Addis Ababa University

Addis Ababa Institute of Technology

School of Civil and Environmental Engineering

Toll Price Elasticity for the Addis Adama Expressway

By

Nebiyu Nebabu

A Thesis submitted for the partial fulfillment of the requirements of Degree of

Master of Science in Road and Transport Engineering.

Advisor

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SCHOOL OF GRADUATE STUDIES

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UNDERTAKING

I certify that the research work titled "Toll Price Elasticity for the Addis-Adama Expressway" is my own work performed under the supervision of my research advisor Dr. Fitsum Teklu and has not been presented elsewhere for assessment and for a degree in any other university. Where material has been used from other sources it has been properly acknowledged / referred.

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Abstract

This research investigates the toll price elasticity of demand for the Addis Adama Expressway. The study aims to quantify how changes in toll prices affect traffic volume across various vehicle categories. Through econometric analysis using historical data from July 2019 to June 2023, the research incorporates key factors such as toll prices, fuel prices, GDP per capita, and external influences like security concerns and overburden restrictions.

The findings show that toll price elasticity varies across vehicle categories, with short-term elasticities ranging from -0.25 to -0.51, indicating a negative but inelastic response to toll price increases. Over the long term, toll price elasticity becomes more pronounced, suggesting that drivers adjust their behavior over time in response to price changes. Fuel price elasticity was found to be unexpectedly positive, reflecting the cost-saving advantages of using the expressway compared to non-tolled roads.

The research highlights the importance of integrating toll price elasticity into pricing strategies to optimize revenue while maintaining traffic levels. The results provide valuable insights for policymakers, supporting data-driven decisions on toll pricing and infrastructure development for the Ethiopian Expressway Network.

Key words: toll roads, expressway network, econometrics, elasticity

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1. INTRODUCTION

1.1 Background

Roads, often referred to as the arteries through which the economy pulses, serve as vital pathways facilitating economic activity by linking producers to markets, workers to jobs, students to schools, and individuals in need of medical care to hospitals. Given their crucial role, it's no surprise that many developed and developing countries prioritize investing in road infrastructure. Notably, studies reveal that expanding the paved road network by investing $1 typically results in an average increase of $4.6 (or approximately five times) in the country's Gross National Product (GNP) (Gautam, 1992). This underscores the significant economic impact of road development initiatives. In the Ethiopian government's budget, the largest allocation after public debt is directed towards the road sector, averaging 11.8% for the years 2022/23 and 2023/24 (ETRE, 2023). This substantial investment reflects the recognition of roads as essential components of national development strategies. Furthermore, since 2002, the World Bank has been actively involved in the construction or repair of over 260,000 kilometers of roads, demonstrating the global recognition of the importance of road infrastructure, with the World Bank allocating a greater portion of its funding to road projects compared to investments in education, healthcare, and social services combined (Berg, 2015). With such widespread recognition, nations employ diverse strategies to fund road construction, maintenance, and operation.

Among these strategies are road user charges and private financing initiatives, where the private sector contributes to infrastructure funding through conventional Build-Operate-Transfer (BOT) concessions under public-private partnership (PPP) agreements. Generally, road financing relies on road users covering the costs. The most widely used road user charges include a combination of fuel taxes, vehicle-distance traveled charges, charges on the purchase of new vehicles, annual vehicle registration fees, special charges on non-standard and overweight vehicles, and tolls (Uribe, 2016). These innovative financing methods ensure sustainable funding for road infrastructure projects and contribute to the efficient management of transportation networks. This research will focus specifically on toll charges collected from toll roads, which serve as a crucial financial mechanism for specific projects or infrastructure enhancements.

A toll road, also referred to as a tollway or turnpike, requires drivers to pay a fee for usage, collected at toll booths or through automated systems, to generate funds for the construction, maintenance, administration, and operation of road infrastructure. The history of tolls can be traced back to the 7th to 3rd centuries B.C., with references in Greek, Mesopotamian, and Egyptian mythology where a ferryman transported souls across the River Styx for Hades, the god of the underworld, and payment was made by placing a coin in the mouth of the dead. Transitioning to the Middle Ages (A.D. 500 to the 15th century), tolls were utilized to fund the construction and maintenance of bridges, charging travelers for crossing them. By the 17th century, parishes in the UK relied on property taxes and labor contributions to finance road work. However, in the 18th and 19th centuries, Turnpike trusts replaced parishes, becoming some of the first official organizations to impose tolls for road improvements (Liebhaber, 2022). In the United States, the history of toll roads dates back to the construction of the Philadelphia and Lancaster Turnpike in 1791, authorized by the state government. Led by Scottish road builder John Loudon McAdam, a private company built and maintained the road, implementing tolls to cover costs and generate profits (Garber, 2009).

In Ethiopia, three tolled expressways are currently in service, playing a crucial role in facilitating transportation across the country. These expressways serve as vital arteries, connecting major cities and regions and enhancing both domestic and international trade. The first of these expressways is the Addis-Adama expressway, covering 84.7 kilometers and forming an integral part of the Addis-Awash-Djibouti corridor. Operational since 2014, it has significantly reduced travel times and facilitated smoother movement of goods and people between Addis Ababa, Dukem, Mojo, and Adama. The second expressway, the Diredawa-Dawelle expressway, located in the eastern region as part of the Addis Ababa-Djibouti corridor, spans 202 kilometers and has been operational since 2018. This expressway has been instrumental in improving connectivity and accessibility to the eastern regions of the country, fostering economic development and regional integration. The third expressway, the Mojo-Batu expressway, contributes to the Trans-East Africa Road project, spanning 92 kilometers and serving as a vital link in the regional transportation network. According to Proclamation Number 310/2006, the Ethiopian Toll Roads Enterprise (ETRE) is authorized to manage the operation, maintenance, and administration of toll roads. The enterprise sets tariffs and collects revenue from road users, utilizing these funds for the roads' operation and maintenance while also allocating a profit margin to the government (ETRE, 2023).

In 2022 and 2023, ETRE conducted a study to revise tariffs, leading to an update of the existing tariff on expressways by considering two adjustment options. The first method, termed the cost recovery approach, sets tariffs based on covering operation and maintenance costs while also generating a specific profit margin. The second option evaluates tariffs based on perceived user benefits, including time savings and fuel cost savings. This method does not consider vehicle operating cost savings, road safety, and comfort benefits.

Despite these changes, ETRE’s study does not take account of the impact of tariff adjustments on the level of traffic demand and revenue generation for the tolled roads (ETRE, 2023). Therefore, to analyze the toll price change on the level of demand on tolled roads, the concept of elasticity is crucial. Elasticity provides a framework for understanding how changes in toll prices may affect the responsiveness of road users, offering valuable insights into the dynamics of traffic flow and revenue generation. By considering elasticity alongside the implemented tariff adjustments, ETRE can make more informed decisions to optimize toll pricing strategies and effectively manage expressway usage.

Elasticity is a crucial concept in transport economics, providing valuable insights into the responsiveness of transportation demand to changes in price, income, or other influencing factors. According to Litman (2023), demographics, economic activity, travel options, geography, land use patterns, demand management strategies, and price (monetary costs) are the main factors influencing the level of demand for travel. Understanding demand elasticity in the realm of transportation is essential for policymakers, planners, and industry stakeholders.

The price elasticity of demand for transport services refers to consumers' responsiveness to changes in price. According to Bain (2017), the mean toll price elasticity is -0.25, derived from analyzing Traffic and Revenue (T&R) study reports, which included primary data on empirically observed traffic responses to toll tariff changes across international toll roads, bridges, and tunnels., However, the larger standard deviation indicates the context-dependency of the coefficients, with values of 0.21 for trucks and 0.09 for cars.

The primary analytical challenge in estimating price elasticities lies in the need to isolate the impact of changes in price from various influencing factors affecting demand. This challenge is encapsulated in the concept of ceteris paribus, requiring researchers to hold all other influences constant to truly isolate price elasticity. However, this assumption is frequently violated in applied research. For instance, changes in toll prices may coincide with operational developments on the toll road, network developments on competing routes, fluctuations in other motoring costs, macroeconomic conditions, and various external factors like fiscal and credit changes. Navigating these complexities is crucial for researchers to accurately estimate price elasticities and understand the true impact of price changes on demand (Bain, 2017).

This research aims to investigate the price elasticity of toll roads, with a focus on the Addis Ababa-Adama Expressway. The findings from this study seek to establish an evidence-based foundation for decision-making, contributing to the overall enhancement of the Ethiopian Expressway's efficiency. Notably, the Ethiopian Toll Road Enterprise has implemented toll price changes two times since starting operations on the Addis-Adama Expressway. The main trigger factors for tariff changes are increasing operational and maintenance costs to maintain the level of service of the roads and to gain some amount of profit. The lack of a policy for making tariff revisions is stated as a limitation in ETRE's study on tariff adjustment (ETRE, 2023). Therefore, understanding the price elasticity of these expressways would provide valuable input for policymakers.

1.2 Statement of the Problem

The toll pricing mechanism for the Ethiopian expressway network faces significant challenges due to an inadequate understanding of toll price elasticity and its interaction with socio-economic factors. The ETRE toll pricing mechanism, which considers cost recovery and user-perceived benefits, is limited by insufficient knowledge about traffic demand forecasting and revenue generation based on adjusted tariffs. This gap restricts effective predictions of traffic demand and revenue outcomes.

This knowledge gap hampers policymakers' ability to make informed decisions on toll rates and expressway development. Therefore, a comprehensive investigation is necessary to address these gaps, optimize toll pricing strategies, and promote the sustainable growth of the Ethiopian expressway network in alignment with economic and transportation objectives.

1.3 Research Questions

Based on the problem statement, the following questions would be addressed in this study:

1. What is the toll price elasticity of demand for the Addis -Adama expressways?
2. How do socio-economic factors, fuel prices and demographic characteristics influence travel demand on Addis-Adama toll road?
3. What are the potential impacts of revised toll increments on traffic demand and revenue generation for the Addis Adama Expressway?
4. How can the findings on toll price elasticity be utilized to improve toll pricing strategies and support the financially sustainable development of the Ethiopian expressway network?

1.4 Objectives of the Research

The objectives of this research are:

a) To quantify the toll price elasticity of demand for the Addis Adama Expressway.

b) To identify and analyze the socioeconomic factors influencing travel demand on the Addis Adama expressway, including variables such as fuel prices, income, and other relevant factors.

c) To strengthen decision-making processes by providing policymakers with data-driven insights from the toll price elasticity analysis, enabling more informed decisions on toll pricing strategies and the development of the expressway network.

Additionally, this study will serve as a foundation for other researchers, encouraging further studies in this and related areas. It will also offer valuable insights for academics on the impact of toll prices, fuel costs, and economic growth on travel demand, particularly in developing countries.

1.5 Scope and Limitations

This research focuses on analyzing the price elasticity within the Addis Adama expressway network. Initially, we intended to include the Modjo-Batu and Diredawa-Dawelle expressways in the research. However, we faced challenges in obtaining data for these two expressways due to a lack of coordination among the toll centers. Data is collected at their respective locations and forwarded to the Addis Ababa center, which has hindered timely access to the necessary information. Therefore, it would be beneficial for future researchers to include this data to demonstrate how the elasticity estimates differ. The study aims to quantify the toll price elasticity and identify the socio-economic factors influencing travel demand on this tolled expressway. By doing so, the research intends to provide actionable insights that can guide policymakers in setting optimal toll prices and inform expressway development strategies.

There are several limitations of this study that should be noted. Firstly, the research relies on incomplete historical data, as full records since the expressway's opening were unavailable, limiting the ability to capture the full dynamics of traffic patterns over time. Additionally, within the available data, unusual traffic trends were observed during certain periods. While the study accounts for factors such as COVID-19, security concerns, and overburden restrictions as potential causes of these unusual traffic trends, other relevant factors may have contributed to these fluctuations but were not investigated due to a lack of study by the Ethiopian Toll Road Enterprise (ETRE). Furthermore, the study primarily focuses on Addis Adama expressway, which may limit the generalizability of the findings to other tolled roads or transportation contexts within Ethiopia or beyond. Lastly, the research is constrained by the current methodologies and data collection practices of the ETRE, which may not fully encompass all relevant socio-economic variables or reflect the most recent developments in toll road management.

1.6 Significance of the Study

This study offers valuable insights for policymakers, academics, and the research community by providing data-driven analysis of toll price elasticity and its socio-economic impacts on travel demand in Ethiopia. For policymakers, it delivers critical information for optimizing toll pricing strategies and aligning expressway management with national economic goals. For academics, the research fills a gap in the literature by analyzing toll pricing in a developing country context and highlights the interaction between toll prices, fuel costs, and economic growth. The study also sets the foundation for future research, contributing to the broader discourse on toll road management and transportation policy in developing regions.

1.7 Thesis Structure

The remainder of this thesis is structured as follows:

Chapter 2: Literature Review

This chapter reviews various articles and examines relevant research and theories that form the foundation of the study. It identifies gaps in existing knowledge, which helps justify the research question. By analyzing past work, the literature review positions the research within the broader academic context. Additionally, it reviews and adapts methodologies from previous studies to ensure they are suitable for the data and model used in this research.

Chapter 3: Methodology

This chapter describes the approach and methods employed in conducting the research. It outlines the research design, data collection techniques, and analytical tools used. This section is crucial for ensuring the research can be replicated and that the results are reliable.

Chapter 4: Results and Discussion

This chapter presents and analyzes the research findings. Results are typically illustrated using figures, tables, or charts to highlight key trends. The discussion interprets these findings, linking them to the research question and comparing them with previous studies.

Chapter 5: Conclusion, Recommendations and Future Research Directions

This chapter summarizes the key outcomes of the research, emphasizing its contribution to knowledge. It reflects on the implications of the findings for theory, practice, or policy, provides recommendations for future research, acknowledges the limitations of the current study, and gives direction for future researchers.

2. LITERATURE REVIEW

2.1 Introduction

The literature review covers several key topics: toll pricing, demand functions and elasticity, demand elasticity models, factors influencing travel demand on toll roads, and applications of demand elasticity models on toll roads. These topics are discussed in detail in Sections 2.2, 2.3, 2.4, 2.5, and 2.6, respectively.

2.2 Toll pricing

Toll roads, primarily controlled-access highways, charge fees for passage to recover construction and maintenance costs, often managed through systems like Build-Operate-Transfer (BOT) by private companies or government entities. Lembhe (2019) highlights challenges in toll road financing, including high initial costs and the need for accurate demand forecasting, as overestimated traffic volumes can threaten financial stability. Factors such as economic conditions and land-use changes influence traffic demand, leading to recommendations for demand-based pricing and public-private partnerships to enhance economic viability and project success.

Dong (2012) proposes a toll pricing method for highway traffic that aims to balance the total cost of road segments with the total toll charges collected at exits. It compares this method with other pricing methods and demonstrates its ability to satisfy desirable properties. The paper proposes a highway toll pricing method that is based on the following formula:

$$y_{ij} = \sum_{l=i}^{j} \frac{C_l(d_l)}{d_l} . x_{ij}$$

Where y_{ij} is the total toll charged to agent (i, j), who enters at entrance i and exits at exit j, $C_l(d_l)$ is the cost of road segment l, can be decomposed into a fixed part and a variable part and the variable part is influenced by traffic volume on that segment, and x_{ij} is the number of vehicles that belong to agent (i, j).

2.2.1 ETRE’s Approach to Setting Tariffs

As mentioned in Section 1.1, the ETRE employs two approaches for adjusting toll prices, leading to the proposal of two tariff options. The first method, the adjusted cost recovery method, calculates the tariff per kilometer by dividing the annual operational and maintenance costs, including a 20% marginal profit, by the annual vehicle kilometers traveled (VKT). This is then adjusted using the passenger car unit (PCU) for each vehicle category.

The second method, perceived user benefits, involves calculating fuel savings in liters and time savings in minutes for a 148 km stretch of road for each vehicle type. These fuel and time savings are then converted into monetary values using fuel prices and the value of time (VOT), with the tariff per kilometer determined by dividing the total monetary savings by 148 km.

The toll price data provided in , shows the proposed tariff per kilometer for both methods.

Table 2. 1 Historical Toll price data (ETRE, 2023)

Vehicle Category	**~ Jun.2022**	**Jun.2022 - Nov.2023**		**Nov.2023 -**	
	Birr/km	**Choice-1 Cost Recovery (Birr/km)**	**Choice-2 User perceived Benefit (Birr/km)**	**Choice-1 Cost Recovery (Birr/km)**	**Choice-2 User perceived Benefit (Birr/km)**
1 & 2	0.76	1.19	1.13	1.56	1.29
3	0.82	1.35	1.40	1.76	2.15
4	0.97	1.59	1.80	2.07	4.64
5,6 & 7	1.05	1.99	2.13	2.59	4.00
Avg.	**0.90**	**1.53**	1.62	**2.00**	3.02

Although ETRE could have potentially gained more revenue by implementing Choice Two, several considerations led to the recommendation of Choice One. Some of the main factors include:-

- Affordability: Considering the ability of vehicle owners to pay while accounting for both the short- and long-term benefits users gain from using the toll road.
- Impact on Pavement Distress: Vehicle classes 1 and 2, which have a relatively low impact on pavement distress, were considered. Given their ability to pay, covering 53 percent of the total benefits they receive was determined to have minimal financial strain on them.

- Supporting the National Economy: For heavy vehicles, particularly those in vehicle classes 5-7, paying 22 percent of the total benefits they receive was seen as reasonable. These vehicles typically travel longer distances and play a critical role in supporting the national economy by contributing to key sectors such as trade and logistics.

Based on these factors, Choice One (Cost Recovery) was recommended and applied on the toll road, as it offered a balanced approach between affordability and economic sustainability. Despite these considerations, the impact of these tariff adjustments on traffic demand and revenue generation for the tolled roads has not yet been fully examined (ETRE, 2022)

2.3 Demand Function and Elasticity

The demand models used to analyze the travel market are based on economic theory, which views travelers as making choices to maximize their "utility" or satisfaction. Travelers choose among different options based on constraints such as limited time and money, and the time required for travel itself. The relationship between the number of trips and various factors like cost, travel time, and income is represented by a demand function, which is a simplified mathematical model of this complex decision-making process. A general formulation of a demand function is:

$$y = f(X_1, \dots, X_n)$$

Where y is the dependent variable (level of demand) and X_i (i = I,…,n) are the explanatory variables (Balcombe, 2004).

A measure frequently used to summarize the responsiveness of demand to changes in the factors determining the level of demand is the elasticity. Elasticity measures responsiveness of the consumer to changes in any of the determinants of demand. It is an economic ratio for an assessment of relative changes in the quantity demanded to relative changes in price. In general, it can be expressed by a formula:

$$elasticity\ of\ demand = \frac{percentage\ change\ in\ quantity\ demand}{percentage\ change\ in\ demand\ impact\ variable}$$

$$ED = \frac{\Delta Q / Q}{\Delta X_i / X_i} = \frac{\Delta Q X_i}{\Delta X_i Q}$$

Where ED represents demand elasticity, Q represents the demand, X_i indicates the demand impact variable, ΔQ indicates the amount of change in demand before and after, and ΔX_i indicates the amount of change in influencing factors before and after (Cowie, 2010).

The formula illustrates that demand elasticity can be positive or negative, indicating correlations between demand-influencing factors and demand. A negative value implies a negative correlation, while a positive value indicates a positive correlation. When |E| exceeds 1, demand is elastic, reflecting sensitivity to characteristic changes. If |E| equals 1, demand exhibits unit elasticity, with characteristic changes causing proportional demand shifts. |E| less than 1 signifies inelastic demand, where characteristic changes lead to minor demand shifts. An E value of 0 denotes complete inelasticity, with characteristic changes having no impact on demand. In the context of price elasticity, X represents the price, such as expressway road charges, fuel fees and so on (Yunyi Li, 2023).

The basic definition refers to a change Δxi which is vanishingly small, however, so that it may be written mathematically as:

$$e_{X_i}^{point} = \frac{Limit}{\Delta X_i \to 0}\left(\frac{\Delta y}{y}\Big/\frac{\Delta X_i}{X_i}\right) = \frac{X_i}{y}\left(\frac{\partial y}{\partial X_i}\right)$$

Where, in the limit of the changes being vanishingly small, $\partial y/\partial X_i$ is the partial derivative of the demand function with respect to the factor X_i. This is called the 'point' elasticity, and in general the size of the elasticity measured might be expected to be different for larger changes in X_i (Balcombe, 2004).

Although the above formula is easy to use, it is only accurate for relatively small price changes. For larger changes in the explanatory variables, a more accurate method for calculating transportation elasticities (symbolized η) is the arc elasticity and its variation, the mid-point arc elasticity. Unlike simple linear methods, it considers numerous incremental adjustments, offering a more accurate representation of the impact of price changes on consumption. Each step affects an incrementally smaller base, resulting in an exponential function. The formula is given as follows:

Arc elasticity

$$\eta = \frac{\Delta\, logQ}{\Delta\, logP} \quad or \;\; \eta = \frac{logQ_2 - logQ_1}{logP_2 - logP_1}$$

Mid-point arc elasticity

$$\eta = \left[\frac{\Delta\, Q}{\frac{1}{2}(Q_1{+}Q_2)}\right] \div \left[\frac{\Delta P}{\frac{1}{2}(P_1 + P_2)}\right] \quad or \;\; \eta = \frac{(Q_2 - Q_1)(P_1 + P_2)}{(P_2 - P_1)(Q_1 + Q_2)}$$

Where η is the elasticity value, Q1 and Q2 are before and after consumption, and P1 and P2 are before and after price or service (Litman, 2023).

Arc elasticity is a logarithmic formulation and, except for very large changes in price or service, and quantity demanded, is closely approximated by a mid-point formulation based on the average value of each independent variable (Pratt 1999).

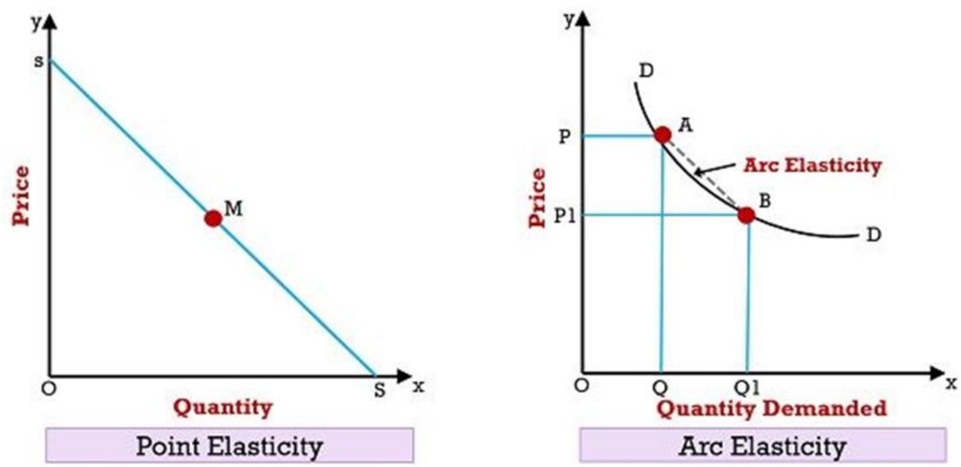

Figure 2. 1 Difference between Point and Arc elasticity

In the context of econometric models, elasticity can be derived in two key forms: constant elasticity models and non-constant elasticity models. These approaches provide a mathematical framework for estimating how a dependent variable, such as traffic volume, responds to changes in independent variables, like toll price, fuel price, or GDP per capita.

1. **Model with Constant Elasticity:** in constant elasticity models, the responsiveness of the dependent variable to changes in the independent variable remains the same, irrespective of the level of the independent variable. This simplicity makes these models easy to

interpret and widely used for understanding relationships where the response is proportionate across all levels of the variable. This is expressed mathematically as:

$$V = X^{\beta}$$

In this case, V represents the dependent variable (e.g., traffic volume), and X is the independent variable (e.g., toll price or fuel price). The elasticity with respect to X is given by:

$$\text{Elasticity} = \frac{\partial V}{\partial X} \cdot \frac{X}{V} = \beta$$

2. **Models for Non-Constant Elasticities:** Non-constant elasticity models account for cases where elasticity varies depending on the level of X. Two common forms include:
   I. Exponential Demand Model:

   $$V = e^{\beta X}$$

   In this model, elasticity changes with the value of X. The elasticity with respect to X is expressed as:

   $$\text{Elasticity} = \frac{\partial V}{\partial X} \cdot \frac{X}{V} = \beta X$$

   II. Damped Exponential Model:

   $$V = e^{\beta X^{\lambda}}$$

   In this model, elasticity is damped, meaning it varies in a controlled manner depending on the dampness coefficient λ. The elasticity with respect to X is:

   $$\text{Elasticity} = \frac{\partial V}{\partial X} \cdot \frac{X}{V} = \beta X^{\lambda}$$

   The parameter λ controls the degree of damping: as λ approaches 0, elasticity converges to a constant value; as λ approaches 1, the elasticity behaves similarly to the exponential model.

2.4 Demand Elasticity Models

The traditional approach to demand analysis has often focused on static models that emphasize equilibrium states. However, more recent research highlights the importance of dynamic processes in understanding how these equilibrium states are achieved or prevented. A critical aspect of this dynamic approach is distinguishing between elasticities with different time horizons. For example, short-run elasticities reflect demand responses within a year or two of a change, medium-run elasticities within about five years, and long-run elasticities over a decade.

The sequence of changes also plays a significant role in shaping demand. For instance, a service that increases fares by 20% in real terms in the first year and then reduces them by 25% in the second year, leading to an overall reduction of 10%, will produce a different demand profile over time compared to a service that simply reduces fares by 10% in the second year. This illustrates the concept of path dependency, where the order and nature of changes impact demand differently, sometimes leading to a phenomenon known as hysteresis. Other factors contributing to the importance of dynamic processes include the time it takes for consumers to become aware of changes, the gradual overcoming of habitual behaviors, and short-run constraints like fixed residential and workplace locations (Balcombe,2004).

The conventional and simplest method to model dynamic effects in traffic demand is by using lagged dependent variables. For convenience, we have assumed a constant elasticity formulation but variable elasticity versions can be devised. The constant elasticity formulation involves estimation of an equation of the following form:

$$V_{it} = \alpha . T_{it}^{\beta} Z_{it}^{\gamma} V_{it-1}^{\delta}$$

Where:

- V_{it}= Traffic volume at time period t
- T_{it} = Toll price at time period t
- Z_{it} = Set of other relevant explanatory variables
- V_{it-1}= Traffic volume during the previous time period t−1
- α, β, γ, δ = Parameters to be estimated.

In this model, the short-run fare elasticity is represented by the parameter β, while the long-run fare elasticity is calculated as β/ (1−δ). The medium run fares elasticity is more difficult to estimate. To do so, it becomes helpful to re-write the above equation in logarithms:

$$\ln V_{it} = \ln \alpha + \beta \ln F_{it} + \gamma \ln Z_{it} + \delta \ln V_{it-1}$$

The above equation can be modeled using time series model.

A **time series model** is a statistical tool used to analyze and forecast data points collected or recorded at successive points in time, considering patterns like trends, seasonality, and autocorrelation within the data. In time series model there is dynamic relationship between variables, that is the change in a variable now has an impact on that same variable, or other variables, in one or more future time periods. These effects do not occur instantaneously but are spread, or **distributed**, over future time periods as shown in Figure 2. 2 below.

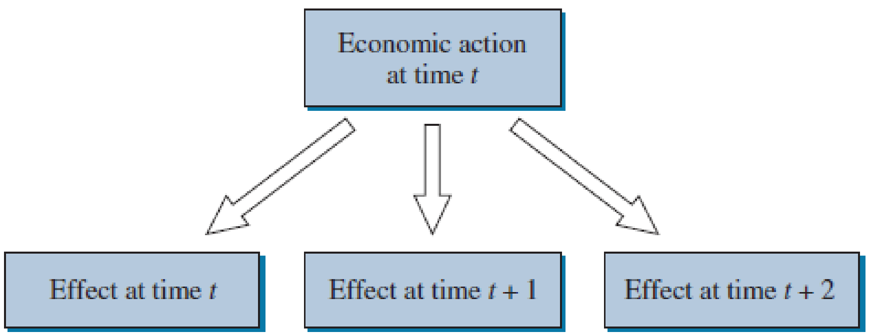

Figure 2. 2 The distributed lag effect

Given that time-series variables are dynamic, with their current values often correlated with past values and related to both current and past values of other variables, we can model time series data by introducing lagged variables into the model. These lags can take the form of lagged values of an explanatory variable (X_{t-1}, X_{t-2}, ..., X_{t-q}) and lagged values of a dependent variable (Y_{t-1}, Y_{t-2}, …, Y_{t-p}).The equation can be expressed as:

$$y_t = \delta + \theta_1 y_{t-1} + \cdots + \theta_p y_{t-p} + \delta_0 x_t + \delta_1 x_{t-1} + \cdots + \delta_q x_{t-q} + e_t$$

This model, with *p* lags of *y*, the current value *x*, and *q* lags of *x*, is **called Autoregressive Distributed Lag** model. It is abbreviated as an **ARDL (*p, q*) model**. The AR component of the name ARDL comes from the regression of y on lagged values of itself and the DL component comes from the distributed lag effect of the lagged x's.

The Autocorrelation function and partial Auto correlation function measures correlation between a time series and its lagged values. The autocorrelation function correlates the sequence and itself and the partial auto correlation function measures the correlation between a time series and its lagged values after removing the effects of intervening lags (Hill, 2018).

Another dynamic time series model that gradually adjusts the dependent variable towards its long-run or equilibrium value over time is called the **Partial Adjustment Model (PAM)**. It consists of two key components:

1. **Static Component**: This part defines how the desired or target level of the dependent variable is determined:

$$y_t^* = \alpha_o + \alpha_1 x_t + u_t$$

2. **Dynamic Adjustment Process**: The actual value of y_t adjusts gradually towards its desired level y_t* over time. The adjustment process is expressed as:

$$y_t - y_{t-1} = \lambda(y_t^* - y_{t-1})$$

   Where λ represents the speed of adjustment. By substituting the expression for y_t∗ into this equation, we derive the following estimating equation:

$$y_t = \alpha_0\lambda + (1-\lambda)y_{t-1} + \lambda\alpha_0 x_t + \lambda u_t$$

This equation can be estimated using a general ARDL model of the form:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 x_t + e_t$$

In this model, the parameters of the original equation can be identified as follows:

$\beta_1 = (1-\lambda) \Rightarrow \lambda = 1-\beta_1$, $\beta_2 = \alpha_1\lambda$, and $\beta_0 = \alpha_0\lambda$

The adjustment parameter λ measures the speed of adjustment and lies between 0 and 1. The closer it is to 1 the faster the speed of adjustment.

2.5 Factors Influencing Travel Demand on Toll Roads

Travel demand on toll roads is influenced by a variety of factors that interact to determine how much and how often people use these roads. Key determinants include demographics, such as population size in catchment area and income levels, which can directly affect travel patterns. Economic activity also plays a crucial role, as higher levels of economic engagement typically lead to increased movement of goods and people.

The availability of transport options significantly impacts toll road demand. The presence of alternative routes, public transportation, or other modes of travel can either reduce or increase the attractiveness of toll roads. This choice is often guided by convenience, cost, and time efficiency, which vary based on the alternatives available.

Geography and land use patterns further contribute to this dynamic by determining the physical layout and accessibility of toll roads in relation to residential and commercial areas. Urban planning and the distribution of land uses, such as residential, commercial, and industrial zones, play a critical role in shaping travel behavior and demand for toll roads.

Demand management strategies and pricing, particularly the monetary costs associated with using toll roads, are also crucial factors. Pricing can either deter or encourage usage depending on its affordability and perceived value. Together, these factors combine to shape the overall demand for travel on toll roads, influencing not only individual travel decisions but also broader traffic patterns (Litman, 2023).

2.6 Applications of Demand Elasticity Models on Toll Roads

Raymond (2011) uses time series model to investigate demand elasticity of tolled motorways in Spain over an 18-year period, aiming to assess the impact of GDP, gasoline prices, and tolls on traffic volume. Utilizing a panel dataset covering 72 road sections from 1981 to 1998, the study employs a panel data approach and a partial adjustment model. Findings reveal an elastic demand concerning economic activity and gasoline prices, underscoring tolling's substantial influence on traffic.

Regarding the model specification, demand equation, and results, the authors utilize a panel data approach that integrates cross-sectional and time-series data to capture toll elasticities' variation across motorway sections and over time. Stationarity, cointegration, and functional form tests guide the authors' selection of a partial adjustment model using first differences of logarithms. Lags of dependent and explanatory variables are included for dynamic effects and partial adjustment. The comparison of three functional forms linear, semi-log, and log-linear—results in the preference for the log-linear specification. The demand equation they estimated is:

$$\Delta \ln(V_{it}) = \gamma \Delta \ln(G_t) + \alpha \Delta \ln(F_t) + \beta \Delta \ln(T_i) + \delta \Delta \ln(V_{it-1}) + \theta \Delta Z_{it} + \varepsilon_{it}$$

Where V_{it} is the traffic volume on motorway section *i* in period *t*, G_t is the real GDP, F_t is the real gasoline price, T_i is the real toll price per kilometer, Z_{it} is a vector of dummy variables, ϵ_{it} is the error term, β is toll price elasticity, α is fuel price elasticity, and γ is GDP elasticity. The coefficient δ measures the speed of adjustment of demand to changes in the explanatory variables. All the monetary variables were deflated by the CPI.

The results show that traffic volume is positively related to GDP and negatively related to gasoline price and toll. The estimated short-term and long-term elasticities are 0.89 and 1.41 for GDP, 0.34 and 0.53 for gasoline price, and vary from 0.21 to 0.83 and 0.33 to 1.31 for toll, depending on the group of motorway sections. The results also show that demand is more elastic when the alternative free road is of better quality, when the motorway section is longer, and when the motorway is not located in a tourist area.

Huang (2015) utilizes a time series model to analyze the impact of changing gas prices on travelers' choice of toll routes in the United States. The study examines the short-run elasticity of demand for toll facility use in response to gas price changes, using monthly and quarterly data from 2000 to 2010 for toll facilities operated by 13 agencies across the country. To isolate the effect of gas price fluctuations, the study also considers other influencing factors such as toll rates, unemployment rates, and metropolitan population. The study employs an ARDL model to estimate the relationship, capturing the dynamics of how these variables affect toll facility usage over time. The model is represented by the following equation:

$$\log(V_t) = c + \delta \log(V_{t-1}) + \alpha \log(F_t) + \beta \log(T_t) + \theta UEMP_t + \rho \log(Pop_t) + U_t$$

Where $Log(V_t)$ denotes the logarithm of seasonally adjusted toll traffic volume in month t, $Log(V_{t-1})$ denotes the 1st lag of $Log(V_t)$, $Log(F_t)$ denotes the logarithm of retail price of gas in month t for the specific metropolitan area/state/region, $Log(T_t)$ denotes the logarithm of the CPI-adjusted toll rate in month t for the toll facilities, $UEMP_t$ denotes the unemployment rate in month t for the specific metropolitan area/state/region, $Log(Pop_t)$ denotes the logarithm of the population of the metropolitan area/state/region where the toll facility is located in period t, U_t denotes an error term with a mean of zero.

Table 2. 2 Summary of elasticity for toll roads in the United State (Huang, 2015)

	2 axle	5axle	For vehicles not disaggregated by class
Fuel price elasticity	-0.11 to -0.002 Mean=-0.06	-0.22 to 0.14 Mean=-0.03	-0.36 to 0.14 Mean=-0.06
Toll price elasticity	-0.79 to -0.02 Mean=-0.3	-0.85 to -0.09 Mean=-0.35	-0.31 to -0.05 Mean=-0.18
Unemployment rate elasticity	-0.18 to 0.03 Mean=-0.01		

The study finds that toll rate elasticity for 2-axle vehicles ranged from -0.79 to -0.02, with a mean of -0.30, and for 5-axle vehicles, from -0.85 to -0.09, with a mean of -0.35, indicating that toll rate changes have a more significant impact on demand than gas price changes. In cases where vehicle volumes were not disaggregated by class, toll rate elasticity ranged from -0.31 to -0.05, with a mean of -0.18. Overall, the study concludes that while gas prices do influence toll facility usage, the impact is generally smaller than that of toll rate changes, and toll facility users, particularly those with 5-axle vehicles, are less responsive to gas price increases than users of non-toll facilities.

Batarce (2023) examines the elasticity of demand on urban highways in Santiago, Chile, with a focus on tolls, fuel prices, and economic activity. The study uses five years of data (2013-2018) from Autopista Central, an urban highway in Santiago. The data includes vehicle flow, toll rates, fuel prices, and economic activity indices. Considering the dependent variable is total monthly flow by vehicle category and gantry and the independent variables include tariff per kilometer, fuel prices and the monthly economic activity indicator in Chile, Índice Mensual de Actividad Económica (IMACEC), which is disaggregated into mining and non-mining sectors. The author developed the following model:

$$\ln V_{pt} = \beta \ln T_t + \alpha \ln F_t + \theta \ln M_t + \rho \ln NM_t + \mu \ln P_{Pt} + \sigma \ln S_{st} + \delta V_{p(t-1)} + \sum_{i=1}^{11} \varphi_m d_{mi}$$

where V^c_{pt} represents the flow of category c through the gantry p in the month t, T^c_t is the tariff per kilometer, F^c_t is the fuel price, M_t IMACEC of mining sector and NM_t of non-mining sector, P_{pt}

and S_{pt} represents the number of periods of the day with a peak or saturation tariff, and d_{mj} are dummy variables that represent each month (except for April, used as a reference).

The results of model estimation is summarized in the Table 2.3 below.

The study presents findings on the elasticity of urban highway traffic flow in relation to tariffs, fuel prices, and economic activity, with a focus on underdeveloped countries. The study reveals that economic growth has a significantly larger impact on traffic flow in Chile compared to previous studies from the US and Europe. It also highlights the importance of differentiating the effects of economic activity by sector in econometric models to avoid bias. In the short term, highway flow is inelastic to tariffs, but it becomes elastic in the long term. These results suggest that economic growth drives increased vehicle use, raising concerns for the design of concession contracts in developing countries, where tenders should account for the impact of economic growth on vehicle flows.

Table 2.3 Summary of elasticities for case of Santiago (Batarce, 2023)

	Light vehicles		Buses and trucks		Trucks over 2 axles	
	Short term	Long term	Short term	Long term	Short term	Long term
Tariff per kilometer	-0.82	-1.29	-0.68	-0.96	-0.66	-1.15
Fuel price	-0.23	-0.36	-0.09	-0.12	-0.01	-0.02
Non-Mining IMACEC	3.60	5.66	2.74	3.89	2.15	3.72
Mining IMACEC	-0.22	-0.34	-0.10	-0.14	-0.01	-0.02

Musso (2012) investigates the impact of fuel price increases on traffic demand along the Elefsina – Korinthos – Patra – Pyrgos - Tsakona (EKPTT) Greek motorway using different methodologies. In response to the 2008 economic crisis, the Greek government imposed a special tax on fuel, including levies and VAT, to help restore the primary budget surplus. To assess the effect of this fuel price increase on motorway traffic, the author used quarterly average traffic data from 2008 to 2011, collected from 10 survey stations along the EKPTT motorway. Then the author developed three macro-econometric model, incorporating toll fare, fuel price, and GDP as key variables.

These are:

a. Flat elasticity: $\left(\frac{V}{V_0}\right) = \left(\frac{T}{T_0}\right)^{\beta} . \left(\frac{F}{F_0}\right)^{\alpha} . \left(\frac{G}{G_0}\right)^{\gamma}$

b. Linear elasticity: $\left(\frac{V}{V_0}\right) = \left(\frac{T}{T_0}\right)^{\beta} . e^{\theta(F-F_0)} \left(\frac{F}{F_0}\right)^{K_2} . \left(\frac{G}{G_0}\right)^{\gamma}$ where, $\alpha = \theta F + K_2$

c. Power elasticity: $\left(\frac{V}{V_0}\right) = \left(\frac{T}{T_0}\right)^{\beta} e^{\left[\frac{K_2}{\theta}.\left(\left(\frac{F}{F_0}\right)^{\theta} - 1\right)\right]} \left(\frac{G}{G_0}\right)^{\gamma}$ where, $\alpha = K_2 \left(\frac{F}{F_0}\right)^{\theta}$

Where V_0 and T_0, F_0, and G_0 represent the respective values in the baseline situation and β, α and γ are the traffic elasticities respectively to toll price, fuel price and GDP variables. Using maximum likelihood estimation the power elasticity provided the best match for the Greek case. The findings reveal that the toll price elasticity is -0.08 for light vehicles and -0.38 for heavy vehicles. GDP elasticity is 0.54 for light vehicles and 1.01 for heavy vehicles. Fuel price elasticity, for prices ranging from 0.8 euros to 2 euros, varies between -0.15 and -0.95 for light vehicles and between -0.1 and -0.7 for heavy vehicles.

Other researchers have also conducted studies on demand elasticity relative to toll prices. Among them, Li (2023) investigated the demand price elasticity of expressway tolls in Shanghai for vehicles with seven seats or fewer, utilizing data from the Shanghai Expressway Electronic Toll Collection (ETC) between 2019 and 2020. The study aimed to ascertain the price elasticity of demand for expressway charges and assess the impact of COVID-19 and the surge in ETC users on traffic flow in Shanghai. The methodology employed Empirical Mode Decomposition (EMD) to analyze the effect of adjusting expressway rates on traffic flow, excluding factors like the ETC user surge and COVID-19 effects. Road flow was categorized by starting and ending points, and the midpoint formula for arc elasticity was employed to calculate demand price elasticity. The results revealed that road users with higher charges are more responsive to price changes. The study emphasized the necessity for region-specific studies on congestion charges, cautioning against hastily applying demand elasticity findings from one region to another. In a separate study, Wang (2017) investigated the road pricing elasticity of freight travel demand in New York State through a Stated Preference Survey (Lee, 1992; McFadden and Train, 2000) of freight carriers using toll roads. The authors designed a survey for logistic company managers, presenting hypothetical toll-increase scenarios and analyzing responses using an ordered probit model. Based on the stated preference survey data, the variables included hypothetical toll-increase amount, company size, payment method, current toll fee, vehicle size, locational characteristics, and commodity type. The road pricing elasticity was determined as -0.37, indicating that a 10% toll increase leads to a 3.7% decrease in vehicle miles traveled (VMT), with variations among truck groups.

3. METHODOLOGY

3.1 Research Design

This study employs a quantitative research design, utilizing econometric analysis to investigate the price elasticity of demand on the Addis Adama Expressway Network. The primary objective is to quantify how changes in toll prices influence traffic volume across the different vehicle categories on the expressway. This design is well-suited to address the research questions through the application of statistical methods to historical data.

3.1.1 Econometric Analysis

The research is structured around multiple regression analysis, a method that allows for the estimation of the relationships between the dependent variable (traffic volume) and several independent variables, including toll prices, fuel prices, and GDP per capita. Additionally, dummy variables are incorporated to account for seasonal effects (monthly variations) and origin/destination pair specific fixed effects, as well as external factors such as security concerns and overweight restrictions.

3.1.2 Study Structure

The study follows a systematic approach, beginning with data collection and preprocessing. This is followed by the specification of regression models that account for the log-transformed continuous variables and dummy variables. The analysis progresses through the estimation of these models using ordinary least squares (OLS) techniques, and concludes with the interpretation of elasticity results, which provide insights into the sensitivity of traffic volume to changes in economic factors.

3.1.3 Research Hypotheses

The following hypotheses present the expected results of the research:

1. Based on a survey conducted by the ETRE, where over 88% of expressway users reported using the expressway for business purposes, we anticipate inelastic and negative elasticity with respect to toll increases. While toll increases may discourage some users, the majority are expected to remain relatively insensitive to these changes since most trips are business-related.

2. Fuel price elasticity is similarly anticipated to be negative and inelastic, as is toll price elasticity.
3. GDP elasticity is anticipated to be positive, as higher GDP typically leads to greater disposable income and increased vehicle ownership, a trend supported by findings in existing literature.

3.1.4 Time Horizon

The analysis is conducted using time-series data provided by ETRE, spanning from July 2019 to June 2023. Data from previous years was not available from the ETRE, and should be considered in future research. This longitudinal approach enables the study to capture the dynamic nature of traffic demand in response to economic changes over this four-year period.

3.2 Study Area

3.2.1 Addis-Adama Toll Road

The Addis -Adama expressway connects the cities of Addis Ababa, Dukem, Bishoftu, Mojo, and Adama, linking the eastern part of the country. Starting from Addis Ababa, it ends at the Adama city exit, leading to the Welanchiti road. The expressway has three lanes in one direction, with a width of 10.5 meters and a 1.5-meter divide, and is fully paved. The road is over 78 kilometers long and includes seven exit and entry toll plazas. It has been opened to traffic and providing service since September 2014.

The Addis-Adama Expressway handles the highest daily traffic among all arterial roads in the country. By the end of 2023, it had processed a total of 67,062,334 vehicles since operations began. The variation in its Average Annual Daily Traffic (AADT) from 2014 to 2023 is illustrated in the Figure 3. 2 below.

On the Addis-Adama Expressway, vehicles are categorized into seven classes based on axle number, axle spacing, tire number, and vehicle height, reflecting their potential impact on road infrastructure. For further clarification, see Appendix A. The tariff varies accordingly by vehicle class. Additionally, the variation in Average Annual Daily Traffic (AADT) across different vehicle classes is illustrated in Figure 3. 3 below.

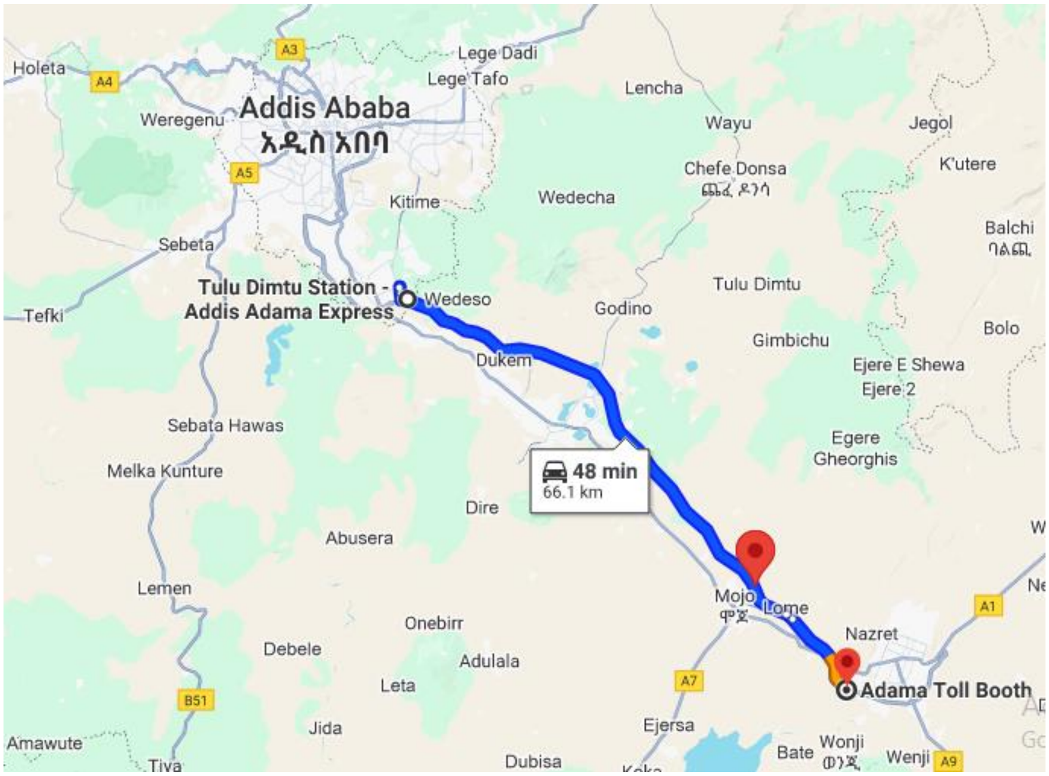

Figure 3. 1 Addis Adama Express Way

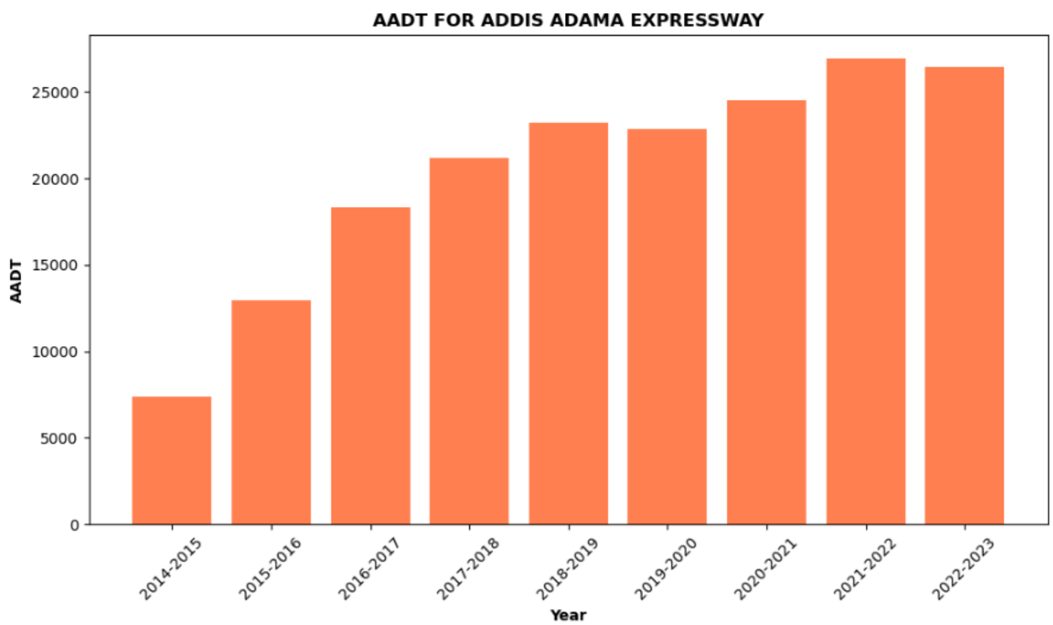

Figure 3. 2 AADT variation along the Addis Adama Expressway

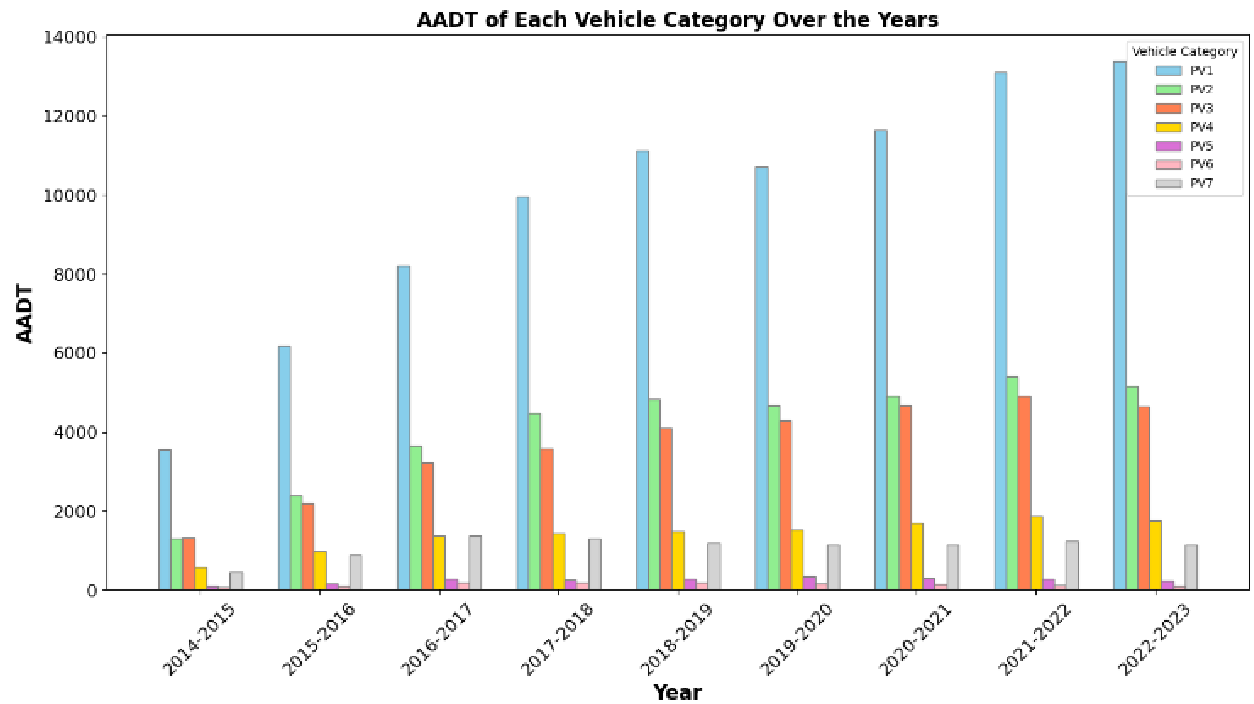

Figure 3. 3 Variation in AADT across the vehicle classes

Based on the survey of 277 respondents who use the Addis-Adama Expressway, 88% travel for work and business purposes, while the remaining trips are for entertainment, family visits, and other reasons. Furthermore, 42% of respondents use the expressway primarily to save time, 22% for comfort, and the rest for reasons such as safety, security, and gaining all the associated benefits of the expressway (ETRE, 2023).

3.3 Data Collection

This study relies on secondary data sources to examine the price elasticity of demand on the Addis Adama Expressway Network.

3.3.1 Traffic Volume Data

The traffic volume data was collected from the ETRE. This dataset contains detailed records of all vehicles that used the Addis-Adama Expressway between July 2019 and June 2023. The data includes the following information for each vehicle:

- **Entrance and Exit Plaza ID:** The identification numbers of the toll plazas where each vehicle entered and exited the expressway.
- **Vehicle Type:** The classification of vehicles based on ETRE categories

- **Distance Traveled:** The total distance covered by each vehicle on the expressway.
- **Entrance and Exit Time:** The specific timestamps when each vehicle entered and exited the expressway.
- **Vehicle Height:** The recorded height of each vehicle.
- **Vehicle Total Weight:** The total weight of each vehicle.

The structure of the raw traffic data is provided in Appendix E.

3.3.2 Toll Price Data

Historical toll price data was obtained from the ETRE, the organization responsible for managing the expressway. The toll prices differ for each vehicle category based on the potential damage each type of vehicle imposes on the expressway. ETRE has made tariff adjustments twice since the expressway began operation. As previously mentioned, these adjustments were based on two approaches: cost recovery and users' perceived benefits. The tariff is different for each vehicle class. This variation in charges is designed to account for differences in vehicle types, which include factors such as axle spacing, axle number, tire number, vehicle height, and their impact on road usage. The toll price data is provided as shown in the Table 3. 1 below.

Table 3. 1 Historical Toll price data

Vehicle category	~ Jun.2022 (Birr/km)	Jun.2022 - Nov.2023 (Birr/km)	Nov.2023 ~ (Birr/km)
1&2	0.76	1.19	1.56
3	0.82	1.35	1.76
4	0.97	1.59	2.07
5,6&7	1.05	1.99	2.59
Avg.	0.90	1.53	2.00

3.3.3 Fuel Price Data

Monthly fuel price data was sourced from the Ethiopian Petroleum and Energy Authority (EPEA).

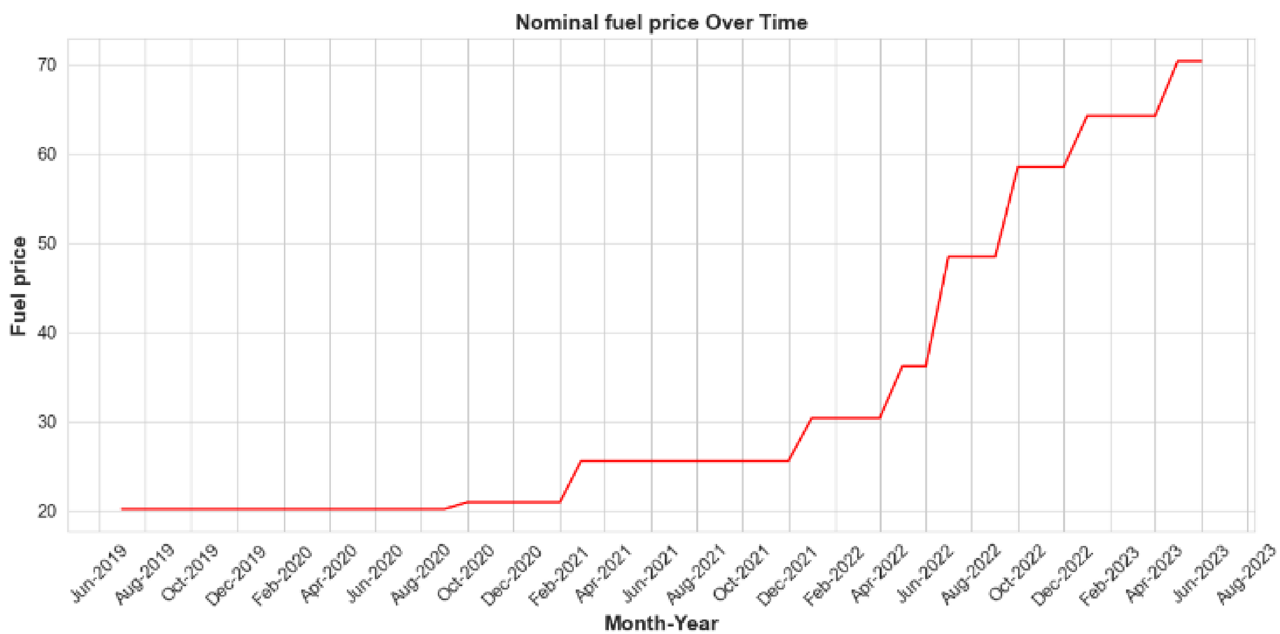

Figure 3. 4 Fuel price data in Ethiopian Birr (ETB) over time

Fuel prices increased significantly starting in December 2021, with a particularly sharp rise following the Ethiopian government's revision of petroleum product subsidies in July 2022. Overall, fuel prices increased by 250% between July 2019 and June 2023.

3.3.4 GDP per Capita

Economic data on GDP per capita was gathered from the website (Macrotrends, n.d.). This data is reported annually and was interpolated to obtain monthly estimates, ensuring alignment with the traffic and price data.

Table 3. 2 Historical GDP/Capita data since 2019

Year	GDP/Capita	Annual Increment
2019	$840	10.83%
2020	$919	9.3%
2021	$925	0.69%
2022	$1028	11.09%
2023	$1034	0.58%

External Factors: Data on external factors such as security issues and the impact of the overweight restriction for trucks were collected from government reports and news archives. These factors are represented as dummy variables in the analysis.

3.4 Data processing

3.4.1 Data Filtering and Aggregation

The raw traffic data, which contains detailed records for each vehicle, was filtered to obtain monthly traffic data for each origin-destination (OD) pair. There are 15 OD pairs, and the data was further categorized by vehicle type. Although the dataset originally included 7 vehicle types, vehicle classes 5-7 were aggregated into a single class (Class 5) due to their similar toll rates and low traffic volume. This resulted in a simplified dataset with 5 distinct vehicle classes.

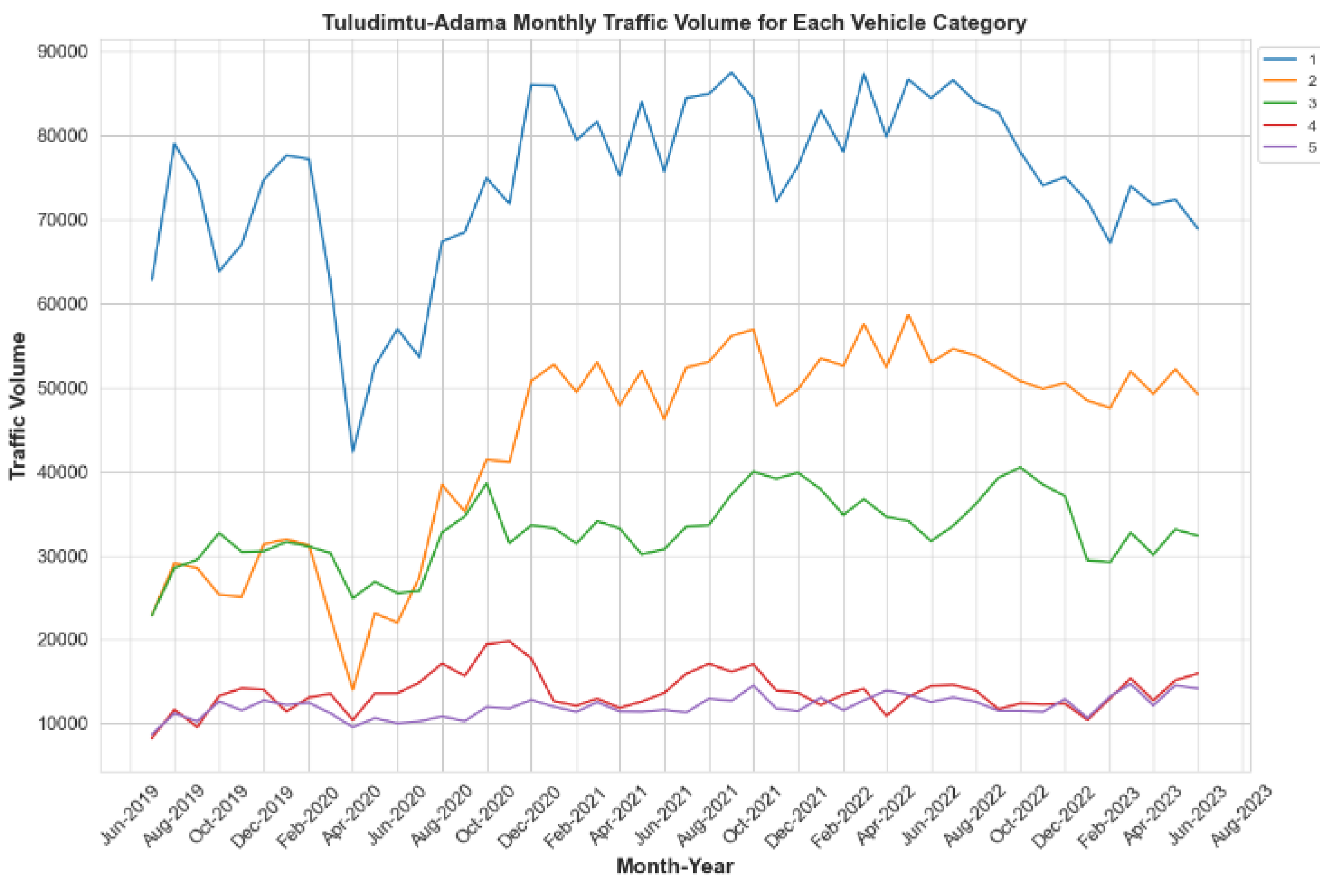

Figure 3. 5 Monthly traffic variation

3.4.2 Data Transformation

GDP per Capita Distribution:

The GDP per capita data, which was originally provided annually, is now allocated to each month to correspond with the traffic and price data. Details of this conversion process can be found in Appendix C. After this monthly distribution, the GDP per capita, initially in USD, is converted to Ethiopian Birr based on the relevant exchange rates for each month.

Real Price Adjustment:

Price elasticity analyses are typically conducted using real prices that have been adjusted for inflation, rather than relying on nominal prices. This approach ensures that the analysis accounts for changes in the purchasing power of money over time, providing a more accurate measure of how price changes affect demand. (Litman, 2023).To account for inflation and ensure that economic variables are expressed in real terms, the GDP per capita, fuel prices, and toll prices were adjusted using the Consumer Price Index (CPI). The CPI data was collected from the Ethiopian Statistical Agency, with the CPI values shown in the Figure 3. 6 below.

Using the CPI values, the nominal value of each monetary variable was converted to its real price as follows:

$$Real\ price = \left(\frac{Nominal\ price}{CPI(\%)}\right) * 100$$

The converted real prices for fuel prices, GDP per Capita and toll prices are shown in the Figure 3. 7, Figure 3. 8, and Figure 3. 9 respectively, below.

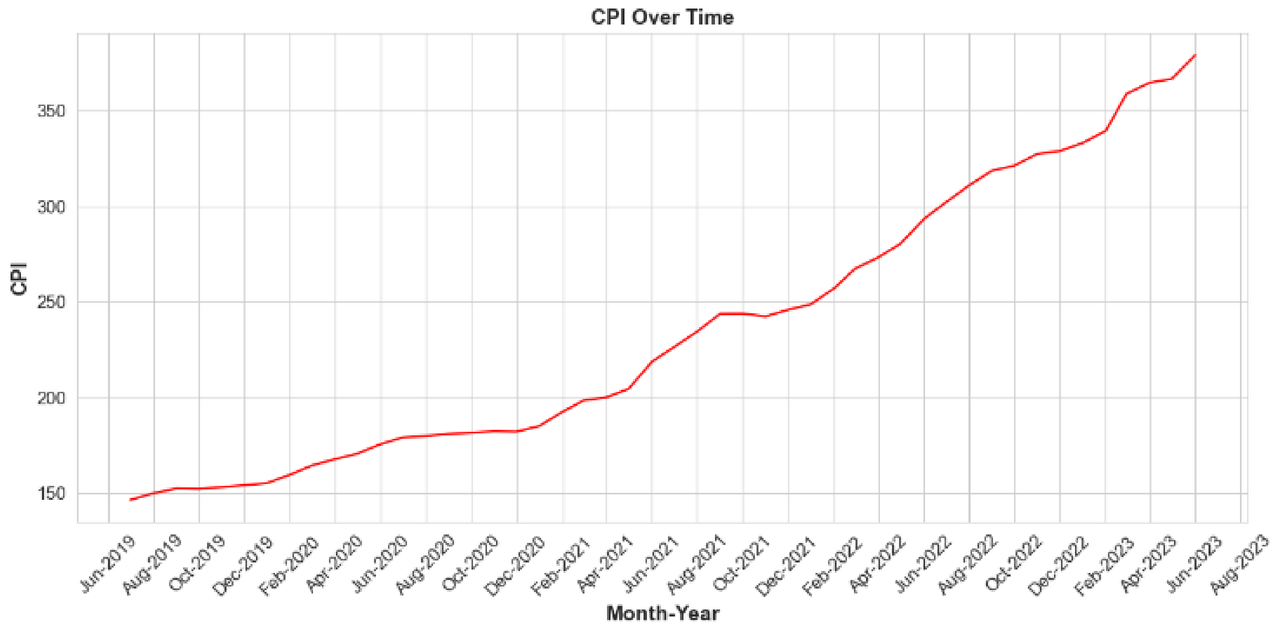

Figure 3. 6 CPI value over time

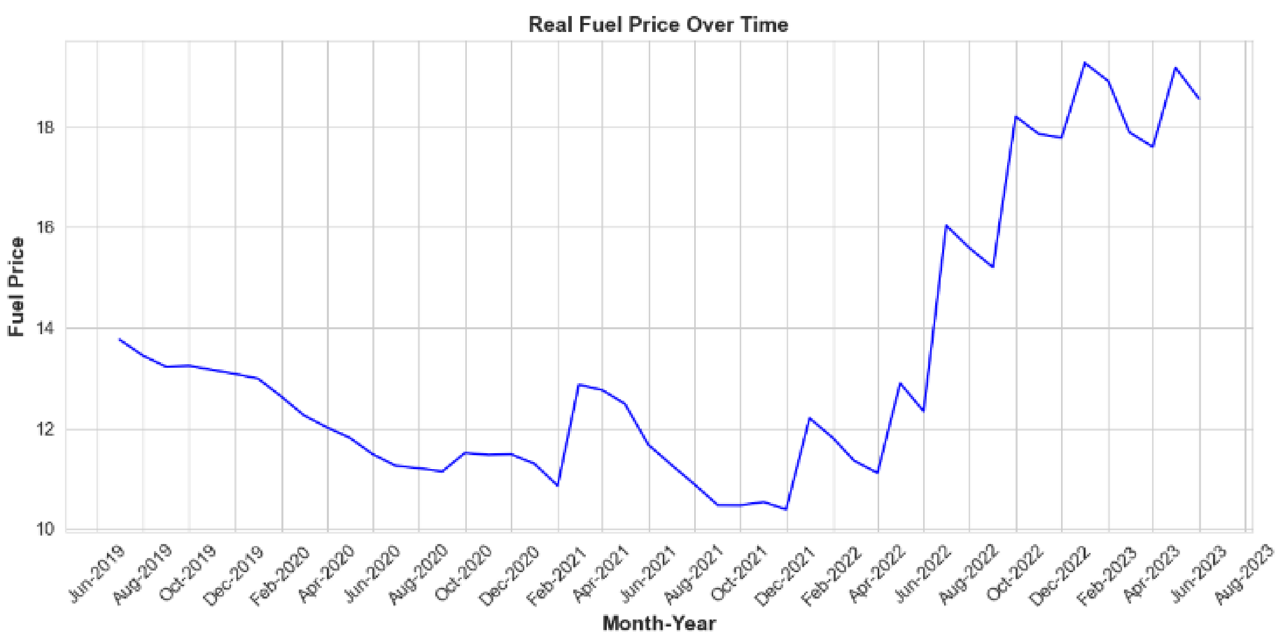

Figure 3. 7 Real fuel price in Ethiopian Birr (ETB) over time

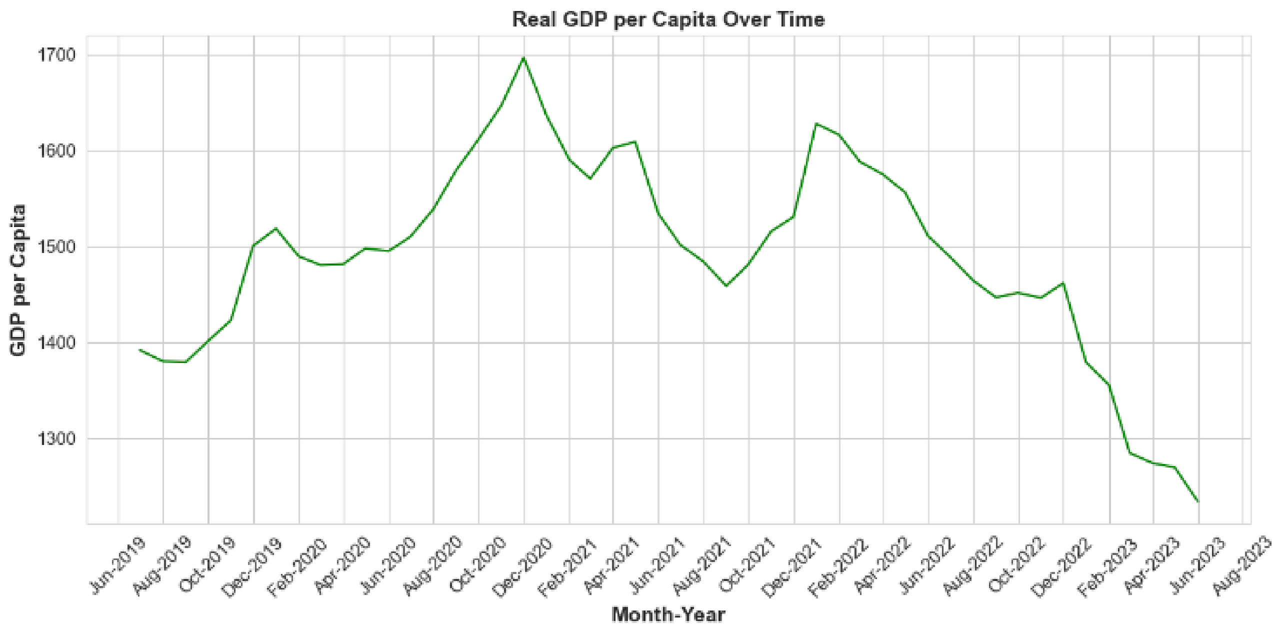

Figure 3. 8 Real GDP/Capita in Ethiopian Birr (ETB) over time

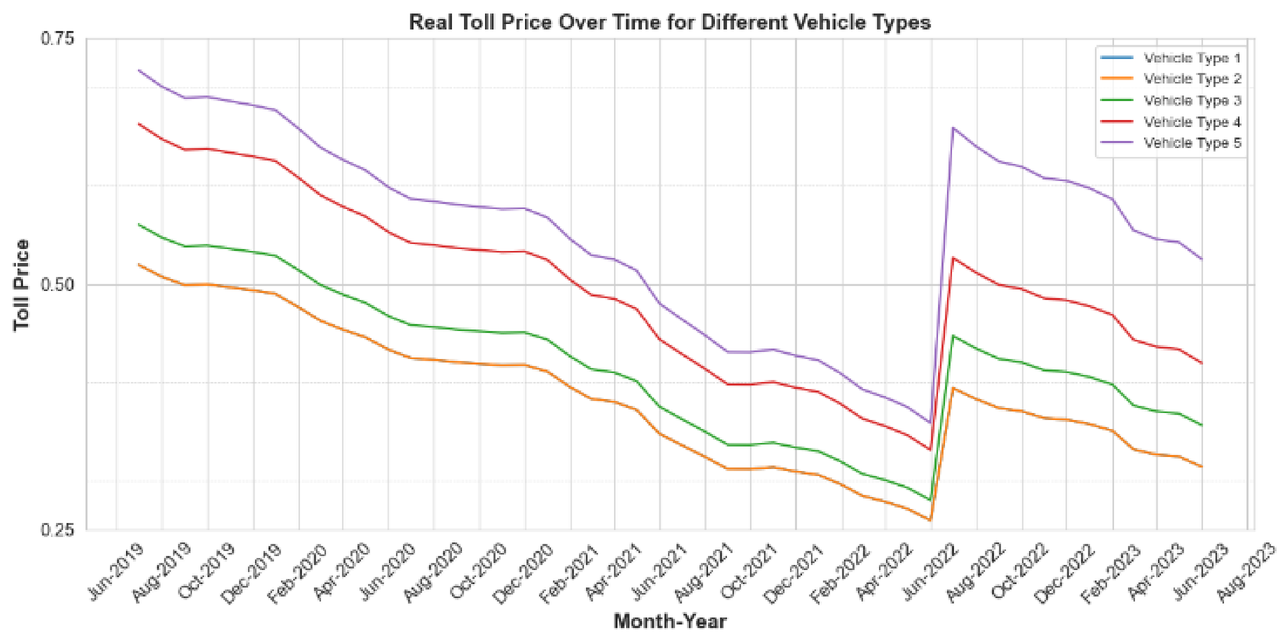

Figure 3. 9 Real toll price in Ethiopian Birr (ETB) over time

3.5 Data Analysis

3.5.1 Demand Function

Based on the literature, travel demand on toll roads is primarily influenced by toll prices, fuel prices, and economic growth. A study conducted by the Ethiopian Toll Road Enterprise (ETRE) also suggests that travel demand on the Addis Ababa-Adama expressway is affected by these factors, along with economic activity and security issues.

Toll Prices and Fuel Costs: Toll prices and fuel costs play a crucial role in determining travel demand on the Addis Ababa-Adama expressway. For public transport, increases in tolls and fuel prices can lead to a temporary halt in operations until tariff adjustments are made to accommodate the higher costs.

Economic Activity: The overall economic activity in the region, including resorts, hotels, industries, and other businesses, also impacts travel demand on the expressway. Due to the lack of detailed data on specific economic activities around the expressway, the country's GDP per capita is used as a proxy to represent the economic activity in the area.

Security Issues: Security concerns have significantly impacted traffic flow on the Addis Ababa-Adama expressway. Due to safety issues, certain routes, such as the Adama-Minjar road, have been temporarily closed, leading to reduced travel. Additionally, the fear of attacks, particularly during night travel, has further decreased the volume of vehicles on these roads. These security concerns have also led to a decline in resort and hotel activities in Sodere, Bishoftu, Adama, and Mojo, contributing to an overall reduction in traffic on the expressway.

Overburden Restriction: Since 2021, a regulation has been in place restricting the overloading of heavy trucks. This has led to a reduction in the volume of trucks using the expressway, particularly for vehicle classes PV3 to PV5. We attempted to capture this effect in the model using dummy variables.

Therefore, the demand function can be expressed as:

$$D = f(T, F, G, S, O)$$

Where:

- D represents travel demand,

- T represents toll price,
- F represents fuel price,
- G represents GDP/Capita,
- S represents security and,
- O represents the impact of overburden restriction.

3.5.2 Demand Model

The travel demand model for the Addis Ababa-Adama expressway can be expressed in a multiplicative form as follows:

$$V_{it} = k.T_{it}^{\beta} F_{it}^{\alpha} G_{it}^{\gamma} V_{it-1}^{\delta}$$

Where:

- V_{it} represents volume of transport travel at time t
- T_{it} represents toll price at time t
- F_{it} represents fuel price at time t
- G_{it} represents GDP/Capita at time t
- V_{it-1} represents lag dependent variable at time t-1
- α, β, γ, δ are elasticity parameters to be estimated.
- K is constant

To facilitate estimation and interpretation, the model is transformed into its logarithmic form. Taking the natural logarithm of both sides, we obtain:

$$\ln V_{it} = \ln k + \alpha \ln T_{it} + \beta \ln F_{it} + \gamma \ln G_{it} + \delta \ln V_{it-1} + \rho S + \sigma O + \sum_{i=2}^{12} \theta_i Z_i + \sum_{j=2}^{15} \mu_i OD_i$$

Where:

- $\ln(V_{it})$ is the natural logarithm of the volume of transport travel.
- $\ln(T_{it})$ is the natural logarithm of the toll price.

- $\ln(F_{it})$ is the natural logarithm of the fuel price.
- $\ln(G_{it})$ is the natural logarithm of GDP per capita.
- $\ln(V_{i(t-1)})$ is the natural logarithm of the lagged volume of transport travel.
- S is a dummy variable for security issues, capturing the impact of security-related disruptions on travel demand.
- O is a dummy variable representing the impact of overburden, reflecting the effects of restrictions on carrying overburden on travel behavior.
- Z_i represents dummy variables for monthly variations to account for seasonal effects and other periodic fluctuations.
- OD_i is a dummy variable used to capture the variation among OD pairs.

This model provides a comprehensive framework to understand how travel demand is influenced by various factors, including toll prices, fuel costs, economic conditions, security issues, and extraordinary events like overburden restriction on trucks.

The above equation can be modeled using multiple regression equation.

3.5.3 Multiple Regression

A regression model that contains more than one explanatory variable is called a multiple regression model. A multiple regression model that might describe this relationship is:

$$y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon$$

Where y is the dependent variable $X_1, X_2, \dots, X_n$ are dependent variables and the parameters $\beta_0, \beta_1, \dots, \beta_n$ are regression coefficients.

The independent variables can be either quantitative or qualitative. Quantitative variables are measured on a numerical scale, while qualitative or categorical variables can take binary values, typically 1 or 0. These categorical variables are also referred to as dummy or indicator variables.

Methods for estimating model parameters are included in Appendix D.

3.5.4 Significance of Regression

The coefficient of multiple determination R^2 is a statistic used to assess the fit of a multiple regression model. It is calculated as:

$$R^2 = \frac{SS_R}{SS_T} = 1 - \frac{SS_E}{SS_T}$$

Where SS_E is the sum of squares of errors and SS_T is the total sum of squares. R^2 indicates the proportion of variability in the response variable that is explained by the model. An R^2 value close to 1 suggests that the model explains a large proportion of the variability in the response. For example, an R^2 of 0.9811 means that the model accounts for 98% of the variability in the response.

However, R^2 has a limitation: it never decreases when a new variable is added to the model, which can make it difficult to assess whether the new variable significantly improves the model.

To address this, the adjusted R^2 statistic is used, which adjusts R^2 for the number of predictors in the model. The formula for adjusted R^2 is:

$$R^2_{adj} = 1 - \frac{SS_E/(n-p)}{SS_T/(n-1)}$$

Where:

- n is the number of observations,
- p is the number of predictors (including the intercept).

Adjusted R^2 increases only when the inclusion of a new predictor reduces the residual mean square error. This makes it a more reliable measure for comparing and evaluating different regression models, as it penalizes the inclusion of unnecessary variables, helping to guard against overfitting (Montgomery, 2014).

3.6 Software Used

In analyzing travel demand on the Addis Ababa-Adama expressway, Python was used to build a multiple regression model with the statsmodels library. The dataset included variables such as toll price, fuel price, GDP per capita, lagged transport volume, and dummy variables for security and overweight restriction impacts. Data preparation and visualization were carried out using pandas and numpy, while matplotlib and seaborn helped create plots to illustrate the model's performance. This approach provided a clear understanding of how toll prices, fuel costs, economic activity, security issues, and the overweight restriction affected traffic flow.

4. RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the findings of the analysis on toll price elasticity for the Ethiopian expressway network. The results are structured to provide a detailed understanding of how changes in toll prices influence traffic demand across different vehicle types. Key aspects include descriptive statistics of the data, estimation results from the ARDL model, and an in-depth discussion of toll price elasticity estimates for various vehicle categories. The chapter also explores the impact of external factors, such as GDP and fuel prices, on traffic demand and elasticity. Additionally, comparisons with previous studies are made to contextualize the findings within the broader literature. The implications of these results for toll pricing policies are discussed, providing insights that can inform future decision-making on the Ethiopian expressway network.

The subsequent sections detail the analytical results, highlighting significant patterns, interpreting key elasticity estimates, and discussing the broader policy implications of the findings.

Building on this overview, section 4.2 to 4.3 explore the specific results for each vehicle category, combining descriptive statistics and model estimation outcomes. This integrated approach provides a comprehensive analysis of how toll price changes and external factors like GDP and fuel prices impact traffic demand. The detailed results offer essential insights into the toll price elasticity across different vehicle types, setting the stage for a deeper discussion on the implications of these findings.

4.2 Model Results and Discussion

4.2.1 Vehicle Category 1 (PV1)

This category includes small cars, such as automobiles, with 2 axles, 4 tires, a vehicle height of less than 1.3 meters, and an axle spacing of less than 2.4 meters. Vehicles in this category account for approximately 50% of the total traffic volume on the Addis Adama Expressway. The variation in Average Annual Daily Traffic (AADT) and monthly traffic flow for these vehicles from 2019 to 2023 is illustrated in Figure 4. 1 and Figure 4. 2 below. As shown in the figure, the Average Annual Daily Traffic (AADT) increased by 8.73% in 2020, 12.62% in 2021, and 2.05% in 2022. However, there was a significant decrease of 24.60% in 2023. According to ETRE (2023), this decline is primarily due to security issues and a rise in commodity prices, which have considerably slowed economic activity in the hotel industry in Bishoftu, Adama, Mojo, Sodere, and Langano. Consequently, fewer people have traveled for recreational purposes due to fear to get out of Addis, leading to a reduction in the traffic flow of Vehicle Category 1 (PV1) on the Addis Adama Expressway. This volume change is captured in the model by taking out one year data using a dummy variable called "Security."

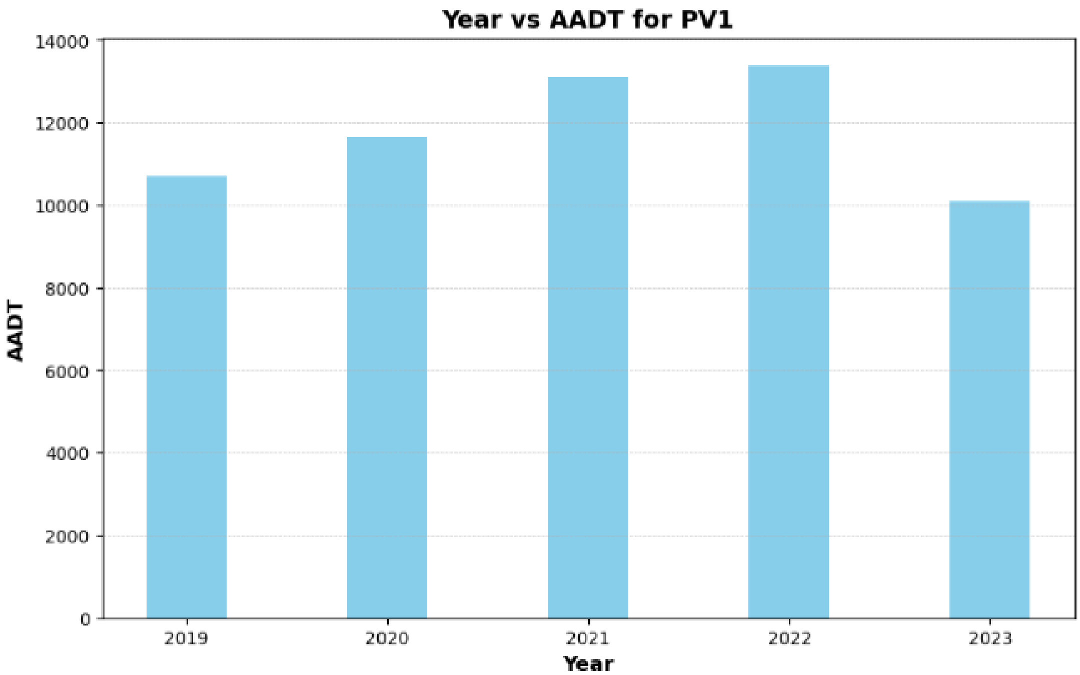

Figure 4. 1 Historical AADT data for PV1

The ETRE toll payment mechanism is based on cost recovery. Vehicle Class 1 (PV1) pays a lower toll relative to other classes because they cause less damage. Until June 2022, the toll fee was 0.76 Birr/km, but it was increased to 1.193 Birr/km, a 56.97% rise. Meanwhile, fuel prices have increased significantly since December 2021, rising by over 175% up to June 2023. This sharp increase is due to the Ethiopian government's decision to cease subsidizing private cars and the rising global fuel prices.

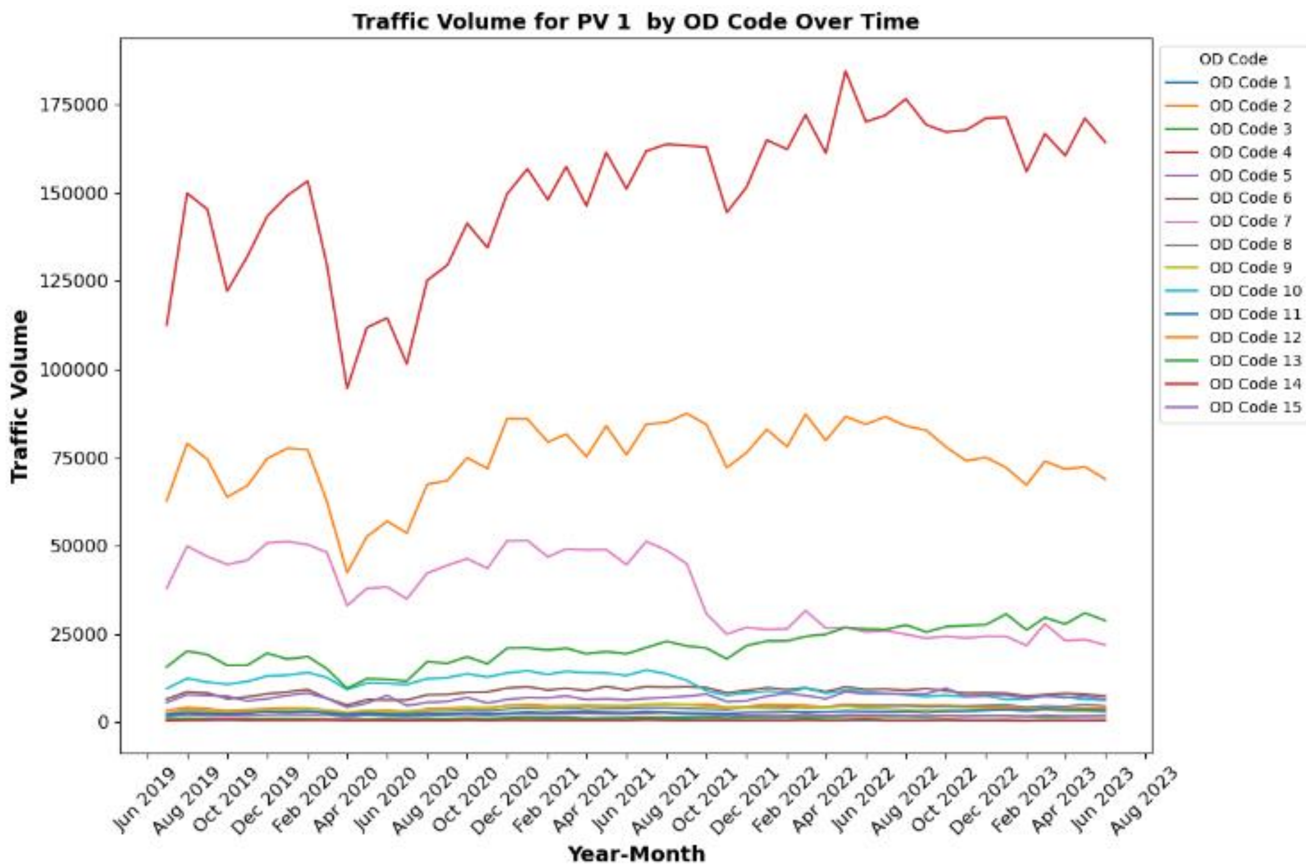

Figure 4. 2 Historical monthly traffic data for PV1

For the analysis, all monetary costs—toll price, fuel price, and GDP per capita—are adjusted to real prices from nominal prices using the Consumer Price Index (CPI), with 2016 as the base year. Thus, all monetary variables are converted to 2016 prices. The variation between real and nominal prices of tolls and fuel is illustrated in Figure 4. 3. In the model, the variations in the real prices of tolls, fuel, and GDP per capita are captured by the respective variables: toll, fuel, and GDP per capita.

In the model, toll price, fuel price, GDP per capita, and one lag of traffic volume are used as independent variables, while traffic volume is the dependent variable. To capture monthly variations, 11 dummy variables are included for each month. With 15 origin-destination (OD) pairs, 14 dummy variables are used to account for variations among each OD pair. As mentioned earlier, security issues are also captured using a dummy variable. The final regression output is presented in Table 4. 1 below.

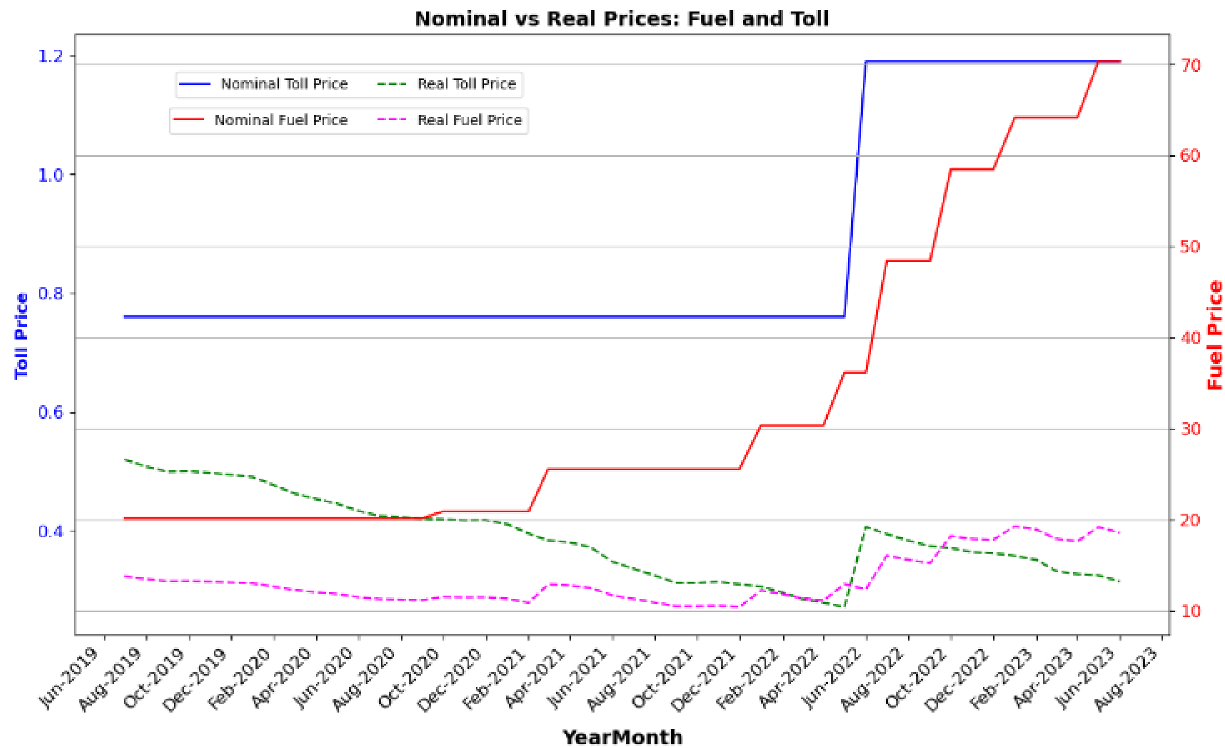

Figure 4. 3 Nominal vs Real toll and fuel price data for PV1

From Table 4. 1, the short-term elasticity of toll price for PV1 is -0.2521, indicating that a 1% increase in toll price results in a 0.2521% decrease in traffic volume. The negative sign aligns with expectations, reflecting the discouraging effect of higher tolls. The long-term elasticity is calculated as -0.2521 / (1 - 0.8032) = -1.2752, showing that the impact of toll price changes is more pronounced over time.

The fuel price elasticity is 0.1966, meaning that a 1% increase in fuel price leads to a 0.1966% increase in traffic volume. Although this positive relationship might seem unexpected at first, it is consistent with the expressway's cost-saving benefits. ETRE studies show that using the expressway can save 1.48 Birr per kilometer in fuel costs for PV1 vehicles compared to alternative, non-tolled roads, attracting more traffic when fuel prices rise. The long term elasticity of fuel price elasticity is 0.9889, which is lower than the toll price elasticity.

The elasticity of GDP per capita is 0.3469, indicating that a 1% increase in GDP per capita results in a 0.3469% increase in traffic volume.

Table 4. 1 Model result summary for PV1

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      ln_Traffic_Volume   R-squared:                       0.997
Model:                            OLS   Adj. R-squared:                  0.997
Method:                 Least Squares   F-statistic:                     4603.
Date:                Thu, 19 Sep 2024   Prob (F-statistic):               0.00
Time:                        13:39:39   Log-Likelihood:                 438.25
No. Observations:                 420   AIC:                            -814.5
Df Residuals:                     389   BIC:                            -689.2
Df Model:                          30
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                    -1.4053      0.850     -1.653      0.099      -3.077       0.266
ln_R_Toll_Price          -0.2521      0.066     -3.792      0.000      -0.383      -0.121
ln_R_Fuel_Price           0.1966      0.061      3.217      0.001       0.076       0.317
ln_R_GDP_Capita           0.3469      0.106      3.280      0.001       0.139       0.555
Security                 -0.0456      0.018     -2.578      0.010      -0.080      -0.011
ln_Traffic_Volume_lag     0.8032      0.030     27.045      0.000       0.745       0.862
OD_2                      0.7691      0.108      7.153      0.000       0.558       0.980
OD_3                      0.4727      0.073      6.476      0.000       0.329       0.616
OD_4                      0.0464      0.024      1.916      0.056      -0.001       0.094
OD_5                      0.4868      0.070      6.956      0.000       0.349       0.624
OD_6                      0.8250      0.107      7.732      0.000       0.615       1.035
OD_7                      1.1081      0.143      7.729      0.000       0.826       1.390
OD_8                      0.5737      0.074      7.786      0.000       0.429       0.719
OD_9                      0.4508      0.066      6.843      0.000       0.321       0.580
OD_10                     0.6612      0.091      7.243      0.000       0.482       0.841
OD_11                     0.2013      0.075      2.677      0.008       0.053       0.349
OD_12                     1.3943      0.177      7.874      0.000       1.046       1.742
OD_13                     1.1168      0.141      7.944      0.000       0.840       1.393
OD_14                     1.1193      0.174      6.432      0.000       0.777       1.461
OD_15                     0.7116      0.092      7.772      0.000       0.532       0.892
Month_2                  -0.0804      0.023     -3.501      0.001      -0.126      -0.035
Month_3                   0.0807      0.022      3.693      0.000       0.038       0.124
Month_4                  -0.0450      0.023     -1.962      0.050      -0.090    8.99e-05
Month_5                   0.0426      0.021      1.992      0.047       0.001       0.085
Month_6                  -0.0227      0.023     -0.993      0.322      -0.068       0.022
Month_7                   0.0758      0.026      2.862      0.004       0.024       0.128
Month_8                   0.0353      0.027      1.303      0.193      -0.018       0.089
Month_9                   0.0132      0.028      0.474      0.636      -0.042       0.068
Month_10                  0.0205      0.025      0.828      0.408      -0.028       0.069
Month_11                 -0.0913      0.024     -3.738      0.000      -0.139      -0.043
Month_12                  0.0430      0.024      1.767      0.078      -0.005       0.091
==============================================================================
Omnibus:                       64.066   Durbin-Watson:                   1.783
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              692.759
Skew:                           0.051   Prob(JB):                    3.71e-151
Kurtosis:                       9.291   Cond. No.                     2.40e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.4e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Overall, the model's high goodness of fit, with an adjusted R^2 of 99.7%, indicates that the included variables explain nearly all the variation in traffic volume for PV1. The strong statistical significance at the 5% level across all variables supports the reliability and robustness of the model's results. The inclusion of dummy variables enhances the model fit and significance levels.

4.2.2 Vehicle Category 2 (PV2)

This category includes minibuses with 2 axles, 4 tires, a vehicle height of more than 1.3 meters, and an axle spacing of more than 2.4 meters. Vehicles in this category account for approximately 20% of the total traffic volume on the Addis Adama Expressway. The variation in Average Annual Daily Traffic (AADT) and monthly traffic flow for these vehicles from 2019 to 2023 is illustrated in Figure 4. 4 and Figure 4. 5 below. As shown in the figures, AADT increased by 4.75% in 2020 and 10.52% in 2021. However, the volume decreased by 4.73% in 2022 and 27.37% in 2023. Similar to Vehicle Category 1, this decline is primarily due to security issues and rising commodity prices.

The model for PV2 uses toll price, fuel price, GDP per capita, and one lag of traffic volume as independent variables, with traffic volume as the dependent variable. It includes 11 monthly dummy variables, 14 OD pair dummies, and a security dummy to capture variations. The regression results are shown in Table 2.

From Table 4. 2, the short-term elasticity of toll price for PV2 is -0.3542, which means that a 1% increase in toll price results in a 0.3542% decrease in traffic volume. This negative value aligns with economic theory, as higher toll prices discourage road use. The long-term elasticity of toll price is calculated as -0.3542 / (1 - 0.7280) = -1.302, suggesting that in the long run, the traffic volume's response to toll price changes is more pronounced. This higher long-term elasticity indicates that over time, drivers adjust more significantly to toll price increases, such as by finding alternative routes or reducing trips. Comparing PV2 to vehicle category 1 (PV1), PV2 shows greater sensitivity to toll price changes, implying that users of PV2 vehicles are more responsive to price fluctuations than those of PV1.

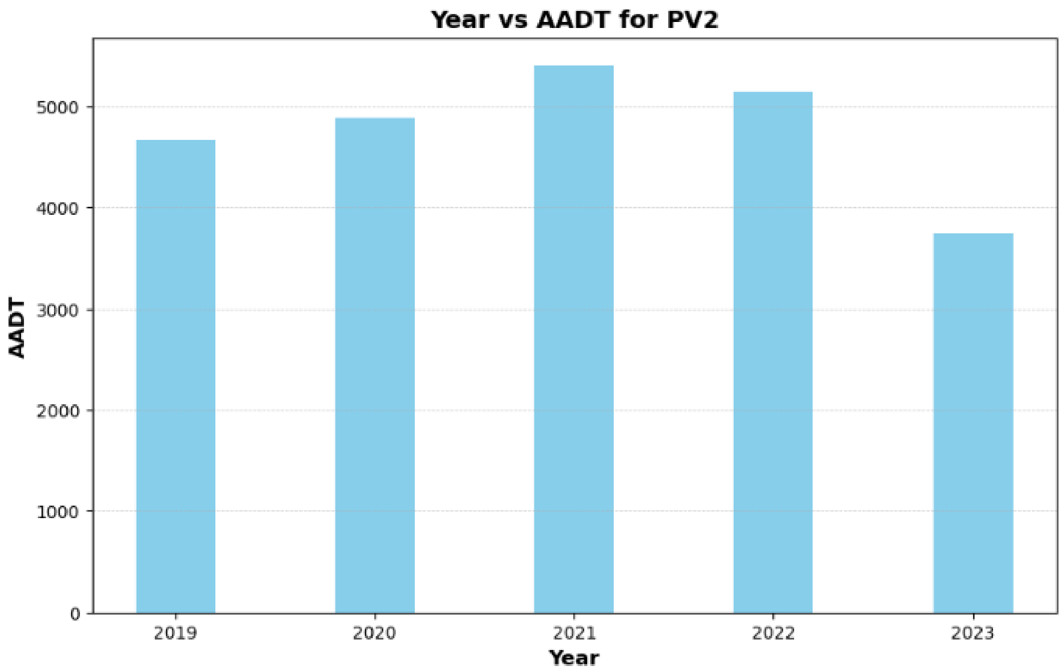

Figure 4. 4 Historical AADT data for PV2

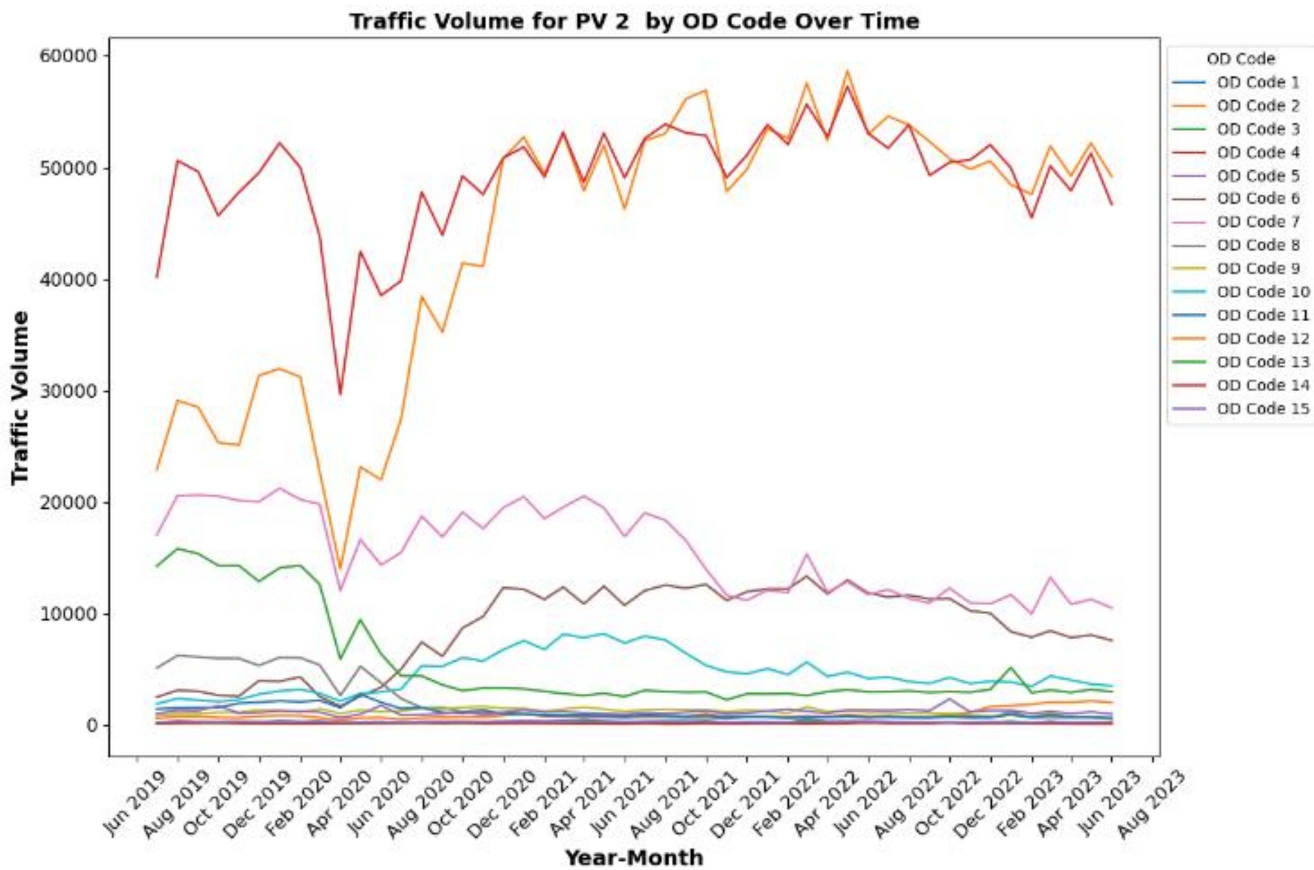

Figure 4. 5 Historical monthly traffic data for PV2

The fuel price elasticity for PV2 is 0.3234, indicating that a 1% increase in fuel price leads to a 0.3234% increase in traffic volume. This positive elasticity may seem counterintuitive, but it makes sense in the context of the expressway's cost-saving benefits. According to ETRE studies, using the expressway can save 1.48 Birr per kilometer in fuel costs for PV2 vehicles compared to alternative, non-tolled roads. This cost advantage attracts more traffic to the expressway when fuel prices rise, as drivers seek to maximize savings on fuel expenses, leading to an increase in expressway usage.

The GDP per capita elasticity of 0.5386 indicates that a 1% increase in GDP per capita results in a 0.5386% increase in traffic volume. This positive relationship aligns with expectations, as rising income levels generally lead to increased vehicle ownership and road usage, reflecting higher demand for travel.

The negative coefficient for the security variable suggests that security concerns negatively impact road usage. This indicates that when security issues are present, they deter drivers from using the expressway, reflecting the broader impacts of instability on transportation demand.

Overall, the model's high goodness of fit, with an adjusted R^2 of 99.4%, indicates that the included variables explain nearly all the variation in traffic volume for PV2. This strong statistical significance at the 5% level across all variables supports the reliability and robustness of the model's results.

Table 4. 2 Model result summary for PV2

OLS Regression Results

Dep. Variable:	ln_Traffic_Volume	R-squared:	0.994
Model:	OLS	Adj. R-squared:	0.994
Method:	Least Squares	F-statistic:	2174.
Date:	Thu, 19 Sep 2024	Prob (F-statistic):	0.00
Time:	22:17:01	Log-Likelihood:	213.86
No. Observations:	405	AIC:	-365.7
Df Residuals:	374	BIC:	-241.6
Df Model:	30		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-2.6907	1.554	-1.731	0.084	-5.747	0.365
ln_R_Toll_Price	-0.3542	0.138	-2.565	0.011	-0.626	-0.083
ln_R_Fuel_Price	0.3234	0.122	2.642	0.009	0.083	0.564
ln_R_GDP_Capita	0.5386	0.192	2.801	0.005	0.161	0.917
Security	-0.0855	0.033	-2.571	0.011	-0.151	-0.020
ln_Traffic_Volume_lag	0.7280	0.037	19.423	0.000	0.654	0.802
OD_2	0.9193	0.190	4.850	0.000	0.547	1.292
OD_3	0.3129	0.139	2.245	0.025	0.039	0.587
OD_4	-0.1427	0.049	-2.885	0.004	-0.240	-0.045
OD_5	0.3742	0.119	3.136	0.002	0.140	0.609
OD_6	1.4045	0.191	7.340	0.000	1.028	1.781
OD_7	1.5384	0.216	7.127	0.000	1.114	1.963
OD_8	0.5002	0.089	5.616	0.000	0.325	0.675
OD_9	0.4787	0.073	6.578	0.000	0.336	0.622
OD_10	0.9709	0.128	7.584	0.000	0.719	1.223
OD_11	0.0999	0.115	0.871	0.384	-0.126	0.326
OD_12	2.0379	0.280	7.285	0.000	1.488	2.588
OD_13	1.1789	0.198	5.954	0.000	0.790	1.568
OD_14	1.4537	0.207	7.014	0.000	1.046	1.861
OD_15	0.7091	0.114	6.202	0.000	0.484	0.934
Month_2	-0.1461	0.039	-3.785	0.000	-0.222	-0.070
Month_3	0.1710	0.045	3.761	0.000	0.082	0.260
Month_4	-0.0477	0.041	-1.164	0.245	-0.128	0.033
Month_5	0.0255	0.037	0.689	0.491	-0.047	0.098
Month_6	-0.0770	0.040	-1.932	0.054	-0.155	0.001
Month_7	0.1146	0.048	2.379	0.018	0.020	0.209
Month_8	0.0264	0.049	0.536	0.592	-0.070	0.123
Month_9	0.0207	0.051	0.408	0.684	-0.079	0.120
Month_10	0.0920	0.043	2.118	0.035	0.007	0.177
Month_11	-0.1551	0.043	-3.632	0.000	-0.239	-0.071
Month_12	0.0787	0.042	1.852	0.065	-0.005	0.162

Omnibus:	74.350	Durbin-Watson:	2.070
Prob(Omnibus):	0.000	Jarque-Bera (JB):	287.961
Skew:	0.754	Prob(JB):	2.95e-63
Kurtosis:	6.845	Cond. No.	2.40e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.4e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

4.2.3 Vehicle Category 3 (PV3)

This category includes medium bus and medium truck with 2 axles, 6 tires. Vehicles in this category account for approximately 18% of the total traffic volume on the Addis Adama Expressway. The variation in Average Annual Daily Traffic (AADT) and monthly traffic flow for these vehicles from 2019 to 2023 is illustrated in Figure 4. 6 and Figure 4. 7 below. As shown in the figure, the Average Annual Daily Traffic (AADT) increased by 9.21% in 2020 and 4.73% in 2021, and decreased by 5.01% in 2022 and by 20.87% in 2023. This shows the traffic decreased at decreasing rate of -2.99%.

This decline is mainly caused by security issues and strict enforcement of weight restrictions by the toll enterprise. Security concerns have reduced travel for recreation and night trips, lowering traffic volume. Additionally, the enforcement of weight restrictions has led to a decrease in medium truck volumes, as these trucks prefer non-tolled roads where such restrictions do not exist, especially on the Addis-Modjo OD pair. These changes in traffic volume are captured in the model using dummy variables for "Security" and "Overload."

As described earlier, the ETRE toll payment mechanism for the expressway is based on cost recovery, with Vehicle Class 3 (PV3) paying higher tolls than Classes 1 and 2 (PV1 & PV2) due to the greater damage they cause. Until June 2022, the toll fee was 0.82 Birr/km, but it was increased to 1.35 Birr/km, a 64.63% rise. Additionally, fuel prices have surged by over 175% from December 2021 to June 2023, following the Ethiopian government's decision to end fuel subsidies and rising global fuel prices. For analysis, all monetary costs, including toll price, fuel price, and GDP per capita, are adjusted to real prices using the Consumer Price Index (CPI) with 2016 as the base year, ensuring that the values reflect the purchasing power relative to 2016. Figure 4. 8 illustrates the differences between real and nominal prices of tolls and fuel, with these variations captured in the model through the variables for toll, fuel, and GDP per capita.

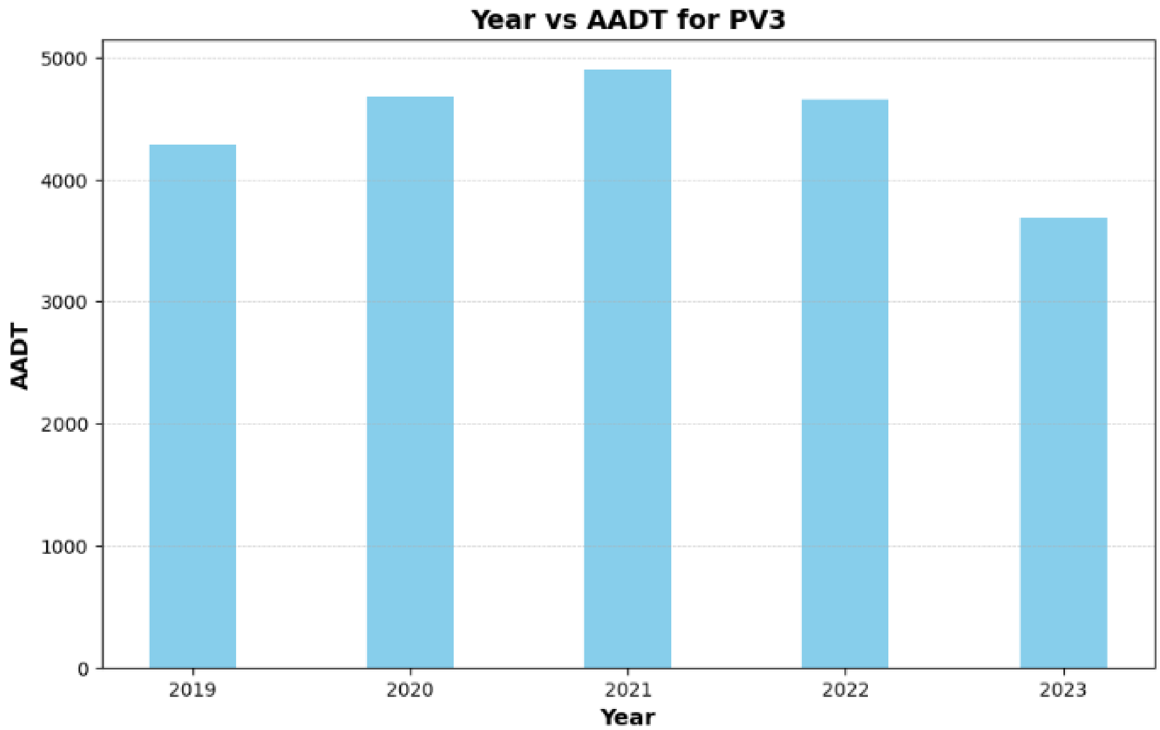

Figure 4. 6 Historical AADT data for PV3

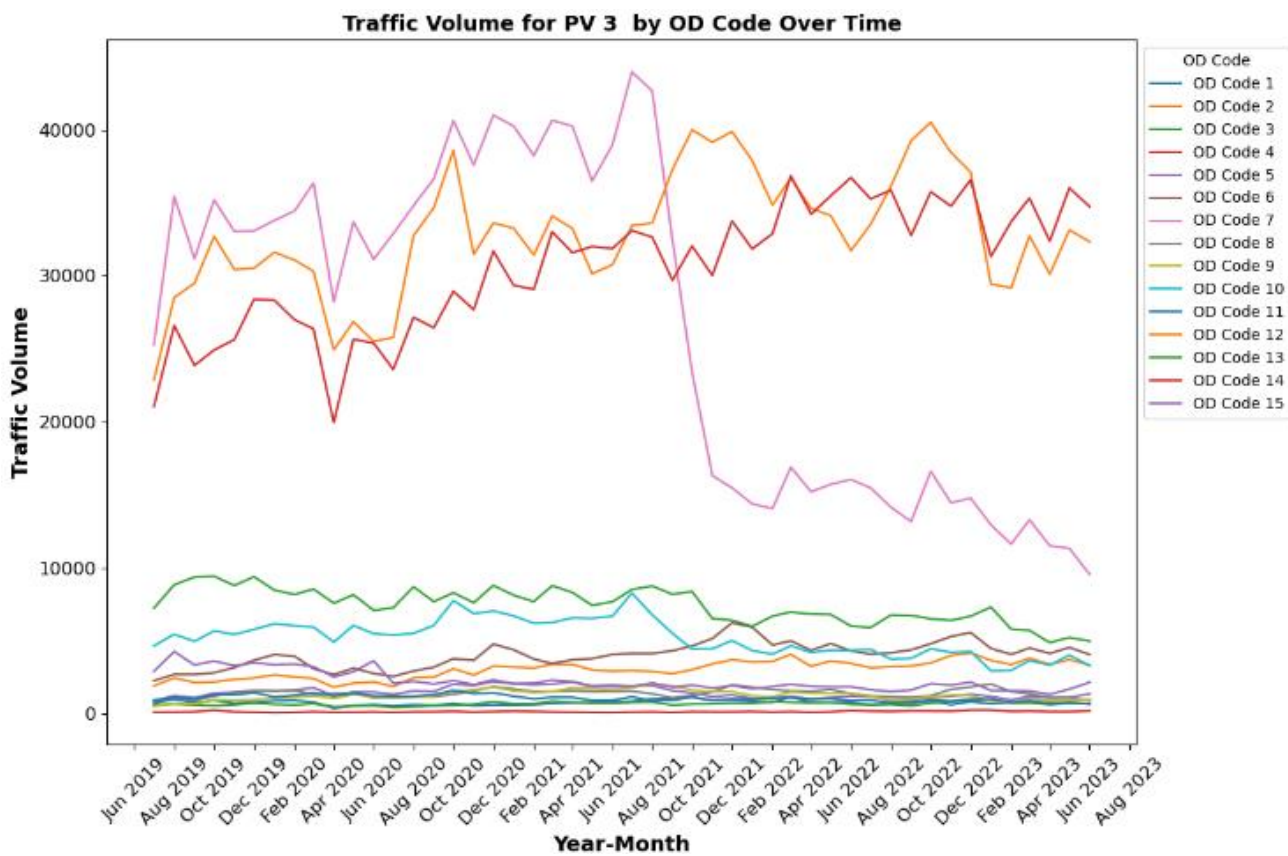

Figure 4. 7 Historical monthly traffic data for PV3

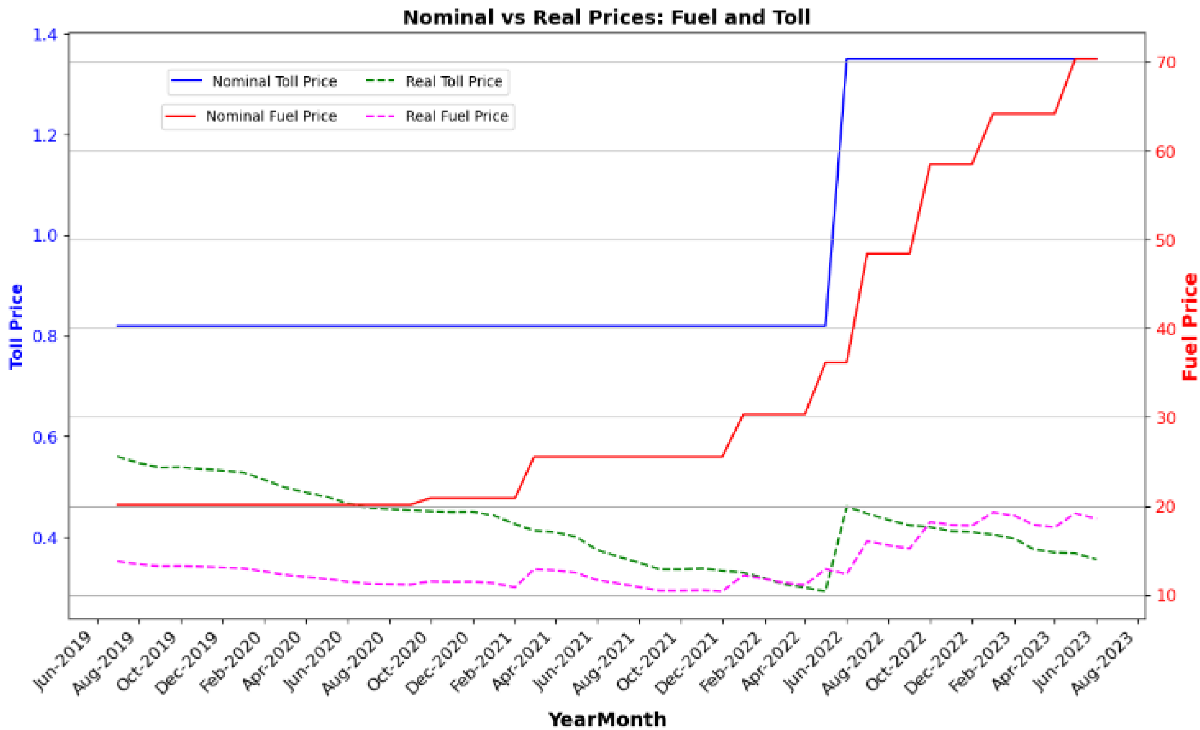

Figure 4. 8 Nominal vs Real toll and fuel price data for PV3

From Table 4. 3.,the short-term elasticity of toll price for PV is -0.4565, indicating that a 1% increase in toll price results in a 0.4565% decrease in traffic volume, with the long-term elasticity rising to 2.02, showing a stronger response over time. This suggests that PV3 is more sensitive to toll price changes compared to PV1 and PV2. The fuel price elasticity of 0.4948 indicates that a 1% increase in fuel price leads to a 0.4948% increase in traffic volume, likely due to the expressway's fuel-saving benefits, as using the expressway saves 2.96 Birr per kilometer compared to non-tolled roads, attracting more traffic as drivers seek to save on fuel. The GDP per capita elasticity of 0.7272 aligns with expectations, as higher income levels typically lead to increased vehicle ownership and road usage. With an adjusted R^2 of 99.4%, the model demonstrates that the included variables account for nearly all the variation in traffic volume for PV3, with strong statistical significance supporting the model's reliability.

Table 4. 3 Model result summary for PV3

OLS Regression Results

Dep. Variable:	ln_Traffic_Volume	R-squared:	0.994
Model:	OLS	Adj. R-squared:	0.994
Method:	Least Squares	F-statistic:	2108.
Date:	Fri, 20 Sep 2024	Prob (F-statistic):	0.00
Time:	21:02:52	Log-Likelihood:	319.24
No. Observations:	405	AIC:	-574.5
Df Residuals:	373	BIC:	-446.4
Df Model:	31		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-4.3551	1.505	-2.893	0.004	-7.315	-1.395
ln_R_Toll_Price	-0.4565	0.136	-3.357	0.001	-0.724	-0.189
ln_R_Fuel_Price	0.4948	0.140	3.539	0.000	0.220	0.770
ln_R_GDP_Capita	0.7272	0.184	3.955	0.000	0.366	1.089
OverLoad	-0.2410	0.076	-3.151	0.002	-0.391	-0.091
Security	-0.1132	0.033	-3.441	0.001	-0.178	-0.049
ln_Traffic_Volume_lag	0.7743	0.031	24.682	0.000	0.713	0.836
OD_2	0.9083	0.189	4.809	0.000	0.537	1.280
OD_3	0.4178	0.142	2.937	0.004	0.138	0.698
OD_4	-0.3336	0.061	-5.439	0.000	-0.454	-0.213
OD_5	0.4451	0.116	3.823	0.000	0.216	0.674
OD_6	0.8248	0.149	5.554	0.000	0.533	1.117
OD_7	1.3730	0.214	6.403	0.000	0.951	1.795
OD_8	0.3346	0.080	4.164	0.000	0.177	0.493
OD_9	0.1521	0.041	3.669	0.000	0.071	0.234
OD_10	0.5352	0.084	6.403	0.000	0.371	0.699
OD_11	-0.3117	0.097	-3.215	0.001	-0.502	-0.121
OD_12	1.5291	0.243	6.289	0.000	1.051	2.007
OD_13	1.0337	0.192	5.378	0.000	0.656	1.412
OD_14	0.7732	0.120	6.438	0.000	0.537	1.009
OD_15	0.4756	0.102	4.675	0.000	0.276	0.676
Month_2	0.0650	0.034	1.915	0.056	-0.002	0.132
Month_3	0.2623	0.039	6.693	0.000	0.185	0.339
Month_4	0.0821	0.035	2.360	0.019	0.014	0.150
Month_5	0.1267	0.029	4.302	0.000	0.069	0.185
Month_6	0.1361	0.033	4.137	0.000	0.071	0.201
Month_7	0.2086	0.043	4.856	0.000	0.124	0.293
Month_8	0.1927	0.045	4.304	0.000	0.105	0.281
Month_9	0.1709	0.047	3.643	0.000	0.079	0.263
Month_10	0.2332	0.037	6.316	0.000	0.161	0.306
Month_11	0.1291	0.036	3.600	0.000	0.059	0.200
Month_12	0.2344	0.035	6.671	0.000	0.165	0.303

Omnibus:	18.702	Durbin-Watson:	1.874
Prob(Omnibus):	0.000	Jarque-Bera (JB):	29.728
Skew:	0.329	Prob(JB):	3.51e-07
Kurtosis:	4.152	Cond. No.	3.14e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.14e+03. This might indicate that there are strong multicollinearity or other numerical problems.

4.2.4 Vehicle Category 4 (PV4)

This category includes bus and Sino truck with 3 axles. Vehicles in this category account for approximately 6% of the total traffic volume on the Addis Adama Expressway. The variation in Average Annual Daily Traffic (AADT) and monthly traffic flow for these vehicles from 2019 to 2023 is illustrated in Figure 4. 9 and Figure 4. 10 below. As shown in the figure, the Average Annual Daily Traffic (AADT) increased by 10.47% in 2020 and 10.45% in 2021, and decreased by 5.95% in 2022 and by 26.99% in 2023. This shows the traffic decreased at decreasing rate of -3.00%.

The ETRE toll system is based on cost recovery, with higher tolls for heavier vehicles like Class 4 (PV4). In June 2022, toll fees rose by 63.91%, and fuel prices surged by over 175% from December 2021 to June 2023 due to the end of fuel subsidies and global price increases. To ensure consistency, tolls, fuel prices, and GDP per capita are adjusted to 2016 real prices using the CPI. Figure 4. 11 shows the difference between real and nominal prices, which are incorporated into the model.

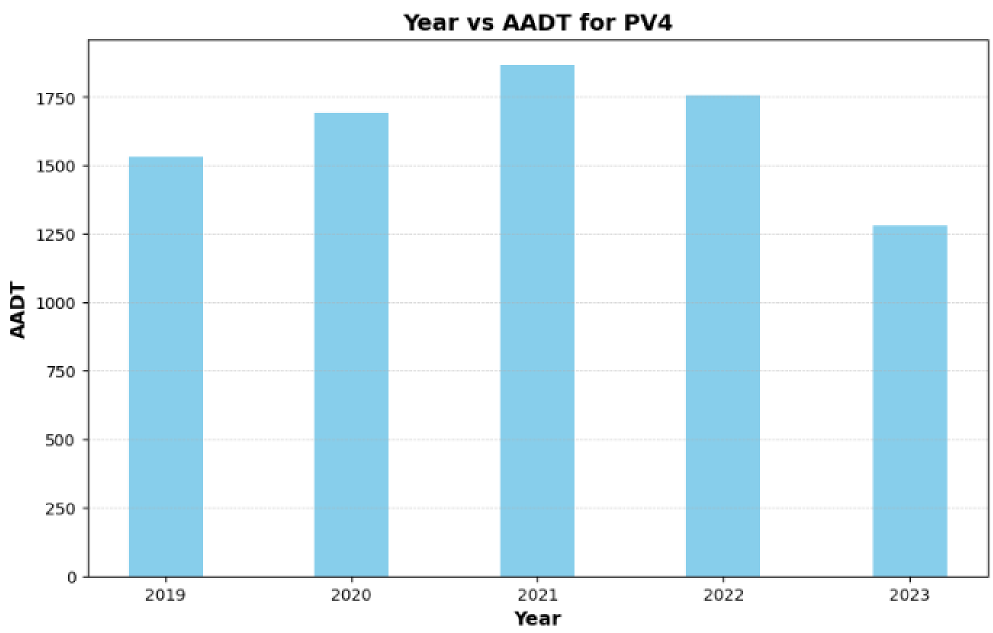

Figure 4. 9 Historical AADT data for PV4

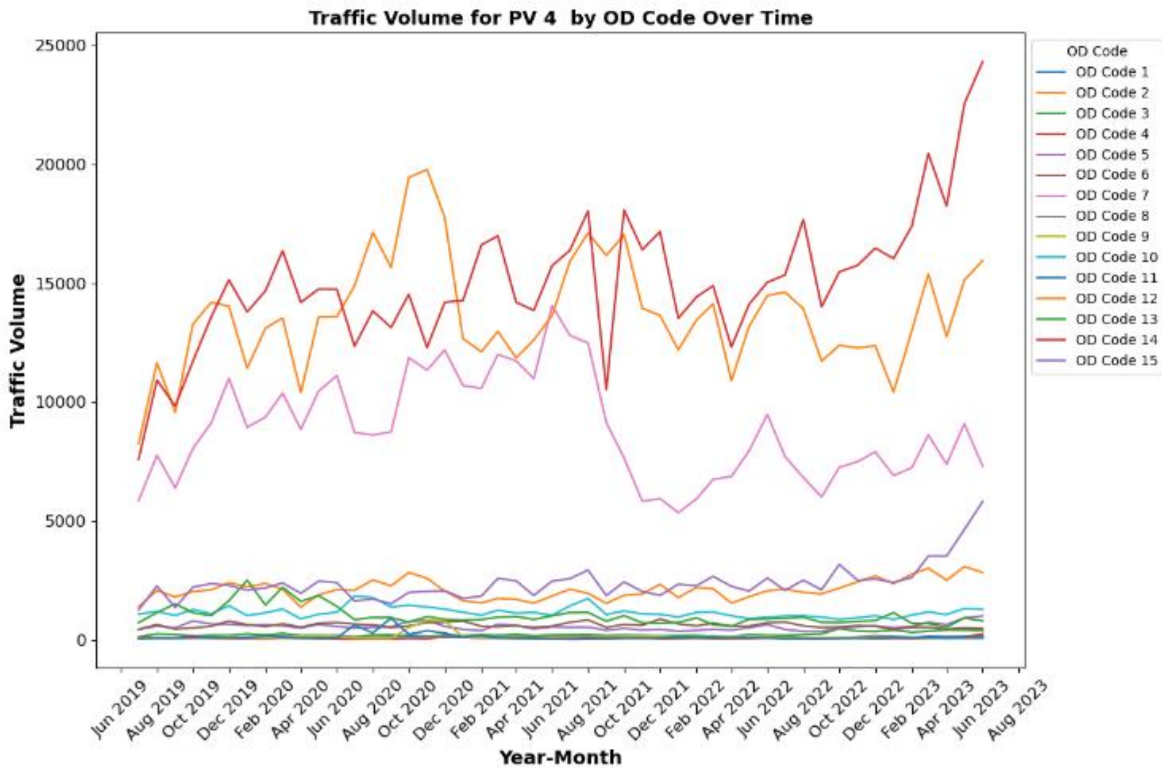

Figure 4. 10 Historical monthly traffic data for PV4

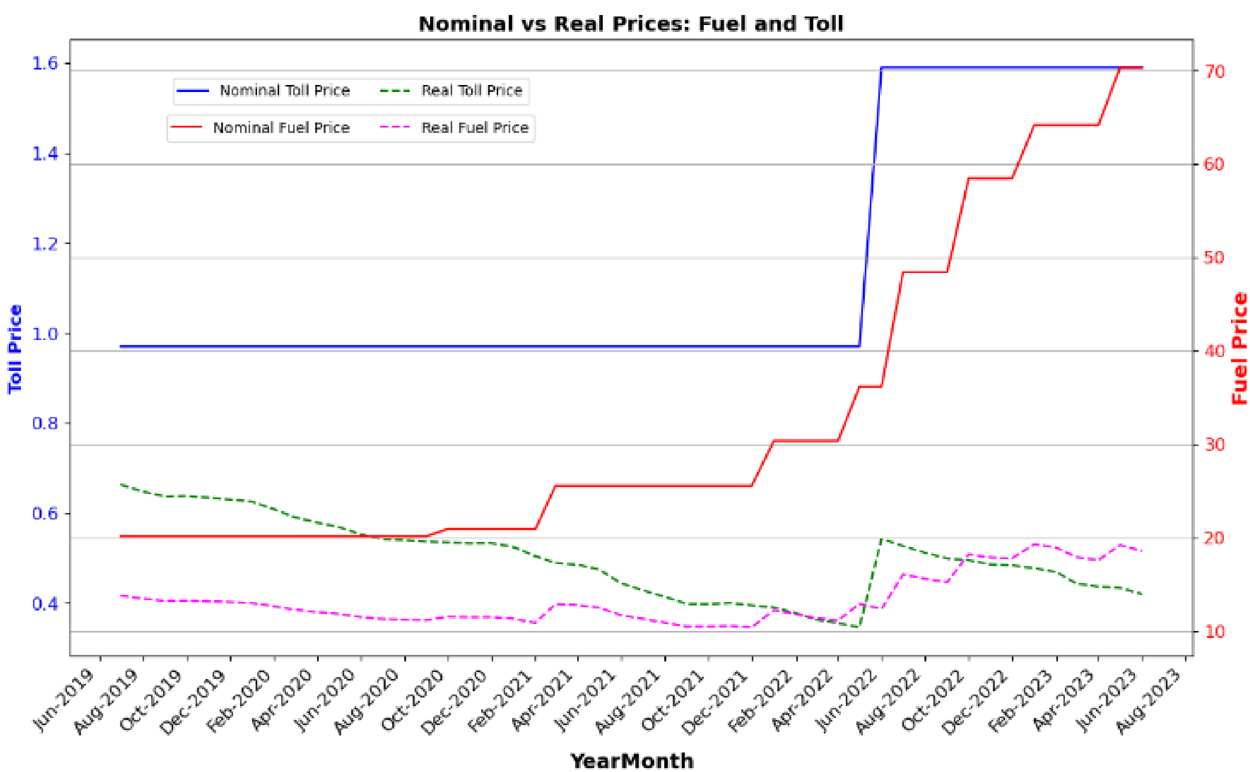

Figure 4. 11 Nominal vs Real toll and fuel price data for PV4

Table 4. 4 Model result summary for PV4

OLS Regression Results

Dep. Variable:	ln_Traffic_Volume	R-squared:	0.991
Model:	OLS	Adj. R-squared:	0.990
Method:	Least Squares	F-statistic:	1261.
Date:	Sun, 22 Sep 2024	Prob (F-statistic):	0.00
Time:	11:08:54	Log-Likelihood:	130.63
No. Observations:	405	AIC:	-197.3
Df Residuals:	373	BIC:	-69.14
Df Model:	31		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.4342	0.371	3.869	0.000	0.705	2.163
ln_R_Toll_Price	-0.4995	0.131	-3.808	0.000	-0.757	-0.242
ln_R_Fuel_Price	0.4357	0.089	4.884	0.000	0.260	0.611
ln_R_GDP_Capita	0.0320	0.037	0.877	0.381	-0.040	0.104
OverLoad	-0.2405	0.095	-2.526	0.012	-0.428	-0.053
Security	-0.1121	0.034	-3.281	0.001	-0.179	-0.045
ln_Traffic_Volume_lag	0.6045	0.043	14.038	0.000	0.520	0.689
OD_2	1.7386	0.219	7.945	0.000	1.308	2.169
OD_3	0.8208	0.148	5.529	0.000	0.529	1.113
OD_4	-0.1636	0.057	-2.880	0.004	-0.275	-0.052
OD_5	0.9956	0.138	7.225	0.000	0.725	1.267
OD_6	1.1256	0.160	7.016	0.000	0.810	1.441
OD_7	2.4151	0.277	8.714	0.000	1.870	2.960
OD_8	0.2612	0.085	3.063	0.002	0.094	0.429
OD_9	0.0719	0.054	1.325	0.186	-0.035	0.179
OD_10	1.0738	0.123	8.741	0.000	0.832	1.315
OD_11	-0.5056	0.107	-4.707	0.000	-0.717	-0.294
OD_12	2.5734	0.295	8.724	0.000	1.993	3.153
OD_13	1.4080	0.203	6.942	0.000	1.009	1.807
OD_14	1.8224	0.211	8.642	0.000	1.408	2.237
OD_15	1.5020	0.165	9.102	0.000	1.178	1.826
Month_2	0.0652	0.047	1.378	0.169	-0.028	0.158
Month_3	0.1371	0.049	2.786	0.006	0.040	0.234
Month_4	0.0509	0.045	1.126	0.261	-0.038	0.140
Month_5	0.1083	0.044	2.477	0.014	0.022	0.194
Month_6	0.1783	0.044	4.008	0.000	0.091	0.266
Month_7	0.1075	0.053	2.029	0.043	0.003	0.212
Month_8	0.1671	0.052	3.193	0.002	0.064	0.270
Month_9	-0.0279	0.052	-0.535	0.593	-0.130	0.075
Month_10	0.2348	0.049	4.751	0.000	0.138	0.332
Month_11	0.1054	0.049	2.145	0.033	0.009	0.202
Month_12	0.1152	0.049	2.352	0.019	0.019	0.212

Omnibus:	9.343	Durbin-Watson:	1.689
Prob(Omnibus):	0.009	Jarque-Bera (JB):	15.902
Skew:	0.065	Prob(JB):	0.000352
Kurtosis:	3.962	Cond. No.	750.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

From Table 4. 4, the short-term elasticity of toll price for PV4 is -0.4995, indicating that a 1% increase in toll price results in a 0.4995% decrease in traffic volume. The long-term elasticity rises to 1.26, suggesting a stronger response to toll price changes over time, making PV4 more sensitive compared to PV1, PV2, and PV3. The fuel price elasticity of 0.4357 shows that a 1% increase in fuel price leads to a 0.4357% increase in traffic volume, likely due to the expressway's fuel-saving benefits, as it saves 5.94 Birr per kilometer compared to non-tolled road. This cost advantage attracts more traffic as drivers seek to reduce fuel expenses. Although the GDP per capita elasticity is 0.034, it is not statistically significant at the 5% level. The negative coefficients for security and overburden indicate adverse impacts on traffic volume on the tolled roadway. With an adjusted R^2 of 99.1%, the model demonstrates that the included variables explain nearly all the variation in traffic volume for PV4, supporting the model's reliability and robustness.

4.2.5 Vehicle Category 5 (PV5)

This category includes medium truck and long trailer trucks with more than 4 axles. Vehicles in this category account for approximately 7% of the total traffic volume on the Addis Adama Expressway. The variation in Average Annual Daily Traffic (AADT) and monthly traffic flow for these vehicles from 2019 to 2023 is illustrated in Figure 4. 12 and Figure 4. 13 below.

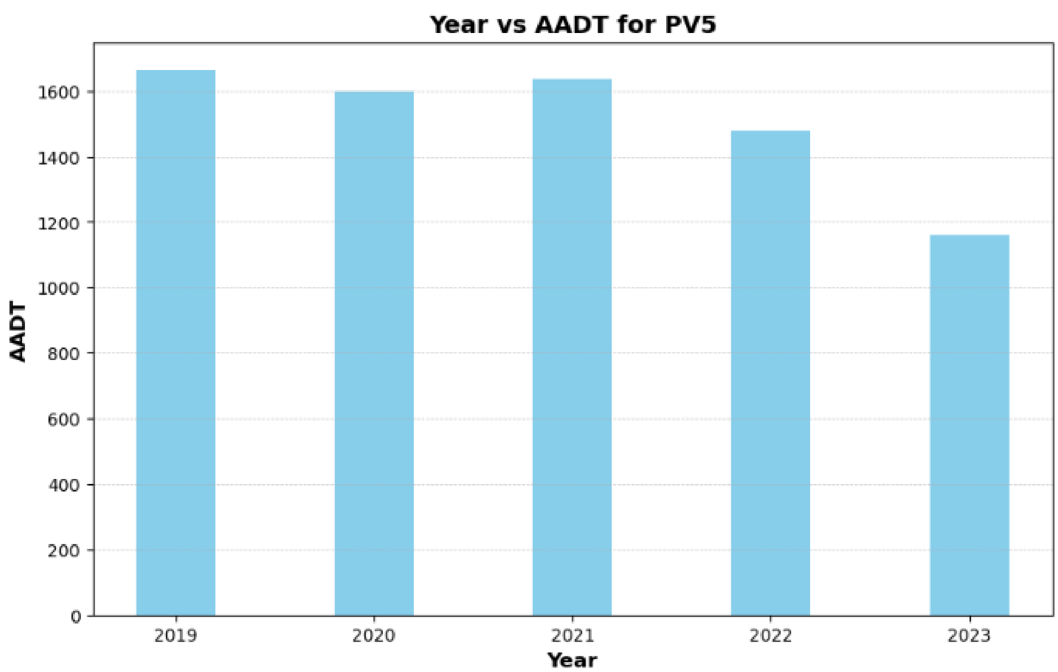

Figure 4. 12 Historical AADT data for PV5

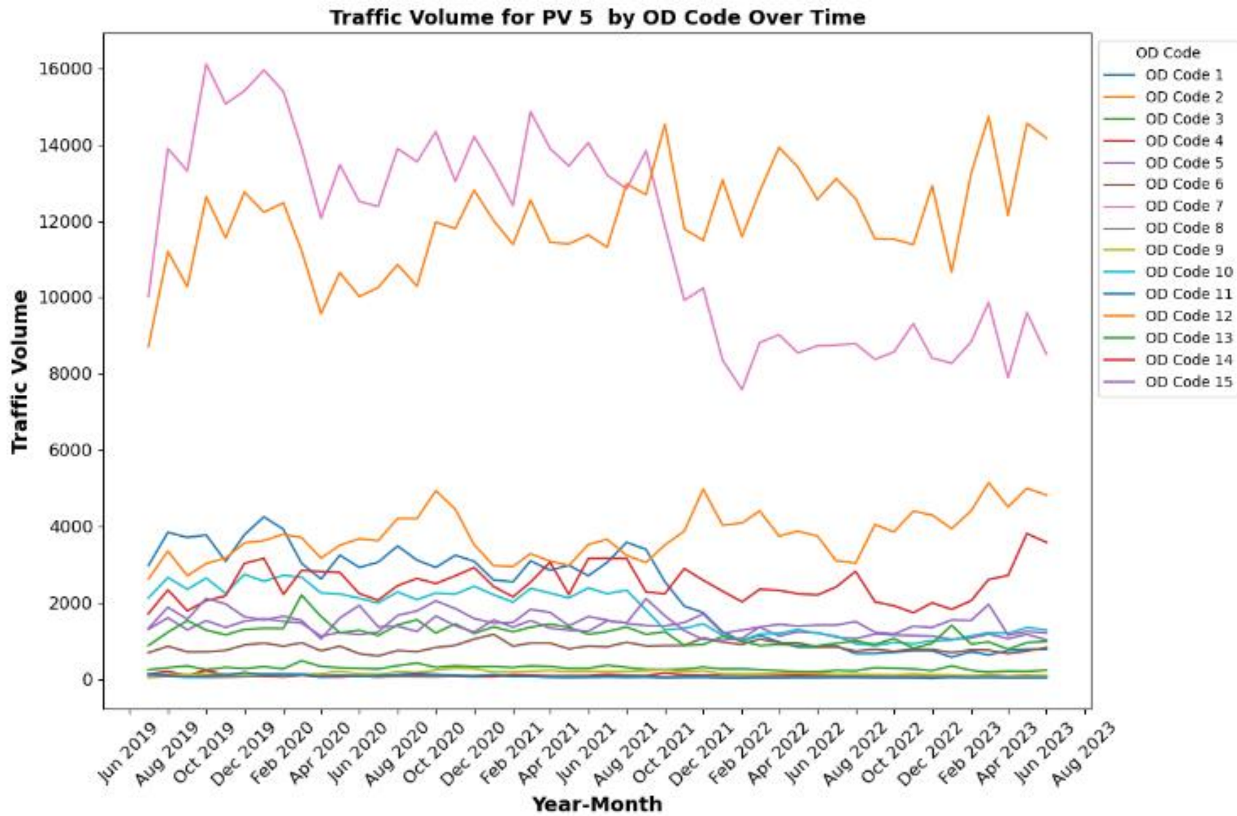

Figure 4. 13 Historical monthly traffic data for PV5

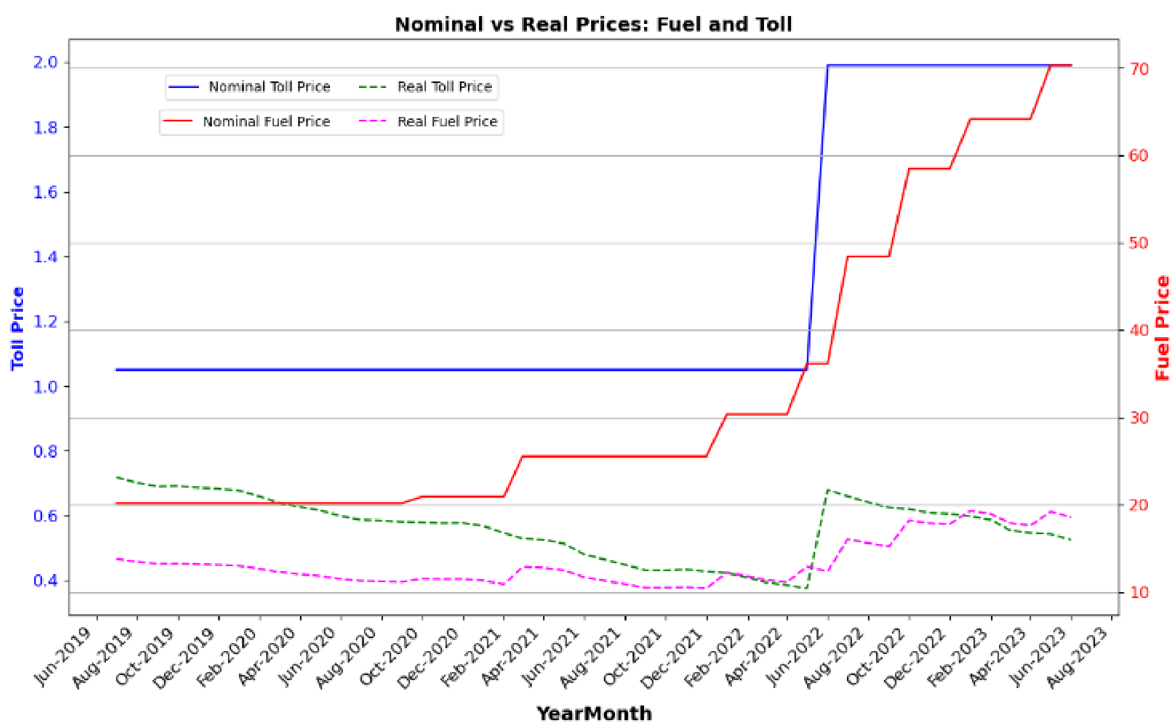

Figure 4. 14 Nominal vs Real toll and fuel price data for PV5

The ETRE toll payment mechanism for the expressway is based on cost recovery, with Vehicle Class 4 (PV4) paying higher tolls than Classes 1 and 2 (PV1, PV2, PV3 & PV4) due to the greater damage they cause. Until June 2022, the toll fee was 1.05 Birr/km, but it was increased to 1.99 Birr/km, a 89.52% rise. Additionally, fuel prices have surged by over 175% from December 2021 to June 2023, following the Ethiopian government's decision to end fuel subsidies and rising global fuel prices. For analysis, all monetary costs, including toll price, fuel price, and GDP per capita, are adjusted to real prices using the Consumer Price Index (CPI) with 2016 as the base year, ensuring that the values reflect the purchasing power relative to 2016. Figure 4. 14 illustrates the differences between real and nominal prices of tolls and fuel, with these variations captured in the model through the variables for toll, fuel, and GDP per capita.

From Table 4. 5, the short-term elasticity of toll price for PV4 is -0.5128, indicating that a 1% increase in toll price results in a 0.5128% decrease in traffic volume. The long-term elasticity rises to 1.16, suggesting a stronger response to toll price changes over time. The fuel price elasticity of 0.4183 shows that a 1% increase in fuel price leads to a 0.4183% increase in traffic volume, likely due to the expressway's fuel-saving benefits, as it saves 8.22 Birr per kilometer compared to non-tolled road. Although the GDP per capita elasticity is 0.095, it is not statistically significant at the 5% level. The negative coefficients for security indicate adverse impacts on traffic volume on the tolled roadway. With an adjusted R^2 of 99.1%, the model demonstrates that the included variables explain nearly all the variation in traffic volume for PV5.

Table 4. 5 Model result summary for PV5

OLS Regression Results

Dep. Variable:	ln_Traffic_Volume	R-squared:	0.991
Model:	OLS	Adj. R-squared:	0.991
Method:	Least Squares	F-statistic:	1210.
Date:	Sun, 22 Sep 2024	Prob (F-statistic):	4.40e-318
Time:	11:54:08	Log-Likelihood:	142.13
No. Observations:	360	AIC:	-220.3
Df Residuals:	328	BIC:	-95.90
Df Model:	31		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.9965	0.591	5.066	0.000	1.833	4.160
ln_R_Toll_Price	-0.5128	0.244	-2.102	0.036	-0.993	-0.033
ln_R_Fuel_Price	0.4183	0.195	2.144	0.033	0.035	0.802
ln_R_GDP_Capita	0.0095	0.055	0.173	0.863	-0.098	0.117
OverLoad	-0.0271	0.078	-0.347	0.728	-0.181	0.126
Security	-0.1632	0.037	-4.402	0.000	-0.236	-0.090
ln_Traffic_Volume_lag	0.5594	0.044	12.752	0.000	0.473	0.646
OD_2	1.1804	0.337	3.503	0.001	0.518	1.843
OD_3	-0.1022	0.259	-0.395	0.693	-0.611	0.407
OD_4	-1.0136	0.120	-8.445	0.000	-1.250	-0.777
OD_5	0.5032	0.206	2.446	0.015	0.098	0.908
OD_6	0.4344	0.247	1.760	0.079	-0.051	0.920
OD_7	1.4553	0.305	4.773	0.000	0.856	2.055
OD_8	-1.0099	0.186	-5.423	0.000	-1.376	-0.644
OD_9	-0.8115	0.110	-7.372	0.000	-1.028	-0.595
OD_10	0.2933	0.113	2.605	0.010	0.072	0.515
OD_11	-1.8755	0.241	-7.778	0.000	-2.350	-1.401
OD_12	1.7961	0.400	4.488	0.000	1.009	2.583
OD_13	0.6650	0.321	2.070	0.039	0.033	1.297
OD_14	0.3474	0.064	5.469	0.000	0.222	0.472
OD_15	0.4950	0.175	2.829	0.005	0.151	0.839
Month_2	-0.0308	0.045	-0.686	0.493	-0.119	0.058
Month_3	0.0814	0.046	1.767	0.078	-0.009	0.172
Month_4	-0.0605	0.046	-1.307	0.192	-0.152	0.031
Month_5	0.0230	0.055	0.420	0.675	-0.085	0.131
Month_6	-0.0539	0.059	-0.918	0.359	-0.169	0.062
Month_7	0.1568	0.066	2.382	0.018	0.027	0.286
Month_8	0.1204	0.066	1.817	0.070	-0.010	0.251
Month_9	0.0942	0.065	1.445	0.149	-0.034	0.222
Month_10	0.0455	0.053	0.861	0.390	-0.058	0.149
Month_11	0.0148	0.051	0.290	0.772	-0.086	0.115
Month_12	0.0506	0.053	0.962	0.337	-0.053	0.154

Omnibus:	37.334	Durbin-Watson:	2.117
Prob(Omnibus):	0.000	Jarque-Bera (JB):	185.357
Skew:	0.189	Prob(JB):	5.63e-41
Kurtosis:	6.495	Cond. No.	1.07e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.07e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

4.3 Summary of Elasticity Estimates for the Addis-Adama Expressway

In the above section, toll price elasticity, fuel price elasticity, and GDP per capita elasticity estimates were presented and discussed separately for each vehicle category. Those short-term and long-term elasticity values are now summarized in *Table 4.* 6 for vehicle categories PV1 to PV5.

Table 4. 6 Summary of short term and long term elasticity for Addis Adama Expressway

Vehicle Category	**PV1**		**PV2**		**PV3**		**PV4**		**PV5**	
	Short term	**Long term**	**Short term**	**Long term**	**Short term**	**Long term**	**Short term**	**Long term**	**Short term**	**Long term**
Toll price elasticity	-0.25	-1.27	-0.35	-1.30	-0.46	-2.02	-0.50	-1.26	-0.51	-1.16
Fuel price elasticity	0.20	0.99	0.32	1.19	0.49	2.19	0.44	1.10	0.42	0.95
GDP/capita elasticity	0.35	1.78	0.53	1.96	0.73	3.22	0.03*	0.08*	0.01*	0.02*

* Not significant at the 95% level

4.4 Comparison with Existing Literature

Bain (2017) provides a valuable benchmark for comparing the toll price elasticities. Drawing on data from 60 toll road traffic and revenue (T&R) reports, Bain's analysis focuses on recent data from 2011 onwards and examines 368 toll price elasticity coefficients. The study finds a mean short-term elasticity of -0.25, with over 80% of values ranging between -0.03 and -0.50, as depicted in Figure 4. 15.

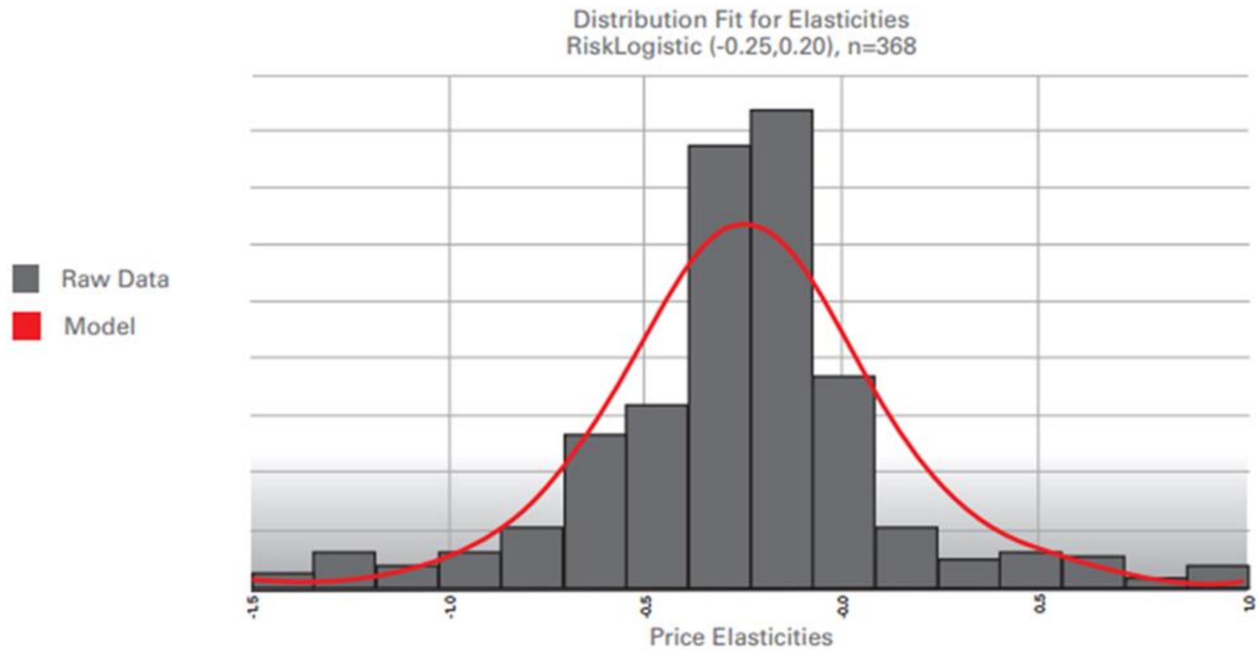

Figure 4. 15 Distribution of toll price elasticities

Compared to Bain's findings, the short-term elasticities observed in this study, particularly for PV4 (-0.50) and PV5 (-0.51), are at the higher end of the reported range, indicating a relatively stronger response to toll price changes. This comparison suggests that vehicles on the Addis Adama Expressway is more price-sensitive than the average observed in Bain's study, likely due to the expressway's cost recovery-based toll tariff structure, which imposes higher fees on heavier vehicles. The results align with Bain's broader distribution.

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This research aimed to quantify toll price elasticity and evaluate the impact of socio-economic factors such as GDP per capita and fuel prices, as well as external factors like security, on travel demand, with a specific focus on the Addis-Adama Expressway. Historical data from June 2019 to June 2023 was analyzed using an autoregressive (AR) regression model, incorporating variables such as past traffic demand, GDP per capita, and fuel prices to explore their influence on travel patterns. The analysis covered five vehicle categories, and the results provided the following key findings:

Toll Price Elasticity:

- Toll price elasticity varies across vehicle categories, with short-term elasticity ranging from -0.25 to -0.51. Vehicles paying higher tolls, such as PV5, show a stronger response (-0.51), compared to lighter vehicles like PV1 (-0.25). This variation reflects ETRE's cost-recovery-based toll tariff structure, where heavier vehicles are charged higher tolls due to their impact on road maintenance. The inelastic short-term elasticity for all categories aligns with ETRE's survey, which found that over 88% of expressway users travel for business purposes, making them less sensitive to toll changes in the short term.
- Long-term elasticity ranges from -1.16 to -2.02, indicating a more elastic response to toll price increases over time. These findings suggest that as users have more time to adjust, they explore alternatives, such as relocating workplaces, choosing different recreational areas, or switching to improved alternative routes.

Socio-Economic and External Factors:

- Fuel price elasticity is positive, ranging from 0.20 to 0.49 in the short term and 0.95 to 2.19 in the long term. This reflects the expressway's fuel-saving benefits compared to alternative routes. Over time, drivers become more aware of these savings, resulting in a stronger long-term response.

- GDP per capita positively correlates with traffic volume, with short-term elasticity ranging from 0.35 to 0.73 and long-term elasticity from 1.78 to 3.22. Economic growth drives increased traffic, though the effect is less pronounced for heavier vehicles (PV4 and PV5) due to their differing usage patterns. This underscores the need for infrastructure planning to accommodate future demand.
- Security concerns negatively impact traffic volume, as travelers reduce non-essential trips or avoid insecure areas. Addressing these issues is crucial to restoring traveler confidence and ensuring effective utilization of the expressway.

Policy Implications:

The findings offer several insights for policymakers and infrastructure managers:

- Implement tailored pricing strategies for vehicle categories to optimize revenue, reduce maintenance costs, and balance traffic distribution.
- Address safety concerns to boost expressway usage and restore traveler confidence.
- Monitor fuel price trends and consider temporary toll adjustments during significant fuel price fluctuations to maintain traffic levels.
- Promote the expressway's benefits, such as fuel savings and reduced travel time, to encourage broader acceptance and usage.

While this study provides valuable insights, it has certain limitations. These include the use of incomplete historical data, a focus solely on the Addis-Adama Expressway, reliance on national economic indicators like GDP per capita, and limitations in ETRE's data collection methods. Future research should address these gaps to enhance the generalizability and robustness of findings.

5.2 Recommendation

To build upon the findings of this study and enhance the understanding of Toll price elasticity in the Ethiopia Expressway Network, future research should consider the following directions:

➢ Future research should aim to utilize a more extensive dataset that encompasses additional years, as this study was limited by the availability of data.

- Future studies should consider a broader range of variables to examine their effects on elasticity values.
- Future studies should focus on region-specific data, such as GDP or other economic activity indices, to capture more accurate economic dynamics.
- Future studies should include other expressways in Ethiopia to compare elasticity estimates and identify potential differences among them.

Appendices

Appendix A: Vehicle Classification According to ETRE

Vehicle category	Vehicle Category Criteria				
	Axle number	Tyre number	Vehicle height	Axle spacing	Vehicle description
 Vehicle1(pv1)	2	4	< 1.3	< 2.4	Automobile
 Vehicle2(pv2)	2	4	≥ 1.3	≥ 2.4	Minibus
 Vehicle3(pv3)	2	6	–	–	Medium bus, Medium truck
 Vehicle4(pv4)	3	–	–	–	Bus,Sino truck
 Vehicle5(pv5)	4	–	–	–	Medium truck
 Vehicle6(pv6)	5	–	–	–	Long trailer truck
 Vehicle7(pv7)	≥ 6	–	–	–	Long trailer truck

Appendix B: Python Code for Fitting the ARDL Model

Analyzing Toll Price Elasticity by Vehicle Type

This notebook analyzes the toll price elasticity for different vehicle types using monthly traffic data. The analysis involves data loading, preparation, and model fitting.

Data Loading and Preparation

In this section, we load the dataset, convert date formats, and prompt the user for a date range to filter the data.

```
# Import necessary libraries for data manipulation, modeling, and visualization
import pandas as pd  # Pandas is used for data manipulation and analysis, especially for handling data in DataFrame format.
import numpy as np   # NumPy provides support for numerical operations and array manipulation.
import statsmodels.api as sm  # Statsmodels is used for statistical modeling, including regression analysis.
import matplotlib.pyplot as plt  # Matplotlib is used for creating static, animated, and interactive visualizations.
import seaborn as sns  # Seaborn is a statistical data visualization library.

# Load the dataset from the provided file path
file_path = r"file_path"
df = pd.read_excel(file_path)

# Convert YearMonth column to datetime format for filtering
df['YearMonth'] = pd.to_datetime(df['YearMonth'], format='%B %Y')

# Prompt user for start and end dates
start_date = input("Enter the start date (e.g., July 2019): ")
end_date = input("Enter the end date (e.g., June 2023): ")

# Convert user input to datetime
start_date = pd.to_datetime(start_date, format='%B %Y')
end_date = pd.to_datetime(end_date, format='%B %Y')

# Filter the dataset based on the provided date range
df = df[(df['YearMonth'] >= start_date) & (df['YearMonth'] <= end_date)]

```

Data Transformation

Here, we log-transform the continuous variables and drop any rows with missing values due to lagging.

```
# Log-transform the continuous variables: Traffic Volume, R_Toll_Price, R_Fuel_Price, R_GDP_Capita
df['ln_Traffic_Volume'] = np.log(df['Traffic_Volume'])
df['ln_R_Toll_Price'] = np.log(df['R_Toll_Price'])
df['ln_R_Fuel_Price'] = np.log(df['R_Fuel_Price'])
df['ln_R_GDP_Capita'] = np.log(df['R_GDP/Capita'])
df['ln_Traffic_Volume_lag'] = np.log(df['Traffic_Volume_lag'])

# Drop rows with missing values due to lagging
df = df.dropna()
```

Model Fitting

We will run a separate regression model for each vehicle type (ENT_VehType) and store the results.

```
# Run a separate model for each vehicle type (ENT_VehType)
vehicle_types = df['ENT_VehType'].unique()

for veh_type in vehicle_types:
    df_veh = df[df['ENT_VehType'] == veh_type]

    # Select the dependent and independent variables
    X = df_veh[['ln_R_Toll_Price', 'ln_R_Fuel_Price', 'ln_R_GDP_Capita', 'OverLoad', 'Security', 'ln_Traffic_Volume_lag'] +
               df_veh.filter(regex='OD_|Month_').columns.tolist()]  # Include predefined OD and Month dummies

    # Add constant for the regression
    X = sm.add_constant(X)

    # Define the dependent variable (log of Traffic Volume)
    y = df_veh['ln_Traffic_Volume']

    # Fit the OLS model
    model = sm.OLS(y, X).fit()

    # Output model summary for each vehicle type
    print(f"Elasticity Parameters for Vehicle Type {veh_type}")
    print(model.summary())  # Display model summary
    print("\n" + "="*80 + "\n")  # Separator for readability
```

Appendix C: Procedure for Distributing Annual GDP Values to Each Month

- **Calculate the yearly growth rate (r)**: The yearly growth rate of each year is calculated as follows:

$$r = \frac{GDP/Capita_{year(t)} - GDP/Capita_{year(t-1)}}{GDP/Capita_{t-1}}$$

- **Calculate the monthly growth rate (r_m):** The yearly growth rate is converted to a monthly growth rate to distribute the annual data across each month. It is calculated as follows:

$$r_m = (1 + r)^{\frac{1}{12}} - 1$$

- **Calculate the first month's GDP of the year**: Using the geometric series formula, the first month's GDP per capita is calculated as follows:

$$1st\ month\ \frac{GDP}{capita} = \frac{Annual\ GDP/Capita}{\frac{1-(1+r_m)^{12}}{1-(1+r_m)}}$$

- **Using the compounded effect, calculate each month's GDP**: Using the monthly growth rate, the GDP per capita for each subsequent month is calculated using the compounded formula as follows:

$$\frac{GDP}{Capita}_{(m)} = \frac{GDP}{Capita}_{(m-1)} * (1 + r_m)$$

Appendix D: Legend for OD Pairs in Addis-Adama Expressway

Origin -Destination(OD)	OD Code
AdamaWest-AdamaMain	OD-1
BishoftuNorth-AdamaMain	OD-2
BishoftuNorth-AdamaWest	OD-3
BishoftuNorth-BishoftuSouth	OD-4
BishoftuNorth-Modjo	OD-5
BishoftuSouth-AdamaMain	OD-6
Tuludimtu-Modjo	OD-7
BishoftuSouth-AdamaWest	OD-8
BishoftuSouth-Modjo	OD-9
Modjo-AdamaMain	OD-10
Modjo-AdamaWest	OD-11
Tuludimtu-AdamaMain	OD-12
Tuludimtu-AdamaWest	OD-13
Tuludimtu-BishoftuNorth	OD-14
Tuludimtu-BishoftuSouth	OD-15

Appendix E: Sample Raw Traffic Data Provided by ETRE

	Plaza_ID	TransOccurTime	VehType	Distance	ENT_PlazaID	ENT_OccurTime	ENT_VehType	ENT_PayType	ENT_AxisNum	ENT_Height	ENT_TotalWeight
0	102	2019-08-16 08:39:21.000	1	14240	201	2019-08-16 08:25:08.000	1	1	2	2	1200
1	102	2019-08-16 08:39:41.000	3	14240	201	2019-08-16 08:20:50.000	3	1	0	0	0
2	102	2019-08-16 08:40:19.000	2	14240	201	2019-08-16 08:29:04.000	2	1	2	2	3150
3	102	2019-08-16 08:41:11.000	1	73310	601	2019-08-16 08:01:12.000	1	1	0	0	0
4	102	2019-08-16 08:42:04.000	2	57660	501	2019-08-16 08:04:39.000	2	1	2	2	3250
...	...	...	...	...	...	...	...	...	...	...	...
36520265	602	2023-05-17 11:55:51.000	5	15650	503	2023-05-17 11:49:54.000	5	1	0	0	0
36520266	602	2023-05-17 11:56:42.000	4	59070	201	2023-05-17 11:16:40.000	4	1	0	0	0
36520267	602	2023-05-17 11:59:19.000	7	73310	101	2023-05-17 11:00:24.000	7	1	0	0	0
36520268	602	2023-05-17 12:03:29.000	7	59070	201	2023-05-17 06:17:02.000	7	1	0	0	0
36520269	602	2023-05-17 12:04:21.000	5	15650	503	2023-05-17 11:54:59.000	5	1	0	0	0

36520270 rows × 11 columns

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