *48*, 35623576.

Manasseh, C. O. (2019). Oil price fluctuation, oil revenue and well-being in Nigeria. In *Oil price fluctuation, oil revenue and well-being in Nigeria: Manasseh, Charles O.*

Mankiw, N. G. (2016). Principles of Economics (7th ed.). Cengage Learning.

Mayburov, I., & Leontyeva, Y. (2017). Fiscal instruments for regulating the sustainable development of urban transport systems in Russia. In *IOP Conference Series: Earth and Environmental Science* (Vol. 72, No. 1, p. 012016). IOP Publishing.

Miller, B. (2020). 15 Advantages and Disadvantages of Quantitative Research. Available at: https://greengarageblog.org/15-advantages-and-disadvantages-of-quantitative-research

Mtembu, T. T. (2020). *Vehicle ownership for South Africa: Developing a forecasting model and assessing household vehicle ownership* (Doctoral dissertation, Stellenbosch: Stellenbosch University).

Mules, T., & Dwyer, L. (2005). Public sector support for sport tourism events: The role of costbenefit analysis. *Sport in Society*, *8*(2), 338-355.

Naape, B., & Matebula, N. C. (2022). How do petrol prices respond to variations in crude oil and the exchange rate? Evidence from South Africa.

National Development Agency, 2019. Annual Report 2018/2019: Coming together to build a society. Department of Social Development.

National Household Travel Survey 2013. Summary of travel trends, National Household Travel Survey.

Ncanywa, T., & Mgwangqa, N. (2018). The impact of a fuel levy on economic growth in South Africa. Journal of Energy in Southern Africa, 29(1), 41-49.

Ndaguba, E. A., & Hlotywa, A. (2021). Public health expenditure and economic development: The case of South Africa between 1996 and 2016. *Cogent Economics & Finance*, *9*(1), 1905932.

Ndlovu, N. G. (2021). The impact of financial inclusion on poverty in SADC. Available at: https://vital.seals.ac.za/vital/access/manager/Repository/vital:48393?site_name=GlobalView&view=null&f0=sm_publisher%3A%22Faculty+of+Management+and+Commerce%22&f1=sm_type%3A%22Master%27s+theses%22&sort=ss_dateNormalized+desc%2Csort_ss_title+asc&f2=sm_creator%3A%22Ndlovu%2C+Nkazimulo+Glitter%22

Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. Journal of Statistical and Econometric methods, 5(4), 63-91.

Nsiah, A. Y., Yusif, H., Tweneboah, G., Agyei, K., & Baidoo, S. T. (2021). The effect of financial inclusion on poverty reduction in Sub-Sahara Africa: Does threshold matter? *Cogent Social Sciences*, *7*(1), 1903138

Ntshingila, M. L. (2022). Assessment of fuel price, exchange rate and unemployment rate impact on road passenger journeys in South Africa. International Journal of Research in Business and Social Science (2147-4478), 11(6), 362-369.

Pahlavani, M., Wilson, E., & Worthington, A. C. (2005). Trade-GDP nexus in Iran: An application of the autoregressive distributed lag (ARDL) model.

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: The Ragnar Frisch Centennial Symposium (pp. 371-413). Cambridge University Press.

Pesaran, M. H., Shin, Y. C., & Smith, R. J. (2001). Bounds Testing Approachs to the Analysis of Level Relationships. Journal of Applied Econometrics, 16(3), 289-326

Ramudzuli, M. (2019). *The relationship between income inequality, economic growth, and poverty in South Africa* (Doctoral dissertation, North-West University (South Africa). Vanderbijlpark Campus).

Rangasamy, L. (2017). The impact of petrol price movements on South African inflation. Journal of Energy in Southern Africa, 28(1), 120-132.

Regmi, A., & Seale, J. L. (2010). Cross-price elasticities of demand across 114 countries. *USDAERS Technical Bulletin* (1925).

Safespaces, (2023). The state of public transport in South Africa. https://www.saferspaces.org.za/understand/entry/the-state-of-public-transport-in-south-africa

Sanchez T.W, (2007). The connection between public transit and employment: The cases of Portland and Atlanta. Journal of the American Planning Association, Volume 65, 1999, Issue 3, pages 284-296

Sauti G, (2006). Research report: Minibus taxi drivers are they all born from the same mother. *University of the Witwatersrand*.

Sheefeni, J. P. S. (2013). Demand for money in Namibia: an ARDL bounds testing approach.

Shorten, A., & Smith, J. (2017). Mixed methods research: expanding the evidence base. *Evidencebased nursing*, *20*(3), 74-75

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.

Simelane, S. C. (2020). Public transportation in South Africa: factors influencing modal choice for work trips in Johannesburg and Cape Town.

Statistics South Africa. (2023). Inflation rises for a second consecutive month. Available at: https://www.statssa.gov.za/?p=16743

Stats, S. A. (2015). Measuring household expenditure on public transport.

Sustainable Development Commission. (2011). National infrastructure: embedding sustainable development in decision making.

Thiel, S. (2022). How to decide between public or private transport? Available at: https://www.news24.com/life/archive/how-to-decide-between-public-or-private-transport- 20220127

Tijjani, B., Saad, S., & Bernard, A. (2022). IMPACT OF OIL PRICE THRESHOLD ON

TRANSPORTATIONFUELDEMAND IN NIGERIA. Available at: https://www.researchgate.net/publication/363486808_IMPACT_OF_OIL_PRICE_THRESHOLD_ON_TRANSPORTATION_FUEL_DEMAND_IN_NIGERIA

TMMBS. (2023). The effects of fuel prices on the economy. Available at: https://tmmbs.co.za/theeffects-of-fuel-prices-on-the-economy/

Varian, H. R. (2010). *Intermediate Microeconomics: A Modern Approach* (8th ed.). W.W. Norton & Company.

Venter C, (2011). The lurch towards formalization: Lessons from the implementation of BRT in Johannesburg, South Africa. *Paper presented at the 12th Conference on competition and ownership in land passenger transport, Durban, South Africa, September 201*

Walker, J. (2008). Purpose-driven public transport: creating a clear conversation about public transport goals. *Journal of transport geography*, *16*(6), 436-442.

Webster, F. V., & Bly, P. H. (1981). The demand for public transport: Part I. the changing environment in which public transport operates. *Transport Reviews*, *1*(4), 323-351.

Wolff, C., Grashof, K., & Link, H. (2023). *The €9 Ticket in Germany: Travel Behavior Impacts and Policy Implications*. arXiv:2306.08297.

Xinhua, (2022). Ghanaians lament hardships amid fuel price, transport fare hikes. Available at: https://english.news.cn/20220325/26f80ce27c944fc79ddeeabbf3db11c7/c.html

Appendix

ARDL Long Run Form and Bounds Test

ARDL Long Run Form and Bounds Test
Selected Model: ARDL (4, 4, 4, 4, 4)
Trend Date: 05/15/24 Time: 10:41
Sample: 1993 2022
Included observations: 26

Dependent Variable: D(LCPT)
Case 2: Restricted Constant and No

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C				

	213.9096	49.83605	4.292266	0.1457
LCPT (-1)*	-12.74297	2.624181	-4.855981	0.1293
FP (-1)	0.226898	0.046508	4.878657	0.1287
INF (-1)	0.833631	0.156508	5.326457	0.1181
LGDP (-1)	63.09780	12.52811	5.036498	0.1248
LINC (-1)	-76.52458	15.70298	-4.873252	0.1288
D(LCPT (-1))	14.12262	2.925251	4.827832	0.1300
D(LCPT (-2))	12.60025	2.700908	4.665191	0.1344
D(LCPT (-3))	0.271107	0.281377	0.963503	0.5118
D(FP)	0.057066	0.011806	4.833634	0.1299
D(FP (-1))	-0.179034	0.035801	-5.000828	0.1256
D(FP (-2))	-0.178907	0.036677	-4.877977	0.1287
D(FP (-3))	-0.063738	0.011544	-5.521150	0.1141
D(INF)	0.341177	0.071602	4.764923	0.1317
D(INF (-1))	-0.239739	0.036787	-6.516903	0.0969
D(INF (-2))	-0.157036	0.034703	-4.525075	0.1385
D(INF (-3))	-0.347736	0.062266	-5.584654	0.1128
D(LGDP)	5.946073	0.535475	11.10430	0.0572
D(LGDP (-1))	-77.34879	16.47901	-4.693778	0.1336
D(LGDP (-2))	-66.89791	13.40902	-4.989021	0.1259
D(LGDP (-3))	-31.44596	7.846753	-4.007512	0.1557
D(LINC)	-39.78343	7.765246	-5.123268	0.1227
D(LINC (-1))	22.69085	3.046695	7.447695	0.0850
D(LINC (-2))	1.122975	1.199767	0.935995	0.5210
D(LINC (-3))	-6.469514	3.093989	-2.090995	0.2840

* p-value incompatible with t -Bounds distribution.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FP	0.017806	0.001001	17.79076	0.0357
INF	0.065419	0.001919	34.09110	0.0187
LGDP	4.951576	0.093373	53.03015	0.0120
LINC	-6.005237	0.172813	-34.74999	0.0183
C	16.78647	1.014156	16.55216	0.0384

EC = LCPT - (0.0178*FP + 0.0654*INF + 4.9516*LGDP -6.0052*LINC +

16.7865)

Test Statistic	Value	Signif.	I (0)	I (1)

			Asymptotic: n=1000	
F-statistic	29.01501	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Actual Sample Size	26		e Sample: n=35	
		10%	2.46	3.46
		5%	2.947	4.088
		1%	4.093	5.532
			Finit e Sample: n=30	
		10%	2.525	3.56
		5%	3.058	4.223
		1%	4.28	5.84

short run: Error Correction Model

ARDL Error Correction Regression
Dependent Variable: D(LCPT)
Selected Model: ARDL (4, 4, 4, 4, 4)
Case 2: Restricted Constant and No Trend
Date: 05/15/24 Time: 16:21
Sample: 1993 2022
Included observations: 26

D(LCPT (-1))	14.12262	0.427351	33.04691	0.0193
D(LCPT (-2))	12.60025ECM Regression		31.42153	0.0203
0.401007				0.0812
D(LCPT (-3))	0.271107	0.034769	7.797412	0.0205

D(FP)	Case 2: Restricted Constant and No Tren	30.99748	F-Bounds Test Null
0.057066	0.001841		Hypothesis: No levels relationship

D(FP (-1))	-0.179034	0.005320	-33.65551	
D(FP (-2))	0.0189	-0.178907	0.005328	
	-33.58048	0.0190		
D(FP (Variable-3))	-0.063738 Coefficient	0.001742 Std. Error		-
D(INF)	36.59074	t-Statistic	0.0174 Prob.	
D(INF (-1))	0.341177	0.010944	31.17509	0.0204
	-0.239739	0.007774	-30.84025	0.0206
D(INF (-2))	-0.157036	0.005952	-26.38383	0.0241
D(INF (-3))	-0.347736	0.010872	-31.98512	0.0199
D(LGDP)	5.946073	0.117192	50.73798	0.0125
D(LGDP (-1))	-77.34879	2.377047	-32.53986	0.0196

D(LGDP (-2))	-66.89791	2.002579	-33.40588	0.0191
D(LGDP (-3))	-31.44596	0.978289	-32.14382	0.0198
D(LINC)	-39.78344	1.112431	-35.76260	0.0178
D(LINC (-1))	22.69086	0.578676	39.21166	0.0162
D(LINC (-2))	1.122976	0.201929	5.561242	0.1133
D(LINC (-3))	-6.469514	0.380445	-17.00511	0.0374
CointEq (-1)*	-12.74297	0.394283	-32.31935	0.0197

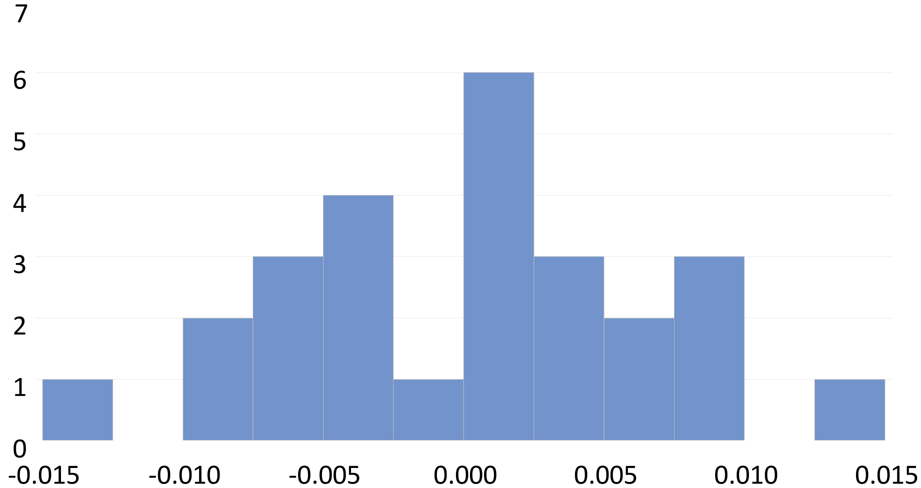
R-squared	0.999746	Mean dependent var	0.101510
Adjusted R-squared	0.998940	S.D. dependent var	0.394372
S.E. of regression	0.012839	Akaike info criterion	-5.800490
Sum squared resid	0.000989	Schwarz criterion	-4.832723
Log likelihood	95.40636	Hannan-Quinn critter.	-5.521808
Durbin-Watson stat	3.500402		

* p-value incompatible with t -Bounds distribution.

F-Bounds Test Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I (0)	I (1)
F-statistic	29.01501	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37

Diagnostic tests



Series: Residuals
Sample 1997 2022
Observations 26

Mean 1.08e-13 Median 0.000337
Maximum 0.012857
Minimum -0.014288 Std. Dev. 0.006290 Skewness -0.131121
Kurtosis 2.681582

Jarque-Bera 0.184341
Probability 0.911950

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	4.033633	Prob. F (24,1)	0.3769
Orbs*R-squared	25.73417	Prob. Chi-Square (24)	0.3668
Scaled explained SS	0.032007	Prob. Chi-Square (24)	1.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/15/24 Time: 16:25
Sample: 1997 2022
Included observations: 26

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.130395	0.040304	-3.235295	0.1908
LCPT (-1)	-0.000849	0.000255	-3.331512	0.1856

LCPT (-2)	0.000497	0.000204	2.439236	0.2477
LCPT (-3)	0.007528	0.002359	3.190806	0.1933
LCPT (-4)	-0.000441	0.000228	-1.939196	0.3031
FP	-2.78E-05	9.55E-06	-2.912238	0.2106
FP (-1)	-2.68E-06	2.39E-06	-1.119738	0.4641
FP (-2)	-8.63E-07	2.31E-06	-0.373292	0.7726
FP (-3)	-6.25E-05	2.05E-05	-3.053990	0.2015
FP (-4)	-2.88E-05	9.34E-06	-3.088691	0.1993
INF	-0.000177	5.79E-05	-3.059056	0.2011
INF (-1)	-0.000116	4.08E-05	-2.852280	0.2147
INF (-2)	7.81E-07	7.89E-06	0.099022	0.9372
INF (-3)	6.48E-05	2.87E-05	2.254482	0.2658
INF (-4)	-0.000125	5.04E-05	-2.488839	0.2432
LGDP	-0.001527	0.000433	-3.525578	0.1760
LGDP (-1)	0.011920	0.003585	3.324581	0.1860
LGDP (-2)	-0.007285	0.002591	-2.812087	0.2175
LGDP (-3)	-0.012527	0.004938	-2.537164	0.2390
LGDP (-4)	-0.022984	0.006346	-3.621838	0.1715
LINC	0.017856	0.006280	2.843259	0.2153
LINC (-1)	0.016276	0.004748	3.427815	0.1807
LINC (-2)	0.006159	0.002089	2.948560	0.2082
LINC (-3)	0.006716	0.002419	2.776067	0.2201
LINC (-4)	-0.006167	0.002502	-2.464620	0.2454

R-squared	0.989776	Mean dependent var	3.80 E-05
Adjusted R-squared	0.744395	S.D. dependent var	5.03E-05
S.E. of regression	2.54E-05	Akaike info criterion	-19.65597
Sum squared resid	6.47E-10	Schwarz criterion	-18.44626
Log likelihood	280.5275	Hannan-Quinn critter.	-19.30761

F-statistic	4.033633	Durbin-Watson stat	3.500402
Prob(F-statistic)	0.376921		

Heteroskedasticity Test: White
Null hypothesis:
Homoskedasticity

F-statistic	94.23682	Prob. F (24,1)	0.0812
Orbs*R-squared	25.98851	Prob. Chi-Square (24)	0.3537
Scaled explained SS	0.032324	Prob. Chi-Square (24)	1.0000

Test Equation:
Dependent Variable:
RESID^2 Method: Least
Squares Date: 05/15/24
Time: 16:31
Sample: 1997 2022
Included observations: 26

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.029735	0.001122	-26.50614	0.0240
LCPT (-1)^2	-2.71E-05	1.23E-06	-21.95657	0.0290
LCPT (-2)^2	2.08E-06	1.19E-06	1.750773	0.3304
LCPT (-3)^2	0.000103	5.91E-06	17.40707	0.0365
LCPT (-4)^2	-4.31E-06	2.45E-06	-1.759713	0.3290
FP^2	-4.89E-08	1.83E-08	-2.674492	0.2278
FP (-1)^2	-2.40E-08	2.89E-08	-0.832960	0.5579
FP (-2)^2	-1.24E-07	1.49E-08	-8.312405	0.0762
FP (-3)^2	-7.76E-07	3.74E-08	-20.73846	0.0307

FP (-4)^2	-1.94E-07	2.02E-08	-9.620368	0.0659
INF^2	-3.98E-06	3.14E-07	-12.68698	0.0501
INF (-1)^2	-1.12E-06	1.84E-07	-6.080591	0.1038
INF (-2)^2	1.35E-06	1.69E-07	8.005414	0.0791
INF (-3)^2	3.76E-06	2.31E-07	16.28127	0.0391
INF (-4)^2	-1.83E-06	2.97E-07	-6.164945	0.1024
LGDP^2	-3.68E-06	2.63E-06	-1.396510	0.3956
LGDP (-1)^2	0.000222	1.15E-05	19.24100	0.0331
LGDP (-2)^2	5.89E-06	7.01E-06	0.839583	0.5554
LGDP (-3)^2	-0.000224	1.41E-05	-15.83513	0.0401
LGDP (-4)^2	-0.000266	1.19E-05	-22.32123	0.0285
LINC^2	0.000220	1.86E-05	11.83469	0.0537
LINC (-1)^2	0.000174	1.04E-05	16.68727	0.0381
LINC (-2)^2	0.000114	7.93E-06	14.38359	0.0442
LINC (-3)^2	4.13E-05	6.49E-06	6.367102	0.0992
LINC (-4)^2	-7.12E-05	1.57E-05	-4.524354	0.1385

R-squared	0.999558	Mean dependent var	3.80 E-05
Adjusted R-squared	0.988951	S.D. dependent var	5.03E-05
S.E. of regression	5.29E-06	Akaike info criterion	-22.79727
Sum squared resid	2.80E-11	Schwarz criterion	-21.58757
Log likelihood	321.3646	Hannan-Quinn criter.	-22.44892
F-statistic	94.23682	Durbin-Watson stat	3.513952
Prob(F-statistic)	0.081191		

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up lags

F-statistic	0.334974	Prob. F(2,13)	0.7214
Obs*R-squared	1.372245	Prob. Chi-Square(2)	0.5035

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 05/15/24 Time: 16:29
Sample: 1995 2022
Included observations: 28
Presample missing value lagg
zero.

Variable	Coefficient		t-Statistic	Prob.

		Std. Error		
LCPT(-1)	0.005257	0.246427	0.021334	0.9833
LCPT(-2)	0.028123	0.124180	0.226467	0.8244
FP	0.000193	0.004985	0.038686	0.9697
FP(-1)	-0.000303	0.005051	-0.059943	0.9531
FP(-2)	-0.000186	0.005018	-0.036981	0.9711
INF	3.05E-05	0.019167	0.001592	0.9988
INF(-1)	0.000827	0.020636	0.040074	0.9686
LGDP	0.007382	0.882185	0.008368	0.9935
LGDP(-1)	-0.205602	1.667811	-0.123276	0.9038
LINC	-0.124335	1.702444	-0.073033	0.9429
LINC(-1)	0.272390	1.976130	0.137840	0.8925
LINC(-2)	0.055209	1.464657	0.037694	0.9705
C	-0.183616	9.435894	-0.019459	0.9848
RESID(-1)	0.136131	0.373860	0.364123	0.7216
RESID(-2)	-0.222235	0.365804	-0.607525	0.5540

R-squared	0.049009	Mean dependent var	7.99 E-15
Adjusted R-squared	-0.975136	S.D. dependent var	0.100196
S.E. of regression	0.140815	Akaike info criterion	-0.778566
Sum squared resid	0.257775	Schwarz criterion	-0.064885
Log likelihood	25.89992	Hannan-Quinn criter.	-0.560386
F-statistic	0.047853	Durbin-Watson stat	2.030283
Prob(F-statistic)	0.999999		

Ramsey RESET Test Equation: UNTITLED
Omitted Variables: Squares of fitted values
Specification: LCPT LCPT(-1) FP FP(-1) FP(-2) INF INF(-1) LGDP LGDP(-1) LGDP(-2) LGDP(-3) LINC LINC(-1) C

	Value	df	Probability
t-statistic	0.908575	13	0.3801
F-statistic	0.825509	(1, 13)	0.3801
Likelihood ratio	1.662282	1	0.1973

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.014217	1	0.014217

Restricted SSR	0.238112	14	0.017008
Unrestricted SSR	0.223895	13	0.017223

LR test summary:

	Value
Restricted LogL	25.55513
Unrestricted LogL	26.38627

Unrestricted Test Equation:
Dependent Variable: LCPT
Method: Least Squares
Date: 05/15/24 Time: 16:38
Sample: 1996 2022
Included observations: 27

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LCPT(-1)	-0.587460	1.535669	-0.382543	0.7082
FP	-0.000498	0.005623	-0.088566	0.9308
FP(-1)	0.007212	0.017873	0.403532	0.6931
FP(-2)	0.007127	0.017945	0.397166	0.6977
INF	0.006283	0.028534	0.220214	0.8291
INF(-1)	-0.030466	0.081142	-0.375461	0.7134
LGDP	-4.841731	12.28310	-0.394178	0.6998
LGDP(-1)	3.191331	8.211767	0.388629	0.7038
LGDP(-2)	3.216082	7.793414	0.412667	0.6866
LGDP(-3)	-1.836031	3.981276	-0.461167	0.6523
LINC	1.399451	3.209720	0.436004	0.6700
LINC(-1)	-1.597047	5.397483	-0.295887	0.7720
C	12.51724	38.21110	0.327581	0.7484
FITTED^2	0.091046	0.100208	0.908575	0.3801

R-squared	0.989599	Mean dependent var	9.411495
Adjusted R-squared	0.979199	S.D. dependent var	0.909923
S.E. of regression	0.131235	Akaike info criterion	-0.917501
Sum squared resid	0.223895	Schwarz criterion	-0.245586
Log likelihood	26.38627	Hannan-Quinn criter.	-0.717706
F-statistic	95.14758	Durbin-Watson stat	1.728064
Prob(F-statistic)	0.000000		

Date	FP	INC	INF	GDP	CPT
1993	8.385	67080	9.717467	123125	1491
1994	9.397	71066	8.938525	128789	2083
1995	11.143	79682	8.680444	142441	2052
1996	12.579	81937	7.354113	151129	2446
1997	14.357	84154	8.597783	162615	2754
1998	16.093	89987	6.880546	171559	3271
1999	18.604	93970	5.181493	180480	4208
2000	21.364	95071	5.338951	195460	4133
2001	23.58	96624	5.7019	206992	4106
2002	26.351	100873	9.494711	225621	4586
2003	1.41774	103875	5.679418	239944	5767
2004	8.44298	108154	-0.69203	251670	6963
2005	10.55094	110349	2.062846	264995	9168
2006	9.278964	112010	3.243908	278551	12544
2007	8.558517	115346	6.177807	299473	15279
2008	26.78758	113607	10.07458	309955	20434
2009	-2.4615	109974	7.215314	309374	18989
2010	15.38567	114689	4.08973	314565	18622
2011	18.9452	119622	4.999267	325452	22185
2012	14.25149	119850	5.724658	333328	24458
2013	10.61003	117176	5.784469	342841	28224
2014	7.167137	117238	6.129838	351904	32089

2015	-2.34437	118120	4.540642	360326	32115
2016	5.209356	118266	6.571396	365766	33491
2017	6.485185	115825	5.184247	369580	33626
2018	10.34624	118139	4.517165	380339	34609
2019	5.212743	115481	4.120246	378211	34890
2020	-0.09177	123096	3.210036	320394	8376
2021	14.31061	127964	4.611672	336408	10084
2022	23.59661	125167	7.039727	364246	34251