THREE ESSAYS ON OPPORTUNITIES AND CHALLENGES IN THE TRANSPORTATION SERVICE INDUSTRY OF EAST AFRICA

by

WALTER ONDICHO MOTURI

(Under the Direction of Wojciech J. Florkowski)

Abstract

This dissertation consists of three essays investigating the opportunities and direct and indirect challenges in the transportation service industry of East Africa. The findings reveal factors that shape long-haul transportation in East Africa, and the constraints to market integration for the region's staple food crops.

The first essay investigates truck driver perceptions of sources of delays along the main transportation route in East Africa (EA) called the Northern Corridor (NC) road. This study uses survey data collected in October 2018 from truck drivers who frequent the NC. Due to the ordinal nature of the outcome variable, an ordered logit empirical approach is used to model the perception truck drivers have of obstacles causing unnecessary delays during cargo transportation. Findings provide insights for improving long-haul transportation efficiency in East Africa.

The second essay examines factors that shape the economic reward profile and the on-road behavior - in the context of risk - of the NC truck drivers of Kenya. This study also uses survey data collected in October 2018 from truck drivers who frequent the NC. The presence

of endogenous explanatory variables which are either measured as continuous covariates or discrete binary variates when modelling the economic reward profile necessitate the use of three stage least squares (3SLS). The 3SLS recognizes, and allows for, the non-independence of the error structures of the system of equations estimated. To model risk, a two-stage modeling procedure is undertaken where a probit model is estimated first followed by a selectivity regression. Findings highlight the critical areas for policy intervention on road safety.

The third essay examines the constraints to market integration in East Africa by testing the law of one price (LOP) on commonly traded staple food crops. The study takes advantage of a shared price information system that records real-time daily prices of staple food crops commonly traded between Kenya and Uganda. The absolute LOP is tested by running level regressions on relative prices with city-pairs as the unit of observation. This study intends to present the role of macro issues in cross country commodity price differences.

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M.S., Egerton University, Kenya, 2014

A Dissertation Submitted to the Graduate Faculty of the University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2019

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August 2019

DEDICATION

Dedicated to my beloved and supportive mother, and my dear brothers and sisters.

ACKNOWLEDGEMENTS

As I take the final step to complete the journey of pursuing a Ph.D., I would like to express my sincere gratitude and appreciation to all those who have made it possible. The list is no way exhaustive or exclusive.

I am honored to have Dr. Florkowski as my major advisor. Dr. Florkowski has tirelessly guided me throughout my program. His wisdom, patience, encouragement, support, and professional knowledge are greatly appreciated. Besides guiding me in my research and dissertation writing process, Dr. Florkowski also generously supports me to build career. I am really grateful to him for the relationship we have built, and, hopefully, it shall continue in the future.

My sincere gratitude goes to both Dr. Kostandini and Dr. Chen Zhen, my dissertation committee members, for their helpful comments on improving my dissertation. Furthermore, they both gave me invaluable advice on how to prepare publishable manuscripts from the essays of my dissertation.

I am deeply grateful to Dr. Obare for serving as my BHEARD home country advisor during the research period of my dissertation in Kenya. As the major advisor of my master's program at Egerton University, Dr. Obare mentored me thoroughly through the entire process. His professional advice during my master's program helped me to transition well into the somewhat challenging Ph.D. program at the University of Georgia.

My sincere gratitude also goes to the Department of Agricultural and Applied Economics for financial support, to the professors from whom I became more knowledgeable and received

generous help, to the staff members who made my study experience smoother, and to my fellow graduate students for their support and friendship.

Also, my deepest appreciation goes to the Borlaug Higher Education for Agricultural Research and Development (BHEARD) program for facilitating my travel to America and funding my tuition, upkeep, and dissertation project.

Finally, I am sincerely grateful to my mother Florence, my sister Judy, my mentor Prof. Alexander Kahi, and, ultimately, to God. None of my accomplishments would be possible without their endless support, love, and encouragement. Words cannot convey how much they all mean to me.

"This material is based upon work supported by the United States Agency for International Development, as part of the Feed the Future initiative, under the CGIAR Fund, award number BFS-G-11- 00002, and the predecessor fund the Food Security and Crisis Mitigation II grant, award number EEM-G- 00-04-00013."

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

The world's service economy experienced a steady growth in the 20th century and employed more than one third of the world's labor force in the early 21st century (Higgins, 2016). In the United States of America's economy, the service industry's contribution accounted for a one half of the GDP in 1929, two thirds in 1978, and more than three quarters in 1993, respectively (Jones, 2016).

The 2011 World Development Indicators show that the world's service industry was expanding faster than both manufacturing and agricultural industries (World Trade Organization (WTO, 2012). In China, for example, while agriculture employed 28% of the working population in 2017 and manufacturing employed 25%, services, its fastest growing sector employed 43%. A similar trajectory was observable in India and Brazil where services made up 55% and 67% of their respective GDPs (WTO, 2017).

In East Africa (EA), the picture is not different. Kenya's service industry, the largest in the region, is at the center of Kenya's economic growth (Serletis, 2014). The industry outperforms both the manufacturing and agricultural industries (thedailynation.co.ke, 2015). The service industry also contributes substantively to Kenya's GDP through the transport and storage subsector (7.9% contribution to GDP) and the land transport (road and rail) subsector (5.8% contribution to GDP) (Table 1.1). Kenya's land transport service subsector is projected to grow and contribute more to GDP with increasing cargo throughput handled at the Port of Mombasa (Table 1.1). In 2013, the land transport sector rose by 7.2% from Kenya shillings (KES) 928.3

million (or $9,190,170 at the exchange rate as of October 1, 2018) to KES 997.3 million (or $9,873, 270 at exchange rate as of October 1, 2018) relative to 2012. Similarly, the sector recorded a 0.4% growth in 2016, with most of the subsectors under it posting notable growth except railway services. The negative growth posted by the railway subsector in 2016 was due to a decrease in freight stream earnings. On the other hand, the positive growth in road transport was indirectly attributed to growth in the number of new registered trucks which was indicative of increased long-haul transportation services (KNBS, 2017).

Table 1.1 Percentage contribution of the transport sector to GDP in Kenya (at constant prices).

Transport sector branch	2012	2013	2014	2015	2016
Transport and storage	8.0%	8.0%	8.6%	8.3%	7.9%
Land transport	6.0%	6.0%	6.5%	6.2%	5.8%
Air transport including support services	0.4%	0.4%	0.3%	0.3%	0.3%
Other transport including postal and courier	1.6%	1.6%	1.7%	1.8%	1.8%

Source: KNBS, 2017

Besides its contribution to GDP, Kenya's transport subsector creates employment opportunities in both private and public sectors (Table 1.2). In 2016, the sector added 3000 jobs to the economy through vehicle part retail shops, vehicle servicing, and car wash enterprises. In comparison to the public sector, however, the private sector has a better educated and entrepreneurial workforce (ADB, 2013). The sector is also more developed in scale, efficiency, and flexibility than the public sector. Within the private transport service subsector, trucking services dominate (Lalla-Edward et al., 2016). Overall, both private and public subsectors in Kenya employed more workers in 2016 than in 2015.

Table 1.2 Wage employment in the transport sector (in thousands of employed).

Transport and storage sector	2012	2013	2014	2015	2016
Public	17.1	17.2	17.6	17.8	17.9
Private	58.1	58.8	62.1	64.8	67.8

Source: KNBS, 2017

Infrastructural deficiencies, unforeseen operational challenges, and cargo shipping costs are notable drawbacks on efficient cargo transportation in East Africa (Okumu and Nyankori, 2010). Once ships offload at the Port of Mombasa, Kenya, freight forwarders or cargo owners are faced with 2 options for shipping cargo, rail or truck. Rail transport is limited in capacity and Kenya's recently launched standard gauge railway (SGR) that runs adjacent to the main road route is incomplete (Balistreri et al., 2009; Eberhand-Ruiz and Calabrese, 2017). Shipping cargo from Mombasa to Kigali, Rwanda can take as long as 15 days with an average cost of $6500 for a 20-ton container (theeastafrican.co.ke, 2011). Truck drivers shipping cargo through the main trucking corridor called the NC in Kenya - that connects the landlocked countries to the sea - often fall victims to highway robberies (standardmedia.co.ke, 2012) and suffer losses due to accidents. These and other transportation challenges could have a far-reaching effect on EA's economies with regards to commodity market pricing and market integration, timely delivery of cargo, and road safety.

Against this backdrop, an understanding of the challenges and opportunities for the region's transport service industry is critical for East Africa's trade policy, food security, road safety, and ultimately, the region's economic growth. This dissertation adds to this agenda from a different yet related perspective. The dissertation consists of 3 essays investigating sources of

delay on East Africa's main transportation route, the NC, truck driver on-road behavior in light of economic incentives, and constraints to market integration for East Africa's staple crops.

The next three sections present a brief background justifying the economic importance of each topic. The description includes an overview of each essay's objectives. Details regarding the applied methods and data are discussed in the following chapters.

1.1 Sources of delays in road transportation: the view of truck drivers in Kenya.

High transportation costs are a concern for policy makers because they affect the competitiveness of Kenya's economy as well as the region's (Okumu and Nyankori, 2010; Eberhard-Ruiz and Calabrese, 2017). Kenya's Logistics Performance Index (LPI) ranks the country highest in the region (Arvis et al., 2014), but leaves plenty of room for improvement. In contrast, the costs of shipping a container from Mombasa to the United Kingdom was relatively inexpensive and ranged from $2,000 to $4,000 (Atlas Network, 2014).

The costs of cargo shipping severely limit the economic growth of the East African Community (EAC) although the GDP growth of Kenya and other countries in the region was only temporarily stalled by the recent global financial crisis (Fitzmaurice and Hartmann, 2013). With expectations of continued economic growth in the region, the demand for trucking services is likely to increase and wage employment opportunities have been increasing since 2012 (KNBS, 2017). Shipping imported and exported goods results in a steady flow of cargo traffic along the NC. A large portion of the transportation costs along the NC is fuel estimated to account for 50% in 2012 (Fitzmaurice and Hartmann, 2013). However, the remaining 50% of costs are determined by other factors. Causes of high "other costs" involve delays.

The first essay examines truck driver perceptions of specific sources of delays along the NC in Kenya. Information about the trucking industry is rare in countries of East Africa

(Fitzmaurice and Hartmann, 2013), while studies examining truck driver views of obstacles faced daily are virtually non-existent. This study provides rare insights from the perspective of a truck driver, who has to deal with potentially obstructive procedures on a daily basis that lengthen travel time and increase costs. Knowledge of factors associated with specific views of truck drivers reinforces a need for relatively simple interventions, e.g., assuring properly functioning weighbridges, as well as strengthened efforts to modify existing policies and prioritize their implementation to effectively reduce transportation costs. The benefit of learning from truck drivers about impediments along the NC reduces the risk of inappropriate strategies to deal with delays. The importance of logistics reflected in less expensive transportation increases the competitiveness of the EAC and expands trade contributing to economic growth and poverty reduction (World Bank, 2011).

1.2 Trucking and road safety along the Northern Corridor, Kenya

Road Traffic Accidents (RTAs) pose enormous cost implications on the world economy. Out of an estimated world total of US$500 billion a year, about US$100 billion is lost in the developing and transitioning economies (WHO, 2012). Furthermore, annual RTA-related losses in developing countries exceed total annual development aid received. Exclusive of actual loss of life, the annual cost of road accidents to Kenya's economy is in excess of $ 50 million. In the 1980s, the cost was 5% of Kenya's GDP whereas in 2011 the road accident cost's share of total GDP was 11% (Ogendi et al., 2013; Yerrel, 1984).

Studies on RTAs tend to emphasize either the outcomes of bad practice, notably road accidents involving fatalities or by describing the nature of the transport industry structure, and the industry's overall performance (Gichaga, 2017). There exists a dearth of studies, however, that focus on the trucking industry and that are based on enquiry into the underlying causes of

driver behavior and hence levels of exposure to risk of an accident (Kahn and Gotschall, 2015; Matheka et al., 2015; Trade Mark East Africa, 2014).

In the context of exposure to risk, first, this essay investigates the factors that shape truck drivers' economic reward profile including, total work hours, monthly earnings, and the proportion of time spent driving in total working time. Second, the essay seeks to establish the determinants of truck driver exposure to RTAs risk. These determinants are used to explain truck driver on-road behavior.

1.3 Constraints to market integration for East Africa's staple food crops.

Lack of close trade links between most African countries causes instability in food markets, high consumer prices, and poorly developed regional production networks (Walkenhorst, 2013). Additionally, poorly functioning and poorly integrated food markets in sub-Saharan Africa affect supply and demand and, consequently, food productivity (USAID, 2010). Given the economic welfare implications posed by the absence of market integration, it is of utmost concern to understand the constraints that hamper market integration. Tariff and non-tariff barriers, including inefficient transport and communication infrastructure, constrain transmission of price information (Obstfeld and Rogoff, 2000; Portugal-Perez and Wilson, 2008). Consequently, it is difficult to identify the real causes of price disparities across space and time. In EA, trade costs are evidently higher. The argument for higher trade costs is the considerably larger transport costs and in general, a weaker institutional set-up for dealing with issues like rules of origin and other non-tariff barriers (Portugal-Perez and Wilson, 2008).

Literature on international price disparities for commonly traded commodities emphasizes three key findings: distance plays a major role in understanding price deviations, convergence rates back to purchasing power parity (PPP) do not align with the evidence from

micro studies on nominal price stickiness (Rogoff, 1996), and borders give rise to the flagrant violations of the law of one price (LOP) (Broda and Weinstein, 2008). Violation of the law of one price cuts across. However, sizable differences exist in both the nature of the data and the empirical approaches employed in the studies that arrive at the abovementioned key findings on international price deviation.

The third and last essay revisits the LOP by taking advantage of the Uganda-Kenya shared price information system that records real-time daily prices of identical agricultural commodities traded across border between the two countries. Firstly, this study adds to the scarce literature on market integration that relies on highly disaggregated price data of comparable and identical commodities between countries. Secondly, and perhaps more importantly, the study builds on developed country good-specific price literature which employs price data to explain the role played by macro-issues such as exchange rate regimes, non-tariff barriers (NTBs) and electioneering period effects in cross country commodity price deviations (Broda and Weinstein, 2008; Versailles, 2012).

This dissertation consists of three essays. The following section, chapter 2, discusses the first essay in detail followed by the second essay in chapter 3. The last essay on the LOP is discussed in chapter 4 followed by a concluding section.

CHAPTER 2

SOURCES OF DELAYS IN ROAD TRANSPORTATION: THE VIEW OF TRUCK DRIVERS IN KENYA

2.1 Introduction

Kenya's location in East Africa and along the coast of the Indian Ocean creates a natural hub for intra-regional trade. Several land-locked East African countries heavily depend on truck freight for domestic and international shipping. Not surprisingly, the trucking industry is particularly large in Kenya, and accounts for almost 70% of all trucks registered in the East African Community (EAC) (theeastafrican.co.ke, 2017). In 2016, Kenya's ports reported unloading 27.34 million tons of cargo compared with 26.73 million tons the previous year - a respectable increase of 2.4% (KPA, 2017). The country also expanded its cargo handling capacity by opening a second state-of-the-art cargo terminal in 2016. A substantial portion of that cargo was destined for the landlocked countries of the region, including Uganda, Rwanda, Burundi, and the South Sudan, all located hundreds of kilometers away from the coast. Since Kenya's seaports dock ships delivering goods intended for buyers and markets of countries located further inland transportation services are in demand. From 2004 through 2013, the GDP growth in Uganda, Rwanda, and Burundi displayed average real growth of 4% or higher (Gigineishvili et al., 2014). Overall economic growth in EAC was a robust 5.9% in 2017 and is forecasted to continue in 2018 and 2019 (AfDB, 2018).

High transportation costs are a concern for policy makers because they affect the competitiveness of Kenya's economy as well as the region's (Okumu and Nyankori, 2010; Eberhard-Ruiz and Calabrese, 2017). Kenya's Logistics Performance Index (LPI) ranks the country highest in the region (Arvis et al., 2014), but leaves plenty of room for improvement. In contrast, the costs of shipping a container from Mombasa to the United Kingdom (13015.86 km) was relatively inexpensive and ranged between $2,000 and $4,000 (Atlas Network, 2014).

The costs of cargo shipping severely limit the economic growth of the EAC although the GDP growth of Kenya and other countries in the region was only temporarily stalled by the recent global financial crisis (Fitzmaurice and Hartmann, 2013). Following unloading at Kenya's ports, cargo can travel inland by railroad or truck, but rail capacity is severely limited and the network suffers from underinvestment (Balistreri et al., 2009; Njoh, 2012). It takes 14 to 21 days, on average, for cargo to travel between Mombasa, Kenya and Kampala, Uganda, a distance of 1137 km (Faye et al., 2004). With expectations of continued economic growth in the region the demand for trucking services is likely to increase and wage employment opportunities have been increasing since 2012 (KNBS, 2017). Shipping imported and exported goods results in a steady flow of cargo traffic along the main route called the NC in Kenya connecting the land-locked countries to the sea. A large portion of the transportation costs along the NC is fuel-related and was estimated to account for 50% in 2012 (Fitzmaurice and Hartmann, 2013). However, the remaining 50% of costs are determined by other factors. Causes of high "other costs" involve delays.

This essay examines truck driver perceptions of identified sources of delays along the NC in Kenya. Information about the trucking industry is rare in countries of East Africa (Fitzmaurice and Hartmann, 2013), while studies examining truck driver views of obstacles faced daily are

virtually non-existent. This study provides rare insights from the perspective of a truck driver, who has to deal with potentially obstructive procedures on a daily basis that lengthen travel time and increase costs. Knowledge of factors associated with specific views of truck drivers reinforces a need for relatively simple interventions, e.g., assuring properly functioning weighbridges, as well as strengthened efforts to modify existing policies and prioritize their implementation to effectively reduce transportation costs. The benefit of learning from truck drivers about impediments along the NC reduces the risk of inappropriate strategies to deal with delays. The importance of logistics reflected in less expensive transportation increases the competitiveness of the EAC and expands trade contributing to economic growth and poverty reduction (World Bank, 2011).

2.2 Sources of delay

Delays have been classified as "other costs" in providing transportation services in East Africa (Fitzmaurice and Hartmann, 2013). Multiple weighbridges and checks lead to unexpected delays (Faye et al., 2004; East African, 2015), while wait time at border crossings can average hours (atlasnetwork.org, 2014). Additional challenges faced by cargo drivers plying the NC include rent-seeking behavior by traffic police, cumbersome custom documentation procedures, onerous inspection requirements, and varying trade regulations among partner states (Rotich, 2014; Lalla-Edward et al., 2016). Although there is concerted effort by the EAC to eliminate many sources of delayed transportation, including cooperation in transport infrastructure (Faye et al., 2004) most of them persist and directly impede the growth of trade, and even food security to the NC trade-dependent countries, e.g., South Sudan.

The average delays in transit were estimated at 4.3 days in Kenya for a shipment from Mombasa to Kampala, Uganda, in 2009 (World Bank, 2011). This study narrows the broad

category of delays to events commonly experienced by truck drivers along the NC in Kenya. The considered events occur regularly, like weighbridges whose locations are known in advance, and events associated with a degree of uncertainty such as police roadblocks. Although a truck driver can expect some of them and factor the additional time needed to clear the obstacle, the delays result from unforeseen additional time requirements due to equipment malfunction or unanticipated procedures, all of which are time-consuming.

Police roadblocks intend to enhance transportation safety since overloading of trucks is common in sub-Saharan Africa (Martinez et al., 2018) although the Kenyan government agreed to enforce some regulations in this area (Pedersen, 2001). Police can stop a truck at random and inspect its technical condition, the content and condition of cargo, and the condition of the driver. However, being stopped at a roadblock is associated with potential delays in transporting cargo and adding to costs if no fault is found. Under some circumstances, a stop at a roadblock may deteriorate into harassing the truck driver and may involve unsolicited payments. Inspection requirements, also intended to improve road safety and limit road accidents, can easily turn into needlessly long checks costing the trucker time and, on occasion, money, while delaying the delivery.

The NC is a major route for transshipment of cargo to geographically challenged countries, including Burundi and Rwanda, because of the poor transportation infrastructure (Faye et al., 2004). Transiting various borders increases transportation costs and induces loss of time due to delays at the border (Naudé, 2009). The East African Customs Union (EACU) was established in 2005 (Versailles, 2012) and the member-countries agreed to implement one-stop border posts expected to cut in half transit time at the borders (Balistreri et al., 2009). The reality often clashes with the intent of the program. Besides immigration procedures, burdensome

paperwork and procedures required when crossing borders (Faye et al., 2004; Barka, 2012) and poor traffic management, congestion, and delays characterize the EACU border crossings (World Bank, 2005). Truck drivers who repeatedly cross borders may have a specific view of the existing procedures, which add time needed to cross the border. The conditions at borders differ, but in some instances, they may involve unduly long procedures and unsolicited payments (World Bank, 2011). Customs officials have been known to display negative attitudes towards transit trade for various reasons (Zanamwe, 2005). Learning about truck driver views regarding the duplication of functions can lead to streamlining procedures and reduction of transportation costs that policy makers may overlook. Transparent and predictable procedures will reduce duplication and expedite the shipment.

Transportation costs in Africa are high (Pedersen, 2001). The reduction of the delays directly enhances the competitiveness of trucking and expands trade opportunities. Recently, the shipping of a standard 20-ton container from the Port of Mombasa in Kenya to Kigali, Rwanda (1470 km), has shipping costs of $3,400-$6,500 (Atlas Network, 2014), while other sources estimate it at $3,625 (East African, 2017). The UNCTAD (2015) report on the review of maritime transport reveals that between 2005 and 2014, the cost of international transport, excluding insurance costs as a percentage of the "cost, insurance, freight" for imported goods was highest (11.4%) in developing countries of sub-Saharan Africa and least in developed countries (6.8%). Also, Fitzmaurice and Hartmann (2013) indicated the price of transporting a truckload from Mombasa to Kampala (1137 km) at about $3,200 in 2012. The cost of shipping a container from Mombasa to Nairobi (487.5 km) less than two years later was estimated at $1,050 in 2014 (East African, 2015). The decrease in cost may be associated with fluctuating fuel costs,

but may also reflect the competitive pressures in bidding for loads leading to lower cost of services, and encouraging more trips to offset possible erosion of margins.

2.3 Modeling approach

2.3.1 The random utility model

A qualitative choice model based on random utility maximization first considered by McCullagh (1980) provides the theoretical foundation for the model specification. For an individual faced with a choice decision, it is hypothesized that there is a continuously varying strength of preferences for the choice decision he makes that would underlie the integer value he submits. Let's label the strength of preference "utility," U^*. Given there is no natural units of measurement, the utility is described as ranging over the entire interval line (Greene and Hensher, 2010).

$$-\infty < {U_{im}}^* < +\infty \tag{2.0}$$

where *i* indicates the individual and *m* indicates the choice decision. Individuals are invited to express their preference (P_{im}) for the choice decision on an integer scale from 1 to 3, where a higher number implies higher level of utility. Logically then, the translation from underlying utility to their integer value could be viewed as a censoring of the underlying utility:

$$\begin{aligned} P_{im} &= 1 \text{ if } -\infty < {U_{im}}^* \leq \mu_{i1} \\ P_{im} &= 2 \text{ if } \mu_{i1} < {U_{im}}^* \leq \mu_{i2} \\ P_{im} &= 3 \text{ if } \mu_{i2} < {U_{im}}^* \leq \infty. \end{aligned} \tag{2.1}$$

Presumably, the individual has and knows a continuous range of integer levels that he could express if he was compelled to provide only an integer from 1 to 3. Therefore, the observed values represent a censored version of the true underlying preference. The *thresholds*, μ_{ij}, are specific to the individual and number (*J*-1), where *J* is the maximum number of integer values (here, 3) – *J-1* values are needed to divide the range of utility into *J* cells. The thresholds divide the range of utility into cells that are then identified with the observed integers. Admittedly, an unrealistic assumption in many applications is that these threshold values are the same for all individuals. However, in principle, the difference between two levels of an integer scale (e.g., one compared to two, two compared to three) is not similar on a utility scale; hence there is a strictly nonlinear transformation captured by the thresholds, which are estimable parameters in an ordered choice model.

Each individual brings his own set of personal *characteristics* to the utility function, which is denoted x_{i1} x_{i2},……, x_{iK}. Likewise, each individual brings his own unmeasurable (by the statistician) and unmeasured idiosyncrasy, denoted as ε_{im} for individual i and choice m. Conventionally, the personal features are presumed to enter the utility function through a linear function which produces a familiar *random utility function*

$$U_{im}{}^{*} = \beta_{i0} + \beta_{i1}x_{i1} + \beta_{i2}x_{i2} + \ldots + \beta_{iK}x_{iK} + \varepsilon_{im}. \quad (2.2)$$

Since coefficients are allowed to vary across individuals, individual intrinsic heterogeneity is accounted for by the model.

2.3.2 Econometric modelling

Given the outcome variable bears more than two categories and the values of each category have a meaningful sequential order, i.e., a value is indeed higher than the previous one,

the ordered logit econometric approach is the appropriate estimation choice. Formally, y is an ordered response taking on the values of, for instance, $1, 2,$ and 3 representing "disagree", "neither agree nor disagree", and "agree" response options, respectively. The ordered logit model is derived from a latent variable (y^*) model. Assuming that y^* is determined by

$$y^* = \mathbf{X}'\beta + \varepsilon, \tag{2.3}$$

where β is $K\times1$ and for reasons to be seen, $\mathbf{X}'$, a vector of explanatory variables does not contain an intercept. Let $\mu_1 < \mu_2 < \mu_3$ be unknown cut points (threshold parameters) to be estimated with β**.** Define

$$\begin{aligned} y = 1 \text{ if } y^* &\leq \mu_2 \\ y = 2 \text{ if } \mu_2 &\leq \mu_3 \\ y = 3 \text{ if } y^* &> \mu_3, \end{aligned} \tag{2.4}$$

also written as

$$\begin{aligned} y = 1 \ if \ -\infty < \mathbf{X}'\beta + \varepsilon &\leq \mu_2 \\ y = 2 \ if \ \mu_2 < \mathbf{X}'\beta + \varepsilon &\leq \mu_3 \\ y = 3 \ if \ \mathbf{X}'\beta + \varepsilon &> \mu_3. \end{aligned} \tag{2.5}$$

Given the logistic distribution assumption for ε, it becomes straightforward to derive the conditional distribution of y given $\boldsymbol{X}$. Simply compute each response probability:

$$\begin{aligned} \text{P}\,(\text{y} = 1|\mathbf{x}) &= P(y^* \leq \mu_2|\mathbf{x}) = \text{P}(\text{x}\beta + \varepsilon \leq \mu_2|\mathbf{x}) = \Lambda(\mu_2 - \mathbf{x}\beta) \\ \text{P}\,(\text{y} = 2|\mathbf{x}) &= P(\mu_2 < y^* \leq \mu_3|\mathbf{x}) = \Lambda(\alpha_2 - \text{x}\beta) - \Lambda(\mu_3 - \mathbf{x}\beta) \\ \text{P}\,(\text{y} = 3|\mathbf{x}) &= P(y^* > \mu_3|\mathbf{x}) = 1 - \Lambda(\mu_3 - \text{x}\beta) \end{aligned} \tag{2.6}$$

where Λ is the logistic cumulative density function (CDF) and **P** is the probability.

The parameters μ and β can be estimated by maximum likelihood whereby for each i, the log-likelihood function is

$$\ell_i(\mu, \beta) = 1[y_i = 1]\log[\Lambda(\mu_2 - \mathrm{x}\beta)] + 1[y_i = 2]\log[\Lambda(\mu_3 - \mathrm{x}\beta) - \Lambda(\mu_2 - \mathrm{x}\beta)] + \mathbf{1}[y_i = 3]\log[1 - \Lambda(\mu_3 - \mathrm{x}_i\beta)]. \quad (2.7)$$

2.3.3 Marginal effects

Because y_i^* is an abstract construct, emphasis is not placed on values of the coefficients in $E(y^*|\mathrm{x}) = \mathbf{x}\beta$. Instead, interest lies in response probabilities. Formally, the partial effects of the changes in the regressors are (Greene, 2003; Gujarati, 2014):

$$\frac{\partial \Pr(y = 1|\mathrm{x})}{\partial \mathrm{x}_j} = -\wedge(\mathrm{x}'\beta - \mu_2)\beta_j$$

$$\frac{\partial \Pr(y = 2|\mathrm{x})}{\partial \mathrm{x}_j} = (\wedge(\mathrm{x}'\beta - \mu_2) - \wedge(\mathrm{x}'\beta - \mu_2))\,\beta_j$$

$$\frac{\partial \Pr(y=3|\mathrm{x})}{\partial \mathrm{x}_j} = \wedge(\mathrm{x}'\beta - \mu_3)\beta_j \quad (2.8)$$

where if x_j is discrete, one calculates the discrete change in the predicted probabilities associated with changing x_j, and $\wedge$ is the logistic probability density function.

2.4 Data and variable selection

2.4.1 Drivers' perceptions and transportation impediments

A schematic illustration links the truck driver perceptions of obstacles encountered during a trip and the delays caused by structural constraints and transitory events (Figure 2.1). The perceptions are shaped by several groups of factors, including personal and job

characteristics, and trip and vehicle features. Despite the automation of weighbridges, the malfunctioning equipment disrupts control causing delays in Kenya (Obwocha, 2016).

With regard to personal characteristics, the driver's educational attainment level is important because it enables a driver to access and process new information. Not all surveyed drivers received formal education. Age of the driver and his number of years in trucking are factors because they allowed gaining overall experience and ability to deal with unpredictable transitory events such as road blocks (Figure 2.1). A high monthly salary may reduce the pressure on the truck driver and make it easier to accept some delays. Job-related factors may lessen perceiving structural and transitory events as obstacles if the pay per trip or per month is set and does not depend on accelerating the delivery and if the company monitors the trips (Figure 2.1).

Vehicle-related factors such as vehicle condition are associated with another set of factors affecting truck driver perceptions of structural and transitory events (Figure 2.1). Factors that influence the vehicle operating costs are associated with the type, condition, maintenance, and age of a vehicle. Day-to-day operation of a truck is the responsibility of the driver. Various vehicle-related features have been mentioned in the context of the East African trucking industry (Fitzmaurice and Hartmann, 2013), but were not examined in the context of driver behavior as reflected in performing routine maintenance checks. The checks prevent potential incidents on the road reducing delays and saving costs of shipping. Regulations dictated by transportation policy, including insurance conditions, may also encourage systematic checking of vehicle condition. Owning a truck may encourage viewing of the selected events as obstacles, for example if the owner-driver follows the common habit of overloading (Martinez et al., 2018). Truck age is a general measure of the technical condition and the risk of repairs due to failure of

some mechanism. It is possible that the older the truck, the more likely a driver views selected events as obstacles since they may lead to additional inspection. Kenyan truck owners are more likely to prefer new vehicles compared to other countries in the EAC. The average truck is about seven years old in Kenya (Hartmann, 2013).

Trip features and cargo-related issues also influence truck driver perception of various events as an obstacle (Figure 2.1). Trip monitoring provides real-time updates and scheduled reporting on truck movement for truck company owners or freight forwarders. Monitoring also records statistics such as idle time, cruise time and driver hours of service (Bordhoff and Noel 2008). The longer the trip, the higher the likelihood of unnecessary delays due to traffic accidents, or fatigue of a driver. The length of a trip increases if a truck crosses multiple borders and has to comply with regulations that vary between countries. A long trip likely increases the number of weighbridges creating a potential for more delays due to congestion or equipment malfunction. Transporting perishable cargo also shapes a trucker's perception of events as sources of delay. Truck drivers elicit a sense of urgency when shipping perishable cargo because of potential loss if cargo spoils (Shahparvari and Bodaghi, 2018).

2.4.1 Data

The data applied in this study were collected between the 25th of September and the 16th of October 2018. A total of 511 truck drivers were interviewed at a single location along the NC in Kenya by a team of 10 enumerators. However, only 202 truck drivers provided complete responses to all the questions of variables used in the empirical section. The interviews took place at various times of the day by intercepting the truck drivers as they were waiting in line to be cleared at the Kenya-Uganda border crossing station at Busia. Approaching waiting drivers proved effective in a survey among Australian truck drivers (Hensher et al., 1989). The sample

includes randomly selected truck drivers and plausibly reflects views of drivers frequenting the NC corridor on the way to an international destination. An average interview lasted about 60 minutes, which by itself indicates the length of time to complete procedures at a border crossing stop because none of the surveyed drivers interrupted the interview. The drivers transported goods from the Port of Mombasa primarily to Uganda. Of note, driver participation in the study was voluntary and not incentivized.

The structured questionnaire consisted of several parts focusing on various aspects regarding transported cargo, truck condition and maintenance practices, road conditions and services, challenges along the route, as well as institutional arrangements. Truck drivers also shared opinions about life on the road including the perception of various situations resulting from existing regulations. Finally, the interviewed trucker provided socio-economic and demographic information.

2.4.2 Empirical approach

This essay focuses on local (Kenya) and border-related obstacles grouped into structural and transitory events and examines perceiving them as time-consuming obstacles leading to higher transportation costs. The questions posed to truck drivers involved a Likert-type (balanced) scale. The scale allowed for choosing a response ranging from “strongly disagree” to “strongly agree”; the middle step implied “neither disagree nor agree”.

Five phenomena were selected as the focus of this analysis: varying trade regulations, transiting procedures, custom documentation requirements, weighbridge capacity, and police road blocks. The summary of survey results revealed the concentration of responses regarding sources of delay suggesting that the majority of respondents differed in “strongly disagreeing” and “disagreeing” and also in “agreeing” and “strongly agreeing” to the importance of obstacles.

Recognizing the frustration of drivers was reflected in how agreeable they were responding to each source of delay by choosing among options offered and the final specification of the dependent variable was limited to three categories, where 1 = disagree, 2 = neither disagree nor agree, and 3 = agree. The ordered logit technique is suitable in the estimation of the equation with a categorical dependent variable.

The study estimates an empirical relationship linking the importance of a truck driver's attitudes to the five types of obstacles causing delays in transporting goods in East Africa. Ordered choice models are appropriate when the choice between three or more ordered alternatives depends on the characteristics of the problem (Pindyck and Rubinfeld, 1998) and since the model accounts for the extra information implicit in the ordinal nature of the dependent variable (Kennedy, 2003).

2.4.3 Variable selection

The explanatory variables associated with the perceived importance of the selected sources of delay included in the empirical relationships are drawn from four groups of factors: trucker characteristics, job, trip, and vehicle features (Figure 2.1). The selection of factors in a particular relationship varies somewhat across equations because some variables were deemed irrelevant to examine the importance of a particular source of delay.

The perception of any of the five events as important obstacle causing delays is expected to be influenced differently by various driver characteristics, his diligence in maintaining a vehicle, and the working conditions. A driver who received any formal education is expected to be able to better adjust to unforeseen events or requirements and view an obstacle as less important in comparison to a driver without education. Experience supplements formal education and provides insights that are only gained from practicing an occupation. Consequently, the more

experience a driver has been able to accumulate, the more likely the experience enables him to successfully deal with various obstacles, and he views them as less important.

Monthly salary determines the flexibility of consumption. The higher the salary a trucker earns, the less pressure on him to perform more trips allowing time flexibility. Time flexibility changes the perception of an obstacle's importance causing the monthly salary to lower the likelihood of viewing any of the considered events as an obstacle. Similarly, having other sources of income and charging a fee for carrying hitchhikers changes the perception of an obstacle's importance by lessening the pressure to perform more trips per month. If a trucker operates under a "per trip payment schedule", and is paid a pre-specified amount per trip, he has an incentive to comply with all regulations and procedures. As a result, being paid per trip can be expected to lower the importance attached to potential obstacles.

The vehicle age is expected to be associated with the incidence of breakdowns and repairs. Moreover, older vehicles generally require additional effort in monitoring their condition. It is reasonable to expect that the older the vehicle, the more likely a driver can view any of the four events as an important obstacle. In contrast, the larger the number of vehicle parts checked prior to a trip, the more confident the driver is regarding the vehicle's condition and the less likely he is to attach importance to potential obstacles, such as police roadblocks.

A truck driver working according to a set schedule is assured pay and the completion of a trip as fast as possible is not likely to make much of a difference. Set schedules dictate a rhythm of work and account for possible disruptions such as events considered in the current study. It is plausible then that a set schedule lowers the likelihood of attaching importance to the listed events. Furthermore, if a company monitors the trip, it may observe in real time the location of a

vehicle and reduce pressure on the driver. Under such circumstances, a driver attaches less importance to any of the events and their delaying effect.

Truck ownership effect on the perception of any of the events is difficult to anticipate and is determined empirically. Although a driver-owner may view the events as an obstacle causing delays and decreasing his earning potential, he can also understand the importance of operating a vehicle according to all regulations. It is difficult to anticipate the potential effect a priori.

Having a regular contract for cargo affects perception of delays as important. Devoid of competition for cargo characteristic of drivers with no contract, drivers under contractual arrangements are expected not to attach more importance on obstacles as sources of delay. On the contrary, if a trucker ships perishable cargo, he is faced with pressure to deliver the cargo in time lest it spoils. Therefore, he is expected to view any time-wasting obstacles as important.

2.5 Results

Table 2.1 shows the descriptive statistics of selected factors considered for inclusion in the empirical relationships modeling perceptions of varying trade regulations, transiting procedures, custom documentation procedures, weighbridge capacity, and police road blocks as important obstacles. The average age of the interviewed trucker was about 40 years (Table 2.1), while 59% of Kenya's population is 24 years old or younger (The World Factbook, 2018). However, a study of truck drivers in West Africa showed the majority to be 30-55 years of age (Ubogu et al., 2011). All drivers were male and majority, 97%, were married with a household size of 6. The majority, 57%, reported having formal education above primary school level, but, interestingly, not all truck drivers attended school. The drivers averaged 13 years of driving experience and 86% were Kenyans. A typical route was about 988 km long (for example, the distance from Mombasa to the border with Uganda is 795 km) took around 76 hours to complete.

A truck driver completed an average of 3 trips per month, with 35% ensuring they checked their vehicle for water, oil, or fuel leaks before starting a trip. The majority of drivers, 86%, indicated that their company monitored the trip and 56% operated by set schedule. Relatively few, 11%, of the truck drivers were paid through a per trip payment schedule, while on average a trucker received a monthly salary of KES 30,000 (or $297 at the exchange rate as of October 1, 2018) (Kenya Central Bank Indicative Exchange Rates, 2018). One half, 50%, indicated they had other sources of income. Few drivers, 5%, had fixed contractual arrangements for cargo, 26% shipped perishable cargo in their trip, and 13% had carried hitchhikers within 12 months preceding the interview. Of the total sample, 71%, admitted to making an unsolicited payment. The majority worked for a company, but 42% were independent drivers. An average truck was 9 years old.

2.5.0 Empirical results

The ordered logit estimation results of five equations regarding the perceived importance of five sources, and the changes in probabilities of viewing each event as an important obstacle in response to a change in a given explanatory variable of delays are shown in Tables 2.2, 2.3, 2.4, 2.5, and 2.6. For validity of results, we test the proportional odds assumption on a generalized ordered logit (Fu, 1999) using the Brant test to ascertain whether the coefficients for each variable are consistent across the different pairs of outcomes (Brant, 1990). Results from the Brant tests indicate that the coefficients of the independent variables are unchanged across the pairs of outcomes, and therefore we conclude the ordered logit technique is valid.

2.5.1 Border related issues

2.5.1.1 Varying trade regulations

Table 2.2 presents the results of the first ordered logit model with perception of varying trade regulations as the dependent variable. Truck drivers were allowed to choose between disagreeing, agreeing or remaining neutral that varying trade regulations between Kenya and Uganda was an obstacle causing unnecessary delay. A Likert scale was used to represent perception of varying trade regulations as an obstacle. Five factors positively associated with varying trade regulations as an obstacle, i.e., marital status, years of experience in trucking, the type of payment schedule through which the driver is paid, his monthly salary, and contractual arrangements for cargo. Trucker's age, the number of trips per month, and truck ownership were negatively associated with perception of varying trade regulations as an obstacle.

In particular, being married increased the likelihood of perceiving varying trade regulations as barriers and 93% of the surveyed drivers were married. Drivers with spouses whom they had not seen for as long as the duration of the trip may perceive the uncoordinated trade regulations as time-consuming, particularly if the imposed regulations require additional time to clear. Also, drivers who are paid per trip are more likely to perceive varying trade regulations as obstacles. The additional time to clear trade restriction requirements reduces the number of trips per month and, thus, less pay. Similarly, the higher the monthly salary paid to a trucker, the higher the likelihood of viewing varying trade regulations as obstacles. Highly paid drivers may view trade regulations as a threat to their high pay due to its time-consuming nature translating into fewer trips or untimely delivery. Fewer trips, in turn, mean a lower turnover and subsequently a cut in salary. Likewise, trade regulations could be viewed as a threat to

sustainability of current contract and consequently job security because they delay timely delivery of shipped cargo.

Conversely, the older the trucker, the less likely he viewed the trade regulations as obstacles. Possibly, his experiential knowledge on how adhering to the trade regulations impact both the trucking business and his trucking career in the long run. The higher the number of monthly trips a trucker makes, the less likely he views varying trade regulations as obstacles. More trips assure the trucker of a higher pay and gives him a sense of job security for drivers under cargo contractual arrangements. Frequent border crossing also allows to accumulate experience in typical procedures and such knowledge expedites the process. Truck driver-owners are less likely to view varying trade regulations as obstacles. Driving own truck allows for setting own schedule that accounts for delays caused by varying trade regulations.

To further derive practical implications for the estimated model, the coefficients had to be converted into measurable effects. Using the delta method (Williams, 2011), marginal effects were calculated from the ordered logit regression. The marginal effects indicate the change in probability of the dependent variable falling within one of the ordinal categories as a result in the change in the value of explanatory variable (Table 2.2, columns 2, 3, and 4). The calculated probability changes suggesting the movement away from the trucker disagreeing to agreeing that varying trade regulations are an important obstacle are associated with the marital status of trucker; the probability decreases by 34.5% that a married respondent would disagree that varying trade regulations are important. Similarly, years of experience in trucking and per trip payment schedule change the probabilities in a similar direction. Specifically, the years of experience in trucking decreased the probability of disagreeing that varying trade regulations are important by 14.2%. If a trucker was paid per trip, he was 26.1% less likely to disagree that

varying trade regulations are important. Having a regular fixed contract for cargo increased the probability of disagreeing that varying trade regulations are important by 38.6%, but 18.3% more likely to agree they are an important source of delay (Table 2.2 column 2).

On the other hand, a trucker's age increases the probability of disagreeing that varying trade regulations are important obstacles by 32.9% (Table 2.2 column 2). Likewise, the probability of disagreeing increases by 6.4% with each additional monthly trip. In addition, a trucker who operates by a set schedule was 20.9% more likely to disagree that trade regulations are important obstacles. Lastly, a truck driver and owner was 13.4% more likely to disagree that trade regulations are important obstacles.

2.5.1.2 Transiting procedures

Table 2.3 presents the results of the second ordered logit model with perception of transiting procedures as an obstacle. Truck drivers were allowed to choose between disagreeing, agreeing or remaining neutral that transiting procedures when shipping cargo along the NC were causing unnecessary delay. As before, a Likert scale was used to represent the underlying perception of transiting procedures as an obstacle based on whether drivers agreed, disagreed or remained neutral.

Crossing borders between Kenya and another East African country requires the driver to comply with immigration regulations, which requires additional time spent dealing with formalities and could result in delays. Regular crossing of a border makes the procedure a routine that may occasionally change, but with the EAC emphasis on facilitating trade, the frequency of changes can be expected to be reduced. Not surprisingly, the longer the driver accumulated experience (captured by the number of years of truck operation; Table 2.3), the more likely the view of immigration procedures as a source of unnecessary delay. It is possible that those

routinely crossing the border may be identified and channeled to a lane for an expedited immigration procedure at a border. A trucker reporting another source of income more likely viewed immigration procedures as a source of delay. It is possible the source of income was a part time job that depended on his available time off working as a trucker. Interestingly, an older trucker was less likely to perceive immigration procedures as an obstacle causing delay. The result may be due to a trucker's general experience with immigration and the indispensability of the procedures thereof which may contribute to that perception. Similarly, drivers with a formal education above primary school level were less likely to view immigration procedures as a source of delay. Truck drivers that are more educated possibly understood the role of the seemingly time-consuming procedures and thus did not view them as an obstacle. Operating by set schedule made a driver less likely to view immigration procedures as a source of delay. Scheduled trips may account for the time needed to clear transiting procedures, which consequently lifts the undue pressure to timely deliver cargo regardless of the immigration procedures. A truck driver-owner had a lower likelihood of viewing transiting procedures as a delay source.

The changes in probability associated with the perception of immigration as an obstacle causing delays are shown in Table 2.3, columns 2, 3, and 4. The probability that drivers disagree that immigration is an obstacle decreases by nearly 14% in response to an increase in years of experience. This result is not a surprise because drivers experienced in international routes routinely cross borders and deal with the process regularly. They are more interested in delivering cargo than in seeking residency in another country. Additionally, the probability of disagreeing that immigration is an obstacle decreases by 20.3% for respondents with other sources of income. However, the probability of disagreeing that immigration procedure is a

source of delay increases by a large percentage, 57%, in response to an increase in age of a driver. Also, a trucker operating by set schedule was 23.2% more likely to disagree that transiting procedures is an important source of delay. The result is not surprising because truck companies may account for immigration procedure-related delays when setting the trip schedule, which relieves any pressure to deliver cargo regardless of obstacle. Lastly, a truck driver-owner was 15.4% more likely to disagree that immigration procedures is a source of delay.

2.5.1.3 Custom documentation procedures

Table 2.4 presents results of the third ordered logit model with perception of customs documentation procedures as the dependent variable. Truck drivers were allowed to choose between disagreeing, agreeing or remaining neutral that customs documentation procedures at the border crossing station between Kenya and Uganda were causing unnecessary delay. As before, a Likert scale was used to represent the underlying perception of custom documentations as an obstacle based on whether drivers agreed, disagreed or remained neutral.

The perception of importance regarding custom documentation procedures as a source of delays decreases with the increase in two measures (Table 2.4). Operating by set schedule decreased the likelihood of perceiving custom documentation procedures as an obstacle. The time taken to document cargo details at the customs office is probably accounted for by the company's trip scheduling which may make the driver feel less pressured to deliver cargo if he encounters any issues at customs. Similarly, the higher the monthly salary a trucker receives, the less likely the perception that custom documentation procedure is a source of delay. A higher fixed monthly salary cushions the driver against getting a lower pay because of fewer tips consequent of custom documentation procedures. It is plausible that the company well prepares all the necessary documentation prior to dispatching the driver. As expected, however, shipping

of perishable commodities increased the likelihood of viewing custom documentation procedures as a source of delay. Perishable goods present a higher risk of loss due to spoilage during the trip due to delays. A trucker shipping cargo using an older truck was more likely to perceive custom documentation procedures as a source of delay. Possibly, an older truck did not perform as well as a newer truck on the challenging NC conditions and drivers of older trucks tried to avoid any unproductive use of their time.

Table 2.4 columns 2, 3, and 4 presents the changes in the probability of importance attached to custom documentation procedures. Operating by set schedule increases the probability of disagreeing that custom documentation procedures are a source of delay by 5.9%. Likewise, one hundred Kenyan shillings increase in monthly salary increases the probability of disagreeing that custom documentation procedures was an important obstacle by almost 11%. In contrast, the probability of disagreeing that custom documentation procedures was an important obstacle decreases by nearly 7.5% for perishable cargo shipping. Also, for every year added to a truck's age above the mean, the probability of disagreeing that customs documentation procedures are a source of delay decreases by 6.1%.

2.5.2 Local issues

2.5.2.1 Weighbridge capacity

The Kenya Traffic (Amendment) Act 2013 (Odula, 2016) details the maximum weight capacity of heavy commercial vehicles allowed on Kenyan roads. The Act is aimed at protecting the roads from fast wear and tear. Each vehicle other than a personal car (all types, including SUVs), vans, and small delivery vehicles must detour to the weighbridge. To enforce the law, there are multiple weighbridges distributed along major highways to control the weight of all long-haul vehicles and ensure they adhere to the regulations. Efficiency of weighing and clearing

heavy vehicles depends on the weighbridge capacity, in particular, the number of vehicles that can be weighed at any particular time. Truck drivers who have to wait in line to perform this task vary in their perceptions about it as a source of unnecessary delay.

Table 2.5 presents results of the fourth ordered logit model with perception of insufficient weighbridge capacity as the outcome variable. Truck drivers were required to either disagree, agree or remain neutral that weighbridge capacity was an indirect obstacle causing delays. As before, a Likert scale is used to represent the underlying perception of weighbridge capacity as an indirect obstacle based on whether drivers agreed, disagreed or were neutral that it made them spend more time at the station waiting in line for their vehicles to be weighed. Drivers with a formal education above primary school are more likely to perceive weighbridge capacity as a source of delay (Table 2.5). Respondents with more education may view the multiple stops at weighbridge stations as unnecessary, especially if weighbridge delays are due to unsolicited payments to weighbridge officials. A driver with more years of trucking experience is more likely to view weighbridge capacity as a source of delay. Also, weighbridge capacity is more likely to be perceived as a source of delay by drivers who are paid per trip.

Several factors are associated with perceiving the weighbridge control as not representing a source of delays. An older trucker is less likely to view weighbridge capacity as a source of delay. In like manner, truck drivers with a higher number of monthly trips were less likely to view weighbridge capacity as a source of delay. Lastly, respondents with fixed regular contract for cargo are less likely to view weighbridge capacity as a source of delay.

Additional insights are gained from calculating the change in probability of viewing a weighbridge stopping as a delay source. The probability of disagreeing that weighbridge capacity is an important obstacle decreases by nearly 12% if the respondent had formal education beyond

primary school (Table 2.5 columns 2, 3, and 4). Also, one additional year of experience in trucking decreases the probability of disagreeing that the obstacle is important by nearly 15%. The result suggests that the very experienced drivers accept the regulation and are less bothered by the wait than their younger colleagues. For drivers paid per trip, the probability they disagree that the obstacle is important decreases by nearly 26.5%. Conversely, the probability of disagreeing that weighbridge capacity is an important obstacle increases by nearly 33.9 % with each additional year above the mean in age of trucker (Table 2.5). Similarly, there is nearly a 5% increase in probability of a trucker disagreeing that weighbridge capacity is an important obstacle with each additional monthly trip. Finally, having a fixed contract for cargo increases the probability of disagreeing that weighbridge capacity is an important obstacle by nearly 31.3%.

2.5.2.2 Police roadblocks

Table 2.6 presents results of the fifth and last ordered logit model with perception of police roadblocks as the dependent variable. Truck drivers were allowed to either disagree, agree or remain neutral that police roadblocks was an indirect obstacle causing unnecessary delays while shipping cargo. As in the previous section, a Likert scale was used to represent the underlying perception of police roadblocks as an indirect obstacle causing delays based on whether drivers agreed, disagreed or were neutral that it was unnecessarily increasing their time on the road

Perception of roadblocks as an obstacle was positively associated with five factors including trip length, driver inspection of truck for water, oil, and fuel leaks before starting trip, contractual arrangement for cargo, perishable cargo shipping, and in-transit unsolicited payments (Table 2.6). Specifically, the longer the trip length the higher the likelihood of perceiving

roadblocks as barriers. A longer traveled distance limits the driver's number of monthly trips and a stop at a road block reduces travel time and exacerbates the prevailing limitation. A trucker who performed general inspection of vehicle before starting a trip by checking water and oil levels and fuel leaks, was more likely to perceive police roadblocks as a source of delay (Table 2.6). Additionally, having a fixed contract for cargo was associated with a higher likelihood of perceiving roadblocks as a source of delay. Respondents who shipped perishable cargo were more likely to perceive roadblocks as a source of delay. Every stop at a roadblock consumes time and increases the risk of the spoilage of perishable cargo. As expected, a police roadblock stop that involves having to make an unsolicited payment increases the likelihood of perceiving police roadblocks as obstacles. Field interviews confirmed that majority, 71%, of drivers had to pay an unsolicited fee at some police roadblocks to facilitate their continuation of trip (Table 2.1). Furthermore, drivers who incurred an unsolicited charge were not refunded by the trucking company because they did not have proof of payment.

Three factors, however, were negatively associated with the perception of police roadblocks as sources of delay. Unsurprisingly, a driver of Kenyan origin is less likely to perceive police roadblocks as a source of delay. Kenyan drivers are used to multiple routine police checks necessitated by the impending threat of terrorist slipping into the country from neighboring Somali through porous borders (Mkutu and Sabala, 2007). As expected, drivers with higher monthly salaries were less likely to view police roadblocks as obstacles. A monthly salary, in most cases, is not linked to number of monthly trips, therefore, a trucker is assured of fixed pay regardless of roadblock- related delays that have an effect on the number of completed monthly trips. Also, truck drivers who carried hitch hikers were less likely to view roadblocks as a source of delay.

Changes in the probability of disagreeing that police roadblocks are an important source of delay are presented in Table 2.6, columns 2, 3, and 4. One additional kilometer to trip distance above the mean decreases the probability of disagreeing that police roadblocks are a source of delay by nearly 9.3%. Similarly, the probability of disagreeing that police roadblocks are an important obstacle decreases by nearly 11.8% for drivers who did a general check for water, oil, and fuel leaks before starting their trip. Also, having a fixed contract for cargo decreased the probability of disagreeing that police obstacles are important by nearly 27.3%. But several variables are associated with viewing the police roadblock as an obstacle. A trucker who shipped perishable goods was 10.3% more likely to disagree that police obstacles are a source of delay (Table 2.6). Truck drivers who made an in-transit unsolicited payment were 18.2% less likely to disagree that police roadblocks are an important source of delay. Interestingly, drivers who make such payments do so to expedite the stop leading to a shorter stop and less waste of time. On the other hand, a trucker of Kenyan origin was 14.1% more likely to disagree that police roadblocks are a source of delay possibly because Kenyan motorist, including truck drivers treat bribe solicitation by police as a roadblock ritual that expedites stops hence time saving (Okumu and Nyankori, 2010). The probability of disagreeing that police roadblocks are a source of delay increased by nearly 20% with a shilling increase above the average monthly salary. Lastly a trucker who carried hitchhikers was 24.6% more likely to disagree that police roadblocks are a source of delay. Perhaps, hitchhikrers contributed to any unsolicited payments relieving that financial burden.

2.6 Conclusions

High road transportation costs characterize sub-Saharan Africa. In East Africa, despite the progress made by the formation of the EACU, transportation costs are still an obstacle to economic growth especially for landlocked countries. Next to fuel costs, which account for a large portion of the total cost, a separate source of costs are delays that occur along the route, after the truck leaves the Port of Mombasa. This paper considered two classes of potential delays, namely structural events associated with existing procedures and transitory obstacles that take place at unpredictable intervals, and their perceived importance in opinions of truck drivers. All considered obstacles disrupt travel in the already long journey impacted by the state of road infrastructure.

The examination of four groups of factors associated with the importance attached to any of the five obstacles and sources of delays identified relevant characteristics and the magnitude of their effects. It appears that the approach to managing the trip is very important in easing driver perception of obstacles. Truck companies, where the driver works according to a set schedule seem to ease driver anxiety lowering perception of selected events as obstacles. However, the set schedule likely adds time to the total trip due to various events and as such does not lower transportation costs. It may, however, have an indirect effect because a driver working according to a schedule may drive more carefully reducing the risk of wrecks, police stops, and repairs stemming from abuse of the truck.

A similar effect appears when making a specified payment (monthly salary) to the driver rather than linking it to such factors as the speed of delivery. Drivers assured of their earnings are less likely to associate obstacles with delays in contrast to those drivers whose earnings may be conditioned on factors that vary from trip to trip. Such approach to managing drivers and trucks

benefits the driver and the company, but may lack a direct effect on lowering transportation costs. Overloading is a likely result of the driver's decision to earn more money with excess cargo, and truck companies may implement a system to eliminate this behavior. Independent drivers may not be as keen on giving up a possibility of additional earnings by taking more cargo. This behavior may be encouraged by the reported lack of cargo on return trips from landlocked countries, which, in turn, is influenced by the high transportation costs, diminishing drivers' competitive advantage. The dimension of this problem is outside the immediate scope of this study.

Limiting a load to the allowable limit and controlling tire pressure are simple ways to improve performance. Driver education programs and reminders posted at border crossings or weighbridges may help instill habits consistent with vehicle preventive maintenance. The burden of implementing driver education falls on the appropriate government agencies because of the necessary funding to support such efforts.

Police roadblocks are intended to increase safety on the roads, lower the number of accidents, and protect drivers and the public from injuries. They are a transitory, but a time-consuming obstacle that adds costs and thwarts transportation cost reduction. This study reveals that truck driver characteristics, and vehicle and job features increase the probability of attaching importance to police roadblocks as time-delaying obstacles. The driver age and earnings per trip that increase the probability of viewing roadblocks as an obstacle may suggest a link to unsolicited payments a driver makes to continue the trip. Such unrecorded payments are factored into the price of transportation services and weaken the ability to reduce costs. Attention to police training, assuring competitive pay for the police, and internal monitoring are some of the tools available to the government. To accomplish transportation cost reduction by eliminating

unwanted police behavior requires a long-term commitment to changing existing attitudes. Such policies would be more effective in reducing shipping rates if coordinated within the EACU member-countries.

The operation of weighbridges, an obstacle classified as structural, appears to be a very important issue. Reports of frequent malfunctioning of the equipment at weighbridges are confirmed. The Kenya National Highway Authority (KeNHA) that manages weighbridges needs additional support to eliminate equipment failures, add additional lanes at the stations, and employ trained personnel to minimize the amount of time it takes to clear a truck. It appears that this bottleneck can be realistically eliminated within a reasonable amount of time and with immediate reductions of transportation costs. Since such efforts have not yet been undertaken, there may be institutional resistance to such improvements that need to be addressed within the government and, possibly, with financial assistance from the trucking industry and international financial institutions.

Overall, the identified factors and their measurable effects on the perception of obstacles as very important points towards the need for changes in operations within truck companies and by independent drivers, changes in functioning of the government agencies and their officials, as well as possible coordination of efforts within the EACU. With the expectations of increasing cargo movement along the NC in Kenya, most of which is destined for the landlocked countries in the region, all parties involved must improve their procedures to enhance the competitiveness of the whole transportation system.

Table 2.1 Descriptive statistics of the surveyed truck drivers, Kenya, 2018

Variable name	Mean	Standard deviation	Min	Max
Truck driver's age in years	40.41	9.63	21	80
Marital status (1 = married)	0.93	0.25	0	1
Household size	6.13	2.17	2	18
Driver's education (1 = beyond primary school level)	0.57	0.50	0	1
Number of years truck driving	13.13	8.94	1	56
Country of origin (1 = Kenya)	0.86	0.35	0	1
Trip distance in kilometers	987.93	500.71	95.2	3928.9
Total work hours for forward trip	75.79	53.00	8.40	369.25
Number of trips per month	3.57	1.39	1	11
Driver's check index (1 = water, oil, and fuel leaks)	0.35	0.48	0	1
Trip monitoring (1 = company monitors trips)	0.86	0.34	0	1
Set schedule (1 = operates by set schedule)	0.56	0.50	0	1
Payment schedule (1= paid per trip)	0.11	0.31	0	1
Monthly salary in Kenyan shillings	30460.10	9029.93	5600	65000
Other income (1 = had another source of income)	0.50	0.50	0	1
Fixed contract for cargo (1= regular contract)	0.05	0.21	0	1
Perishable cargo (1= shipped perishables cargo)	0.26	0.44	0	1
Have you ever carried hitch hikers in the last 12 months	0.13	0.33	0	1
Hidden fee (1= paid unsolicited fee during last trip)	0.71	0.45	o	1
Truck ownership (1 = independent owner)	0.42	0.49	0	1
Age of truck in years	9.04	6.30	1	36
Number of observations	511			

Table 2.2 Ordered logit results and marginal effects for perceptions of varying trade regulations

Variable name	Varying trade regulations coefficient	Marginal effects		
		Disagree (D)	Neither D nor A	Agree (A)
Log of truck driver's age	-1.636*	0.329*	-0.174*	-0.156*
	(0.974)	(0.192)	(0.102)	(0.094)
Marital status (1=married)	1.714**	-0.345**	0.182**	0.163**
	(0.844)	(0.165)	(0.090)	(0.081)
Driver's education (1=above primary school)	0.119	-0.024	0.013	0.011
	(0.325)	(0.065)	(0.034)	(0.031)
Log of years of experience in trucking	0.704**	-0.142**	0.075**	0.067**
	(0.341)	(0.066)	(0.035)	(0.033)
Log of trip distance in kilometers	-0.169	0.034	-0.018	-0.016
	(0.317)	(0.064)	(0.034)	(0.030)
Number of trips per month	-0.318**	0.064**	-0.034**	-0.030**
	(0.143)	(0.028)	(0.015)	(0.014)
Monitored trips (1=company monitors trips)	-0.039	0.008	-0.004	-0.004
	(0.540)	(0.109)	(0.057)	(0.051)
Set schedule (1=operates under a schedule)	-1.038***	0.209***	-0.110***	-0.099***
	(0.339)	(0.063)	(0.035)	(0.034)
Payment schedule (1=paid per trip)	1.296**	-0.261**	0.137**	0.123**
	(0.614)	(0.120)	(0.065)	(0.059)
Log of monthly salary	1.402**	-0.282**	0.149**	0.133**
	(0.576)	(0.110)	(0.060)	(0.056)
Contract for cargo (1= regular contract)	1.920***	-0.386***	0.204**	0.183***
	(0.693)	(0.137)	(0.083)	(0.062)
Shipped perishables (1=shipped perishables)	0.155	-0.031	0.016	0.015
	(0.351)	(0.071)	(0.037)	(0.033)
Hitch hikers (1 = carried hitch hikers)	0.637	-0.128	0.068	0.061
	(0.475)	(0.095)	(0.051)	(0.045)
Truck ownership (1=independently owned)	-0.664*	0.134*	-0.070*	-0.063*
	(0.375)	(0.074)	(0.039)	(0.036)
Log of age of truck	0.071	-0.014	0.008	0.007
	(0.229)	(0.046)	(0.024)	(0.022)
Cut 1 (Constant)	9.323 (6.919)	-	-	-
Cut 2 (Constant)	11.281(6.936)	-	-	-
AIC	370.962			
BIC	427.203			
Number of observations	202	202	202	202

Note: Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3 Ordered logit results and marginal effects for perception of transiting procedures

Variable name	Transiting procedures coefficient	Marginal effects		
		Disagree (D)	Neither D nor A	Agree(A)
Log of truck driver's age	-2.907***	0.576***	-0.343***	-0.233***
	(1.017)	(0.189)	(0.114)	(0.088)
Marital status (1=married)	0.879	-0.174	0.104	0.070
	(0.745)	(0.146)	(0.087)	(0.061)
Driver's education (1=above primary school)	-0.850**	0.168***	-0.100***	-0.068**
	(0.331)	(0.063)	(0.038)	(0.028)
Log of years of experience in trucking	0.706**	-0.140**	0.083**	0.057**
	(0.329)	(0.063)	(0.037)	(0.028)
Country of origin (1=Kenya)	0.325	-0.064	0.038	0.026
	(0.473)	(0.093)	(0.056)	(0.038)
Log of trip's distance in kilometers	0.066	-0.013	0.008	0.005
	(0.312)	(0.062)	(0.037)	(0.025)
Number of trips per month	-0.224	0.044	-0.026	-0.018
	(0.142)	(0.028)	(0.017)	(0.012)
Set schedule (1=operates under a schedule)	-1.170***	0.232***	-0.138***	-0.094***
	(0.347)	(0.063)	(0.040)	(0.030)
Payment schedule (1= paid per trip)	0.819	-0.162	0.097	0.066
	(0.585)	(0.114)	(0.068)	(0.048)
Log of monthly salary	0.448	-0.089	0.053	0.036
	(0.542)	(0.107)	(0.064)	(0.044)
Other source of income (1=yes)	1.026***	-0.203***	0.121***	0.082***
	(0.322)	(0.059)	(0.036)	(0.028)
Fixed contract for cargo (1= regular contract)	-0.055	0.011	-0.007	-0.004
	(0.646)	(0.128)	(0.076)	(0.052)
Cargo perishables (1=shipped perishables)	-0.078	0.015	-0.009	-0.006
	(0.356)	(0.071)	(0.042)	(0.029)
Hitch hikers (1= carried hitch hikers)	0.595	-0.118	0.070	0.048
	(0.469)	(0.092)	(0.056)	(0.038)
Truck ownership (1 = independently owned)	-0.775**	0.154**	-0.091**	-0.062**
	(0.368)	(0.071)	(0.043)	(0.030)
Log of age of truck in years	0.293	-0.058	0.035	0.023
	(0.226)	(0.044)	(0.026)	(0.018)
Cut1 (Constant)	-3.739	-	-	-
	(6.641)			
Cut2 (Constant)	-1.362	-	-	-
	(6.633)			
AIC	361.525			
BIC	421.074			
Number of observations	202	202	202	202

Note: Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4 Ordered logit results and marginal effects for custom documentation procedures

Variable name	Custom documentation coefficient	Marginal effects		
		Disagree (D)	Neither A nor D	Agree (A)
Log of truck driver's age	0.644	-0.069	-0.073	0.143
	(0.905)	(0.098)	(0.103)	(0.200)
Marital status (1=married)	0.013	-0.001	-0.001	0.003
	(0.624)	(0.067)	(0.071)	(0.138)
Drive's education (1=above primary school)	0.358	-0.039	-0.041	0.079
	(0.315)	(0.034)	(0.036)	(0.069)
Log of years of experience in trucking	0.150	-0.016	-0.017	0.033
	(0.311)	(0.034)	(0.035)	(0.069)
Log of trip's distance in kilometers	-0.141	0.015	0.016	-0.031
	(0.298)	(0.032)	(0.034)	(0.066)
Number of trips per month	0.189	-0.020	-0.022	0.042
	(0.131)	(0.014)	(0.015)	(0.029)
Monitored trips (1=company monitors trips)	-0.788	0.085	0.090	-0.175
	(0.542)	(0.060)	(0.061)	(0.118)
Set schedule (1=operates under a schedule)	-0.547*	0.059*	0.062*	-0.121*
	(0.321)	(0.035)	(0.037)	(0.070)
Payment schedule (1=paid per trip)	-0.902	0.097	0.103	-0.200*
	(0.559)	(0.061)	(0.063)	(0.121)
Log of monthly salary	-0.980*	0.106*	0.112*	-0.217*
	(0.545)	(0.060)	(0.062)	(0.118)
Contract for cargo (1= regular contract)	-0.122	0.013	0.014	-0.027
	(0.676)	(0.073)	(0.077)	(0.150)
Shipped perishables (1=shipped perishables)	0.692**	-0.075*	-0.079**	0.153**
	(0.349)	(0.039)	(0.039)	(0.075)
Hitch hikers (1= carried hikers)	-0.280	0.030	0.032	-0.062
	(0.488)	(0.053)	(0.055)	(0.108)
Truck ownership	-0.235	0.025	0.027	-0.052
	(0.354)	(0.038)	(0.040)	(0.078)
Log of age of truck	0.567***	-0.061**	-0.065***	0.126***
	(0.217)	(0.025)	(0.024)	(0.046)
Cut1 (Constant)	-9.379 (6.451)	-	-	-
Cut2(Constant)	-7.416 (6.439)	-	-	-
AIC	401.283			
BIC	457.524			
Number of observations	202	202	202	202

Note: Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5 Ordered logit results and marginal effects for perception of weighbridge capacity

Variable name	Weighbridge capacity coefficient	Marginal effects		
		Disagree (D)	Neither D nor A	Agree (A)
Log of truck driver's age	-1.529*	0.339*	-0.078	-0.261*
	(0.909)	(0.197)	(0.049)	(0.154)
Marital status (1=married)	0.295	-0.065	0.015	0.050
	(0.684)	(0.151)	(0.035)	(0.117)
Driver's education (1=above primary school)	0.530*	-0.118*	0.027	0.090*
	(0.308)	(0.067)	(0.017)	(0.052)
Log of years of experience in trucking	0.677**	-0.150**	0.035*	0.116**
	(0.317)	(0.068)	(0.018)	(0.053)
Log of trip's distance in kilometers	0.322	-0.071	0.016	0.055
	(0.303)	(0.066)	(0.016)	(0.051)
Number of trips per month	-0.245*	0.054*	-0.013*	-0.042*
	(0.133)	(0.029)	(0.007)	(0.022)
Monitored trips (1=company monitors trips)	0.284	-0.063	0.014	0.048
	(0.514)	(0.114)	(0.027)	(0.088)
Set schedule (1=operates under a schedule)	-0.783**	0.174***	-0.040**	-0.134***
	(0.313)	(0.067)	(0.019)	(0.052)
Payment schedule (1=per trip)	1.196**	-0.265**	0.061*	0.204**
	(0.566)	(0.122)	(0.033)	(0.094)
Log of monthly salary	0.649	-0.144	0.033	0.111
	(0.501)	(0.110)	(0.027)	(0.085)
Contract for cargo (1= regular contract)	-1.413**	0.313**	-0.072**	-0.241**
	(0.675)	(0.145)	(0.036)	(0.115)
Shipped perishables (1=shipped perishables)	-0.037	0.008	-0.002	-0.006
	(0.328)	(0.073)	(0.017)	(0.056)
Hitch hikers (1 = carried hitch hikers)	0.054	-0.012	0.003	0.009
	(0.450)	(0.100)	(0.023)	(0.077)
Truck ownership	0.102	-0.023	0.005	0.017
	(0.339)	(0.075)	(0.017)	(0.058)
Log of age of truck	-0.233	0.052	-0.012	-0.040
	(0.212)	(0.046)	(0.011)	(0.036)
Cut1 (Constant)	3.810 (6.142)	-	-	-
Cut2 (Constant)	5.126 (6.147)	-	-	-
AIC	433.226			
BIC	489.467			
Number of observations	202	202	202	202

Note: Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6 Ordered logit results and marginal effects for perception of police road blocks

Variable name	Police road blocks coefficient	Marginal effects		
		Disagree (D)	Neither D nor A	Agree (A)
Log of truck driver's age	0.417	-0.066	-0.014	0.079
	(0.914)	(0.145)	(0.030)	(0.174)
Marital status (1=married)	0.016	-0.002	-0.001	0.003
	(0.689)	(0.109)	(0.022)	(0.131)
Driver's education (1=above primary school)	0.513	-0.081	-0.017	0.098*
	(0.317)	(0.050)	(0.011)	(0.059)
Log of years of experience in trucking	0.292	-0.046	-0.009	0.056
	(0.296)	(0.047)	(0.010)	(0.056)
Country of origin (1=Kenya)	-0.892**	0.141**	0.029*	-0.170**
	(0.454)	(0.071)	(0.017)	(0.084)
Log of trip's distance in kilometers	0.591*	-0.093*	-0.019	0.113*
	(0.308)	(0.048)	(0.012)	(0.058)
Number of trips per month	-0.096	0.015	0.003	-0.018
	(0.131)	(0.021)	(0.004)	(0.025)
Driver's check index (1= water, oil, fuel leaks)	0.747**	-0.118**	-0.024*	0.142**
	(0.371)	(0.058)	(0.014)	(0.069)
Set schedule (1=operates under a schedule)	0.456	-0.072	-0.015	0.087
	(0.329)	(0.052)	(0.012)	(0.062)
Payment schedule (1=paid per trip)	0.804	-0.127	-0.026	0.153
	(0.596)	(0.094)	(0.020)	(0.112)
Log of monthly salary	-1.260**	0.199**	0.041**	-0.240**
	(0.534)	(0.083)	(0.021)	(0.098)
Other source of income (1=yes)	0.153	-0.024	-0.005	0.029
	(0.306)	(0.048)	(0.010)	(0.058)
Contract for cargo (1= regular contract)	1.724**	-0.273**	-0.056*	0.329**
	(0.801)	(0.125)	(0.030)	(0.148)
Shipped perishables (1=shipped perishables)	0.650*	-0.103**	-0.021	0.124**
	(0.337)	(0.052)	(0.013)	(0.063)
Hitchhikers (1=carried hitch hikers)	-1.553***	0.246***	0.050**	-0.296***
	(0.495)	(0.074)	(0.024)	(0.090)
Hidden fee (1= made unsolicited payment)	1.153***	-0.182***	-0.037**	0.220***
	(0.335)	(0.050)	(0.017)	(0.060)
Truck ownership (1= independent ownership)	0.237	-0.038	-0.008	0.045
	(0.354)	(0.056)	(0.012)	(0.067)
Log of age of truck in years	-0.079	0.012	0.003	-0.015
	(0.213)	(0.034)	(0.007)	(0.041)
Cut 1 (Constant)	-7.388 (6.364)	-	-	-
Cut 2 (Constant)	-5.718 (6.354)	-	-	-
AIC	413.810			
BIC	479.975			
Number of observations	202	202	202	202

Note: Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

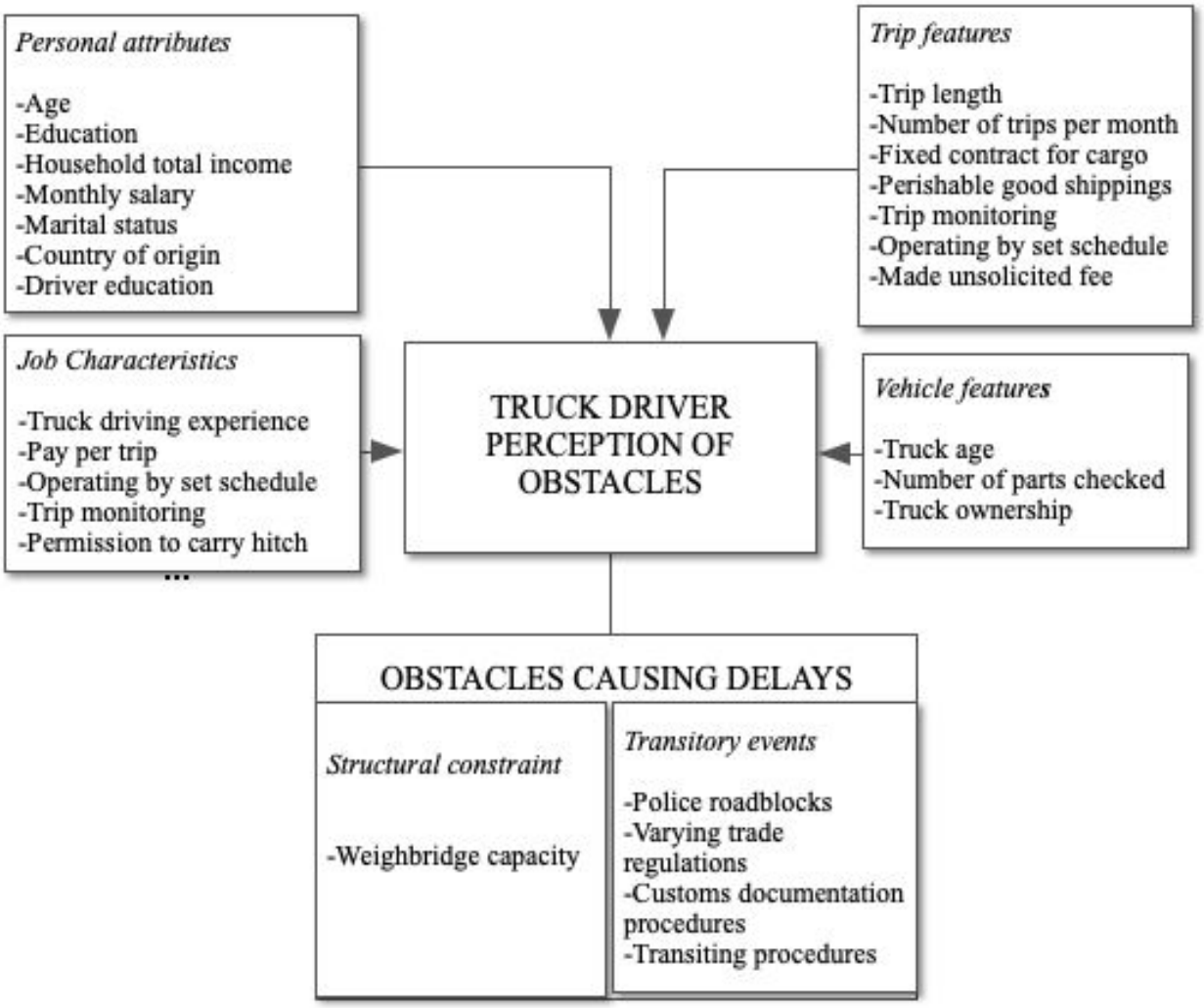

Figure 2.1 Relationship between factors influencing the truck driver perceptions of obstacles

CHAPTER 3

TRUCKING AND ROAD SAFETY ALONG THE NORTHERN CORRIDOR, KENYA

3.1 Introduction

On average, an estimated 13 million deaths and 20-50 million disabilities occur worldwide due to road accidents (WHO, 2012). Of all worldwide reported injury deaths in 2007, road accidents accounted for 23% (WHO, 2007). In Africa, road traffic accidents[1] (RTAs) are estimated to claim over 300,000 lives every year. The actual number for sub-Saharan Africa, which could be higher, is unknown due to poor accident data record keeping pervasive in the region (Manyara, 2013). With 52% of the world's registered vehicles, 72% of the world population, and almost 80% of road accidents, developing countries, including Kenya, are laden with a disproportionate share of RTA fatalities (Manyara, 2013). The yearly road traffic fatality rate for these countries in 2012 stood at 20.1 per 100 000 population compared to 8.7 per 100 000 population in the developed countries (WHO, 2012). Pedestrians and motorized two or three-wheeled vehicles (cycles) are the most vulnerable road users in Kenya (Ogendi et al., 2013) Deaths among vulnerable groups account for 57% of all recorded deaths in developing countries compared to 51% in middle-income countries and 39% percentage in high-income countries, respectively.

[1]Involves personal injury occurring on the public highway in which at least one road vehicle or a vehicle in collision with a pedestrian is involved and which becomes known to the police within 30 days of its occurrence (WHO, 2012)

The RTAs pose enormous cost implications on the world economy. Out of an estimated world total of US$500 billion a year, about US$100 billion[2] is lost in the developing and transitioning economies (WHO, 2012). Furthermore, annual RTA-related losses in developing countries exceed total annual development aid received. For instance, exclusive of actual loss of life, the cost of road accidents to Kenya's economy is in excess of US$ 50 million. In the 1980s and early 2010s, RTAs cost in Kenya as a share of GDP has more than doubled from 5% to 11% (Yerrel, 1984; Ogendi et al., 2013). Unsurprisingly, an estimated 23% of all reported RTAs in Kenya in 2016 were caused by heavy commercial vehicles. The majority of which are trucks (Kenya Forum, 2016). In 2017, the share of RTAs accounted for by heavy commercial vehicles rose by 1% from the previous year (businessdaily.com, 2017).

Studies on the global causes of truck related RTAs and in Kenya have emphasized either the outcomes of bad practice, notably road accidents involving fatalities (Li, Braver, and Chen, 2003; Tefft, 2017), or the effect of on-road behavior on the ratio of truck accidents (Hensher et al., 1991; Gichaga, 2017). Truck driver excessive sleepiness, obesity that imposes limited range of movements for major body joints, tight timetables that lead to fatigue of drivers, and the use of alcohol, cannabis and cocaine that impair judgement of time and distance while driving are some of the identified behavior-related issues in RTA literature (Luke, R., and Heyns, G. J. 2014; Elshamly, El-Hakim, and Afify, 2017). As part of strategic behavior to 'stay ahead of the pack' in terms of the number of trips, some drivers modify the lifestyle element of trucking.

[2] These costs include, direct costs such as medical, hospital, and rehabilitation expenses, workers' compensation payments, and higher insurance premiums or even loss of insurability

Typically, drivers rarely sleep at their 'permanent residence' in the quest to secure a load. Some, instead, spend considerable hours in the cabin of their truck and eat unbalanced meals. For instance, drivers in Australia were found to use pills to stay awake and gain more on-road hours (Hensher et al., 1991). In sub-Saharan Africa, however, drivers smoke cigarettes or chew khat (*Catha edulis*, the leaves of an Arabian addictive stimulant shrub) to maintain concentration for prolonged periods of time on the road (Nyongesa and Onyango, 2010; Odenwald et al., 2011). There exists a dearth of studies particularly in sub-Saharan Africa, however, based on enquiry into the underlying causes of driver behavior and hence levels of exposure to risk of an accident (Kopits and Cropper, 2005; Kahn and Gotschall, 2015; Matheka et al., 2015; Trade Mark East Africa, 2014). In addition to contributing to applied economics literature, this study investigates the indirect influence khat use has on truck related RTA.

The trucking industry's areas of investigation that can provide insights on the real causes of RTAs include: the infrastructural environment, the pressure from cargo and truck owners, the driver's personal attributes and his household's characteristics, and the economic incentives from trucking (including the competitive nature of load-acquisition). In the context of exposure to risk, this essay first investigates the factors that shape truck drivers' economic reward profile including, total work hours, monthly earnings, and the proportion of time spent driving in total working time. Second, the essay seeks to establish the determinants of exposure to RTAs risk among truck drivers. These factors are used to explain truck driver on-road behavior.

Besides contributing to the dearth of literature on truck related RTAs, results from this study provide insights that are useful in public health education regarding the trucking industry. Furthermore, the findings are useful in establishing guidelines for positive change in EAs

trucking industry that plays a pivotal role in facilitating agricultural commodity trade in the region.

3.2 Trucking in East Africa

Trucking plays a crucial role in sustaining East Africa's (EA) economies through intra-regional trade. The trucks mostly transport goods across EA partner countries including Kenya, Uganda, Rwanda, and Burundi, with a significant proportion of trucks serving within their respective local economies. The highest percentage of registered trucks in EA is by Kenyan companies followed closely by Tanzania and, then, Rwanda as shown in Table 3.1. Official and reliable information on registered number of trucks in Uganda and Burundi is unavailable, however. Corporate companies own a large share of the total fleet, while the remaining share is family-owned (Raballand, Refas, Beuran, and Isik, 2012).

The NC and Central Corridor (CC) are the two main routes of operation for trucks in East Africa with total lengths of 14,108 km and 1,300 km respectively. The former starts at the Port of Mombasa through Kenya, while the latter stretches from the port in Dares Salaam through Tanzania, but both reach the Democratic Republic of Congo (DRC) border on the EA region's western edge (Figure 4.1). The corridors form the backbone of formal intra-EAC trade (World Bank, 2008). Transit of EA's cargo is highly dependent on these corridors.

Road safety along the NC of East Africa

RTAs along the NC are the most common causes of injury to pedestrians, cyclists and truck drivers. In 2013, Kenya and Uganda's segments of the NC reported the highest number of road fatalities (Table 3.2), while Burundi, DRC, Rwanda, and South Sudan had a combined share of 13% of all accidents. In 2017, Kenya's National Transport and Safety Authority (NTSA) also

indicated that Kenya's segment of the NC, i.e., from Mombasa to Busia reported the highest number of RTA fatalities in East Africa (kenyans.co.ke, 2018).

The lead causes of RTAs along the NC as reported by Trade Mark East Africa (2014) include driver error resulting from lack of proper training, heavy work routines devoid of enough rest, non-existence of proper road signs/safety features on the highway, speeding, misjudging clearance, and swerving. The aforementioned last three accounted for over 85% of all NC road accidents in 2017, while vehicle mechanical issues accounted for 10%, and environmental factors accounted for 5% (NCTTCA, 2017).

3.3 Literature review

In fields as diverse as transportation and applied economics, there has been a considerable expansion of the literature on road safety which is indicative of a growing awareness of its economic implications. Research on road safety follows two streams of literature. The first involves the characterization of infrastructure by investment levels, physical properties such as road curves and type of paving, and traffic conditions (including, congestion levels and vehicle mix) (Albalate et al., 2013; Hughes, et al., 2016). The impact of infrastructure variables on fatality and injury counts is modeled by employing count data regressions on field survey data. The second stream of studies considers the impact and enforcement of regulatory measures. The analyses in this category evaluate the effectiveness of speed limits modification and periodic vehicle inspection tests, but some studies are also closely concerned with behavioral attitudes and exposure to risk. The second stream of literature mainly uses aggregate data and time series analytical approaches (Hakkanen and Summala, 2000; Machado and Mazzulla, 2014).

Approaches used in the current study are adopted from aspects from both aforementioned streams of literature. In particular, this study uses survey data to model the effect of behavioral attitudes and exposure to risk.

3.3.1 Factors affecting road accidents

Road safety improving countermeasures are developed from identified causes of RTAs and possible factors that increase accident risk (Hakkanen and Summala, 2000). One branch of literature categorizes these RTA causing factors into 3 broad categories, i.e., according to the physical environment, vehicle features, and user (driver) characteristics (Elander et al., 1993; Parker et al., 1995; de Oña et al., 2014). Another branch divides the factors into two broad categories which include, engineering (road/vehicle/environment related) and user (Wang et al., 2009; Michalaki et al., 2015).

3.3.1.1 Physical environment

The physical environment entails infrastructure characteristics and traffic conditions. Literature on infrastructure and traffic conditions on RTAs is critically case specific. Thus, while findings differ, the majority focuses on the advantages of improved infrastructure (Albalate et al., 2013). For instance, quality of roads, number of traffic lanes, and street lighting along busy highways often feature in literature (Anastasopoulos et al., 2008; Park et al. 2012).

In sub-Saharan Africa, poorly maintained and worn out tarmacked roads with sharp curves have been at the forefront of contributing to RTAs. Also, two-way traffic roads at major highways and nonexistence of road signs to warn drivers of sharp winding curves are blamed for many RTAs along major highways (Gichaga, 2017).

Traffic volume is the most significant variable that affects the number of RTAs (Haynes et al., 2008; Lord et al., 2008). In an urban setting, Ayati and Abbasi (2011) found that a high volume of passenger cars and heavy vehicles is less likely to cause severe accidents but light non-passenger vehicles are more likely. Similarly, Wang et al. (2009) found that passenger vehicle traffic congestion (volume) barely affects frequency of road accidents in England.

3.3.1.2 Vehicle features

Vehicle related issues contribute to RTAs. The type of vehicle, i.e., in terms of weight, length, and height impact both the number and severity of RTAs. Long vehicles, for instance, increase the risk of accidents particularly when overtaking in a two-way road traffic (Jonsson and Lindberg, 2009). Also, severity of RTAs is more pronounced in public passenger vehicles due to the number of casualties involved. Poorly maintained vehicles have also been found to increase the RTA rate. Bair et al. (2012) found that, proper maintenance defined by the recommended kilometers negatively associates with loss probability in the compulsory automobile liability insurance. The probability of loss decreases by 0.23% on average when the vehicle undergoes the scheduled maintenance as recommended after traveling a specific distance.

3.3.1.3 User characteristics

User characteristics also play a crucial role in RTAs. Generally, different categories of drivers bear different risk levels to RTAs. Truck drivers have proven to be a high-risk group (Charbotel et al., 2002; nation.co.ke, 2016). For example, in the United Kingdom (UK), heavy commercial vehicles are twice as likely to be involved in a fatal road accident per 100 million kilometers as private passenger vehicles (Department of Environment, Transport and the Regions, 1998).

Driver fatigue. Falling asleep behind the wheel accounts for up to 15-20% of all traffic accidents in developed countries (Karrer and Roetting, 2007). However, fatigue is often overlooked in police reports because some drivers die in the accidents, while surviving ones fail to admit they were asleep behind the wheel. Truck drivers are disproportionately represented in fatigue-related accidents in developing as well as developed countries (McKenna, 2005).

Sleepiness affects reaction time, a critical element of safe driving. It impairs attention-related activities (such as driving) by reducing the level of vigilance, alertness, and concentration. Among truck drivers, the lead causes of fatigue include, long journeys on monotonous roads, engaging in physically taxing work - related activities (including, loading cargo and vehicle maintenance activities) prior to the start of trip, and lack of enough sleep due to long working hours (Hensher et al., 1991; Summala and Mikkola, 1994).

Drug use. Alcohol and/or certain illicit or medicinal drug use while driving increases the risk of RTAs (Smink et al., 2005). The drugs that feature most among drivers include marijuana, narcotics, stimulants, and depressants. When used in combination with alcohol, drugs are associated with a significantly increased risk of fatal crash involvement (Li et al., 2013).

Drummer et al. (2003) study on driver fatalities in Australia found that when compared to car drivers and motorcyclists, truck drivers elicited the least prevalence of alcohol at or over 0.05 g/100ml (%). Unsurprisingly, stimulants were much more often reported among drivers (23%), which was indicative of their cautionary measure to maintain concentration and alertness because of the demanding work routine. While drivers in most developed countries use pills to stay alert and maintain concentration on the road (Hensher et al., 1991), their counterpart in sub-Saharan Africa rely on khat, the leaves of an Arabian addictive stimulant shrub, or cigarettes (Nyongesa and Onyango, 2010). Khat chemically resembles amphetamine, which generally increases risk-

taking behavior and can develop inappropriate and dangerous driving behavior amongst drivers who use it (Abdul-kader, 2014). Additionally, chronic khat use is associated with "loss of inhibitory control" and subsequently a dysfunctional pre-frontal cortex (PFC) and reduced dopamine (DA) level in the striatum – the neurotransmitter that plays a crucial role in response inhibition (Colzato et al., 2010). Eckersley et al. (2010) also reports that khat use prior to driving is dangerous because it disorients and increases both anxiety and irritability in the user.

3.3.1.4 Socio-demographic characteristics and driver behavior

Socio-demographic characteristics are human factors related to road users' driving behavior which include, gender, age, personal and family income, education level, and current marital status (Wang et al., 2002; Dissanayake, 2004; Tractinsky et al., 2013). On the other hand, driver behavior entails, driving speed, usage of cell phones while driving, and lack of or usage of seat belts. There are studies that have found that socio-demographic factors affect RTAs. For example, Nagata et al. (2012) found that income per capita and total distance traveled were significantly associated with traffic injury and traffic mortality among drivers in Japan. Additionally, the study found older drivers to be more susceptible to truck related injuries and suffer higher mortality rates than younger drivers (Cantor et al., 2010).

3.4 Modeling approach

3.4.1 System equations estimation

Haavelmo (1943)'s Nobel prize winning paper posits that real statistical problems arise if estimable equations that represent economic relationships contain certain stochastic idiosyncrasies (unexplained residuals), in addition to directly observed variables. The paper

further notes that, the idiosyncrasies must have some ascribed properties, a priori, for any meaningful inferences to be made from the variable's statistical parameters. Of bigger concern, econometricians often overlook the details, in their entirety, of the statistical implications of a system of such systematic equations to be simultaneously fulfilled by the data. Pointedly, if it is assumed that the economic variables simultaneously satisfy several stochastic relations, then determining each of the equations from the data separately is not satisfactory without regard to the restrictions, which the other equations might impose upon the same variables.

Empirical application of three stage least squares (3SLS) estimation procedure cuts across different fields of literature mainly because it accommodates the complexity of causal relationships. In finance literature, for instance, Aggarwal and Jacques (2001) examine the simultaneous impact of prompt corrective action (PCA) on both bank capital and credit risk using 3SLS. Also, by using 3SLS, risk-based capital standards have been found to simultaneously affect capital ratios and portfolio risk for commercial banks (Jacques and Nigro, 1997). Likewise, in transportation economics literature, a field in which this study rightly fits, Hensher et al. (1991) apply 3SLS to truck driver survey data to investigate the links between the Australian truck industry's economic and on-road driver performance.

In the backdrop of Haavelmo's (1943) note and the mention of empirical application of system of equation estimation, the econometric procedure for the first section on the factors that shape the economic profile of drivers entails a system of equations that are modeled simultaneously. Specifically, the modeling involves the use of three stage least squares (3SLS). The 3SLS is a special case of Generalized Method of Moments (GMM) estimators (Lee, Liang, Lin and Yang, 2016).

Omitted explanatory variables, simultaneity bias, and measurement errors in variables are

the generally recognized sources of endogeneity in empirical modeling (Lee et al., 2016). Besides being inconsistent, OLS estimates are biased in the presence of endogeneity. Instrumental variable (IV) estimation is widely used to deal with the endogeneity problem. The idea underlying IV estimation is the selection of instruments that are sufficiently correlated with the regressors but uncorrelated with the disturbance terms. The sample orthogonality conditions are made closer to zero by IV estimators (Sargan, 1958). Hansen's (1982) proposed GMM estimator based on orthogonality conditions provides an alternative solution to IV. The GMM estimator is a generalization of Sargan's (1958, 1959) linear and non-linear IV estimators based on an optimal weighting matrix for the moment conditions. Thus, the 3SLS falls within this generalization as a special case of GMM. The only difference between the GMM estimator and 3SLS is that the former's weighting matrix accounts for temporal dependence, heteroskedasticty, or autocorrelation.

3.4.1.1 Econometric modelling

Recognizing the potential endogeneity imposed by endogenous RHS variables in the system of equations, the intended tactic is the simultaneous estimation and the necessitated use of 3SLS. The approach uses all the exogenous variables as instruments and estimates the entire system using GLS estimation (Intriligator et al., 1996). Formally, consider the following linear simultaneous equations model (Lee et al., 2016; Greene, 2010),

$$y_1 = \delta_{12}y_2 + \delta_{13}y_3 \ldots . + \delta_{1J}y_J + X_1\gamma_1 + \varepsilon_1$$

$$y_2 = \delta_{21}y_1 + \delta_{23}y_3 \ldots . + \delta_{2J}y_J + X_{23}\gamma_1 + \varepsilon_2$$

$$\vdots$$

$$y_J = \delta_{J1}y_1 + \delta_{J2}y_2 \ldots . + \delta_{J(J-1)}y_{(J-1)} + X_J\gamma_J + \varepsilon_J \qquad (3.1)$$

where $y = [y_1\ y_2\ \ldots\ y_J]'$ is an $J\times1$ vector of endogenous variables, $x = [x_1, x_2\ \ldots\ x_J]$ is a vector of all exogenous variables in the system which includes constant terms, $\varepsilon = [\varepsilon_1, \varepsilon_2, \ldots\ \varepsilon_J]'$ is an $J\times1$ vector for the disturbances. The parameter matrices of interest, δ and γ are defined as:

$$\delta = \begin{bmatrix} \delta_{12} & \delta_{13} & \cdots & \delta_{1j} \\ \delta_{21} & \delta_{23} & \cdots & \delta_{2J} \\ \vdots & \vdots & \vdots & \vdots \\ \delta_{J1} & \delta_{J2} & \ldots & \delta_{J(J-1)} \end{bmatrix} = \begin{bmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_J \end{bmatrix} \text{ and } \gamma = \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_J \end{bmatrix} \tag{3.2}$$

The structural parameters, δ and γ can be estimated using two approaches; a single equation estimation and system equation. The single equation estimation is as shown below

$$y_j = Y_j\delta_j + X_j\gamma_j + \varepsilon_j\ , j = 1, 2\ , \ldots\ ,\ J \tag{3.3}$$

where y_j denotes the $T\times1$ vectors of observations for the endogenous variables on the left-hand side of the *j*th equation (*T=1* for this study). In this case, Y_j denotes the $T\times J$ data matrix for the endogenous variables on the RHS side of this equation and X_j is a data matrix for all exogenous variables in the equation. Since y_j and Y_j are jointly determined within the system, they are correlated with the disturbance term and, thus, the resulting OLS estimator is inconsistent and biased (Greene, 2012; Lee et al., 2016). The 3SLS is introduced by rewriting the system of equations (3.3) as

$$Y = Z\beta + \varepsilon \tag{3.4}$$

where Y is a vector defined as $[y_1\ y_2\ \ldots\ y_J]'$. Additionally, $Z = \text{diag}\ [Z_1\ Z_2\ \ldots\ Z_J]$ is a block diagonal data matrix for all variables on the right-hand side of this system with the form $Z_j = [Y_j \quad X_J]$ as defined in equation (11). While β is a vector of interest parameters defined as $[\beta_1\ ,\ \ \beta_2\ \ldots.\beta_J]'$ and ε is a vector of disturbances defined as $[\varepsilon_1\ \varepsilon_2\ \ldots\ \varepsilon_J]'$ with $E(\varepsilon) = 0$ and

$\square(\varepsilon\varepsilon') = \sum \otimes I_T$, where $\otimes$ signifies the Kroeneker product. Here, $\sum$ is defined as

$$\sum = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1J} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{J1} & \sigma_{J2} & \ldots & \sigma_{JJ} \end{bmatrix}. \quad (3.5)$$

By using all exogenous variables $\mathrm{X} = [\mathrm{X}_1, \mathrm{X}_2 \ \ldots \ \mathrm{X}_J]$ in each equation of the system, pre-multiplying the model (3.4) by $X_I' = diag[X' \ldots X'] = \mathrm{X} \otimes \mathrm{I_J}$ yields the model

$$X_I'\mathrm{Y} = X_I'\mathrm{Z}\beta + X_I'\varepsilon. \quad (3.6)$$

The covariance matrix from (3.5) is

$$\mathrm{Cov}\,(\mathrm{X_I'}\varepsilon) = \mathrm{X_I'Cov}(\varepsilon\,)\mathrm{X_{I,}} = \mathrm{X_I'}(\sum \otimes \mathrm{I_T})\mathrm{X_{I,}} \text{ [change to coma to period-??]} \quad (3.7)$$

The GLS estimator of the equation (3.5) is the 3SLS estimator. Thus, the 3SLS estimator is given as follows:

$$\hat{\beta}_{3\mathrm{SLS}} = \{\mathrm{Z'X_I}[\mathrm{X_I'}(\sum \otimes \mathrm{I_T})\mathrm{X_I}]^{-1}\mathrm{X_I}'\mathrm{Z}\}^{-1}\mathrm{Z'X_I}[\mathrm{X_I'}(\sum \otimes \mathrm{I_T})\mathrm{X_I}]^{-1}\mathrm{X_I'Y}. \quad (3.8)$$

3.4.2 Random utility theory

The econometric approach used to estimate exposure to risk, the second part of this study, is motivated by the random utility theory (RUM). The theory involves utility maximization by the decision maker. The theory is founded on the psychological stimuli concept that was first developed by Thurstone (1927) and eventually led to the development of the binary probit model. Afterwards, the stimuli concept was interpreted as utility and derived from utility maximization by Marchak (1960). Formally (Train, 2009),a decision maker *m*, faces a choice among *J* alternatives. Each alternative bears different levels of utility (*U*). From alternative *j* decision maker *m* obtains utility $U_{mj},\ j\ =\ 1\ ,\ldots,J$. The decision maker chooses the alternative that provides the greatest utility, i.e.,

$$U_{mi,} > U_{mj,} \forall j \quad (3.9)$$

where U_{mi} and U_{mj} represent decision maker m's utility for alternative *i* and *j*, respectively.

The researcher observes some attributes ($x_{mj,}$) of the alternatives as faced by the decision maker $\forall j$ and some attributes of the decision maker, labeled S_n, and can specify a function that associates the observed factors to the decision maker's utility. Formally,

$$V_{m\,j} = V\,(x_{m\,j}\,, s_m\,)\,\forall\, j \quad (3.10)$$

where $V_{m\,j}$ is the representative utility that is dependent on parameters unknown to the researcher and, therefore estimated statistically. Because of the unknown, unobserved, and unobservable aspects of utility,

$$V_{mj} \neq U_{mj} \quad (3.11)$$

and utility is decomposed as

$$U_{mj} = V_{mj} + \varepsilon_{mj}, \quad (3.12)$$

where ε_{mj} captures the factors that affect utility, but are not included in V_{mj}. Since the researcher does not know $\varepsilon_{mj}\ \forall\, j$, he treats these terms as random. The joint density of the random vector $\varepsilon_m = \langle \varepsilon_{m1}, \ldots, \varepsilon_{mJ} \rangle$ is denoted as $f\ (\varepsilon_m\ )$. Based on this density, the researcher can make probabilistic statements about the decision maker's choice. Therefore, the probability that decision maker *m* chooses alternative *i* is

$$P_{mi} = Prob\ (U_{mi} > U_{mj})\ \ \forall j \neq i$$

$$= Prob(\varepsilon_{mj} - \varepsilon_{mi} < V_{mi} - V_{mj}\ \forall j \neq i). \quad (3.13)$$

The cumulative distribution is P_{mi} , i.e., the probability that each random term $\varepsilon_{mj} - \varepsilon_{mi}$ falls

under the observed quantity $V_{mi} - V_{mj}$. By using $f(\varepsilon_m)$, the cumulative probability can be rewritten as,

$$P_{mi} = Prob(\varepsilon_{mj} - \varepsilon_{mi} < V_{mi} - V_{mj} \forall j \neq i)$$
$$= \int_{\varepsilon} I(\varepsilon_{mj} - \varepsilon_{mi} < V_{mi} - V_{mj} \forall j \neq i) f(\varepsilon_m) d\varepsilon_m, \quad (3.14)$$

where *I*(.) is the indicator function, equaling 1 when the expression in parentheses is true and 0 otherwise, $\int_{\varepsilon}$ is the multidimensional integral over the density of the unobserved portion of utility, $f(\varepsilon_n)$. The probit, and by extension the bivariate probit model, are derived under the assumption that $f(\varepsilon_n)$ is a multivariate normal. Simply put, the alternatives' observed attributes ($x_{mj,}$) and the decision maker characteristics (s_m) enter the utility function through a linear function that produces the familiar RUM,

$$U_{mj}{}^{*} = \beta' X_{mj} + \alpha' S_m + \varepsilon_{im}, \quad (3.15)$$

where X_{mj} and S_m represent vectors of variables of alternative attributes and decision makers characteristics, respectively. The corresponding parameters, β and α are estimated statistically.

3.4.2.1 Econometric modelling for exposure to risk

To model risk behavior involves the estimation of OLS and bivariate probit relationships. In particular, there are two binary endogenous variables that are used as regressors in the OLS model. Consequently, parameter estimates from the OLS approach would be inconsistent and biased (Woodridge, 2010). The endogeneity problem is accounted for by first estimating probit models for each endogenous variable to obtain two selectivity (the causes of endogeneity) regressors, herein called lambda 1 and lambda 2, that are introduced in the final selectivity OLS model. Also, because the two binary endogenous variables are assumed to jointly influence the

dependent variable in the OLS model, a bivariate probit model is used instead of estimating two separate probit equations to ascertain the significance of their correlation coefficient. Formally, assume the sample of khat using and non-khat using drivers are taken from a single population of drivers. For the *i*th trucker where (*i* = 1,…,d, …D), let y_i be the average speed - the on-road measure of performance; k_1 the khat using behavior (1 = uses khat, 0 = does not use khat); ξ_i the unobserved behavior attributes and trucking industry pressures; x_{1i} vector of exogenous *k* background variables, x_{2i} vector of *m* exogenous background variables and z^* is the unobserved continuous variable that determines khat use. The model that recognizes the described set of elements is

$$y_i = \xi_i + \psi k_i + \varepsilon_{0i} \tag{3.16}$$

$$\xi_i = \mathrm{x}'_{1i}\beta_1 + \varepsilon_{1i} \tag{3.17}$$

$$k_i = \mathrm{x}'_{2i}\beta_2 + u_{2i} \tag{3.18}$$

$$k_i = \begin{cases} 1 \text{ if } k_i^* > 0 \\ 0 \text{ if } k_i^* \leq 0 \end{cases}. \tag{3.19}$$

Substituting equation (3.17) into (3.16) results in equation (3.20):

$$y_i = \mathrm{x}'_{1i}\beta_1 + \psi k_i + u_{1i} \tag{3.20}$$

where $u_{1i} = \varepsilon_{0i} + \varepsilon_{1i}$ with u_{2i} assumed to be normally distributed, and $E(u_{1i}|u_{2i})$ is a linear function of u_{2i} such that:

$$\mathrm{Var}\ (u_{1i}) = \sigma_1^2$$

$$\mathrm{Var}\ (u_{2i}) = 1$$

Cov $(u_{1i}, u_{2i}) = \rho\,\sigma_1$

$cov(u_{1i}, u_{1i}) = cov(u_{1i}, u_{2i}) = cov(u_{1i}, u_{3i}) = 0$ if i ≠ j.

Without loss of generality, a constraint of unit variance is imposed on u_{2i}. By defining $\vartheta = -\mathrm{x}'_{2i}\beta_2$, Hensher et al. (1991) and Cameron and Trivedi (2005) have shown that:

$$E(u_{2i}|\vartheta, k_i) = \frac{k_i f(\vartheta_i)}{1-F(\vartheta_i)} - \frac{(1-k_i)f(\vartheta_i)}{F(\vartheta_i)} = h_i(\vartheta_i, k_i) \text{ or } h_i \quad (3.21)$$

where $f(\vartheta_i)$ and $F(\vartheta_i)$ designate the standard normal density and the cumulative distribution functions, respectively. It thus follows that

$$E(u_{2i}|\vartheta, k_i) = \rho\,\sigma_1 h_i. \quad (3.22)$$

Only if $\rho\,\sigma_1 h_i = 0$ will the OLS applied to equation (3.20) produce unbiased estimates of ψ and β_1. This condition is satisfied if and only if either one or all of the following conditions are met: (a) equation (3.18) predicts khat use without error ($\mathrm{u_{2i}} = 0$ for all drivers); (b) assignment of khat use categories is done randomly (i.e., var $(u_{1i}) \neq 0$, var $(u_{2i}) \neq 0$, cov $(\xi_i, k_i^*) = 0$ and thus Cov $(u_{1i}, u_{2i}) = 0$), and (c) when, although unobserved behavior attributes and trucking industry pressures are correlated in the driver population [cov $(\xi_i, k_i^*) \neq 0$], there is no correlation between behavior attributes/industry pressures and khat use after conditioning on observed $\mathrm{x_2}$[cov $(\xi_i, k_i^*)|\mathrm{x_2}$]=0 for all drivers.

The condition (a) is unlikely, but requirements (b) and (c) can be tested. Assuming the sample is from a single population of drivers and that khat use is independent of the values of β_1, then consistent parameters estimates can be derived by implementing a binary probit model for the endogenous variable, followed by constructing the selectivity regressor which is substituted back into equation (3.20) to obtain consistent estimates. In case there are 2 endogenous regressor

variables that are assumed to jointly determine y_i (as in this study), two probit models are applied jointly through a bivariate probit model to obtain two selectivity regressors (lambda 1 and lambda 2).

Formulation of the basic bivariate probit model follows Woodridge (2010), where letting *i* in k_i denote 1 and 2, it follow

$$k_1 = 1[\mathrm{x}'_{2i}\beta_2 + u_{2i} > 0]$$

$$k_2 = 1[\mathrm{x}'_{3i}\beta_3 + u_{3i} > 0]. \quad (3.23)$$

The outcome variables labeled as k_1 and k_2, both take one of two values

$$k = \begin{cases} 1 & with\ probability\ p \\ 0 & with\ probability\ 1-p \end{cases}$$

and (u_{2i}, u_{3i}) is independent of $\mathrm{X} = (\mathrm{x}'_{2i}, \mathrm{x}'_{3i})$ and distributed as bivariate normal with mean zero; each has unit variance, and $\rho_1 = Corr\,(u_{2i}, u_{3i})$. If $\rho_1 \neq 0$, then u_{2i} and k_2 are correlated, and the probit estimation is inconsistent for β_2. Thus, the basic model is extended to the bivariate probit model written as (Cameron and Trivedi, 2005),

$$k_1^* = \mathrm{x}'_{2i}\beta_2 + \varepsilon_{2i}$$

$$k_2^* = \mathrm{x}'_{3i}\beta_3 + \varepsilon_{3i} \quad (3.24)$$

where $k_1^*$and k_2^* are latent outcome variables, ε_{2i} and ε_{3i} are joint normal with means 0, variances 1, and correlation ρ. The observed outcomes in the bivariate probit model are thus specified as,

$$k_1 = \begin{cases} 1 \; if \; y_1^* > 0 \\ 0 \text{ if } y_1^* \leq 0 \end{cases}$$

and

$$k_2 = \begin{cases} 1 \; if \; k_1^* > 0 \\ 0 \text{ if } k_2^* \leq 0 \end{cases}$$

The above model collapses into two separate probit equations for k_1 and k_2, when the error correlation $\rho = 0$**.** When $\rho \neq 0$, there is no closed form solution for the probabilities. For example,

$$P_{11} = Pr[k_1 = 1, k_2 = 1]$$

$$= Pr[k_1^* > 0, k_2^* > 0]$$

$$= Pr[-\varepsilon_{2i} \; < \mathrm{x}_{2i}'\beta_2 - \varepsilon_{3i} < -\mathrm{x}_{3i}'\beta_3]$$

$$= Pr[\varepsilon_{2i} \; < \mathrm{x}_{2i}'\beta_2 - \varepsilon_{3i} < \mathrm{x}_{3i}'\beta_3]$$

$$= \int_{-\infty}^{\mathrm{x}_1'\beta_1} \int_{-\infty}^{\mathrm{x}_2'\beta_2} \emptyset(z_1, z_2, \rho) \, dz_1 dz_2$$

$$= \Phi(\mathrm{x}_{2i}^{'}\beta_2, \mathrm{x}_{3i}^{'}\beta_3, \rho \,) \tag{3.25}$$

where $\emptyset(z_1, z_2, \rho)$ and $\Phi(z_1, z_2, \rho)$ are, respectively, the standardized bivariate normal density and cumulative density for (z_1, z_2) with zero means, unit variances, and correlation ρ, and the bivariate holds for the normal with mean zero. The probabilities that enter the likelihood function are (Greene, 2010)

$Prob(K_1 = k_{i1}, K_2 = k_{i2}|\mathrm{x}_{2i}\mathrm{x}_{3i}) = \Phi(\mathrm{x}'_{2i}\beta_2, \mathrm{x}'_{3i}\beta_3, \rho)$, and (3.26)

letting $k_1 = k_{i1}$, $k_2 = k_{i2}$ for $i = 1, \ldots, N$, the log-likelihood function is

$$\mathrm{logL} = \sum_{i=1}^{n} log\ \Phi \begin{bmatrix} (2k_{i1} - 1)\mathrm{x}'_{2i}\beta_2 \\ (2k_{i2} - 1)\mathrm{x}'_{3i}\beta_3 \\ (2k_{i1} - 1)(2k_{i2} - 1)\rho \end{bmatrix}$$

$$= \sum_{i=1}^{n} log\ \Phi[q_{i1}\mathrm{x}'_{2i}\beta_2, q_{i2}\mathrm{x}'_{3i}\beta_3, q_{i1}q_{i2}\rho]. \quad (3.27)$$

Note, $q_{i1} = (2k_{i1} - 1)\beta'_2 = -1$ if $k_{i1} = 0$ and +1 if $k_{i1} = 1$, Φ is the bivariate normal CDF that is computed using quadrature and maximized with respect to β_2, β_3 and ρ.[3]

3.5 Materials and methods

3.5.1 Economic incentives

East Africa's trucking industry does not have a particular policy that defines the rate at which truck drivers ought to be paid for the work done. In fact, some truck drivers revealed that the amount they get paid varies with availability of shipping opportunities and the type of truck owner employing the driver. Therefore, based on prior work (Hensher et al., 1991), the current study defines the economic reward profile for interviewed drivers as encompassing the overall working time, the actual time spent behind the wheel, the annual fines for speeding, and the monthly gross earnings from trucking. Those factors are used to operationalize the on-road behavioral aspect of truck drivers with regard to economic incentives.

[3] Computer programs such as STATA, R, and Matlab have built-in commands that can execute calculation of the selectivity regressors from the probit models.

Figure 3.1 illustrates the links between the abovementioned economic reward profile behavioral aspects of truck drivers and the corresponding set of explanatory variables hypothesized to influence each of them. Specifically, the explanatory variables are categorized according to: i) on-road profile, ii) preferential treatment in cargo acquisition, iii) drivers' personal attributes, iv) safety and security factors, v) industry experience factors, vi) lifestyle attributes, and vii) structural constraints (Table 3.3). The succeeding paragraphs describe relevance of the explanatory variables in shaping the economic reward profile as defined in (Hensher et al., 1991).

With regard to total work hours, the first economic reward profile dependent variable, age of driver is a factor because it allows gaining experience on working efficiently and allocating enough time to rest (Cantor, 2012). It could also be viewed that younger drivers would tend to work more hours because of their relatively higher energy levels and a strong drive to perform and earn. Similarly, the ability to access and process new information is enabled by a driver's education level, hence education is considered. Presumably, those with more formal education are able to gain and utilize knowledge more effectively than drivers with less education. Also, drivers who use khat are expected to work more hours because of the drug's short-lived positive effect on alertness and concentration while driving. Finally, truck-owner drivers defined by the truck ownership dummy variable, could be somewhat more flexible with the number of hours they work.

The annual number of trips and sick days, and whether the driver uses khat to maintain concentration and alertness while driving are associated with the second economic reward profile dependent variable, i.e., number of annual fines a trucker receives for speeding. It is possible that the larger the annual number of trips a trucker completes, the higher the number of speeding

fines he gets due to his higher levels of exposure to control by traffic police. Similarly, it could be that because truck companies pay drivers by the number of trips completed, more annual sick days could incite the driver to speed in order to complete more trips, thus cover the lost days. Using khat increases risk-taking behavior such as speeding (Abdul-kader, 2014).

The endogenous variable, total number of work hours (defined as the total time it takes the driver to deliver cargo from origin to destination), trip distance, and pay per trip are hypothesized to influence the incidence of driving time in total working time, the third economic reward profile dependent variable (Figure 3.1). Specifically, there is a possibility that availability of more work hours lowers the truck driver urgency to deliver cargo, hence increasing the incidence of driving time in total working time. Likewise, drivers who travel longer distances could have to increase the number of driving time in the total number of hours worked. Similarly, pay per trip could serve as an incentive for drivers to complete more trips, thus a higher incidence of driving time in total working time.

With regard to monthly gross earnings from trucking, a shorter (i.e. less than 12 hours) load waiting time allows completion of more monthly trips and allows for higher gross earnings – assuming there is availability of cargo to ship. The opposite is true for longer load wait times (i.e. more than 24 hours). Finally, it is possible that having regular and fixed contracts for cargo secures a stream of earnings for the trucking company/cargo owner but the effect such situation imposes on the total monthly gross earning has to be empirically verified.

3.5.2 Trip specific exposure to risk

Figure 3.2 conceptualizes the exposure to risk as modeled in the current study. The trip speed (i.e., average leg speed), the propensity to use khat, and the propensity to impose own schedule represent key analyzed aspects that draw on evidence from the observed relationships

between risk-related on-road performance of drivers and the underlying conditions in the trucking industry of EA. Of note, Hensher et al. (1991) used a somewhat similar set of aspects in their study of Australian truck drivers. However, while their study considered propensity to use mental alertness pills, the current study examines the propensity to use khat. The current study also differs in the structure of trucking industry, level of country's economic development, and geographical scope. In particular, the former was geographically limited and specific to Australia, while the latter involves Kenya, Uganda, Rwanda, and Burundi.

As described in the previous section, the total number of working hours, whether the driver ships perishable cargo, the number of stops for rest and/or sleep, whether the trucker has fixed and regular contractual arrangements for cargo, truck ownership, and speeding fines associate with the propensity of a driver to self-impose a schedule. To be specific, the total available working time allows the trucker to schedule his trip effectively with the aim of completing it in the shortest time possible (Crum and Morrow, 2002). Likewise, shipping perishable cargo may encourage drivers to self-impose schedules in order to deliver cargo in time to avoid spoilage (Braver and Ulmer, 1999). It is possible that rest and/or sleep stops presence along the route could likely affect self-imposition of schedules (Goel, 2012). On the other hand, owning a truck could encourage flexibility of operation and hence allow for self-imposition of schedules.

The propensity to use khat is associated with the number of sleep/rest hours within the 8 hours preceding the start of a trip, pay per trip, years of driving experience, the trucker's age, and the number of annual speeding fines. In particular, it may be that a driver is less fatigued and less likely to use khat if he rests for a longer time within 8 hours prior to starting a trip (Hensher et al., 1991). Likewise, a per trip payment schedule is expected to encourage a trucker to adjust his

trip schedule to allow for more trips and hence higher pay which in turn may necessitate the use of khat to maintain his level of concentration on the road (Eckersley and Gebru, 2010). Years of driving experience could shape the frequency of khat use because of the acquired experience on when to rest and when khat use is necessary to efficiently manage time. Similarly, age of trucker allows for gaining experience on effective driving, while saving time for enough rest, hence less need of khat. Lastly, drivers with more speeding fines are less likely to use khat because it increases risk taking behavior and consequently higher chances of getting speeding fines (Colzato et al., 2010).

With regard to average trip speed, using khat allows for increased risk-taking behavior including traveling above the posted speed limit. Likewise, drivers who self-impose schedules are mostly hurried to complete more trips and thus earn higher pay. Having fixed contractual arrangements for cargo may discourage speeding because drivers feel less pressure to obtain the next load as is common among drivers who have no contracts. Also, younger truck drivers are expected to be less risk averse (Jonah, 1986) and, thus, more likely to speed. On the other hand, longer trip distance is expected to discourage speeding because it may involve border crossing into countries with different traffic regulations on speed therefore drivers traversing those territories would be more cautious because of the fear of having to deal with unfamiliar institutional arrangements. Among physical attributes of a vehicle, the gross weight of a truck is also a factor because the regulations impose stricter speed limits on heavy vehicles in most countries due to the potential for larger damages they pose in case of accidents as compared to light vehicles (Harwood et al., 2003).

3.5.3 Data

The study uses survey data collected between the 25th of September and the 16th of October 2018. A total of 511 truck drivers were interviewed at the Kenya-Uganda border crossing station at Busia, Kenya. Truck drivers were intercepted at various times of the day for interviews as they were waiting to be cleared by the customs officers. The sample includes randomly selected drivers who frequent the NC on their way to Uganda and other east African countries. Enumerators randomly picked one among every three next drivers that were waiting in line to be cleared by the customs office. An average interview lasted one hour. The drivers transported goods from the Port of Mombasa primarily to Uganda.

The structured questionnaire included several sections focused on transported cargo, truck features, trucker characteristics, challenges faced while shipping cargo, and the infrastructural environment. Opinions about life on the road were also shared by drivers. The type of questions posed to drivers differed by information needed for the study. Specifically, some questions such as whether a trucker used khat, or whether he self-imposed a schedule required a yes/no response. Other questions sought responses using a Likert-type balanced scale offering a respondent several response options along a multi-step scale. The scale permitted the recording of the level of agreement or importance a truck-driver attached to a presented issue.

Of note, the form and content of the questions included in the survey was subject to a test involving a pilot study that was conducted between the 5th of July and the 7th of July 2017. In the pilot study, a total of 42 truck drivers were interviewed at different locations along the NC road, i.e., at various weighbridge stations. Majority of the structured questions from the pilot study were retained in the main study, but some had to be fine-tuned to extract the accurate information from the drivers.

3.5.4 Empirical approach

The first part of this essay involves modeling truck drivers' economic reward profiles as a function of the on-road profile, preferential treatment in cargo acquisition, drivers' personal attributes, safety and security factors, industry experience factors, lifestyle attributes and structural constraints (Figure 3.1). Truck drivers were asked questions that sought responses that relied largely on recall. The drivers were expected to state a positive numerical value for some outcome variables while other outcome variables were constructed from the responses that drivers had submitted in the interviews. The equations describing the links in figure 3.1 are[4]:

$$ln(Totwkhrs)_1 = \delta_0 + \delta_{1\,2} ln(Drver\_age)_2 + \delta_{2\,3} Truck\_educ_3 \ldots . + \delta_{3\,4} khat_{use_4} + \varepsilon_1. \quad (3.28)$$

$$Nmb\_speedf_2 = \beta_0 + \beta_{1\,2} ln(Totwkhrs)_2 + \beta_{2\,3} ln(Nmb\_annltrips)_3 + \beta_{3\,4}\, ln(Nmb\_annsckdys)_4 + \beta_{4\,5}\, ln(khat\_use)_5 + \varepsilon_2. \quad (3.29)$$

$$ln(drivincd)_3 = \psi_0 + \psi_{1\,2}\, ln(Totwkhrs)_2 + \psi_{2\,3} khat\_use_3 + \psi_{3\,4}\, ln(Trip\_dist)_4 + \psi_{4\,5}\, ln(Pay\_ptrip)_5 + \varepsilon_3. \quad (3.30)$$

$$ln\,(GrosEARN)_4 = \alpha_0 + \alpha_{1\,2} ln(driv\_incdnc)_2 + \alpha_{2\,3} 24hrswait_3 + \alpha_{3\,4} 12hrswait_4 + \varepsilon_3. \quad (3.31)$$

Four variables representing a trucker's economic reward profile were selected as outcome variables. The variables include, total working time in the most recent trip, the incidence of driving time in total working time, the average monthly gross earnings from trucking, and the number of fines/stops due to speeding faced by the driver during12 months prior to the survey.

[4] Definition of the variables is presented in Table 3.3.

The total working time is a continuous variable measured in hours, incidence of driving time in total working time is constructed by dividing the number of driving hours by the total hours in a forward trip[5], average gross earnings is a continuous variable measured in Kenyan shillings, and the number of annual fines due to speeding is a discrete continuous variable.

An empirical relationship is estimated that associates particular explanatory variables (Table 3.3) with each outcome variable. The 3SLS econometric approach is appropriate for deriving estimates associated with RHS endogenous and exogenous influence in a system of simultaneous equations. The model is cognizant of, and allows for, the non-independence of the error terms of the equations.

The second part of the essay entails estimating an empirical relationship linking trip-specific exposure to risk as measured by average speed to drivers' on-road behavioral attributes, trip specific features, and truck features. The main outcome variable is average speed. The equations describing the links in figure 3.2 are presented below[6]:

$$Khat\_use_1^* = \beta_1 + Pay\_ptrip_2\beta_2 + Driving\_exp_3\beta_3 + \ln(Drver\_age)_4\beta_4 + \varepsilon_1 -> \hat{\lambda}_1. \quad (3.32)$$

$$Selfsch_2^* = \alpha_1 + drivincd_2\alpha_2 + Perishale_3\alpha_3 + ln(Drver\_age)_4\beta_4 + StopsRsl_5\beta_5 + Nmb\_speedf_6\beta_6 + Trk\_ownership_7\beta_7 + \varepsilon_1 -> \hat{\lambda}_2. \quad (3.33)$$

and the selectivity equation is

$$LogAVtspeed_1^* = \psi_1 + Regfxdc_2\psi_2 + khat\_use_3\psi_3 + Selfsch_4\psi_4 + ln(Trip\_dist)_5\psi_5 + Gross\_weightTR_6\psi_6 + (\widehat{\lambda}_1)\psi_7 + (\widehat{\lambda}_2)\psi_8 + \varepsilon_1. \quad (3.34)$$

[5] A one-way trip involving a truck loaded with cargo.
[6] Definition of the variables is presented in Table 3.3.

The total trip distance in kilometers is divided by the actual number of hours the trucker spent driving to construct the average trip speed used as a variable. Particular behavioral endogenous explanatory variables, including the probability to use khat and to self-impose a schedule determined the choice of estimation approaches. Specifically, first, a bivariate probit econometric procedure is estimated, where the probability to use khat and to self-impose a schedule are used as dependent variables. Second, an OLS regression is undertaken consisting of average trip speed as the dependent variable and 2 selectivity regressors from the bivariate probit procedure, including other trip-specific features and driver attributes as exogenous explanatory variables.

3.5.5 Summary statistics

Descriptive statistics for dependent variables and selected explanatory variables are shown in Table 3.4. The average age of the interviewed trucker was about 40 years suggesting that truck drivers represent a relatively older group of men given that 59% of Kenya's population is 24 years old or younger (The World Factbook, 2018). Majority of the drivers, 57%, were educated beyond primary school level (equivalent to the 8^{th} grade or the middle school level in the United States). Further, of the interviewed drivers, 14% admitted to using khat to stay alert while driving, whereas majority, 64%, reported to have been fined or stopped once for a speeding offence (the enforced speed limit along the NC of Kenya is 80 kilometers per hour) within the 12 months preceding the interview date. The surveyed trucks were majorly company owned (58%) and 26% of trucks shipped perishable cargo from time to time. Also, of the total shipped cargo, 5% was acquired through contractual arrangements. An average truck driver completed an annual average of 42 trips with a typical route covering a distance of 987 kilometers (for example, the distance from Mombasa to the border with Uganda is 795 km) which took approximately 76 hours to complete (Table 3.4). On average, a truck driver spent

32% of his trip's work hours behind the wheel - driving. Also, for each completed trip, a trucker was paid KES 9670 (or $95 at the exchange rate as of October 1, 2018) (Kenya Central Bank Indicative Exchange Rates, 2018), while gross monthly earnings from trucking averaged KES130641 (or $1293 at the exchange rate as of October 1, 2018) (Kenya Central Bank Indicative Exchange Rates, 2018). Majority, 71%, of drivers spent less than 12 hours waiting for next load after completing their trip, while 14%, had to wait for more than one day (more than 24 hours). Lastly, a truck driver reported to have lost approximately 4 working days per year due to sickness, which is slightly less than the 7 days reported by Morris and Ferguson (2006).

3.6 Results

3.6.1 Factors influencing the economic reward profile of drivers

The choice of the key variables used for this section was largely informed by the pilot interviews with drivers that were undertaken in the mid-2017. The drivers revealed a lifestyle and working routine shaped by, among others, long hours of loading cargo, driving, trip scheduling, border documentation procedures for truck clearance at the customs office, and multiple stops for security checks, and resting.

Of the four economic reward profile variables, the total work hours and incidence of driving time in total working time were selected to shed light on the role of un-productive and productive time in relation to on-road performance. The total hours worked is endogenous and simultaneously associated with both the incidence of driving time in total working time and the number of annual speeding fines. Notably, the total worked hours influences the number of annual speeding fines because it could be expected that drivers who drive more hours per week are at a greater risk of being stopped for speeding and, thus, being stopped and fined. Further, together with pay per trip and trip distance, the incidence of driving time, which represents trip

productive time for drivers, was related to the average gross income from trucking (Figure 3.1). Pointedly, inclusion of khat use as an explanatory variable in equation 3.28, 3.29, and 3.30 poses a problem of endogeneity in the model. However, a variable representing the number of sleep hours within 8 hours prior to trip start is used to instrument for khat use. The instrumenting variable is correlated with khat use but uncorrelated with either, log of total work hours, number of speeding fines over the 12-month period preceding the interview date, or log of driving incidence in total working time. Intuitively, resting for fewer hours prior to starting a trip is expected to necessitate khat use and vice versa.

Estimated results of the simultaneous equations 3.28, 3.29, 3.30, and 3.31 are presented in Table 3.5. The key truck driver-determined factor expected to establish the opportunity for economic reward is the total number of working hours. The amount of time committed to work has a significant effect on the driving time, which subsequently explains variations in monthly gross earnings of the truck (Table 3.5).

Surprisingly, the total work hours variable was negatively correlated with majority of the identified explanatory variables. However, only khat use was statistically significant. Specifically, truck drivers who use khat regularly tend to work fewer hours. It could be expected that drivers who travel shorter distances, as inferred from the fewer number of total work hours, indulge more in khat use for leisure purposes and not necessarily to keep them alert (Eckersley et al. 2010).

The total number of hours worked, the number of trips per year, and khat use had positive effects on the number of annual speeding fines. Specifically, drivers who work longer hours are more likely to be stopped or/and fined for speeding. The longer the time a driver spends on the road, the higher his exposure to traffic police who often impose trumped-up charges

(thedailynation.co.ke, 2016), including speeding fines to instill fear of imprisonment and thus make it easier to solicit bribes. It is also possible that drivers who work more hours travel longer distances which sometimes involves crossing borders into countries with more stringent traffic regulations. The foreign country traffic rules that include speed limits could render them vulnerable to speeding fines. Likewise, drivers who complete more trips per year have a higher rate of speeding fines since being on the road for extended period of time exposes them to more frequent encounters with traffic police. As expected, a trucker who uses khat gets more speeding fines and/or stops than his counterpart who do not. This scenario could be explained by the fact that khat use is associated with risk taking behavior and can develop inappropriate and dangerous driving behavior including speeding (Abdul-kader, 2014)

The variation in the incidence of driving time in total working time was influenced by four exogenous variables including khat use, total work hours, trip distance, and the pay per trip. A khat user driver was less likely to dedicate more hours to driving than non-user. Similarly, the more the total working time reported by a driver, the lower the proportion of time he spent driving. It is possible the trucker spends a considerable portion of his total work hours doing other, non-driving, activities such as loading and unloading of cargo, routine vehicle maintenance, and dealing with cargo shipping documentation procedures (Arnold et al., 1997). Truck drivers who had to travel for longer distances spent a larger proportion of their total working time driving. It is obvious that a larger distance would require longer driving time, but it appears that the share of non-driving time decreases. Also, the higher the pay per trip, the higher the share of driving time in total working time. Higher pay per trip motivates drivers to complete more trips (Golob and Hensher, 1996).

The duration of time a trucker had to wait for the next load after the trip completion, and whether he operated under contractual arrangements for cargo explained the variation in truck's average gross monthly earnings. As expected, trucks whose drivers wait less than 12 hours before acquiring next load earn more per month. The availability of cargo allows for more trips per month that in turn translates into higher earnings (Anyango, 1997). Trucks with contractual arrangements for cargo have lower monthly gross earnings. The interviewed truck drivers revealed that although contractual arrangement for cargo does insure the availability of load for shipping, it does not allow for higher pay as would non-contractual arrangements because contracts limit the number of trips trucks make and contracts have a fixed salary for drivers.

3.6.2 Trip specific exposure to risk

Aspects of the trucking industry, which incidentally constrain the effect of economic reward are work practices the driver adopts to remain competitive. It could be that some work practices may affect the margin of safety on the road. Pointedly, due to economic pressures, the driver may find himself progressively more tired working (driving and loading) long hours, attempting to shorten his trip by increasing speed, or having fewer rest stops by relying on stimulant drugs to maintain alertness. In this study, the behavioral aspects of trucking that are dictated by: i) on-road profile, ii) preferential treatment in cargo acquisition, iii) drivers' personal attributes, iv) safety and security factors, v) industry experience factors, vi) lifestyle attributes, and vii) structural constraints (Table 3.3), include the propensity to use khat, self-impose a schedule, and engage in speeding. The corresponding estimation results are presented in the following section.

3.6.2.1 Determinants of trip specific exposure to risk: the bivariate probit model

The bivariate probit and OLS regression results on trip specific exposure to risk are presented in Tables 3.6 and 3.7, respectively. First, the determinants of the propensity to use khat and to self-impose a schedule, two key on-road behavioral factors are analyzed using the bivariate probit model (Table 3.6). Table 3.7 shows the estimation results of the equation modelling the truck speed, self-imposed trip scheduling, and use of khat.

The rho coefficient between the error terms on the propensity to use khat and to self-impose a schedule is -0.062 and not significant at a chosen alpha level of 0.10 (Table 3.6, column 2). Given the p-value of 0.5038, the null hypothesis is not ejected. The result allows to conclude that the propensity to use khat is independent of the propensity to self-impose a schedule. The result implies that estimating two separate probit models would produce similar results.

Variation in khat use is explained by the duration of sleep time a driver had within 8 hours prior to trip, pay per trip, and the truck driver's age. Specifically, the propensity to use khat increases with the number of sleep hours within 8 hours prior to starting a trip (Table 3.6, column 2). Perhaps, drivers who sleep more within the 8-hour time frame, particularly hours closer to starting their trip, feel less rested and sleepy and thus the urge to use khat, although the corresponding probability change is 1.1% for one additional hour pf sleep above the average. As could be expected, a higher pay per trip increases the propensity to use khat. Higher pay encourages more trips, which in turn negatively impacts the amount of rest time the driver has. A less rested driver indulges more in khat use to stay alert and maintain concentration (Colzato et al., 2010). As reported by Patel et al. (2005), older drivers are less likely to use khat. Similarly, Lifson et al. (2017) found that khat use is more prevalent among men aged between 15 – 35

years. It could be that the long term medical implications, or the negative impacts from the experience of using khat dissuades older drivers from using it (Colzato et al., 2010).

The change in probability of the dependent variable describing the propensity to use khat as a result in the changes in the value of the explanatory variables is presented in Table 3.6, column 3. The calculated probability change suggests the increase in propensity to use khat is associated with the change in the amount of sleep time within eight hours prior to trip start; the probability increases by nearly 1% that a trucker would likely use khat. Similarly, the probability increases by nearly 9% for drivers with a higher pay per trip. An even larger change in the probability, 21%, although lowering the chances of using khat could be expected for every additional year of driver's age above the mean.

Five factors negatively associated with the propensity to self-impose schedules were in the average driving time in total working time, whether the trucker shipped perishables (Table 3.6), the number of stops for sleeping and/or resting, whether the trucker had contractual arrangements for cargo, and truck ownership. Truck drivers whose proportion of driving time in total working time was higher had a lower propensity to self-impose schedules. It could be that such drivers operated under company imposed scheduling which is somewhat less flexible in sub-Saharan Africa (Anyango, 1997). Likewise, the propensity to self-impose a schedule was less likely for drivers who shipped perishable cargo (Table 3.6). The nature of perishable cargo constrains truck drivers to a schedule that would ensure timely delivery to avoid losses due to spoilage (Djankov et al., 2010). Furthermore, drivers confided with enumerators that cargo owners and truck companies closely monitored their trips whenever they were shipping perishable cargo. As expected, the propensity to self-impose a schedule decreased with the number stops for resting and/or sleeping. It is possible that drivers who had many stops operated

under truck company or cargo owners scheduling. Truck company or cargo owner scheduling allows for adequate rest and sleep time for drivers shipping cargo. Consequently, the well-rested drivers are alert while driving and ensure safe delivery of cargo (Williamson and Friswell, 2013). Truck drivers who had contractual arrangement for cargo were less likely to self-impose schedules. It could be the terms of reference for most contract arrangements for cargo include scheduling thus limiting most drivers to contract imposed schedules. Surprisingly, truck owner-drivers were less likely to self-impose schedules. Perhaps, truck owner-drivers adhere to cargo owner scheduling instead of self-imposed ones because, besides maintaining their trucks in good working condition, the truck service they offer through their trucks pays them well (Arboleda et al., 2003).

A unit share increase in the ratio of driving time in total working time decreases the probability of self-imposing a schedule by nearly 51% (Table 3.6). Likewise, the probability decreases by nearly 18.8% for drivers who ship perishable cargo. Having contractual arrangements for cargo decreases the probability to self-impose schedules by nearly 18%. Lastly, drivers who are owners are approximately 22% less likely to self-impose schedules.

3.6.2.2 Determinants of trip specific exposure to risk: selectivity model

Since this study confirms that the propensity to use khat is indeed independent of the propensity to self-impose a schedule (see section 3.6.2.1), probit models for each of the aforementioned dependent variables are estimated to obtain selectivity regressors (Kennedy, 2003). The regressors are named lambda 1 and lambda 2 (Table 3.7) and contain information on the variances of the error terms of the two probit equations, the average speed selectivity regression equation, as well as the correlation between them. It follows that the correlations between the selectivity equation and the probit equation for khat use (lambda 1) is -0.222 with at

0.01 level, and its correlation with the self-imposed schedules equation (lambda 2) is -0.2 at 0.05 level. The underlying implication is that if self-imposed scheduling is to explain the variation in average speed, it is likely to do so via its joint influence with the propensity to use khat.

Interestingly, drivers with contractual arrangements for cargo are more likely to engage in risky on-road behavior (Table 3.7). It is possible that conditions underlying cargo contracts include timely delivery of cargo for shipping payment to be completed. Such conditions put pressure on the trucker who may have to engage in risky driving behavior to fulfil his employer's part of the contract agreement.

3.7 Conclusions

Truck-related RTAs pose enormous cost implications for East Africa, a region that largely relies on the NC route for shipping cargo. RTAs along the route compound the already high transportation costs that characterize the region. Despite concerted efforts made by the EA individual member states to reduce the RTAs, accident occurrence rate and consequent cost implications have barely changed. This essay examined aspects of the trucking industry that are hardly considered when investigating the root causes of truck-related RTAs. The aspects include the economic reward profile for truck drivers and trip specific exposure to risk.

The considered groups of factors that shape the economic reward profile of drivers and their exposure to risk are used to explain the causes of RTAs. It appears, furnishing a long-distance truck driver with relevant information on traffic rules of neighboring countries through which his route passes could be critically important. Truck drivers who work for longer hours by travelling for longer distances often face speeding fines. It is possible the drivers lack relevant information on the speed limits of the foreign states to which they ship cargo. Similarly, this

study finds that drivers who complete more trips per month tend to engage in risky behavior as inferred from the number of speeding fines they receive. Thus, limiting the number of monthly trips that a trucker completes appears to be a plausible idea worth adopting by cargo owners and trucking companies to control risky behavior. A long-term alternative is to expand and improve the NC to divided lane highway, which could enhance the fluent flow of traffic, but that solution is unlikely in the foreseeable future.

Khat use, a behavioral factor among truck drivers of EA seems to be a very important factor that shapes both the economic profile of the trucker and his trip specific exposure to risk. The influence of khat use on speeding occurs jointly with the propensity to self-impose a schedule. Besides enforcing regulation of khat use through policy, an approach that may take longer to achieve, lies with the trucking companies, which could change their payment schedule from a per trip type to monthly salary without pegging the pay to the number of monthly trips. The former appears to encourage khat use. Likewise, trucking companies should ensure truck drivers are well rested before starting a trip. Furthermore, cargo shipping contractual arrangements should take into account the various sources of delay encountered by drivers along the NC. This recognition by cargo owners and trucking companies could ease the pressure they impose on drivers which often times compel them to speed, thus predisposing them to RTAs risk.

Traffic regulations are intended to improve safety on the roads, lower RTA rates, and indirectly keep trucks in good working conditions. This study reveals, albeit indirectly, that besides the traffic police who make right judgement calls on addressing the breaking of traffic rules by drivers, there are some who impose trumped-up traffic-related charges on drivers. In fact, the interviewed drivers reported that their employers do not recognize and compensate for

the unsolicited payments drivers are forced to make. Thus, a policy that would require all traffic police to undertake periodic training that equips them with the necessary knowledge on how to handle motorists justly would improve on-road engagement and mutually benefit drivers and traffic police.

Insufficient rest stops along the NC may explain why drivers are forced to self impose schedules. However, drivers who operate under truck company-imposed cargo contractual arrangements that recognize the scarcity of rest stops could allow for adequate rest between trip legs. Similarly, encouraging investment in the construction of rest stops and eateries equipped to serve driver and truck needs could contribute to reducing the rate of fatigue-related truck RTAs.

Table 3.1 Number of registered trucks in East Africa

Company and truck number	Kenya	Tanzania	Rwanda
Registered companies	1574	732	220
Truck fleet	17066	12356	444

Source: SSATP, 2013

Table 3.2 Number and share of RTAs in East African states

Country	Fatalities	Percentage
Burundi	275	4%
DRC	309	4%
Kenya	3179	45%
Rwanda	308	4%
Uganda	2937	41%
South Sudan	96	1%
Total	7104	100%

Source: Trademark East Africa, 2014.

Table 3.3 Definition of variables used in the economic reward and risky behavior models

On-road profile	**Preferential treatment in cargo acquisition**
Incidence of driving time in total work time (*drivincd*) (dv)	Driver has regular fixed contract (*Regfxdc*)
Pay per trip (*Pay_ptrip*)	
Trip distance (*Trip_dist)*	
Total working time (*Totwkhrs*) (dv)	
Driver's personal attributes	**Safety and security factors**
Driver's age (*Drver_age*)	Number of annual fines or stops due to speeding (*Nmb_speed*) (dv)
Number of annual sick days (*Nmb_annsckdys)*	Number of stops for rest and/or sleep *(StopsRsl)*
	Log of average leg speed *(LogAVtspeed)*
Industry experience factors	**Lifestyle attributes**
Number of annual trips (*Nmb_annltrips*)	Khat use (*khat_use*) (dv)
Truck ownership (*Trk_ownershp*)	Self-imposed scheduling *(Selfsch*) (dv)
Perishable cargo shipping (*Perishable*)	
Structural constraints	**Reward determination**
Less than 12 hours waiting for next load (1*2hrswait*)	Average monthly gross earnings *(GrosEARN)*
More than 24 hours waiting for next load(*24hrswait)*	

Note: dv = dependent variable.

Table 3.4 Descriptive statistics for the economic reward profile of truck drivers

Variable name	Mean	Standard deviation	Min.	Max.
Total work hours for forward trip	75.79	53.00	8.40	369.25
Incidence of driving time in total working hours	0.32	0.16	0.01	0.86
Number of speeding fines over the last one year	0.64	1.42	0.00	10.00
Monthly gross truck earning	130640.51	78853.10	12000	550000
Average leg speed in Kilometers/hour	56.54	33.06	3.70	150
Truck driver's age in years	40.41	9.63	21.00	80.00
Driver's education (1=above primary school)	0.57	0.50	0.00	1.00
Khat use (1=used khat)	0.14	0.35	0.00	1.00
Truck ownership (1= driver owned or individual)	0.42	0.49	0.00	1.00
Gross weight of truck (1=More than 20 tons)	0.78	0.41	0.00	1.00
Perishable cargo (1= shipped perishables cargo)	0.26	0.44	0.00	1.00
Contract for cargo (1= has regular fixed contract)	0.05	0.21	0.00	1.00
Annual routine trips	42.86	16.69	12.00	132.00
Trip distance in kilometers (last trip)	987.93	500.71	95.20	3928.90
Pay per trip	9670.41	4729.01	1400	35000
Less than 12 hours waiting for next load	0.71	0.45	0.00	1.00
24 hours or more waiting for next load	0.14	0.34	0.00	1.00
Annual sick days	4.20	13.29	0.00	120.00
No of observations	511			

Table 3.5 3SLS estimation for the factors that affect the economic reward profile of truck drivers

Variable name	Coefficient	Standard error
log of total work hours (dependent variable)		
Log of truck driver's age in years	-0.284	0.205
Trucker's education (1=above primary school)	-0.016	0.078
Khat use (1 = use khat)	-2.282**	0.890
Truck ownership (1 = driver owned or single truck owner)	0.014	0.082
Constant	5.474***	0.826
Number of speeding fines over the last one year (dependent variable)		
Khat use (1 = use khat)	2.268*	1.169
Log of total work hours	0.861***	0.223
Log of number of annual trips	0.010*	0.006
Log of number of number of annual sick days	0.061	0.058
Constant	-3.659***	1.093
log of driving incidence (dependent variable)		
Khat use (1 = use khat)	1.378***	0.493
Log of total work hours	-1.652***	0.254
Log of trip's distance in kilometers	1.109***	0.138
Log of pay per trip	0.274***	0.087
Constant	0.336	0.641
log of average gross truck earnings (dependent variable)		
Log of driving incidence	0.189	0.121
Less than 12 hours waiting for next load	0.145*	0.079
24 hours or longer waiting time for next load	-0.054	0.104
Contract for cargo (1=has regular fixed contract)	-0.296**	0.134
Constant	10.893***	0.417
AIC	4880.377	-
BIC	4965.104	-
Observations	511	-

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6 Bivariate probit model for trip specific exposure speed related risk

Variable name	Coefficient	Marginal effect
Khat use - dep. variable		
Number of sleep hours 8 hours prior to trip start	0.055*	0.011*
	(0.030)	(0.006)
Pay per trip	0.357*	0.088*
	(0.204)	(0.056)
Driving experience (1 = five years or more)	-0.150	-0.029
	(0.224)	(0.042)
Truck driver's age	-0.985***	-0.208***
	(0.343)	(0.0714)
Constant	2.228*	
	(1.244)	
Self-imposed schedule – dep. variable		
Average ratio of drive time over total work time per trip	-1.323*	-0.514*
	(0.740)	(0.287)
Shipped perishables (1 = shipped perishables)	-0.510***	-0.188***
	(0.139)	(0.048)
Number of stops for resting and/or sleeping	-0.070*	-0.027
	(0.042)	(0.016)
Log of truck driver's age	0.330	0.128
	(0.250)	(0.097)
Fixed contract for cargo (1 = regular contract)	-0.499*	-0.175*
	(0.288)	(0.090)
Number of speeding fines over the last one year	0.028	0.011
	(0.042)	(0.016)
Truck ownership (1 = driver owner)	-0.569***	-0.215***
	(0.123)	(0.044)
Constant	-0.715	
	(0.932)	
Constant (for both models)	-0.062	
	(0.093)	
Rho (ρ)	-0.062	
	(0.092)	
AIC	1061.030	
BIC	1120.339	
No of observations	511	

Note: Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7 Trip specific exposure to speed related risk

Variable name	Coefficient	Standard errors
Khat use (1 = khat use)	0.042	0.049
Self- imposed schedule	-0.124***	0.038
Log of truck driver's age in years	0.052	0.112
Fixed contract for cargo (1 = regular contract)	0.195**	0.084
Log of trip's distance in kilometers	0.005	0.033
What is the gross weight of your truck?	-0.029	(0.043)
Lambda 1 (khat use)	-0.222***	0.059
Lambda 2 (self-impose schedule)	-0.266**	(0.120)
Constant	4.409***	0.389
R^2	0.062	-
AIC	468.934	-
BIC	507.061	-
F test value	4.161	-
No of observations	511	

Note: Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

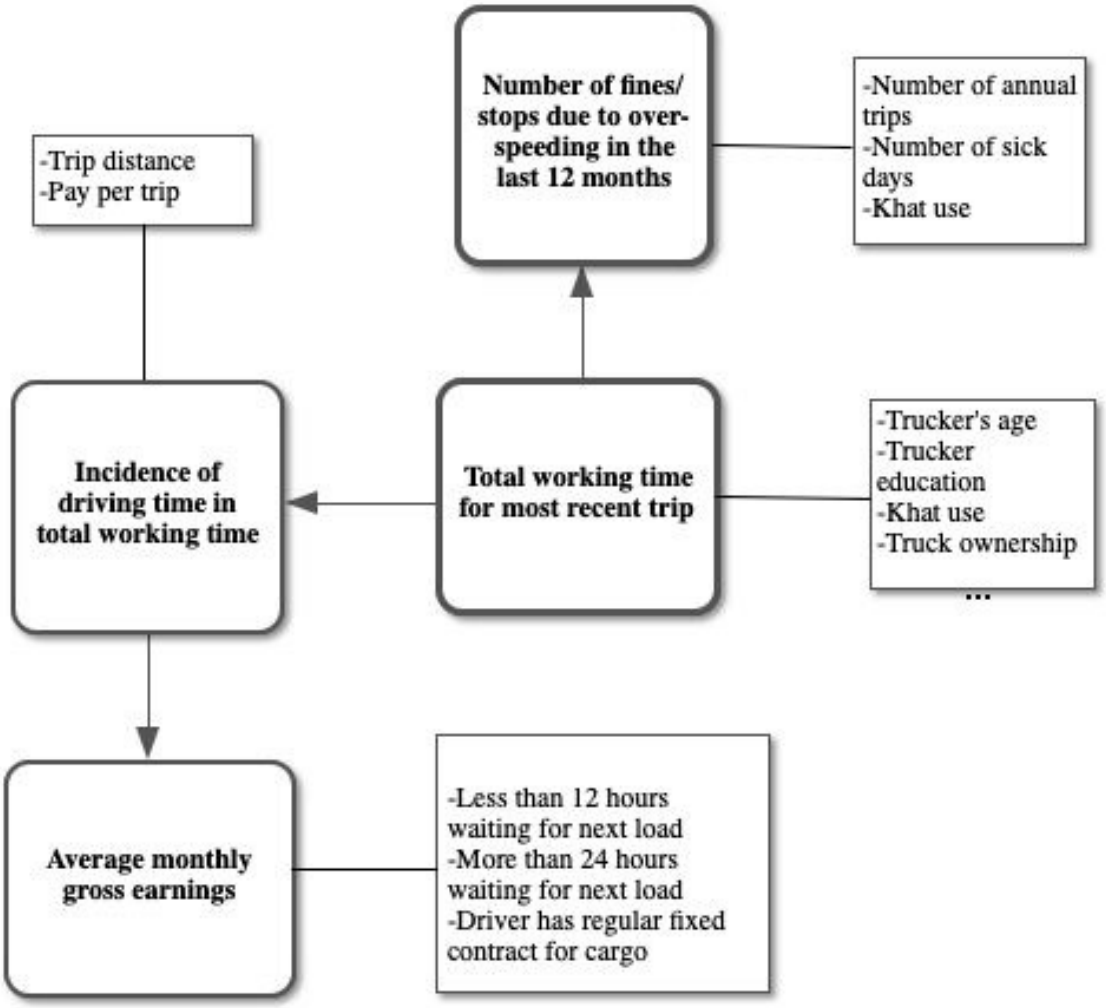

Figure 3.1 Economic reward profile for truck drivers

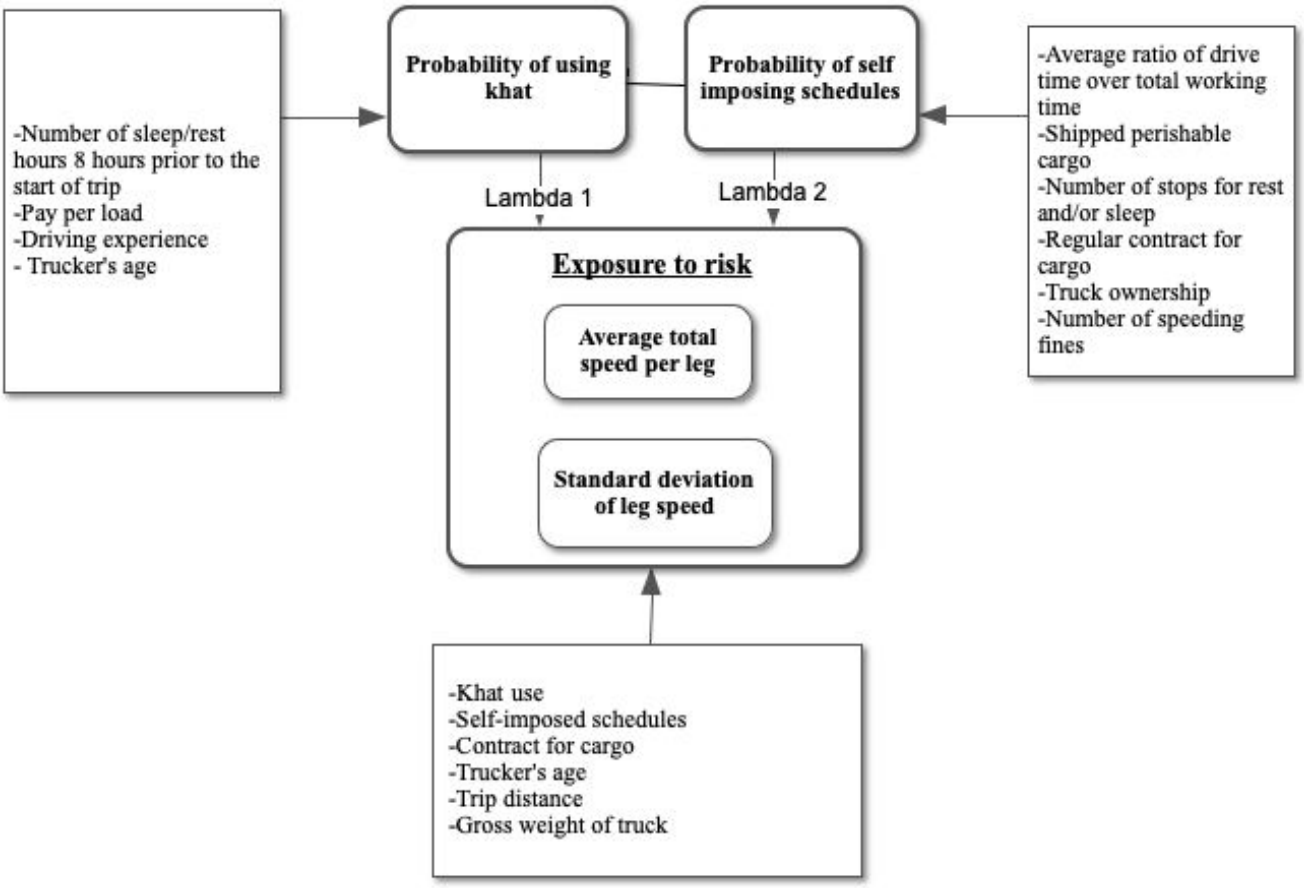

Figure 3.2 Exposure to trip specific RTA risk

CHAPTER 4

CONSTRAINTS TO MARKET INTEGRATION FOR EAST AFRICA'S STAPLE FOOD CROPS

4.1 Introduction

Lack of close trade links between most African countries causes instability in food markets, high consumer prices, and poorly developed regional production networks (Walkenhorst, 2013). Additionally, poorly functioning and poorly integrated food markets between and within countries of sub-Saharan Africa affect demand and supply, and consequently, food productivity (USAID, 2010). Tariff and non-tariff barriers, including inefficient transport and communication infrastructure have been found to constrain transmission of price information (Obstfeld and Rogoff, 2000; Portugal-Perez and Wilson, 2008). In EA, for instance, trade costs are evidently higher than in developed countries due to considerably larger transportation costs and in general, a weaker institutional set-up for dealing with issues involving rules of origin (i.e., criteria needed to determine the national source of a traded product) and other formal trade barriers (Portugal-Perez and Wilson, 2008).

Literature on international price disparities for commonly traded commodities emphasizes three key findings: distance, which plays a major role in understanding price deviations, convergence rates back to purchasing power parity (PPP)[7] do not align with the

[7] This is an economic theory concept that compares different countries' currencies through a "basket of goods" approach. According to this concept, two currencies are in equilibrium (at par) when a basket of goods is priced the same in both countries, taking into account the exchange rates (Rogoff, 1996).

evidence from micro studies on nominal price stickiness (Rogoff, 1996), and borders, which give rise to the flagrant violations of the law of one price (LOP) (Broda and Weinstein, 2008). However, sizable differences exist in both the nature of the data and the empirical approaches employed in the studies that arrive at the abovementioned key findings on international price deviation. Regarding the nature of data, on the one hand, there is considerable number of studies on the LOP in literature that infers the extent of market segmentation from the behavior of aggregate prices of goods that may not be similar, price indices, and a non-random selection of particular goods (Engel and Rogers, 1996; Parsely and Wei,1996; Crucini et al., 2000; Versailles 2012). On the other hand, although still considered challenging, there is a dearth of literature that uses price data to compare identical goods internationally (Atkeson and Burstein 2007; Broda and Weinstein, 2008). Among the used empirical approaches, there is substantial literature that exploits the time series nature of price data to test the persistence of purchasing power parity (PPP) (Rogoff 1996: Crucini and Shintani, 2008), while another stream of research considers the price data cross-section properties (Engel and Rogers, 1996) compares border barriers with regional barriers.

This essay revisits the LOP by taking advantage of the Uganda-Kenya shared price information system that records real-time daily prices of identical agricultural commodities traded across border between the two countries. The nature of the price data allows to test the LOP by comparing price data for five commodities traded within and between Uganda and Kenya. Thus, firstly this study adds to the scarce literature on market integration between countries that relies on highly disaggregated price data of comparable and identical commodities. Secondly, and perhaps more importantly, the study builds on developed country good-specific price literature which employs price data to explain the role played by macro-issues such as

exchange rate regimes, non-tariff barriers (NTBs) and electioneering period effects in cross country commodity price deviations (Broda and Weinstein, 2008; Versailles, 2012). Lastly, this study evaluates the impact of the recently commissioned Uganda-Kenya one-stop border at Busia, meant to ease trade between the two countries. In the wake of the recurring food shortages resulting from unfavorable weather events, for example droughts, in the EA region, knowledge of the causes of market segmentation for traded agricultural commodities within and between Kenya and Uganda paves way for policy interventions that would provide sustainable solutions to EA's staple food supply deficits through efficient trade flows from surplus to deficit locations (USAID, 2010; Zant, 2013).

4.2 Theoretical framework and literature review

The vast literature on international pricing demands reviewing the prior work in a structured way to help identify the gap to be filled by the current study. The basic prediction equation of the theory of the LOP in its exact form (Broda and Weinstein, 2008) is used as the benchmark, and then contrasted with its variations that were estimated and reported in literature. Disparities between the basic prediction equation and empirically estimated equations will be instructive in explaining how the approach adopted for this study fills the void in the existing literature. Of note, the use of the term LOP in empirical literature bears diverse definitions. Therefore, for consistency, this study uses the term as used by Rogoff (1996) and Broda and Weinstein (2008). In particular, "if the prices of a good in two different locations are compared, it is referred as a test of LOP".

4.2.1 The law of one price

A*bsolute* LOP states that the prices of *identical* goods should be the same across locations when denominated in a common currency (Broda and Weinstein, 2008; Versailles, 2012). Put formally, this implies that P_{xzt} (i.e. the domestic-currency price of good *x* in city or market *z* in time *t*) can be writen as

$$P_{xzt} = EX_{zz't}P_{xz't} \tag{4.1}$$

where $P_{xz't}$ is the price of the same good in a different city or country z' and $EX_{zz't}$ is the nominal exchange rate, which equals one if both cities are in the same country (Versailles, 2012).

Tests of equation (4.1) are limited in literature because researchers often work with data from sources specific to a country, whereby identical goods bear different definitions. For instance, large deviations from the LOP have been found in studies that use equation (4.1), including the work on Big Macs by Cumby (1996) and *The Economist Magazine* by Ghosh and Wolf (1994).

More studies, however, have sought to test the LOP using the approximate version of equation (1), coined loosely as *Approximate Absolute LOP*. Formally,

$$P_{xzt} = EX_{zz't}P_{x'z't} \tag{4.2}$$

where goods x and x' belong to a similar product category but are not identical. Thus, tests of LOP based on (4.2) as opposed to (4.1) fail to distinguish deviations due to genuine border effects from deviations of LOP due to the assumption that good x and good x' enter the consumer utility identically. Crucini et al. (2005) test the approximate absolute form using Eurostat data although, it is difficult to apportion how much of the deviation from LOP is due to the fact that borders prevent arbitrage from eliminating price differentials such as "lady's boots" and how much is due to the sample of lady's boots varying across countries (Broda and

Weinstein, 2008). The problem is also common when using price indices like CPI instead of the good level prices, as countries differ in how they construct indices selecting goods and weights. An alternative approach, termed *relative LOP*, involves looking at first differences of log price levels, and testing whether prices tend to remain at constant level apart (Versailles, 2012). Formally,

$$\Delta p_{xzt} = \Delta ex_{zz't} + \Delta p_{xz't} \tag{4.3}$$

where, lower case letters represent natural logarithms of upper case variables in (4.1) and Δ refers to the time differences. Tests of (4.3) do not require prices to converge to the same level, and only verifies whether prices tend to remain a constant level apart. Parsley and Wei (1996) use a slight deviation of (4.3) termed *approximate relative LOP* in their pioneering work on urban prices in the United States. *Approximate relative LOP* is written as:

$$\Delta p_{xzt} = \Delta ex_{zz't} + \Delta p_{x'z't} \tag{4.4}$$

where goods x and x' are as defined in (4.2). Equation (4.4) corrects for any unobserved heterogeneity that causes goods x and x' to enter the consumer utility differently.

Using equation (4.1), the real exchange rate for good z at time t can be defined as

$$R_{xzz't} = \frac{P_{xzt}}{EX_{zz't} * P_{xz't}} . \tag{4.5}$$

Therefore, if the absolute LOP holds, equation (4.1) holds, too, and expression (4.4) equals one.

4.2.2 Sources of LOP breakdown

Prior studies attribute the breakdown of the LOP to "nominal" causes and "real" causes. The major nominal source of the breakdown is the nominal exchange rate (Engel and Rogers 2001). Price rigidity (sticky prices) coupled with fluctuating exchange rates can persuade export producers to set prices in the currency of the foreign consumer rather than their own. This

behavior by export producers is termed as Local Currency Pricing (LCP). Thus, good prices in the local market remain unaffected if LCP applies. Most studies on border effect, including Feenstra and Kendal (1997), find evidence for LCP as a channel determining observed price dispersions.

The "real" sources of LOP breakdown include tariff and non-tariff barriers to trade, transportation costs, non-traded inputs such as marketing and other distribution services that are part of the final good prices, and imperfect competition (Engel and Rogers, 2001; Versailles, 2012). Non-tariff barriers (NTBs), narrowly defined as "an import targeted public policy intervention whose intention is to protect domestic industries, national health, safety and security disrupts goods supply chain and leads to price increases by limiting the volume of imports" (Dean et al., 2009). Dotsey and Duarte (2005), in their study on the importance of non-tradable goods in accounting for exchange rate behavior find that the presence of non-tradable goods in the general price level affect market segmentation by increasing the volatility of exchange rate by about 50%. Likewise, Crucini and Shintani (2008) assert that all retail goods are composites of traded and non-tradable goods, hence, the less the likelihood of price comparisons between markets satisfying the law of one price. The study exploits the time series dimension of micro-price data. However, studies that adopt the Engel and Rogers border effect tradition are largely inconclusive (Versailles, 2012).

A large body of literature argues against expectations of price convergence across different locations because producers are price setters in some sites. Thus, there is imperfect competition and no likelihood of equality of prices because of local monopoly power in segmented markets (Versailles, 2012).

Other macro issues that seldom feature in literature yet contribute to violations in the LOP include political instability within a country during elections, and customs related policy interventions that are meant to ease trade between trading nations. For example, Versailles (2012) finds large departures from the LOP for commodity prices across East Africa's markets during the Kenyan political crisis of 2008. The post-election violence in Kenya that followed the contested presidential results of 2008 disrupted regional markets. The study also found evidence for a custom union effect resulting in departure from the LOP, especially between Kenya and Uganda commodity markets.

4.3 Data and Methodology

4.3.1 Regional Agricultural Trade Intelligence Network (RATIN) data

Data was sourced from RATIN, a price information system whose role is to address the inefficiencies resulting from EA's fragmented regional agricultural commodity market information system (USAID, 2013). RATIN uses smart-phone enabled data collection applications to capture information about cross-border trade and commodity prices. A quality reassuring attribute of the system is that it uses applications that contain controls designed to ensure data integrity/quality (USAID, 2013). For instance, one control uses a smart-phone's built-in GPS system to verify data entry and will not accept information that is entered outside the boundaries of designated markets. Additionally, the system flags data anomalies during entry, which prompts enumerators to double check and re-verify their data before submission for publishing. RATIN extends beyond East Africa and is also linked to price information systems in Malawi and South Africa.

Real-time daily price information data for 20 key agricultural markets representing cities across Kenya and Uganda (see map on Figure 4.1) were obtained for this study. The markets include Nairobi and Kampala, the capital cities and the target cities of Kenya and Uganda, respectively. In particular, maize, rice (local and imported), and beans (red and mixed) daily prices data span over the period of 80 months (January of 2012 – September of 2018). The five commodities were selected because of, i) data availability across Kenya and Uganda, ii) data availability across markets, iii) comparability of the commodities across Kenya and Uganda, and iv) high persistence of the series because maize, rice, and beans mainly constitute the consumption basket in both Kenya and Uganda (Versailles, 2012). To facilitate analysis, the daily price data for each commodity and in each market were aggregated to weekly prices by taking the mean of daily prices from Monday through Sunday. The price information is collected daily, including weekends and public holidays in both Uganda and Kenya. Enumerators, who are in charge of data collection are locals at the designate markets (USAID, 2013).

4.3.2 Empirical approach

This essay focuses on the LOP and the sources of its violation through a comparison of prices for five agricultural commodities traded within and between select markets in Kenya and Uganda. To empirically identify the sources violating the LOP, good-level real exchange rates as defined in equation (4.5) are linked to the cost of trade between locations. Of note, the cost of trade here is defined as anything that would violate equation (4.5).

Following Anderson and Van Wincoop (2004) and Versailles (2012), this study defines $N_{xzz't}$ as the iceberg cost of trade between locations *z* and *z'* per unit of good *x* which allows for trade costs and differences in currency between locations. Then, define the 'band of inaction' as

$$\frac{1}{N_{xzz't}} \leq R_{xzz't} \leq N_{xzz't} \quad (4.6)$$

such that (4.6) ensures the price differential between two locations subject to comparison cannot exceed the cost of trading (i.e., anything that would make equation 4.5 not hold including the 'real' and nominal sources of the violation of the LOP) and $r_{xzz't}$ (log of $R_{xzz't}$) is uniformly distributed across the 'band of inaction' [-$n_{xzz't}$, $n_{xzz't}$][8]. The cost of trade at time t is specified as: $n_{xzz't}$ = f(distance, border, exchange rate, trade costs specific to z or z′).

To test the absolute version of the LOP, it is assumed that $p_{xzt} - e_{xzz't} - p_{xz't}$= f($n_{xzz't}$), where the lowercase letters represent logs. Thus, deviations of the real exchange rate ($p_{xzt} - e_{xzz't} - p_{xz't}$) reveal the size of the cost of trade. The standard empirical model capturing long-run deviations from LOP is a log-linear regression written as:

$$|ln\, R_{xzz't}| = \beta_0 + \beta_1 lnd_{xzz'} + \beta_2 B_{xzz'} + \beta_3 lnEX_{zz't} + \beta_4 + \beta_5 TARRIF_{zz't} + \beta_6 NTB_{zz't} + \sum_{k=1}^{m} \gamma_s D_s + \epsilon_{xzz't} \quad (4.7)$$

where $|ln\, R_{xzz't}|$ is the absolute value of the relative price (real exchange rate) for city-pairs, the unit of observation. Also, $lnd_{xzz'}$ is the log of distance between location *z* and *z'*, $EX_{zz't}$ is the nominal exchange rate, and $B_{xzz'}$ is a dummy variable which takes the value of one if locations *z* and *z*' are in different countries and zero otherwise. The D_s's are *m* city dummies which take on a value of one for D_Z and $D_{Z'}$ and zero for all other locations. The city dummies absorb all fixed effects of the cities. Finally, $NTB_{zz't}$ is the non-tariff barriers measure, while $\epsilon_{xzz't}$ is the error term (Versailles, 2012).

[8] Lowercase letters indicate logs

How does the empirical approach used in this study differ from antecedent studies on the violation of the LOP? To begin with, the Engel-Rogers LOP literature uses the standard deviation of the first difference of $R_{xzz't}$ (the left-hand side variable of equation 4.7) as the dependent variable for two reasons. First, taking the standard deviation renders the variable scale invariant, a feature that is necessary when working with CPI indices as Engel and Rogers (1996) do. Second, because CPI indices are persistent and, thus, could potentially bias border effect estimates by confounding price shocks with price movements related to prices returning to their equilibrium, using the standard deviation of the first difference of exchange rates would avoid the problem (Gorodnichenko and Tesar, 2005). This study sets up the dependent variable differently from the studies using Engel and Rogers specification. However, it follows the specification in equation (4.7) applied by Versailles (2012) and Broda and Weinstein (2001), save for the source of data used, the geographical scope of the studies, and the level of aggregation of the price data. In particular, Broda and Weinstein (2001) use the United States and Canada barcode data on prices to examine the LOP and PPP, while Versailles (2012) uses National Bureau of Statistics price data for the selected EA countries. Concerning the level of aggregation, Versailles (2012) uses monthly price data, whereas Broda and Weinstein rely on daily barcode data.

From a data standpoint, the current study uses good-level prices from a common source, RATIN. Whereby, common sourcing avoids the potential problem of comparing prices of different products as is common in cross-country appraisal of product prices, which bear the different within-country definitions (Versailles, 2012).

4.3.3 Variable selection

The independent variables associated with the violation of the LOP are drawn from two source categories, 'nominal' and 'real' sources. The list of identified and used variables is not exhaustive because of i) data unavailability, and ii) the unit of observation used in the available data. For instance, tariff and non-tariff barriers data are collected yearly and, therefore, cannot be matched to weekly data as used in this study.

4.3.3.1 Nominal exchange

The daily price per kilogram for each considered commodity is denominated in Kenyan shillings for Kenya's markets, and in Ugandan shillings for Uganda's markets. To facilitate price comparison across countries, the Central Bank of Kenya (CBK) mean daily exchange rate is used to convert Kenya's price data into Uganda's currency prior to aggregating the daily observations to weekly rates. The log of those averages is the nominal exchange rate in equation (4.7) as in Versailles (2012). Of note, since our interest is to estimate equation (4.7) as a cross-section level regression the time-varying dependent variable (real exchange rate) and independent variable (nominal exchange rate) should bear similar orders of integration. The underlying reasons are highlighted below.

First, time series concerns have ramification only for the regression specifications having the nominal exchange rate. Second, time specific heterogeneity is dealt with by including monthly dummies in all regression specifications excluding one monthly dummy to avoid a misspecification. It should be noted that, although the daily price data and, hence its corresponding daily nominal exchange rates, are aggregated into weekly observations (i.e., by summing the respective daily values and dividing each by 7 (week) to get the weekly means for both prices and nominal exchange rates variables), the direction and magnitude of coefficient

estimates of the nominal exchange rate using weekly time dummies (i.e., 351 weeks for the whole period) do not differ from the monthly dummies (80) used in this study. For example, instead of having 4 weekly dummies for the month of January, there is a month dummy that takes a value of 1 for each week that falls within the particular month. Therefore, the nominal exchange rate used in the empirical model is the weekly mean obtained by aggregating the daily values for each week and dividing by the seven days that make a week. Lastly, as Versailles (2012) study asserts, the general less persistent (fluctuating) characteristic of food prices, and, hence staples are less likely to contain unit roots, and thus less need for exhaustive unit root testing.

4.3.3.2 Distance

Figure 4.1 shows the physical distances between markets. Distance is measured in kilometers. Table 4.1 shows the average distance of pairs of cities across the border as contrasted with in-country city pairs. Road distance[9] between compared city-pairs is used for the distance measure. Because of this study's focus, the distances are measured along the NC road (Figure 4.1) due to the role played by this transportation route in transshipping cargo from the Port of Mombasa, Kenya, to the landlocked countries, including Uganda (Okumu and Nyankori, 2010).

Studies find that distance contributes significantly to price dispersion (Engel and Rogers, 1996; Parsely and Wei, 2001; Broda and Weinstein, 2008). In particular, Parsely and Wei (1996) find that, although distance accounts for a small portion of the departure from the LOP across national borders, it is still an important control variable in price analysis models. Lutz (2004) in his work using micro-level data from the European car market also finds that distance between

[9] To develop this metric, I used the googlemaps distance measure.

markets is one of the most important factors that explain dispersion of prices between Belgium and Luxembourg.

4.3.3.3 One-stop-border

A binary variable representing the existence of "one stop border post" at Busia, the border crossing between Kenya and Uganda is included. The variable controls for the effect of the border post on price dispersion. The border post project was launched in February of 2018 (theeastafrican.co.ke, 2018) and its operation represents a sufficiently long period (7 months) that could help evaluate the effect of the border post.

The adoption of EA customs union in 2005 was to enhance economic gains from trade, particularly between Uganda, Tanzania, and Kenya. The union was expected to eliminate tariffs and NTBs between the member states and subsequently decrease the time taken to ship cargo across borders (Okumu and Nyankori, 2010). However, the customs union barely achieved its intended goal because the barriers to trade persist. A recent work finds only a minute positive effect of the customs union on price convergence for cross-border markets in Uganda and Kenya, and worse still, the effect is non-existent for markets involving Uganda-Tanzania and Kenya-Tanzania (Versailles, 2012). In 2018, the African Development Fund, the concessional arm of the African Development Bank, extended loans to Kenya, Uganda, and Tanzania to help establish "one stop border posts" at Busia and Namanga on the border between Kenya and Uganda, and Kenya and Tanzania, respectively (AfDB, 2018). The "one stop border post" project was expected to galvanize regional cooperation, facilitate cross-border dialogue, increase cross border traffic for people and long-haul vehicles, and boost market integration. Economic integration enhanced by eliminating physical barriers to cross-border trade and improvement in the flow of production factors were hardly achieved by EAs customs union of 2005.

4.3.3.4 Political instability

Two Kenyan election periods in 2013 and 2017, fall within the timeframe included in the data used in this study. Monthly dummy variables representing the election period in each election year are used to capture the effect of political instability on price convergence across markets within and between Kenya and Uganda. The election period as defined in this study includes the campaign period prior to elections, the actual election days, and one month after the election day.

Versailles (2012) finds that during Kenya's 2008 post-election crisis, increases in LOP-deviations for commodity prices within and between Kenya and other EAC member states were more pronounced. That result highlights the impact of the Kenyan elections on EAs markets. Accounting for the post-election period is relevant since Kenya serves as a transit country for the transport of many goods into the landlocked countries arriving to the Port of Mombasa. Political instability that may persist after the elections can potentially disrupt the markets in those countries.

4.3.3.5 Crop harvesting season

Kenya and Uganda share similar crop planting and harvesting seasons. The seasons are shaped by the rainfall patterns and subsequent dry spells. A crop grown during the long rainy season is harvested between July and September and termed as "main crop". Maize and beans, for instance, are intercropped and harvested at different times of the long rains season (Altieri and Koohafkan, 2008). Thus, monthly dummies indicating harvest are included to control for the potential price shocks that could results from the main crops entering the market.

In price literature, seasonality of production, a noteworthy characteristic of agricultural product prices makes them more volatile, and by extension more likely to affect price

convergence than prices of non-farm products (Schnepf, 2005). The lack of agricultural commodity futures markets in Kenya and EA countries as well as the lack of information about inventories and local supply conditions potentially exacerbates price fluctuations.

4.4 Results

4.4.1 Summary statistics

The summary statistics of the log of the absolute value of goods real exchange rates, $R_{xzz't}$ (see equation 4.5) are shown in Table 4.1. The goods real exchange rates represent the dependent variable across country-pairs and agricultural commodities. Zero entries denote the LOP holds perfectly, while values exceeding zero depict deviations from the LOP. Because of the logarithmic transformation, the average mean for within country-pairs (0.165) expressed in interpretable terms is $e^{0.165}$ or 1.179, or 17.9% higher than the LOP benchmark of 1. The result is less than that the 27.5% reported by Versailles (2012) given the geographical scope of his study encompassed Rwanda, Burundi and Tanzania. As expected, the average between-country pair rises to 25.86%, but still below the previous results, although the countries involved in comparison are different but from the same region. In the case of other geographic regions, for example, Grafe et al. (2008) cite larger departures from the LOP for 31 commodities traded in countries of Central Asia.

The magnitude of the means and standard deviations of between-country pairs are evidently higher than for within-country city pairs. Further, maize has the highest mean amongst the sampled commodities between city-pairs within Kenya, and within Uganda. Similarly, it has the highest mean between cross country city-pairs of the two countries. In East Africa, maize is the primary staple crop and the most traded (Jayne and Tschirley, 2009).

4.4.2 The effect of the border: pooled regression

The available data allow to specify the empirical model as:

$$|ln\, R_{xzz't}| = \beta_0 + \beta_1 lnd_{xzz'} + \beta_2 B_{xzz'} + \beta_3 lnEX_{zz't} + \beta_4 One\ stop\ border + \beta_5 Elect\ 2013 + \beta_5 Elect\ 2017 + \sum_{m=2}^{20} \gamma_m D_m + \sum_{c=2}^{5} \gamma_c D_c + \sum_{f=2}^{80} \gamma_f D_f + + \epsilon_{xzz't}. \quad (4.8)$$

The specification in equation (8) differs from equation (7) in two ways. First, the current dataset does not contain the tariff and NTB information. Second, equation (8) includes the election periods, crop harvesting season, and "one stop border post" variables. Also, dummy variables are added for the 80-month period ($\sum_{f=2}^{80} \gamma_f D_f$), the 5 agricultural commodities ($\sum_{c=2}^{5} \gamma_c D_c$), and the 20 city markets ($\sum_{m=2}^{20} \gamma_m D_m$). One dummy variable is excluded in each set of included dummies, i.e., month, agricultural commodity, and market pair to avoid the identification problem (Gorodnichenko and Tesar, 2005). Clustering of standard errors reported below coefficient estimates is done by city-pair. The clustering of the errors is done because of the suspected error dependency within the city-pair dimension (Broda and Weinstein, 2008).

Table 4.2 reports results for four pooled regression specifications. They are: 1) with the included border binary variable and distance as independent variables, 2) the first specification including log of the nominal exchange rate, 3) the first specification including both the log of the nominal exchange rate and the crop harvesting season, and 4) the first specification including election period dummy variables, the crop harvesting season, and the log of the nominal exchange rate. The total sample size used in the equations covers 950 city-pair combinations over a period of 351 weeks.

The distance equivalents as suggested by Engel and Rogers (1996) are shown in the lower part of Table 4.2. In particular, the study suggests computing the width of the border

(distance equivalent) by regressing a measure of the price dispersion on the log of distance, and a dummy variable that equals one if the price difference is computed for a good purchased in cities that are located in a different country. Hence, in the specifications in Table 4.2, one can compute the width of the border by dividing the border coefficient by the distance coefficient and then exponentiating it.

Table 4.2 documents a positive effect of distance on relative price dispersion, and a positive border effect between Kenya and Uganda. Specifically, the first specification shows that a distance of 50km between two markets allows for departures of approximately 5% from the LOP benchmark[10]. This is less than the distance coefficient obtained by Versailles (2012) but falls within the range of coefficient estimates reported by Broda and Weinstein (2008). The border dummy, which is positive and significant across all specifications, causes departures from the LOP benchmark by between 7.2% and 7.5%. This is within the range of 7% to 13% reported by Versailles (2012) and Engel et al. (2005), respectively.

Inclusion of the log of nominal exchange rate for specification 2-4 (Table 4.2) is an attempt to examine potential economic explanation for the sizable border effect. As expected, the nominal exchange rate has a positive and significant effect on cross-country price dispersion. Apparently, the nominal exchange rate, although important, does not completely account for the border effect. The finding corroborates Parsley and Wei (1996) results who did not confirm a significant change of the border when the nominal exchange rate is included in the regression.

Next, the focus is on the crop harvesting season. The coefficient of the crop harvesting season is negative as expected. Since Uganda and Kenya share similar crop planting and

[10] $0.012 * ln(50)$

harvesting seasons, the harvested crop enters the two countries' respective agricultural commodity markets at nearly similar periods. Hence, the increased supply of agricultural commodities at cross country markets lowers prevailing market prices (Salami et al, 2010) favoring the cross-country price convergence. Surprisingly, the crop harvesting season does not account for the border effect.

In contrast, the election period shocks of 2013 and 2017, both have positive and significant effects on cross border price dispersion. Election violence that is usually precipitated by political disputes is common in sub-Saharan Africa (Collier and Vicente, 2012). The indirect consequence of the "tribally charged" election campaigns is among others, disruption of agricultural commodity markets. Versailles (2012) reports increased deviation from the LOP benchmark of 24 commodity prices compared across East Africa during the Kenya's election of 2007 and the subsequent post-election violence of 2008. Interestingly, in the current study the two election periods do not account for the border effect.

The behavior of price dispersion during the 2013 and 2017 elections is partly explained by two plots (Figure 4.2 and Figure 4.3). The plots show shaded areas indicating the election period in 2013 and 2017. Month dummy coefficients for specification 3 of Table 4.2, which include city-pairs of Kenya and Uganda, were used to plot the figures. During the 2013 election period, marked by the shaded bar on the left side of the graph (Figure 4.2), there is an LOP spike for the full sample, Uganda city-pairs, and Kenya-Uganda city-pairs. Among the plotted lines, the latter category had the highest dispersion during the referenced period. Being the first election after the highly contested and violent 2007 election, the 2013 election period experienced risk aversion behavior from both Kenyan citizens and foreigners in almost all sectors of Kenya's economy (Lebas, 2013). The behavior included the return of foreign migrant

workers to their home countries, and Kenyan urban dwellers to their rural homes to escape potential violence precipitated by elections as was the case in the 2007. Similarly, trade between Kenya and its neighboring countries was disrupted, particularly trade with Uganda, Kenya's main trading partner in East Africa (Dupas and Robinson, 2012). Hence, the Kenyan election period of 2013 could have equally disrupted agricultural commodity markets leading to the observed upward spike in LOP deviations especially between Kenya-Uganda city-pairs.

Interestingly, LOP deviations during the 2017 election period, depicted by the right shaded bar on Figure 4.2, fall steadily. It seems the politically induced effect of 2013 on the LOP deviations did not hold for the 2017 election period. However, that unexpected result could be explained by the large importation of agricultural commodity volume during the referenced election period. In particular, over the election period of 2017, the CBK (2017) reports a short-term increase in import demand for cereals and sugar for which the Kenyan government imported maize, rice, and beans, the main commodities featured in this study. Entry of imports into the Kenyan market could have therefore forced price adjustment and hence the observed convergence of LOP deviations. Figures 4.3 shows the behavior of relative price dispersions for the five commodities considered in the current study. The range of border distance equivalents, i.e., between 200 kilometers and 1000 kilometers fall within the distance found in most earlier studies that does not apply the Engel and Rogers (1996) specification (Broda and Weinstein, Versailles, 2012).

In order to examine the effect of the "one stop border post" at Busia, this study estimates four regression equations that are specified according to specification 3 in Table 4.2. In particular, the first equation (Table 4.3) uses data from January 2012 to December 2017, before the launch of the one stop border post. All election period data are excluded from the first

regression. The second regression equation in Table 4.3 uses data obtained after the launch of the "one stop border post" i.e., March 2018 – September 2018. Regression equation 3, on the other hand, uses the full sample data (January 2012 – September 2018). Additionally, instead of the border dummy, it includes an interaction term between the border dummy and a time trend called "border trend". Similarly, the fourth regression (Table 4.3) includes the border trend interaction variable, but uses the full sample of Kenya-Uganda city-pairs data only.

Surprisingly, results seem to contradict the expected result of the "one stop border post" (Table 4.3). The border coefficient, which is highly significant increases after the launch of the "one stop border post". Also, the distance equivalent increases substantially, i.e., from 210 to 4,204. Likewise, the interaction term, estimated over the sample period (January 2012 – September 2018) is positive and highly significant. Although the border trend variable slightly decreases in magnitude when only Kenya-Uganda city-pairs are considered, it is still positive and significant. The decrease in magnitude of the border trend variable could suggest weak integration of agricultural commodity markets in as much as traffic has increased at the border due to improved infrastructure. Although the traffic across the border has increased due to improved infrastructure and includes widening of the border posts, construction of roads, and expedited processing of trucks.

4.4.3 Border effect regression across the five good categories

Results from estimating equations named specification one, two, and four (Table 4.2) for the five agricultural commodities are presented in Tables 4.4, 4.5, and 4.6. Interestingly, all the commodities have significant and positive border coefficient estimates in all specifications. The fit of the regression models as measured by the R^2 perform relatively well in all specifications and across all commodities. The equation modeling the LOP for local rice has the highest R^2

followed by the equation modeling maize, and hence corroborates Versaille (2012) model fit in the case of staples traded in East Africa. Clearly, the explanatory power of the specified models regarding red beans and mixed beans is less than that of domestic rice and maize since both grains are staples and consumed almost daily by the majority of Kenyans. Beans are prepared differently than rice or maize and consumed often but less frequently than grains. Moreover, beans are a heterogeneous commodity, more difficult for visual assessment of quality, and traded differently than rice or maize.

Considering the first specification, local rice, maize, and red bean prices increase relatively the LOP benchmark by 9.2%, 8.6%, and 7.7%, respectively. Imported rice and mixed beans prices are characterized by noticeably smaller increases above the LOP benchmark of 6% and 5.1% respectively. The difference in magnitude of increases of departures from the LOP benchmark between the highest (9.2%) and the least (5.1%) commodities is substantial. It is possible that the price increases for less homogeneous commodities such as mixed beans or imported rice are smaller because with regard to mixed beans, they are less expensive and less preferred as compared to red beans. Imported rice has been priced already on the international market, is supplied in relatively stable volume, and available regardless of the season. Such availability could limit price fluctuations. However, the overall finding of a single digit (i.e., less than 10%) increases in the departures from the LOP across all commodities corroborate prior findings. Specifically, Von Cramon-Taubadel et al. (2009) and Versailles (2012) in their studies on staples report that, distance drives less of a wedge between prices at different locations for staples than non-staples in East Africa. Further, staples are more easily traded across the region because they are a common and important part of people's diets. Also, markets for the selected staple commodities are 'deep' because of their prominence in household food consumption.

In the second specification, the nominal exchange rate does not seem to impact the border effect for neither of the commodities. The result could be indicative of a high transmission of inflation rates (exchange-rate pass-through) between Kenya and Uganda. Engel and Rogers (1993) finding for industrialized countries that 'pure' commodities do not elicit significant deviations from the LOP is corroborated by the above result on exchange rate. Engel and Rogers (2001) study involved a dataset spanning across 11 European countries.

Interestingly, there is no major impact on the border effect (across all commodities) when the crop harvesting season and the two election period variables are included as explanatory variables (specification 4; Tables 4.4 - 4.6). However, the coefficient on the crop harvesting season is negative as expected, a result similar to that found in the pooled regression.

Maize has the largest distance equivalent values across the three specifications followed closely by imported rice. Based on computation, the high border coefficient for maize translates into high distance equivalents. Note, that the low result of the distance equivalent on local rice, yet it has a high border effect due to the high distance coefficient.

4.4 Conclusions

This essay examines prices for five commonly traded agricultural staples. The data set covers 81 months (352 weeks) of observations collected across 20 cities in Uganda and Kenya. The LOP is tested using level regressions to identify the role played by selected macro issues on market integration in Kenya and between Kenya and Uganda. The border effect as measured by the coefficient on the border binary variable is statistically significant with corresponding distance equivalents varying between as low as 36 kilometers for mixed beans to as high as 46,630 kilometers for maize. The study also finds that city-pairs involving cross-border

locations, i.e., Uganda-Kenya cities, have large departures from the LOP compared to within-country city pairs. Distance plays a crucial role in both intra- and inter-country market price comparisons with the magnitude of statistically significant distance coefficients higher in this study than in prior studies that used the Engel and Rogers empirical specification. Good-specific results reveal that indeed staple food crops have well integrated markets as found in earlier studies. It seems that, although the nominal exchange rate shapes departures from the LOP benchmark, it does not impact the border effect for neither of the individual commodities, which could be indicative of a high exchange rate pass-through between Uganda and Kenya. Similarly, the cropping season and elections period effects bear significant influence on departures from the LOP benchmark, but do not affect the border effect. Finally, the border effect seems to have grown stronger after the launch of the "one stop border" at Busia, a rather unexpected result.

This study confirms that indeed there could be 'real' and nominal sources of influence on the departures from the LOP benchmark particularly using good-city-time series data. The persistence of the border effect even after controlling for the aforementioned macro-issues justifies the need for more work in this field. Especially important for further work would be to find out why the Kenya-Uganda border effect on price dispersion has gotten stronger after the establishment of the one-stop border post. Also, the fact that the nominal exchange rate affects relative price dispersion but does not influence the border effect brings to the fore the importance of policy that would allow comparison of intra EAC inflation statistics, especially between Kenya and Uganda.

Table 4.1 Summary statistics of commodity real exchange rates by city-pair and good-category

WITHIN-COUNTRY (Kenya)	Distance (km)	Mean	St.dev.	Min	Max
Kenya-Kenya	345	0.21	0.15	0	1.31
Maize	349	0.22	0.15	0	1.31
Red beans	342	0.17	0.12	0	0.80
Mixed beans	349	0.19	0.14	0	1.25
Local rice	369	0.24	0.17	0	1.06
Imported rice	204	0.18	0.13	0	0.72
WITHIN COUNTRY (Uganda)	Distance (km)	Mean	St.dev.	Min	Max
Uganda-Uganda	287	0.14	0.13	0	1.61
Maize	280	0.18	0.15	0	1.61
Red beans	277	0.15	0.11	0	0.75
Mixed beans	272	0.13	0.14	0	1.61
Local rice	292	0.11	0.12	0	1.10
Imported rice	282	0.13	0.11	0	0.79
Average (Within country pair)	316	0.165	0.14	0	1.46
BETWEEN-COUNTRIES	Distance (km)	Mean	St.dev.	Min	Max
Kenya-Uganda	648	0.23	0.20	0	1.54
Maize	659	0.28	0.19	0	1.45
Red beans	680	0.21	0.15	0	0.93
Mixed beans	659	0.21	0.16	0	1.37
Local rice	654	0.27	0.17	0	1.54
Imported rice	510	0.19	0.13	0	1.46

Table 4.2 Effect of the border on the LOP, pooled regression

Variable name	Eq. 1	Eq. 2	Eq. 3	Eq. 4
Log of distance in km	0.012***	0.012***	0.011***	0.013***
	(0.00225)	(0.00234)	(0.00225)	(0.00210)
Border (1=cross border)	0.075***	0.074***	0.073***	0.072***
	(0.00370)	(0.00370)	(0.00374)	(0.00357)
Log of exchange rate[a]		0.087***	0.022	0.066***
		(0.01463)	(0.01382)	(0.01512)
Crop harvesting season	-	-	-0.072***	-0.053***
			(0.00375)	(0.00428)
2013 election period (1= Election months)	-	-	-	0.093***
				(0.00544)
2017 election period (1=Election months)	-	-	-	0.029***
				(0.00556)
Constant	0.010	-0.285***	-0.030	-0.218***
	(0.01232)	(0.05317)	(0.05157)	(0.05424)
Engel and Rogers Dist. Eq.	518	477	762	254
City dummies	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes
Agricultural commodity dummies	Yes	Yes	Yes	Yes
R^2	0.226	0.221	0.235	0.229
Observations	255,955	255,955	255,955	255,955

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[a]Exchange rate of Kenyan shilling to Ugandan shilling

Note: Standard errors in parentheses

Table 4.3 "One stop border post" effect pooled regression

	Eq.1	Eq. 2	Eq. 3	KENYA-UGANDA
Variable name	Before[11] launch (01/ 2012 - 12/2017)	After launch (03/2018-09/2018)	Before and after 01/2012 – 09/2018	Only for Kenya-Uganda city-pairs
Log of distance	0.012640***	0.014137**	0.020769***	0.01085***
	(0.00171)	(0.00566)	(0.00300)	(0.00272)
Border	0.067583***	0.117980***	-	-
	(0.00320)	(0.00932)		
Border trend	-	-	0.000315***	0.00028***
			(0.00002)	(0.00003)
Constant	0.095529	0.244007	0.279670***	0.53723***
	(0.06480)	(0.49765)	(0.08013)	(0.10882)
Engels and Rogers Dist. Eq. (km)	210	4204		
R^2	0.170	0.180	0.177	
Observations	206206	24514	230720	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors in parentheses

[11] "one stop border post"

Table 4.4 Effect of the border for maize and mixed beans prices, pooled regressions

Variable name	MAIZE			MIXED BEANS		
Specifications (Table 2)	Eq 1	Eq 2	Eq 4	Eq 1	Eq 2	Eq 4
Log of distance in km	0.008	0.011**	0.010**	0.012***	0.013***	0.014***
	(0.00543)	(0.00507)	(0.00507)	(0.00450)	(0.00476)	(0.00443)
Border (1=cross border)	0.086***	0.082***	0.082***	0.051***	0.050***	0.050***
	(0.00752)	(0.00723)	(0.00732)	(0.00867)	(0.00895)	(0.00888)
Log of exchange rate	-	0.206***	0.111***	-	0.026	0.036
		(0.03414)	(0.03514)		(0.02557)	(0.02676)
Crop harvesting season	-	-	-0.066***	-	-	-0.051***
			(0.00799)			(0.00725)
2013 election period	-	-	0.084***	-	-	0.084***
			(0.00810)			(0.00786)
2017 election period	-	-	0.006	-	-	0.021**
			(0.01182)			(0.01031)
Constant	0.125***	-0.599***	-0.249*	0.065***	-0.030	-0.050
	(0.03026)	(0.12306)	(0.12808)	(0.02440)	(0.09935)	(0.10329)
Engel and Rogers Dist. Eq.	46,630	1,728	3640	70	47	36
R^2	0.257	0.258	0.257	0.140	0.140	0.145
Observations	64965	64965	64965	64965	64965	64965

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors in parentheses

Table 4.5 Effect of the border for red beans and local rice prices, pooled regression

Variable name	RED BEANS			LOCAL RICE		
	Eq 1	Eq 2	Eq 4	Eq 1	Eq 2	Eq 4
Log of distance in km	0.013***	0.011***	0.015***	0.015***	0.015***	0.015***
	(0.00226)	(0.00219)	(0.00186)	(0.00501)	(0.00486)	(0.00526)
Border	0.077***	0.079***	0.072***	0.092***	0.092***	0.093***
	(0.00332)	(0.00323)	(0.00308)	(0.00943)	(0.00944)	(0.00949)
Log of exchange rate	-	0.045	0.062*	-	0.082***	0.095***
		(0.03192)	(0.03193)		(0.03089)	(0.03299)
Crop harvesting season	-	-	-0.027***	-	-	-0.033***
			(0.00931)			(0.00956)
2013 election period	-	-	0.069***	-	-	0.082***
			(0.00969)			(0.01044)
2017 election period	-	-	0.029*	-	-	0.030***
			(0.01530)			(0.01044)
Constant	0.224***	0.073	0.008	0.058**	-0.231**	-0.264**
	(0.01819)	(0.10846)	(0.11010)	(0.02790)	(0.11513)	(0.12428)
Engel and Rogers Dist. Eq.	374	1315	122	461	461	493
R^2	0.186	0.177	0.183	0.296	0.297	0.301
Observations	45795	45795	45795	53250	53250	53250

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors in parentheses

Table 4.6 Effect of the border for imported rice price, pooled regression

Variable name	IMPORTED RICE		
	Eq 1	Eq 2	Eq 4
Log of distance in km	0.007***	0.008***	0.007***
	(0.00203)	(0.00258)	(0.00244)
Border (1= cross border)	0.060***	0.057***	0.059***
	(0.00597)	(0.00549)	(0.00477)
Log of exchange rate	-	0.027	-0.014
		(0.03581)	(0.03980)
Crop harvesting season	-	-	-0.049***
			(0.01256)
2013 election period	-	-	0.099***
			(0.01391)
2017 election period	-	-	0.048**
			(0.01997)
Constant	0.087***	-0.014	0.152
	(0.01706)	(0.12695)	(0.13887)
Engel and Rogers Dist. Eq.	5279	1243	4576
R^2	0.179	0.183	0.185
Observations	26980	26980	26980

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: Standard errors in parentheses

Table 4.7 Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

	Full sample (Ref. Table 4.2)			
Test	Eq. 1	Eq. 2	Eq. 3	Eq. 4
AIC	-193028.68	-190831.1	-192050.71	-193136.37
BIC	-191920.69	-189712.65	-190921.81	-191986.56

	MAIZE (Ref. Table 4.4)			BEANS (Ref. Table 4.4)		
Test	Eq. 1	Eq. 2	Eq. 4	Eq. 1	Eq. 2	Eq. 4
AIC	-46691.64	-46467.73	-46581.16	-52520.95	-51444.67	-52582.89
BIC	-45765.32	-45532.32	-45618.51	-51594.63	-50509.27	-51620.24

	RED BEANS (Ref. Table 4.5)			LOCAL RICE (Ref. Table 4.5)		
Test	Eq. 1	Eq. 2	Eq. 4	Eq. 1	Eq. 2	Eq. 4
AIC	-35720.60	-35360.37	-35929.87	-44080.67	-43511.48	-43748.85
BIC	-34856.14	-34487.17	-35030.49	-43192.39	-42614.32	-42825.04

	IMPORTED RICE (Ref. Table 4.6)		
Test	Eq. 1	Eq. 2	Eq. 4
AIC	-23428.330	-23277.257	-23372.230
BIC	-22821.319	-22670.246	-22765.219

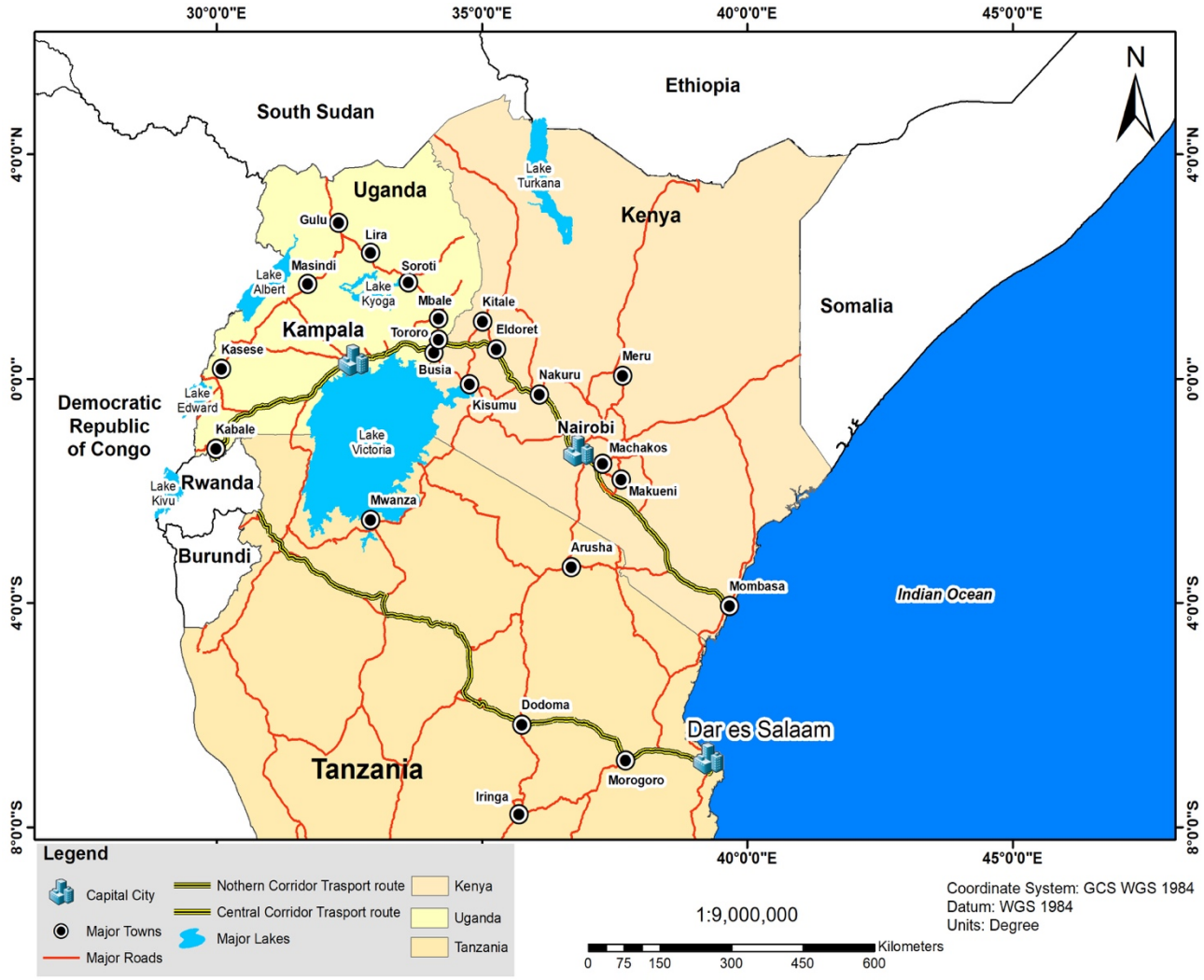

Figure 4.1 Map of study area

Source: Author.

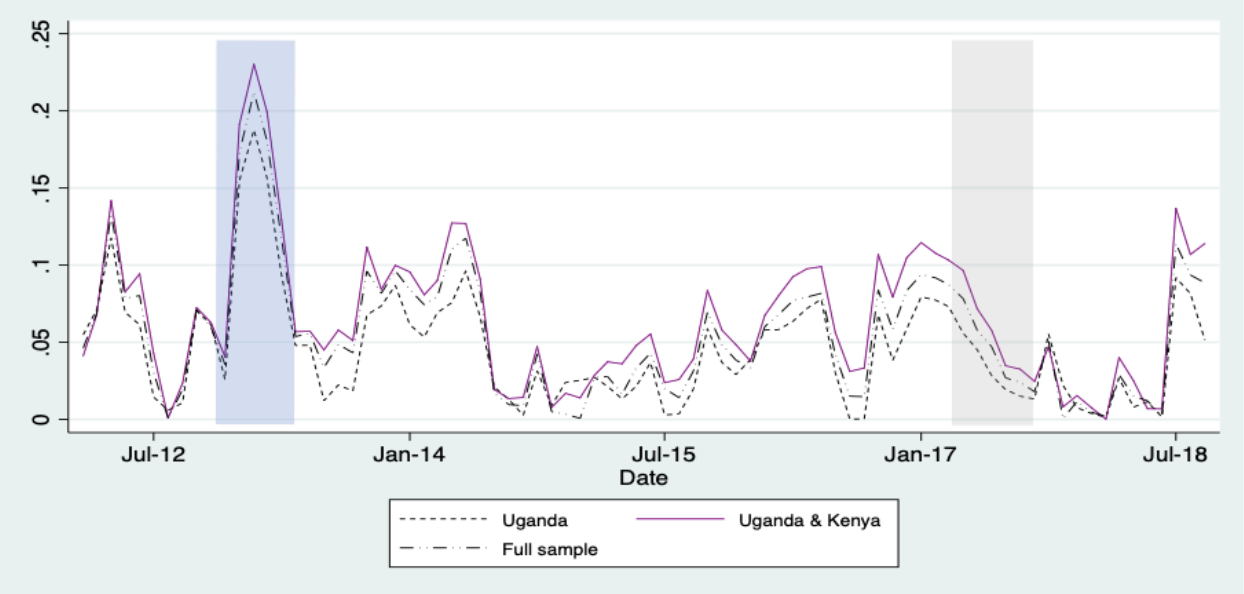

Figure 4.2 The 2013 and 2017 election period effect on price dispersion (by country)

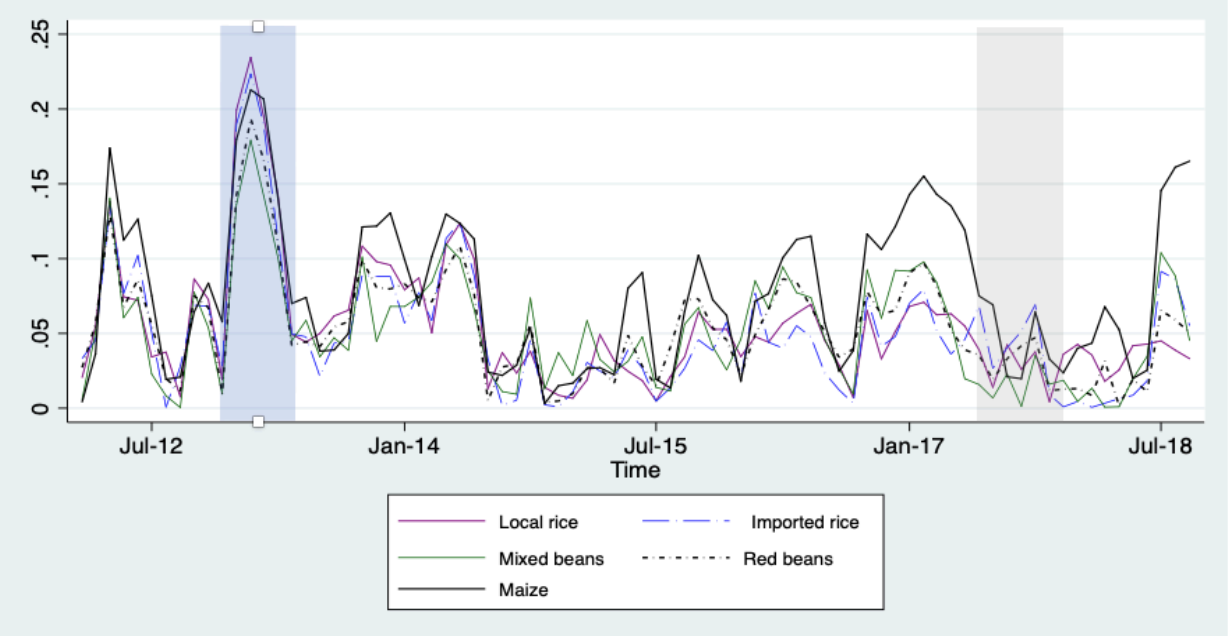

Figure 4.3 The 2013 and 2017 election period effect on price dispersion (by crop)

CONCLUSIONS AND DISCUSSIONS

In East Africa, the long-haul transportation service industry plays a central role in commodity market trade, food security and ultimately, the region's economic growth. An understanding, therefore, of the challenges and opportunities for the regions' trucking industry, and the constraints to market integration could bring to the fore, the core areas on which East Africa's trade policy can be prioritized. This dissertation attempts to contribute to this understanding from three different yet related perspectives.

The first essay examines long-haul truck driver perceptions of sources of delay along the NC road transportation route. Delays are classified as "other costs" in providing transportation services in east Africa. Multiple weighbridges and checks lead to unexpected delays, whereas wait time at borders can average a day. Also, rent-seeking behavior by traffic police, cumbersome customs documentation procedures, and varying trade regulations among partner states are additional challenges. The extent to which such events are causing delays and their elimination could lower transportation costs has not been researched and the anecdotal evidence with that regard varies. Hence, an analysis of how trip features, personal attributes, job characteristics, and vehicle features shape the perception truck drivers have of the delay-causing structural constraints and transitory events remains important.

The first essay uses survey data collected by the author from 511 truck drivers operating along the NC to model the links between perception of importance of the delay sources they face on route and trip features, vehicle features, job characteristics, and personal attributes. An ordered logit estimation technique is chosen to account for the ordinal nature of the outcome

variable and allows to quantify probability changes in the perception of importance and various factors. The insights from truck drivers provide a new perspective to formulate practical solutions leading to lower costs of doing business in EA.

Empirical investigation indicates that structural constraints and transitory events are perceived as sources of delay, albeit differently among drivers. Specifically, truck driver characteristics, and vehicle and job features increase the probability of attaching importance to roadblocks, custom documentation procedures, and varying trade regulations as time-delaying obstacles. All three sources of delay are controlled by government agencies or supranational bodies and require either close monitoring of the existing laws or modification of the existing agreements and obligations. On the other hand, trip scheduling, assured earnings in monthly salary, and whether a trucker is educated eases driver perceptions of sources delay as obstacles. The first two factors involve management of private companies and to broaden the use of procedures easing the driver anxiety, and potentially lower the transportation costs, they may be popularized within the trucking industry. Since the truck drivers in Kenya are organized into an industrial association, events organized by that organization may offer a pathway to reach trucking companies that do not yet use such practices.

The second essay investigates, first, the factors that shape truck drivers' economic reward profile including total working hours, monthly earnings, and the proportion of time spent driving in total working time, and second, the determinants of road traffic accident risk among truck drivers. Road traffic accidents along the NC pose enormous cost implications on East Africa's economy, yet studies that emphasize inquiry into the underlying causes of risky driver behavior and hence levels of exposure to risk of an accident, to the author's knowledge, are non-existing

for East Africa. An analysis of the factors that influence truck drivers' economic reward profile, and the determinants of risky behavior remains important.

Using the same survey data as in essay one, the first part of the essay models truck drivers' economic reward profile as a function of the trip features, preferential treatment in cargo acquisition, driver's personal attributes, safety and security factors, industry experience factors, lifestyle attributes, and structural constraints. The 3SLS econometric approach is chosen to account for potential simultaneity bias common in system of simultaneous equation relationships while allowing for the non-independence of the error terms in the equations.

The second part of essay two involves estimating an empirical relationship that link trip-specific exposure to risk as measured by the average speed to drivers' on-road behavioral attributes including khat use (an addictive drug commonly used among truck drivers of sub-Saharan Africa) and self-imposing trip schedules, trip specific features, and vehicle features. Two empirical approaches are used in the second part of the essay because there is potential for sample selection bias of two choice variables – khat use and self-imposing schedules – that are hypothesized to explain speed in the second step (empirical approach two). First, a bivariate probit econometric procedure is estimated where the probability to use khat and to self-impose a schedule are used as dependent variables. Second, an OLS regression is undertaken consisting of average trip speed as the dependent variable linked to trip features, vehicle features, personal attributes, and two selectivity regressors from the bivariate probit procedure.

Empirical analysis reveals the economic profile of a truck driver is shaped by the number of total working hours i.e., both productive (driving) and unproductive (loading and unloading cargo) time, the incidence of driving time in total working time, and the propensity to use khat.

Likewise, khat use influences speeding, although jointly via the propensity to self-impose own schedule.

The last essay of this dissertation tests the LOP and hence market integration by comparing price data for five staple food crops traded within and between Kenya and Uganda. Lack of close trade links between countries of sub-Saharan Africa, especially between Kenya and other EA's partner states causes instability in food markets, high consumer prices, and exacerbates food insecurity during droughts. However, besides close trade agreements and thus trade links signed by the region's member states' governments, there could be other underlying reasons that would shed light on why within and between country markets are segmented. Knowledge of the causes of market segmentation for traded agricultural commodities within and between Kenya and Uganda could thus set the stage for policy interventions that would provide sustainable solutions to EA's staple food supply deficits through efficient trade.

The third essay takes advantage of the Kenya-Uganda shared price information system that records real-time daily prices of staple food crops commonly traded within and between markets in the two countries. A pooled ordinary least squares (POLS) empirical approach is estimated to test the LOP. The log of the absolute value of good real exchange rate by city-pair and good category represent the dependent variable which is linked to 'nominal' and 'real' sources of influence that are hypothesized to explain the price dispersions between markets.

The analysis indicates that price comparisons involving cross border market pairs have larger departures from LOP when compared to within-country city pairs. Also, distance plays a crucial role in both intra- and inter-country price comparisons with the magnitude of statistically significant distance coefficients higher in the current study than in prior work. Finally, although the nominal exchange rate affects the departures from the LOP benchmark for all staples' prices,

it does not impact the border effect for either of the commodities. This finding is indicative of high exchange rate pass through between Kenya and Uganda.

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