UNIVERSITY OF CAPE COAST

ESSAYS ON TRANSPORT MODE CHOICE, FUEL AND ICT EXPENDITURES IN GHANA

BY

JAMES DICKSON FIAGBORLO

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DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature: …………………………. Date…………………

Name: James Dickson Fiagborlo

Supervisors' Declaration

We hereby declare that the preparation and presentation of this thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast.

Principal Supervisor's Signature……………… Date……………………

Name: Dr. Camara Kwasi Obeng

Co-Supervisor's Signature: ……………………. Date…………………….

Name: Dr. Godwin Kofi Vondolia

ABSTRACT

The main objective of this study was to identify the drivers of transport fuel expenditure and mode choice in Ghana. Specifically, the study analysed the effects of ICT expenditure on transport fuel market participation and consumption decisions of households; examined the effect of real value of travel time on transport mode choice; and assessed how the effect of ICT expenditure on transport fuel intensity differs among household demographic factors (sex). The double hurdle model was applied to five waves of the Ghana Living Standard Surveys to analyse the first objective. The results show that ICT expenditure, income, household size, urbanisation and education are among the significant variables that relate positively to transport fuel market participation and consumption decisions of households in Ghana. The results also indicate that transport fuel is income and ICT elastic. For the second objective, the study fitted a multinomial logit model to data from the National Household Travel Surveys. It was noticed that relative risk of lost labour productivity and distance are among the significant considerations for transport mode choice between motorised transport versus non-motorised transport among workers in Ghanaian society. Finally, three logistic regressions were estimated for objective three, using data from the GLSS Seven. Interestingly, the result shows that female-headed households in the lower income group have the highest odds of being less fuel intensive than male-headed households. The study, therefore, suggests various policy implications based on the drivers that influence transport fuel market participation and consumption decisions, and those that drive transport mode choice as well as transport fuel intensity of households in Ghana.

KEY WORDS

ICT expenditure

Market participation decision

Real value of travel time

Transport fuel expenditure

Transport fuel intensity

Transport mode choice

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DEDICATION

To Nathaniel and my late parents, Hyde and Lizabeth.

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LIST OF ACRONYMS

ACM	All-Cause Mortality
AIC	Akaike's Information Criterion
ANCOVA	Analysis of Covariance
ANOVA	Analysis of Variance
BIC	Bayesian Information Criterion
BRT	Bus Rapid Transport
BTS	Bureau of Transportation Statistics
CBD	Central Business District
CES	City Express Services
CLGT	Conditional Logit
CNLOGIT	Cross-Nested Logit
DAF	Doorne's Automobile Fabriek
DCM	Discrete Choice Models
DVLA	Drivers and Vehicle Licensing Authority
EA	Enumeration Areas
ECOWAS	Economic community of West African States
ECP	Estimates on Conditional Probability
EPA	Environmental Protection Agency
EPP	Estimates on Participation Probability
EUCP	Estimates on Unconditional Probability
FAO	Food and Agriculture Organisation
FILOGIT	Fuel Intensity Logit

GAMA	Greater Accra Metropolitan Area
GDP	Gross Domestic Product
GFEI	Global Fuel Economy Initiative
GLSS	Ghana Living Standard Surveys
GHG	Greenhouse Gases
GLM	General Linear Model
GME	Ghana's Ministry of Energy
GPRTU	Ghana Private Road Transport Union
GSS	Ghana Statistical Service
HMNLTG	Hybrid Multinomial Logit
HTCOME	Household Telecommunication Expenditure
ICT	Information Communications Technology
IEA	International Energy Association
IIA	Independence of Irrelevant Alternatives
ITU	International Telecommunication Union
LCM	Latent Class Modelling
LDC	Less Developed Countries
LPG	Liquefied Petroleum Gas
LPM	Linear Probability Model
LR	Likelihood-Ratio
LSFI	Lower Sulphur Fuel Initiative
LUSPA	Land Use and Spatial Planning Authority
LVT	Luxury Vehicle Tax

MANCOVA	Multivariate Analysis of Covariance
MANOVA	Multivariate Analysis of Variance
MDCEV	Multiple Discrete Continuous Extreme Value Model
MFI	More Fuel Intensive
MLE	Maximum Likelihood Estimates
MLOGIT	Multinomial Logit
MMDA	Metropolitan, Municipal and District Assemblies
MMT	Metro Mass Transit
NGO	Non-Governmental Organisation
NHTS	National Household Transport Survey
NIB	National Investment Bank
NLOGIT	Nested Logit
NMT	Non-Motorised Transport
NTP	National Transport Policy
OLS	Ordinary Least Squares
OSA	Omnibus Services Authority
PHC	Population and Housing Census
PMT	Private Motorised Transport
PROTOA	Progressive Transport Owners Association
RCC	Regional Coordinating Councils
RP	Revealed Preference
RRR	Relative Risk Ratio
RVTT	Real Value of Travel Time

SSA	Sub-Saharan Africa
SAP	Structural Adjustment Programmes
SDG	Sustainable Development Goal
SHS	Senior High School
SIC	State Insurance Company
SP	Stated Preference
SPT	Small Public Transport
SSNIT	Social Security and National Insurance Trust
STC	State Transport Company
TFE	Transport Fuel Expenditure
TFI	Transport Fuel Intensity
TIB	Theory of Interpersonal Behaviour
TMC	Transport Mode Choice
TPB	Theory of Planned Behaviour
TUC	Trades Union Congress
UN	United Nations
VIF	Variance Inflation Factor
VKT	Vehicle Kilometer Travel
WTP	Willingness to Pay

CHAPTER ONE

INTRODUCTION

Mobility of people and freight is imperative for economic growth and standard of living. However, transportation activities have been identified with increasing energy demand and high CO_2 emissions. This has the potential to adversely impact households' welfare and the environment due to climate change effects of CO_2 emissions and high expenditures on energy. Consequently, United Nations (UN) as part of the Sustainable Development Goal (SDG) recognised that achieving mitigation of greenhouse gas by 2030 will ensure sustainable transport and mobility of people. Meanwhile, in emerging economies, energy consumption of the transport sector is expected to increase as a natural consequence of economic growth and improved living standards. This means that developed and developing countries, including Ghana, will continue to face the inevitable challenge of greenhouse gas emissions due to derived energy demand from transport activities.

While it has been scientifically noted that Information Communication Technology (ICT) diminishes physical mobility of households, understanding its link relative to transport fuel expenditure is vital to provide leverage for reducing the expected effect of high energy consumption on the environment to ensure sustainable transport. In this regard, this study sought to identify the drivers of transport fuel expenditure and mode choice in Ghana. The results will guide policies towards accomplishing the SDGs that are anchored on sustainable transport. The first chapter highlights the background, statement of the problem, objectives, hypothesis, significance, scope, as well as the organisation of the study.

Background to the Study

The importance of transport in moving people and goods from one place to another cannot be overemphasised. However, while it conveys socioeconomic benefits, transportation activities account for 23 percent increase in energy consumption and emissions of CO_2 according to International Energy Agency ([IEA], 2012). Similarly, Li, Rose and Hensher (2009) identified automobiles as a major source of greenhouse effect. Meanwhile, policy makers globally have acknowledged sustainability of transportation sector as a solution for sustainable economic growth and development. Thus, the global agenda on SDGs on transport recognised that achieving mitigation of greenhouse gases (GHG) will guarantee sustainable transport and mobility of people (Holzwarth, 2015). Actually, though Sub Saharan Africa (SSA) contributed insignificantly to global CO_2 emissions due to low level of industrialisation, the call for climate change mitigation is imperative.

The reason being that SSA has been experiencing growth resurgence since 2000, after failed Structural Adjustment Programmes (SAP) (Fosu, 2015). This was evident at the recent meeting of the SSA with seven of the world's ten fastest growing economies (Asongu & Nwachukwu,2017). There is the possibility of increasing vehicles and energy demand as an effect of the economic resurgence and enhanced income. This is because SSA has the potential to produce more cars by 2030, and this is expected to increase vehicles and energy demand and adversely impact the environment through the emission of GHG (Asongu *et al.*,2017). While there is urgent drive to control the energy consumption and GHG emissions

(Mraihi, ben Abdallah, & Abid, 2013), SSA lacks elaborate strategy for handling the influence of energy consumption and emission of GHG (Asongu *et al.*,2017).

Meanwhile, the phenomenal sprawling urbanisation and land use change is changing mobility patterns of people, with those living far from economic centres becoming captive to private modes of transport because of unavailability of efficient public transport. Pongthanaisawan and Sorapipatana (2010) concluded that growth in personal income is shifting people from motorcycle to car ownership because car comes with prestige, convenience, comfort, and safety. Also, Bardazzi and Pazienza, (2018) noted that different social norms, including expectations and aspirations, interplayed with material culture and energy practices in shaping car ownership behaviour. While Abrahamse, Steg, Gifford and Vlek (2009) showed that perceived behavioural control and attitudes explained car use, Nordfjærn, Simsekoglu and Rundmo, (2016) revealed that people who did not identify the use of public transport as a sign of low social status have higher propensity of using it.

Increasing car use relative to limited road infrastructure in emerging economies is creating road congestions (Mraihi *et al*., 2013), with consequences for GDP, travel time reliability, safety of transport and the environment due to CO_2 emissions (Holzwarth, 2015). Studies (Blumenberg & Agrawal, 2014; Diaz Olvera, Plat & Pochet, 2013) observed the rippling impact of congestion on transport expenditure, and how this reduces access to social services (Fan & Huang, 2011; Ferdous, Pinjari, Bhat & Pendyala, 2010) as households cannot partake in activities that necessitate mobility. Other Studies (Holzwarth, 2015; Li, Rose & Hensher, 2009) also represented car and passenger fleets as major consumers of fuel.

Therefore, available studies (Pung & Mokhtar, 2019; Holzwarth, 2015) observe how car users are fortified to use bus as a way of guiding fuel use and congestions.

For instance, Mraihi *et al.*(2013) claimed that improving public transport system will lead to reduction in the mobility of private vehicles, promotion of vehicle efficiency as well as of fuel consumption and GHG emissions. While Holzwarth (2015) noted that improving efficiency of the transport system will not only decrease the use of private mode of transport, but this will decrease transport energy consumption, greenhouse gas emissions, in addition to improving personal and communal health consequences. Again, the use of bicycles as sustainable mode of transport to reduce greenhouse gas emissions and improve personal health has also gained traction (Holzwarth, 2015). But, Diaz Olvera, Plat and Pochet (2008a) argued that bicycle usage does not represents an alternative for many people because of the negative social representations associating bicycle use with poverty.

Further, Abrahamse *et al.* (2009) showed that while stronger personal norms were associated with stronger behavioural intentions, this happens only when perceived behavioural control was low. Thus, it has been recommended that policies aim at reducing car use should target important determinants of car use and willingness of people to reduce car use. Pongthanaisawan and Sorapipatana (2010) also recommended that policies to promote high efficiency vehicle technologies for a low income country should focus on motorcycles if these countries have a high share of motorcycles in their overall stock of private vehicles. However, for low income countries, it is critical that policies aim at reducing commuter car use focus on investment in sustainable transport infrastructures for active mode of transport.

While recent report indicates that a low carbon pathway is attainable if transport investment is directed to sustainable transport, the global investment needs for transport infrastructure, according to the UN, are on the increase and estimated to be between US$1.4 and US$2.1 trillion per year. This means that, even when countries globally want to deploy extensive expansion of road infrastructure and investment in fuel efficient public transport vehicle to deal with the growing demand for private transport and its consequential effect on energy consumption, environment and human health (Pung & Mokhtar, 2019), funding for transportation system would be a precarious challenge. Meanwhile, compared to advanced countries, developing countries may be most affected by the funding constraints because most of these countries lack adequate financial resources with which to confront their investment requirements for sustainable transport infrastructures.

Thus, the UN Secretary-General's High-Level Advisory Group on Sustainable Transport recommended that nations should employ regulatory and market-based measures to national and local needs and circumstances to diversify sources of funding towards sustainable transport, while at the same time encouraging changes in behaviour. The group advised that nations should use beneficiary and polluter pays measures including carbon pricing, congestion pricing as part of diverse tool box from which funding for transport can be drawn. While these sources of finance may help bridge the revenue gaps in developing countries, depending on it to fund sustainable transport infrastructures may place a huge burden on users of transport services because transport services providers may shift their burden onto the final consumers. Blumenberg and Agrawal (2014) noted that financing transport using fiscal policy increases fuel prices and transport fares.

Meanwhile the sensitivity of fuel demand to changes in fuel prices is higher for higher-income households compared to low-income ones (Hughes, Knittel & Sperling, 2008). This implies that the extent to which fiscal financing options, through fuel prices, can affect fuel demand depends on the distribution of income in society. The policy infers the possibility of modes switching among higher income households relative to low income households. However, it also suggests moving from driving private car to public bus for only few people in the short run due to sluggish changes over time of factors such as land use, employment structure and transport infrastructure, which push people to easily shift (Hughes *et al*., 2008).

While Montag (2015) suggested the use of uniform fuel tax to decrease fuel consumption and stimulates search for less polluting fuels and vehicles that use them, Timilsina and Dulal (2008) also noted that adaptive behaviour of taxation could reduce driving and congestions. However, studies (Parry & Strand, 2012; Poterba, 1991; Santos & Catchesides, 2005; West & Williams, 2004) observed that in countries where car ownership is widespread across socioeconomic classes, fuel tax incidences are mixed. Sterner (2007) noted that while fuel taxes were less regressive in countries where car ownership was concentrated in higher socioeconomic class, adjustments in these taxes on goods help offset the tax regressivity. Sterner (2007) observed that fuel tax helps reduce income inequalities in countries where the fuel tax is on a luxurious good that is consumed by the rich.

It is significant to note that the absence of efficient investment to eliminate the burden of fiscal financing and their effects on fuel prices will be beneficial to the wealthy at the expense of the poor, and this according to Carruthers, Dick and Saurkar (2005) raises concerns about affordability of public transport in developing countries. Affordability reflects the extent to which the financial cost of journeys puts an individual or household in the position of having to make sacrifices to travel or the extent to which they can afford to travel when they want to (Carruthers *et al*., 2005.). Considering the two scenarios, while a financial cost of journeys might place a family on a journey to work, it might not facilitate that family to afford trips to school for their teenage children or visit a grandparent in the hospital. In the later scenario, transport would have then been considered unaffordable by all standards.

Thus, affordability is the ability to make necessary journeys to work, school, health and other social services, and make visits to other family members or other urgent journeys without decreasing other critical undertakings (Carruthers *et al*., 2005). Studies on affordability focused on how subsidy and regulation affects transport prices (Christoffel Venter, 2011), and provides a significant boost to mobility according to Bryceson *et al*. (2003.). However, with the increasing energy demand within the transport sector of developing countries, it is expected that subsidy would impact the import bills of developing countries. While the debate about affordability is about high cost of driving for lower income households (Sanchez, Makarewicz, Hasa & Dawkins, 2006), policy makers are concerned about whether the justification for exclusion of subsidies should come from an economic standpoint or equity and pro-poor directions (Christoffel Venter, 2011).

Several studies (Diaz Olvera *et al.*, 2013; Fan & Huang, 2011; Christoffel Venter, 2011; Gannon & Liu, 1997) indicated that poorer households pay more (in absolute terms) for public transport trips than their richer counterparts because of sprawling urban development. Similarly, Venter and Behrens (n.d.) observed that long distances have made transport fare higher and unaffordable for poorest people who walk to work in developing countries. This observation underscores the significance of geographical location with respect to urban form and job accessibility, and the effect of location on transport expenditures. Regrettably, policies that support denser and mixed land-use in the context of suburbanised arears have failed to decrease commuter distances unless they complement other policy initiatives to discourage long car trips according to Manaugh *et al*. (2010).

Indeed, studies (Maunder & Fouracre, 1987; Diaz Olvera, Plat & Pochet, 2008a) in SSA and Jamaica, Malaysia and India (Osula, 1999), including the World Bank report in 2004, have all established that between 15 to 25 percent of annual transport expenditure was made in developing countries, and 15 percent of income of urban households accounted for that. Consistent with this result, Diaz Olvera *et al*. (2008a) found similar evidence in selected African countries. However, while Christoffel Venter (2011) used a travel survey to establish similar findings, Dargay and Vythoulkas (1999) found different outcomes, using different data collection and processing methodology (consumption survey). Vasconcellos (2001) after analysing case studies from Latin America drew similar corresponding conclusion.

Recent studies (de Oña & de Oña, 2015; Ojo, 2019; Redman, Friman, Gärling & Hartig, 2013) on the effect of service quality of transport indicated that better service quality in public transportation attracts more commuters and addresses congestion problem in cities. However, these studies did not consider the effect of quality on the cost of a journey. Meanwhile, Christoffel Venter (2011) studied users' monthly spending on transport in relation to their accessibility to transport service. As noted before, limited accessibility to transport services imposed high transport cost that may lead to less spending on other goods to allow for the use of public transport. Therefore, it is expedient that transport operators, transport planners and decision makers in their pursuit to entice and retain passengers, establish strategic goals and determine funding decisions that improve the transport services (de Oña & de Oña, 2015; Ojo, 2019; Redman *et al.*, 2013).

The challenges with global climate change and the need to achieve mitigation of greenhouse gas to ensure sustainable transport and mobility of people, necessitate measures to reduce energy consumption and its effect on GHG emissions. However, the link between transport fuel expenditure and GHG emissions has not been studied quantitatively. Anowar, Eluru and Miranda-Moreno (2018) established number of factors (household composition, employment status, household location, household evolution, and global socioeconomic factors) that affect household budgetary allocations for transport. Although these factors, which can be classified as economic, technological as well as cultural have been identified to influence transportation expenditure, the influence of these factors on GHG emissions through transport fuel expenditure remains unexamined in the literature.

Moreover, accounting for the impact of these factors within budgetary allocation process helps to appreciate how households respond to varying policy measures, environmental changes, fuel price fluctuations and economic challenges (Anowar *et al.*, 2018). Therefore, lack of information about how social, economic and technological factors drive transport fuel expenditures makes it difficult for planners and stakeholders to account for their indirect effect on GHG emissions. Thus, understanding the drivers of transport fuel expenditure of households is relevant to provide a basis for formulating transport policies that may have indirect influence on GHG emissions. For example, a framework to analyse the response of transport fuel expenditures of households to social, economic and technological factors may unveil understanding of how households may adjust their transport fuel expenditures to maintain mobility levels in response to changes in these factors.

The particular frameworks can help explain the latent effects of information communication technology (ICT), as a measure of GHG emissions, on households' transport fuel expenditures in developing countries. Instructively, Asongu *et al.* (2017) found that decreasing ICT (i.e., mobile phones and the internet) use has a net positive effect on CO_2 emissions from liquid fuel consumption in SSA. ICT has helped developed countries to minimise travel time and expenditures, because its infrastructure has made possible interaction and interconnectivity between and across homes, office buildings and transportation systems (Okyere, Poku-Boansi & Adarkwa, 2018). Real-time traffic information and mobile telecommunication devices allow users to circumvent traffic delays (Litman, 2013). While Choo and Mokhtarian (2007) found a bidirectional link amid telecommunication and transportation, four sorts of reverse causalities transpire given demand and supply.

These causalities are: (1) transportation impacts on the demand for telecommunication; (2) transportation impacts on the supply of telecommunication; (3) telecommunication impacts on the demand for transportation; and (4) telecommunication impacts on the supply of transportation. Okyere *et al*. (2018) noted that telecommunication influences demand for transportation by removing or replacing travel of individuals. Mokhtarian and Tal (2013) found complementary and or substitution relationship between telecommunication and transportation. In the case of substitution, the economic price theory behind this is that, decreases in price of telecommunication reduces the demand for transportation; while complementarity occurs where the demand curve for telecommunication shifts to the right as consumers move downwards along the demand curve of transportation.

Regarding the first case, Salomon (1986) argued that the substitution hypothesis assumes that the availability of ICT diminishes the necessity to travel. The intuition is that, ICT allows for individuals and organisations to work far apart than what they did when they were previously within reach with each other. This according to Aguiléra, Guillot & Rallet (2012) promotes competitiveness of the nexus between ICT and transport. Lee and Meyburg (n.d.) also noted substitution as the total or partial elimination of travels. However, Mokhtarian (2002) argued that complete elimination of travel can only be possible with the availability of high quality interactions made possible due to teleconferencing, telecommuting, teleshopping, telebanking and telemedicine at a distance. Despite its criticism, the substitution hypothesis has the ability to moderate road congestion and its effects of fuel consumption, emissions and accidents (Dissanayake & Morikawa, 2008).

The second hypothesis of complementarity is based on the assumption that ICT stimulates travel (Mokhtarian, 1990). According to Salomon (1986), what informed this relationship is the enhancement and efficiency of ICT. Dal Fiore *et al.* (2014) also noted that interaction of ICT with transportation is enhanced when improvement in ICT generates additional travel between two nodes. For example, ICT enhances travel when the use of phone calls or a meeting over the internet prompts a travel. The efficiency interaction occurs when one service contributes to the efficiency of the other. Salomon (1986) concluded that application of ICT ensures efficiency of the transportation system. Similarly, the use of intelligent transportation system provides real time-traffic information that promote travel (Mokhtarian, 1990). Therefore, ICT transforms travel by way of making it possible to teleconference, telecommute, teleshop, telebank in addition to telemedicine.

Putting the discussion in Ghanaian context, this thesis observes that although provision in the constitution lends credence to the importance of mobility of Ghanaian citizens, the transport sector in Ghana is characterised with excess demand and shortage of supply for transport infrastructures. While Article 35 clause (6), paragraph (c) of the constitution enjoins that, "the state shall take appropriate measures to provide adequate facilities for, and encourage, free mobility of people, goods and services throughout Ghana," several factors including limited public investment and inadequate support from donor funds for the transport sector limit governments' ability to ensure that this essential provision in the constitution is upheld to guarantee fairness and just mobility of all citizens.

Additionally, sprawling urban settlement patterns have influenced distance between residences and socioeconomic centres. The Ghana Statistical Service ([GSS], 2008) noted that lots of people live in surrounding cities, where land is cheaper for housing and other uses. The World Bank (2007) also noted how sprawling settlement pattern discourages the use of bicycles and walking, particularly among wealthy households. This makes wealthy households depend on private car making it difficult for them to maintain their daily activity routine without car (Salon & Aligula, 2012; Tranter, 2010). Like many less developed countries (LDCs), car ownership in Ghana is small, but has increased to 7.97 percent (GLSS6) from 1.48 percent in 1992 (GLSS3) according to report from GSS (2014). Increasing car ownership in Ghana may have implication for future energy consumption as oil demand for road transportation has been directly linked with the number of cars as well as other road vehicles in use (Dargay & Gately, 1999).

Congestions due to increasing use of private vehicle among higher income groups has raised concerns because of their implications for transport expenditures and commuting time for poor people. Additionally, the effect of congestions can produce scarcity of savings that may make the poor more vulnerable to shocks of transport costs (Tranter, 2010). Besides, with increasing congestions and lack of alternative fuels for road transportation means that fuel demand will continue to increase, as will the associated negative externalities such as CO_2 emissions and accidents. Given the underlying effects from limited public investment, rapid and sprawling urban settlement as well as growing demand for private cars in Ghana meant that congestions will prevail. Transport planners will need strategic innovative alternatives ways to control the potential rising energy consumption and the quantity of GHG emissions that may arise from transport related activities.

Some of these innovative strategies to deal with the excess demand over supply of transport and its implications for GHG emissions and human health have been noted in the National Transport Policy (NTP) of Ghana. In particular, Ghana implemented modal diversion strategy that sought to divert citizens from private car to public transport. Differential pricing, whereby different toll rates for different types of vehicles were implemented. It was envisaged that rising toll rates for private cars would decrease the use of private vehicles, which are the major source of traffic congestion and GHG emissions. Ghana introduced the Bus Rapid Transport (BRT) systems, which has the objective to provide high quality service to the users; minimise the time buses are stopped for boarding and alighting by passengers; maximise the vehicle cruise speed; facilitate transfers and enhance the reliability of bus operations. These policy strategies are to help mitigate traffic congestion and ensure efficiency and sustainability of the transport sector of Ghana.

Furthermore, Ghana's Ministry of Energy (GME) is collaborating with Global Fuel Economy Initiative (GFEI) as well as ECOWAS on the Lower Sulphur Fuel Initiative (LSFI) to lower the volume of fuel consumed and its impact on fuel prices. At the national level, not only may this effort help reduce increasing pressure on national budget (because of reduced import bill) and free-up fiscal space for the country, the collaboration should ultimately promote sustainable mobility envisaged in the SDG7. Ghana through the Environmental Protection Agency (EPA), in conjunction with the UN Environment, the Ministry of Transport

(MoRT) and the Drivers and Vehicle Licensing Authority (DVLA) and other agencies, has undertaken an inventory on the vehicular fleet and inspection evolution in Ghana from 2005 to 2006 to inform policy options for fuel economy.

Ultimately, the inventory was to lower the volume of fuel consumed and fuel prices. It was also to promote energy conservation, social equity and enhanced economy. Unfortunately, there is no evidence to suggest that this effort has helped decrease the volume of fuel consumed. There are, however, clear rise in the ownership of cars in Ghana (GSS, 2014), which perverse the existing traffic congestions on the major roads in Ghana. This may blur the intent of the SDGs and the efficiency and sustainability of road transport sector (Holzwarth, 2015). Often, lapses of legal, institutional and regulatory regimes are blamed for such failed policies in developing countries. However, Sterner (2007) as well as Russell and Vaughan (2003) noted scant political will as a culprit for failed policy interventions. Higher taxes on vehicles in developing economies fruitlessly reduce car ownership because of lack of political resolve (see Sterner, 2007; Timilsina & Dulal, 2008).

Ghana is not immune to lack of political will. A perfect case is the aborted Luxury Vehicle Tax (LVT). To recall, the Parliament of the Republic of Ghana passed the LVT law, and its implementation took effect from Wednesday, 1st August, 2018. The LVT law was meant to levy an annual tax of 1,000 Ghana cedis on vehicles with engine capacity of 3.0 – 3.5 litres; 1,500 Ghana cedis on vehicles with engine capacity of 3.6 – 4.0 litres, and an annual LVT of 2,000 Ghana cedis on vehicles with engine capacity of 4.1 litres and above. Commercial vehicles were, however, exempted from the LVT, because the tenet of the LVT was to raise more revenue by taxing a little more the wealthy in the society. While its full implementation may have additional tacit effect on pollution emissions, congestion and traffic accidents, lack of political will to sustain the LVT implementation has implication for efficiency as well as sustainability of road transportation in Ghana.

Undoubtedly, transport related activities contribute to rising energy consumption and increasing quantity of GHG emissions. However, what has also assumed global attention is the overarching effects of rising transport related activities on households. For example, it has been observed that transportation expenditures represent chunk of expenditures of American households (Bureau of Transportation Statistics [BTS], 2018). The round five of the Ghana Living Standard Surveys (GLSS5) revealed that average transport expenditures per household rose from GH¢ 624 million to GH¢ 3649 million (GSS, 2014). This represents slightly less than six times increase in transport expenditures. The rising transport expenditures has seen urban households spend more (GH¢874 million) compared to rural households (GH¢ 431 million) (GLSS6). Moreover, a difference was noted between per capita household transport expenditures of rural households (GH¢258 million) and urban households (GH¢59 million) (see GSS, 2014 report).

Several factors may influence spending decision of households. However, previous study (Tobin, 1958*)* assumed that decision to spend is only influenced by income and prices of the goods. Though this assumption can provide some useful evidence for public policy analysis, it is possible that when it is relaxed, the result could reveal some systematic differences about spending decisions of households. For example, at the lower end of households' income quantiles, relative to high end of the households' income quantiles, it is possible to observe systematic differences between the effects of income on the decision to spend. The focus of this study is not on quantile regression. However, it has been argued that households' transport fuel expenditures decision may also be influenced by gender of household heads; technology; and location. The rest are: beauty of the environment, provision of pedestrian walkways, and unrestricted access to non-motorised transport modes.

The effects of these factors on decision to spend using Tobin's assumption may help formulate policy to improve travel condition and promote social equity among households as envisaged in the SDGs. But, it is not sustainable to impose the same restriction on spending decision and the actual amount spent. For this reasoning, this study relaxed the Tobin's constant marginal effect assumption. The ICT provides the platform through which people can have access to information about the effect of transport on the environment (Asongu *et al*.,2017). Thus, the SDG 7 may be realised if the effect of transport on the environment is understood in the context of ICT. Consequently, ICT was included in this analysis to leverage its influence on transport expenditure decision and the environment. This will guide government mainstreams the application of ICT as a major instrument in its development programmes to reduce mobility and transport expenditure in Ghana.

There are general concerns among policymakers and advocates about the effect of transportation expenditures on households in developing countries (Christoffel Venter, 2011). Interestingly, the National Household Transport Survey [NHTS], 2012) indicates that poor women in Ghana who do not have their means of transport have been walking either long distances or commuting on expensive modes of public transport. This has fostered the debate on the ability of vulnerable groups to access needed services centres and livelihood enhancing opportunities that can improve their living conditions. Grieco, Apt and Turner (1996) showed that female traders used public transport for their vital trips when they had money.

Contextually, it is clear that understanding the effect of transport on the environment is critical. This is because it will help achieve sustainable transport and mobility, which are fundamental in achieving goal 7 of the SDGs. While ICT may provide the platform through which people can have information about the effect of transport on the environment, there is limited information about how it could be leveraged for the sustainability of the transport in Ghana. Meanwhile, Asongu *et al*. (2017) found that ICT has a net negative effect on CO_2 emissions from liquid fuel consumption. Further, International Telecommunication Union (ITU) noted that individual using the internet as a percentage of the population in Ghana has risen from zero percent in 1990 to about 39 percent in 2017. While the rise in ICT penetration will last into the foreseeable future, leveraging its implications for public policy is right for attaining the sustainable transport goals.

In light of this level of ICT penetration rate, this study makes a case for understanding the nexus between ICT expenditure and transport fuel expenditures. Again, the study makes a case for understanding the drivers of transport fuel expenditure and transport mode choice in Ghana. Consistent with literature, this study recognised that higher ICT expenditure weakens the ability of people to procure information about the effect of transport on the environment and therefore engage in irresponsible environmental behaviour. On the other hand, lowering ICT expenditure enables people to have access to information and so involve in responsible environmental behaviour. Given these contrasting hypotheses of the effect of ICT expenditure on transport, and to large extent on the environment, it is held that ICT expenditure could be leveraged to provide effective and sustainable policy for realising the SDG 7 of the transport sector in Ghana (Holzwarth, 2015).

In Ghana's transportation and energy sectors, many researchers explored traffic congestion (Agyapong & Ojo, 2018); transport mode choice (Birago, Mensah & Sharma, 2017; Fiagborlo & Kyeremeh, 2016); transport unionism (Fouracre, Kwakye, Okyere & Silcock, 1994); travel behaviour (Abane, 2011); political petrol prices (Akpalu, Robinson & Robinson, 2012); households electricity consumption (Taale & Kyeremeh, 2016), liquefied petroleum gas (LPG) and biomass (Adusah-Poku & Takeuchi, 2019; Akpalu, Dasmani & Aglobitse (2011); service quality (Ojo, Mireku, Dauda & Nutsogbodo, 2014) and politics (Yobo, 2013). These studies provided useful transport policies in Ghana. But, the question that remains unanswered is what factors drive transport fuel market participation and consumption decisions and transport mode choice of Ghanaians.

Additionally, limited information exists of the analysis of the effect of ICT expenditure on transport fuel expenditure (TFE) of households, and how the effect of ICT expenditure on transport fuel intensity (TFI) differentiates demographic attribute (sex) of households in Ghana. While some information exist elsewhere about transport intensity and energy efficiency (Mraihi, 2012), the apparent necessity of policy makers to appreciate the effect of ICT expenditure on TFE of households remains paramount. Moreover, it is imperative to state that the effect of

ICT on travel behaviour of households in cities of progressive economies is well appreciated. However, the case for LDCs like Ghana is inadequate (Okyere *et al*., 2018). This has elevated interests in the problem from the perspective of Ghana.

Recently, Okyere *et al*. (2018) examined the relationship between transportation and telecommunication within the broader framework of smart cities in Ghana. Although the conclusions from the study suggested that relationship amid transport and telecommunication could be leveraged to inform public policy on environmental externalities, it recommended that future study should consider study in this area from micro perspective. Consequently, this work proposes the use of waves of micro data to unravel the dilemma in the relationship between ICT expenditure and transport fuel expenditure to inform public policy. It is noted that telecommunication and transportation are different types of communication (Choo & Mokhtarian, 2007). This hypothesis is from the premise that technologies allow the transmission of services at a distance making it possible to substitute physical mobility with virtual relationship. Aguiléra *et al*. (2012) noted this to be due to spatio-temporal representation of the progress of telecommunication technologies.

Poku-Boansi and Adarkwa (2014) estimated demand for passenger transport from the perspective of transport expenditure in Ghana. Yet, the estimates are limited because of the scope and nature of data used. The study did not also consider specific factors that influence participation and consumption decisions of households in the transport market. Moreover, the study used only 400 commuters and focused on Kumasi, the capital city of the Ashanti Region. While the estimates lacked generalisability, they also did not reflect the dynamics of transport expenditures and how these transport expenditures relate to socioeconomic indicators. Thus, the study rarely accounted for the effects on transport expenditures of the variations in the characteristics of households over time. This is because the static assumption that underpinned the model used suggests that transport demand within one period only depends on the expenditure and prices in that same period.

This assumption further implies an instantaneous response of transport service users to any changes in the attributes of transport services. Meanwhile, there is an evidence that repeated cross sectional data could allow for accurate functional specification that could lead to precise estimates of transport demand *(*Anowar *et al*., 2018). Therefore, though the static assumption is useful, a convenient compromise could be made using multiple cross sectional datasets for different years if an accurate longitudinal dataset collected across several years are not available (Anowar *et al*., 2018). This is imperative because utilising the multiple cross sectional data may help remove the uncertainties and imperfect information regarding economic, transport expenditure as well as alternative modes of transport.

With multiple cross sectional datasets available for different years in Ghana, the present study leveraged on five waves of the Ghana Living Standard Surveys (GLSSs) to analyse the effect of ICT use on TFE, and how this influence on TFI differentiates demographic attribute (sex) of households in Ghana. Admittedly, multiple waves of data are not compiled based on the same set of households (Anowar *et al*., 2018). However, using these data for this study offer suitable information to examine the effect of changing household characteristics and ICT expenditure on transport fuel expenditure of households. Recent study (Eakins,

2016) indicates that estimates of elasticities from multiple data offer a chance to compare the results across many years. This possibly could help trace the impact of household characteristics on transport fuel expenditures from one year to another.

There are three strands of issues unveiled in the background that motivated the study: First, the need to understand the nuances of the effect of ICT expenditure on transport fuel expenditure of households, using multiple waves of the cross-sectional data. Second, the need to show that RVTT as an exogenous factor explains transport choice behaviour of Ghanaian workers; and third, the need to show how the influence of ICT expenditure on TFI of households differentiates demographic attribute (sex) of households in Ghana. These strands, together with global concern about understanding the effect of transport on SDGs, provided spur for this study.

Statement of the Problem

The economy of Ghana is experiencing rapid population growth and structural change in expenditure on goods and services. This socioeconomic transformation has resulted in sprawling urbanisation and land use change. Distances have become longer and access to social and economic centres are becoming difficult for many households because of transport cost, particularly for those in the low-income group. Meanwhile, most households have also changed from their traditional modes of transport to advanced one such as motorised transport. Rising car use has environmental and economic costs, threatening the economic security of the nation (Ministry of Environment, Science, Technology and Innovation [MESTI],2014). This is because increasing energy demand derived from transportation activities has been identified with increasing emission of CO_2. Moreover, increasing share of transport expenditure in households' expenditure is further potentially compromising the mobility among the vulnerable households.

While improving road conditions, providing high quality fuels, promoting eco-driving, better vehicle technologies including promoting electronic vehicles, and complete improvement of urban transport systems were the various types of actions captured in the SDGs to be undertaken to improve the efficiency of transport fuel use, understanding the drivers of transport fuel expenditure decision of households is necessary to ensure effective and efficient policies towards these sustainable transportation practices. Existing literature examined the relationship between transport and telecommunication within the framework of smart cities in Ghana. But, limited information exists about the effect of ICT expenditure on transport fuel cost of households, and how the effect of ICT expenditure on TFI of households differentiates demographic attribute (sex) of household heads in Ghana.

Additionally, though studies (Bris, Pawlak & Polak, 2017; Polydoropoulou & Tsirimpa, 2012) about ICT and its effects on the mobility of households, energy efficiency and transport intensity exist, the results did not reflect the effect of ICT expenditure on transport fuel intensity in the context of demographic attribute (sex) of households in Ghana. Moreover, though previous studies provided useful policy guides on drivers of household energy demand in Ghana, they failed to address imperative policy questions about how much households spent on transport fuel after participation and consumption decisions were made, conditional on ICT use.

Furthermore, studies on transport modes in Ghana admittedly considered personal and mode specific attributes, but failed to consider real value of travel time as a critical explanation for mode choice decision of workers in Ghana. Besides, some of these studies (Amoh-Gyimah & Aidoo, 2013a; Birago *et al.*, 2017) were limited in scope and covered Accra and Kumasi in which case they used qualitative methodology in their analysis. More so, though Agyemang (2017) synchronised the gap in the literature between Amoh-Gyimah and Aidoo (2013a) and Abane (2011) by focusing on formal and informal sector employees who visited the Central Business District (CBD) of Accra, all these studies together did not confirm on a national scale for trip behaviour and drivers of mode choice for workers in Ghana.

Meanwhile, large-scale research on drivers of mode choice may have implications for transport fuel expenditure, which forms significant part of expenditures of households. Macro data were used in transport studies, but using micro data may give valuable information that account for individual level factors that may affect TFE. The gaps concerning ICT relative to transport fuel market participation and consumption, and the need to understand the effect of real value of travel time on mode choice on a large-scale in Ghana warrant further enquiries. This thesis analysed the effect of ICT expenditure on TFE, controlling for other factors, and assessed how the effect of ICT expenditure on TFI differentiates demographic attribute (sex) of household heads, while examining the drivers of transport mode choice of Ghanaian workers. With multiple waves of nationally representative samples on transport, which is a major contributor to GHG in Ghana, a full study was vital to help identify the drivers of TFE to ensure sustainable policy.

Objectives of the Study

Generally, the objective of this study was to identify the drivers of transport fuel expenditure and mode choice in Ghana. Specifically, the study sought to:

i. analyse the effect of ICT expenditure on transport fuel expenditure market participation and consumption decisions of households;

ii. examine the effect of RVTT on transport mode choice of workers in Ghana;

iii. assess how the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of household heads, using disaggregated data from Ghana.

Hypotheses of the Study

The following propositions guided the study:

i. H_0: No effect exists of ICT expenditure on transport fuel market participation and consumption decisions of households;

H_1: Effect exists of ICT expenditure on transport fuel market participation and consumption decisions of households;

ii. H_0: No association exists between real value of travel time (RVTT) and transport mode choice decision of workers in Ghana;

H_1: An association exists between real value of travel time (RVTT) and transport mode choice decision of workers in Ghana;

iii. H_0: No effect exists of ICT expenditure on transport fuel intensity due to differences in demographic attribute (sex) of households, using disaggregated data from Ghana;

H_1: Effect exists of ICT expenditure on transport fuel intensity due to differences in demographic attribute (sex) of households, using disaggregated data from Ghana.

Significance of the Study

There are limited information about how to leverage on ICT to reduce transport fuel expenditure in developing countries, although ICT has been identified to diminish mobility and the effect of energy consumption on the environment (Asongu *et al*., 2017). Given that individual using internet as a percentage of the population will continue to linger into the future, this study contributes to the knowledge on the effect of ICT expenditure on transport fuel market participation and consumption decisions of households. The study provides policy makers with the understanding about how reducing households' spending on ICT would help attains sustainable environmental and transport goals in Ghana.

Moreover, the spread of economic activities at different locations in Ghana has generated movement of people from one place to another, including work, which must be supported by transport system. However, the use of transport has been recognised to be the source of traffic congestion and air pollution, with their attendant effect on productivity and health of people in many countries. With the rising rate of car ownership in developing countries, understanding the relative risk of lost labour productivity of workers is critical in prioritising transport modes that can carry larger numbers of passengers without exponential increase in road space.

Sociodemographic attributes of households are critical determinants of travel behaviour. Yet, gender is often times one of the least examined determinants of transport activities. Since this study assessed how the effect of ICT on transport fuel intensity varies in sociodemographic context in Ghana, it has the capability to provide understanding about policy designs that are gender sensitive, efficient and equitable. Meanwhile, the complexity of transport needs of women compared to men is highlighted in this study and adequate critical policy responses suggested.

Scope of the study

This study sought to identify the drivers of transport fuel expenditure and mode choice in Ghana. It focused on transport fuel expenditure of households, transport mode choice of Ghanaian workers, and transport fuel intensity of households. Specifically, the study used data on transport fuel expenditure of households, which included purchases of fuel for private vehicles and fuel expenditure on public transport. While private mode of transport included any non-shared mode, public transport encompassed all shared modes of transport in Ghana.

The study analysed the effect of ICT on transport fuel market participation and consumption decisions of households, applying the double hurdle model (Cragg, 1971) to the GLSS (3, 4, 5, 6 &7) datasets. The scope extended to cover areas such as RVTT and travel mode decisions of workers, using the NHTS 2012 data, while controlling for other individual and mode specific features. Finally, three logistic regression equations were estimated for households, female-headed and male-headed households to address the third objective, using the GLSS7 data.

Organisation of the Study

The rest of the study was organised as follows: Chapter Two presented an overview of the transport sector in Ghana. Chapter Three highlighted the theoretical and empirical literature on factors driving transport fuel expenditure and mode choice. Some factors considered included personal specific attributes and mode attributes including real value of travel time. The fourth chapter considered the theoretical framework of the study. It commenced with the overview of general linear model and provided detailed information on the theoretical models for the objectives. The chapter also presented the analytical frameworks that informed the empirical equations estimated and evaluated. The methodology was articulated in the fifth chapter, while the sixth, seventh and eighth chapters constituted the empirical chapters, which were based on the three prime objectives of the study. The summary of the study was done in Chapter Nine, the final chapter of this study.

Chapter Summary

This chapter provided the introduction to the study. It considered the background to the study, statement of the problem and objectives of the study. The chapter continued with the hypotheses of the study, significance and scope of the study. It also captured the organisation of the study. The next chapter presents an overview of the transport sector in Ghana. It highlights the abstract definition of transportation in general, while providing some historic facts about Ghana. Chapter Two also covers Government policy on private sector participation in public transport, ICT and transportation, public road transport and operational challenges.

CHAPTER TWO

OVERVIEW OF THE TRANSPORT SECTOR IN GHANA

Introduction

This study sought to identify the drivers of transport mode choice and fuel expenditure. This chapter presents an overview of the transport sector in Ghana. The chapter provides a brief historic context of Ghana, highlighting the abstract definition of transportation in general. Additionally, the chapter considers Government policy position on private sector participation in public transport. This is followed by the discussion on Information Communications Technology where we look at the traditional nexus between ICT and transportation. The chapter further deliberates on the effects of population growth and increasing demand for motorised transport. The final section reviews the public road transport in Ghana, detailing some of the operational challenges pertaining to the transport sector. The next section of the chapter commences with the historical perspective on Ghana.

Brief Historical Context of Ghana

Ghana was the first country in the sub-Saharan Africa to attain independence from Britain in 1957. Prior to this, the Portuguese settled in Ghana in 1471. This was followed later by the Dutch, the French and the Danes, respectively. Meanwhile, the British had settled in Ghana in the 1800 until she gained independence in 1957. Ghana is surrounded by some of her West African neighbours such as Togo to the east, la Cote d'Ivoire to the west, Burkina Faso to the north and Gulf of Guinea to the south. In terms of size, Ghana covers 238,533 km^2, with spatial extent of 357 km from west to east and 672 km from north to south (Okyere *et al.*, 2018). Ghana gained republican status in 1960 and pursued socialist policies. This economic philosophy characterised the creation of many state-owned enterprises in heavy industry, manufacturing and trading, agriculture, banking and services, including transport. The period up to 1960 also saw progress in human capital based on the idea of free education for all up to the tertiary level.

Between 1966 and 1992, Ghana went through periods of military rule, intermingled with two short eras of civilian administration. Nonetheless, from 1992, Ghana regained stable constitutional rule hinged on the model of executive presidency, with a unicameral legislative organisation. Since then, five elections have been held and the democracy of Ghana seems to be entrenched. This is made possible because of the creation of institutions that provide appropriate checks and balances for the fledgling democracy. At the national level, the Executive President is elected every four years by simple majority. The president then appoints a cabinet of Ministers and is constitutionally required to engage 67 percent of the Ministers from Parliament. Moreover, Parliament is constituted by 275 members and also rans for four years analogously with the term of the president. Parliament does law enactment duties, passing bills submitted by the Executive or a private member.

Ghana is a unitary state. Until the current 16 administrative Regions, Ghana had 10 Regions in the past with 216 Metropolitan, Municipal and District Assemblies (MMDAs) and the later serving as the local Government structure within the Regions. The Regional Coordinating Councils (RCCs) headed by Regional Ministers serve as the link between central government and the MMDAs headed by District Chief Executives. Ideally, most ministerial functions are at least entrusted to MMDAs. The population of Ghana has seen not only rapid growth, but rapid urbanisation since independence. It is estimated to be 31 million people in 2020 with 50 percent urban dwellers in 2010 (GSS, 2014). Level of urbanisation varied across regions with the Greater Accra (90.5 percent), Ashanti (60.6 percent), Western (42.4 percent), Central (47.1 percent) and Brong Ahafo (44.5 percent) more urbanised than compared to the Upper West (16.3 percent), Upper East (21.0 percent), Northern (30.3 percent) and the Volta Region (33.7 percent) (GSS, 2014).

Urbanisation may be due to varied reasons including differences in natural increase between geographical areas, the extent of migration and government policies, which may directly or indirectly affect the pace and dynamic of urbanisation (GSS, 2014). Some of the effects of rapid urbanisation are congestion, unregulated urban expansion, limited access to services and affordable quality housing and transport, and inability of institutions to cope with the rapid transition. The concentration of infrastructural facilities, such as hospitals, universities, road construction in urban areas, has to a very large extent, created a rural-urban development gap such that many years of political independence, the living conditions of the rural majority have not changed. Although Ghana has discovered crude oil in commercial quantity, her major foreign exchange earner is still cocoa. The next section discusses the level of Information Communications Technology and transportation growth in Ghana, and their symbiotic historical connections.

Transportation and Information Communication Technology

Transportation can be construed as the conveyance of goods and persons from one place to another. It may also be recognised as transfer of expertise and resources between spatial environment (Schulz, 2004). This definition implies that transportation does not only include mobility of person and goods but also the flow of information between spatial environment. Schulz (2004) considered transportation not only as a means of moving fright and persons but as the flow of information and activity that provides access to resources and opportunities. Krizek, Handy and Forsyth (2009) have broadened the definition to encompass non-motorised modes such as walking, bicycling and animal drawn cart. Schulz (2004) further noted that ICT provides modes to transfer expertise and resources between spatial environment and qualifies it as another layer of transportation.

Hypothetically, there is a symbiotic relationship between transportation and telecommunication. The governance and organisational structure of transport and ICT sectors lend credence to this symbiotic relationship between them. For example, spanning a period of 40years, the transport and communication sectors in Ghana were governed under the Ministry of Transport and Communication. However, due to expanded scope of the telecommunication and transport sectors, the earlier Ministry of Transport and Communication was separated leading to their segregation in 1997. Since then, the telecommunication sector has had its own ministry, the Ministry of Communications, albeit the Ministry of Transport has had to be further bifurcated into several ministries based on the different modes of transport. In particular, portfolios such as the Ministry of Transport, Roads and Highways, Aviation and Railways Development have been created over the period.

It is clear that relationship existed between transport and communications, which are two separate but closely related sub-sectors (Okyere, *et al*., 2018). In deed at the regional level, both telecommunication or telephone penetration and the level of road development have followed the same pattern as areas with high tele-densities are those with the long total road lengths and higher population as well (Okyere *et al*., 2018). The author noted that the two sectors complemented each other and governments over the period did not find it very difficult putting them under one ministry. Okyere *et al*. (2018) indicated that, notwithstanding this significant relationship, the involvement of the private sector and marked improvements in mobile telephony has led to a change in having the two sub-sectors planned together. While the relationship is strong at conceptual level, understanding how it could be leveraged scientifically to provide policy direction remains obscured. Thus, this thesis sought to analyse this relationship to address the environmental effects of increasing transport fuel expenditure of households.

Government Policy on Private Sector Participation in Public Transport

Governments over the years have established bus service companies such as the Omnibus Services Authority (OSA), State Transport Company (STC), City Express Services (CES) among others. The Omnibus Services Authority Decree of 1969 nationalised all City, Municipal, Urban and local Council bus endeavours within one unitary body that was responsible both for the planning and the provision of public transport services. However, the Omnibus Services Decree of 1972 then split these two functions by creating a separate Licensing Authority to regulate the activities of the omnibus sector. The Omnibus Services Authority continued in existence but with the sole objective of bus service provision in its specified areas.

Later, legislation concerning the commercialisation of service delivery groups within the public sector resulted in its restructuring as OSA Transport Limited. Both the Omnibus Services Authority Decree and the Omnibus Services Decree exempted the Authority from such taxes, rates and duties as the Commissioner for Finance may direct. All buses, their spare parts and non-consumable equipment, imported by the Authority shall be exempted from imported duties. These, together with fuel and lubricants purchased locally shall be exempted from purchase and sales taxes. The Authority was also exempted from income tax. Taken together, these concessions were very significant subsidy for the Authority and represented a strong barrier to competitive market participation.

However, the STC, CES and OSA were not seen to be faring well. This forced the Government to divest public interest in them in the 1990s. Specifically, in 1996, the Government decided to privatise the State Transport Corporation and City Express Services Limited. However, it was difficult to find investors for these businesses at that time. This led to their continuing decline because of the absence of public investment in rolling stock and other assets. Consequently, public transport services were largely replaced by private sector participation with paratransit, known as trotro. The transport industry was dominated by Ghana

Private Road Transport Union (GPRTU) and the Progressive Transport Owners Association (PROTOA), which were all allied to the Trade Union Congress (TUC).

In 2000, the elected Government came to power on a policy that included a strong commitment to enhancing the transport sector in general and urban transport services in particular. It also endorsed the market liberalisation of the economy, and the preeminence of the private sector in actual service delivery. Despite this commitments, however, the Government was unwilling to surrender full control over public transport charges as obligated by market orientation. Before then, previous Government had policy of procuring regularly stock of vehicles for leasing to private operators through GPRTU. This policy was also reviewed by the new government in 2000. Efficient transport systems are required to integrate rural, urban and regional economies to promote economic growth and development.

Therefore, as part of environmental and energy considerations, and the need to promote efficient public transportation to increase productivity and economic growth, the Government decided to promote the establishment of a new public transport undertakings as a quasi-private business. This was also in fulfilment of the promise of the government to bus at least about 80 percent of urban passengers in Ghana, through mass transport (GMoRT, 2009). Other projects like Bus Rapid Transit (BRT) systems, School Bussing Scheme and Rail Mass Transport Systems had also been given priority. To undertake regular stock procurement on behalf of the freshly established public transport endeavours, the Government (through the Ministry of Road and Transport, and Local Government and Rural Development) held 45 percent equity interest in the Metro Mass Transit Limited (MMT, 2008).

The balance of the equity stake was subscribed by the Social Security and National Insurance Trust (SSNIT), the National Investment Bank (NIB), the State Insurance Company (SIC) and the Prudential Bank, respectively (MMT, 2008). The 45 percent stake of Government was meant to control interest in MMT Limited, yet the minority equity of the Prudential Bank among other equity holders can be termed as truly private interest. The Government as part of its equity interest moved to MMT physical assets of OSA Transport Limited, which had then been put into liquidation. From an existing public procurement plan, under concessional finance from the Netherlands, the initial stock was delivered via a donation of 164 second-hand Fiat-Iveco buses from Italy, and the allocation of 75 DAF chassis to be assembled by Neoplan in Kumasi. Later, a further 250 buses were ordered from Yaxing in China (mostly urban single-deck buses, but also a number of double-deck and inter-city vehicles) expending public fund as a guarantee (IBIS, 2005).

Moreover, it was then understood that a further tranche of 100 DAF chassis was going to be procured again with grant-aided finance from the Netherlands. Obviously, constituting and equipping MMT Limited this way gave them an unfair advantage over the existing private operators, and this restrained any new investor from entering the market. When you consider what the company does and the fares they charge, no transport company can compete with them. There is the need to restructure the policy to enable possible leasing of buses to private operators. This would reconcile Government policies on private sector participation in the service sector of the economy. As of 2007, the MMT Limited was operating in all the ten regions of Ghana with an initial fleet of 779 buses. At the end of 2007, the number of buses that were in good condition for operation was 400 (51 percent) with 379 (49percent) at workshop (Fiagborlo & Kyeremeh, 2016). Strikingly, the company had 379 buses operational by 2018 with 4,300 workers employed (Bonney, 2018).

Buses are generally comfortable, fast and safe means of transport in Ghana. Hence, apart from MMT buses, the now Intercity STC is the most comprehensive bus service. Intercity STC used to be wholly owned by the government. However, it is presently owned by SSNIT which has majority shares after taking over from VANEF and the Government of Ghana (Agyei, 2015). Intercity STC schedules bus services that run between most major cities, unlike MMT that run between cities and have more flexible schedules. The Intercity STC buses have to be booked days in advance because the tickets of the air condition buses, which are much comfortable, sell faster. While MMT buses are not faster because they pick up commuters alongside the way if spaces are still available, they are less costly and offer related level of luxury and security as Intercity STC services. Another comfortable buses with more variable timetables are the VIP. As well as the Intercity STC, the VIP has its headquarters at Obetsebi Lamptey Circle in Accra.

Apart from MMT limited that run between cities and have more flexible schedules, the Ayalolo bus rapid transit system, another quasi-public bus enterprise, has lately been launched. The company run three services from November 2016 on Amasaman-Accra Central section of the corridor. In 2017, while the service of the company was yet to draw attention from commuters, the management of the Ayalolo BRT had planned to roll out the Adenta-Accra Central corridor, and then the Tema Beach Road-Accra Central corridor (Agyemang, 2017). Meanwhile, management of the Ayalolo bus company had also planned to replicate the BRT mass transit services in other major cities of Ghana (Nyabor, 2017). Therefore, it is imperative to understand the drivers of transport mode choice, particularly for those who commute between their home and work place so as to assist city authorities, planners, other stakeholders and management to assess the success of this initiative.

Public Road Transport

As indicated before, public transport is key to sustainable use of energy since it can provide services to many customers without inevitably increasing the number of vehicles. The aforementioned section discussed Government policy on private sector participation in public transport. At this juncture, the review focuses on the public road transport sector, while subsequently noting some of the effective challenges relating to the sector. This review is necessary because it will provide planners with the information requires to plan mobility needs of urban commuters in Ghana. According to the Ministry of Environment Science, Innovation and Technology, a high proportion of buses and trotros use have poor fuel economy with no emission control. Therefore, Government policy to decongest cities from unnecessary traffic jams and vehicular emission of pollutant gases is critical. To accomplish this, Government requires a combination of a number of strategies such as expansion of roads and investment in fuel efficient public transport vehicles.

Generally, road transport in Ghana is by far the foremost career of freight and passenger in land transport systems. It carries over 95 percent of all passenger and freight traffic and gets to most communities in Ghana (GMoRT, 2009). About

38,000 kilometers of road network was built in Ghana in 2000, and by the end of 2005 this has increased fast to 60,000 kilometers (GMoRT, 2009). Since then, the road sub-sector has slowly been improving at yearly growth rate of 8 percent. Presently, the estimated road network in Ghana is about 72,381 km. Of this, 14,873 km are trunk roads, 42,045 km are feeder roads and 15,463 kilometers are urban roads (GMoRT, 2017). Regrettably, poor roads may cause stress and decline in output among workers. So, while it is uneasy to obtain road condition of 70 percent good, 20 percent fair, and 10 percent poor (GMoRT, 2009), maintaining the current roads may lead to desire accessibility, affordability, reliability and safety of users.

Interestingly, 24 years after independence, it became increasingly difficult to provide adequate funding from the consolidated fund to maintain the road network in Ghana. This has necessitated the establishment of the first generated road fund in 1985 to address the issues. In 1997, the Road Fund Act was enacted to offer legislative support to road maintenance in Ghana. Obviously, the law has led to a significant improvement in funding of road maintenance. At a point, about 60 percent of the estimated road maintenance costs came from the road fund (GMoRT, 2009). In terms of investment in fuel efficient public transport vehicles, the challenge is that control over the operation of public transport by government is restricted to an extent. The operation of the private sector is controlled by unions of which the most potent is the Ghana Private Road Transport Union (GPRTU).

These unions charge membership fees and member drivers are obliged to register with and pay a daily fee to a local branch, which controls a terminal. The unions also control user charges on behalf of the MMDAs, who own the terminals.

Unions, as part of their rules, require a vehicle to be full before it can leave, an exercise, which is contrary to the interest of passengers who are unable repeatedly to board cars between stations and must wait long hours until the vehicles are full.

According to the DVLA, more than one million vehicles of all types were imported into Ghana from 2005 to 2016. Thus, between January and December 2016, the number of cars on the roads of Ghana increased by nearly 23 percent. While the mission of government was to provide safe, affordable, technologically efficient and reliable transport for commuters through BRT system, significant proportion of vehicles plying the road of Ghana are second-hand vehicles, with obsolete technology whose carbon dioxide emissions and fuel consumption might no longer be in compliance with the manufacturers' standards in advanced countries. Undoubtedly, these vehicles contribute to rising energy consumption and increasing quantity of GHG emissions. This threatens the environment of Ghana.

As noted already, significant number of these vehicles operated by the informal sector are branded as trotro. This is a shared mode of transport that holds 12-14 passengers and operates by a driver and mate and works along a pre-defined routes in Ghana (Fiagborlo & Kyeremeh, 2016). While trotro may be comfortable to some commuters, the authors observed that somewhat they are perceived to be risky by some section of users. Albeit, trotros offer a very useful service for short journeys only. One can join them anywhere along the road or from outside the terminal, mostly the non-unionised ones. The trotro fares are also competitively low and regulated by the government. Another mode in the informal sector of Ghana are taxis. Some of the taxis are metered and registered while others are not.

Altogether, taxis in Ghana have a yellow painted mudguard that brands them easily to differentiate them. They can simply be embarked over and charges are haggled.

Problems of Public Road Transport

Generally, quality of services provided by public road transport is poor. This is because most vehicles are old and maintenance standards are to extreme very low. This is because of sky-rocket vehicle maintenance costs arising from poor road surfaces. It is also due to limitations imposed on earnings by congestion on the urban roads constraining the operators to invest in new vehicles. Yobo (2013) noted that the single most predominant urban transport problem in Ghana is vehicular traffic congestion, and this has led to over 67 percent of major roads operating at unacceptable level of less than 20km per hour sometimes during the day (GMoRT, 2017). The result is limited number of low capacities vehicles and resultant long queues during the morning and evening rush hours at most terminals in the country.

While substantial possibility exists to enhance the efficiency of mobility of people via a shift from low capacity public transport vehicles to hefty buses with the prospect to carry over 100 passengers, the concern is the absence of adequate regulatory efficiency. Hence, any effort to move people from one mode to the other is likely to see some challenges due to deficient state-owned mass transit. This is what has provoked the persistent use of sub-standard vehicles by private hands for public transportation in Ghana. Travelers have no enhanced alternative than to be contingent on these clumsy, defective and unsafe private sector service delivery.

Moreover, only a few of the public transport and freight terminals, which serve all forms of vehicles from private commercial cars and taxis to multiple axle trucks are paved in Ghana. Even those that are paved have no clear demarcation between access roads, parking space and passenger waiting areas. Usually, lorry parks have sprung up near markets and at major intersections (GMoRT, 2009). Many of these lorry parks have been developed on ad-hoc basis with little account taken of the impact of the vehicle and pedestrian traffic they attract. This has resulted in vehicles in cities having to follow meandering routes with travelers having to change vehicles frequently before reaching their destinations (GMoRT, 2009). In 2005, the Department of Urban Roads (DoUR) surveyed public transport operators, who saw terminal, route, operational or financial snags as their concerns.

Specifically, the DoUR noted lack of toilets and poor sanitation as the most common problem faced by transport operators at terminals in Accra. Operators also revealed that lack of shelters, congestion at the access points and congestion within the terminal were significant. More so, the DoUR observed that amongst the route problems indicated by the transport operators, 56 percent was congestion with associated long travel time and high operating cost. Additionally, the survey showed that along routes, insufficient provision of lay-bys and bus stops were among some of the identifiable problems by the transport operators. While one-third (33 percent) of the operators mentioned conflict with hawkers and pedestrians as problems, inadequate traffic control at junction and police harassment were also among other travails observed. Furthermore, 28 percent of the operators surveyed have noted poor road signs and absent or faded road markings as their difficulties.

In addition to driver indiscipline, the survey revealed aging vehicles as significant operational glitches. Financially, the operators revealed that high cost of maintenance and spare parts was their major difficult. This problem was narrowly trailed by extraordinary taxes. Meanwhile, over 25 percent of the operators have admitted low transport fares and high vehicle replacement cost as their challenge. While the National Transport Policy envisaged an end to deficiencies in urban transport after its full implementation (GMoRT, 2009), years on these challenges still persist. Thus, the introduction of the US$ 95 million Ayalolo Bus Rapid Transit initiative that aim at effecting Vehicle Fleet Management System to support traffic and enhance efficiency via vehicle scheduling, vehicle monitoring, vehicle location message trigger and management system should be highly hailed. This will safeguard efficient and sustainable service supply compared to private alternatives.

Chapter Summary

This chapter provided an exhaustive overview of the transport sector in Ghana. Throughout, the chapter discussed briefly the historical antecedence of Ghana. Besides, it highlighted the nexus between transportation and ICT, while considering Government policy on private sector participation in public transport. The public road transport was considered focusing on some of the operational challenges affecting the sector. The review revealed that road transport is by far the foremost career of freight and passenger in land transport systems in Ghana. The review further shown that transportation does not only include mobility of person and goods, but also the flow of information between spatial environment.

It was discerned that public transport is key to sustainable use of energy since it can provide services to many customers without increasing the number of vehicles.

However, the review indicated that significant proportion of vehicles plying the road of Ghana are second-hand vehicles, with obsolete technology and so contribute to rising energy consumption and increasing quantity of GHG emissions. It was observed that though NTP has led to the establishment of Ayalolo BRT system to implement Vehicle Fleet Management System to support traffic and enhance efficiency via vehicle scheduling, vehicle monitoring, vehicle location message trigger and management system, challenges in urban transport sector still persist. While studies generally exist on transportation in Ghana, limited evidence exists of any study on the drives of transport mode choice and fuel expenditure in Ghana. Consequently, this study is motivated to contribute to policy on strategy to achieve the goal seven of the SDGs. The next chapter presents the literature review.

CHAPTER THREE

REVIEW OF RELATED LITERATURE

Introduction

This chapter reviews the relevant literature on the study. The review provides an update on understanding and identification of existing gaps and methods used in previous research. It provides justification for the research hypotheses and shows how existing studies compared to current research findings. The scope of the review covers theoretical and empirical works from reports on scholarly works of transport economists, transport practitioners, researchers and other relevant works related particularly to households TFE, transport mode choice and TFI. Some factors considered are personal specific attributes, mode specific attributes and real value of travel time, including issues of telecommunication and transportation. The chapter ends with the summary of the review of the literature.

Theoretical Literature Review

A theory is a cherished tool in the scientific study of phenomena, particularly when connected to human behaviour, which comprises travel behaviour. This subsection of the chapter briefly reviews a few instructive theories from the perspective of different social science disciplines (e.g., economics and psychology) that have found application in the study of travel behaviour These theories explain diverse kinds of social behaviours, using a set of constructs, propositions, boundary conditions, assumptions, and logic (Bhattacherjee, 2012).

Economic Theories

The field of economics has contributed to the progress of theories, analytical methods, and tools to examine travel behaviour, principally in the area of specification, estimation and application of travel demand forecasting models. The common econometric theory used in the transportation realm is the theory of random utility maximisation (RUM). McFadden (1980) popularised this theory to the analysis of discrete choices such as travel mode choice. RUM assumes that the higher the utility of an alternative, the greater the benefit the decision-maker derives from it, and the greater the possibility that this alternative will be selected. If every attributes considered by the decision-maker were known to the analysist for every alternative, a RUM-based discrete choice model could be built to forecast every choice with inevitability. But, the utility of alternatives is not known to the analyst with certainty, as such a portion of each utility is assumed to be a random variable.

This study adopted random utility maximisation theory to model the choice behaviour of workers, because RUM is based on utilitarianism, which is often used as a basis for maximising utility of a choice from a set of alternatives (Chiu Chuen *et al*., 2014). The theory has been extensively applied in research and undeniably, repeatedly used in the models employed in transport planning practice. RUM has also dominated travel behaviour field because it can simply be elegantly, mathematically operationalised through discrete choice framework. A number of assumptions underpin RUM. These are that: individuals make choices by computing the best result for themselves based on cost and benefit analysis of different courses of action; aim at maximising their utility; they make choices based on their self-interest; have full information with which to make an optimal choice; and every decision that is made by individuals is deemed rational (Jonsson, 2011).

Historically, utilisation of discrete choice procedures signified an important step forward in car ownership modelling. The reason is that it was the first time behavioural theory, i.e., rational choice theory, found an expression in mathematical algorithms used in modelling. Consequently, even though the application of mathematical algorithms to rational choice theory was a necessary simplification of human decision making, its validity at that time was challenged (Ben-Akiva, Manski & Sherman, 1981). Nonetheless, many generalisations of basic discrete choice models that fall within RUM theory have been suggested and used to analyse travel behaviour and to model travel demand (Manski, 1977). For an illustration, study (Ben-Akiva *et al*., 1981) applied disaggregated information to model travel demand and household car ownership based on behavioural theory.

Psychological Theories

It is observed that people rarely make choices in economically rational manner. This remark is gleaned from the assumption underpinning traditional utility maximisation in microeconomics. Thus, scholars in travel behaviour have recently recognised a number of alternative behavioural theories from the field of social psychology. This section discusses the theory of planned behaviour (TPB) by Ajzen (1991) and theory of interpersonal behaviour (TIB) by Triandis (1977). These two theories which have been applied extensively to wide range of individual behaviours, presume that, in addition to standard economic factors (time and cost), individual decision making processes are determined by non-objective individual factors like perception, attitudes, beliefs, and preferences (Bhattacherjee, 2012).

Theory of Planned Behaviour (TPB)

The theory of planned behaviour (TPB) was developed as an extension of theory of reasoned action (TRA) to account for behaviours with limited volitional control. TPB postulates that behaviours are based on one's intention about that behaviour, and this in turn is influenced by the person's attitude towards the behaviour, subjective norm regarding that behaviour and perception of control over that behaviour (Bhattacherjee, 2012). While TPB submits that perceived control, in addition to influencing behavioural intention, also moderates the relationship between intention and behaviour, this presumption is in contrast with economic reasons under the utility maximisation frameworks (Fudenberg & Levine, 2009).

The performance of TPB is better than theory of reasoned action in situation where volitional control is limited, such as travel behaviour. Regarding travel decision-making, theory of travel choices is influenced by several factors outside the control of the individual, including intra-and inter-household interactions, the built and natural environments, capability constraints, and other decision factors while travelling. These factors influence the perception of behavioural control, which in turn influence intention and travel choices. Studies (Bamberg, Ajzen & Schmidt, 2003; Schwartz & Howard, 1981) applied the TPB directly to travel mode choice and found significant influence of attitudes, subjective norms, and perceived behavioural control on intentions, and intentions on behaviour, supporting the hypothesis that intention moderates these relationships with behaviour. Abrahamse *et al.* (2009) found that while stronger personal norms were associated with stronger behavioural intentions, this happens when perceived behavioural control was low.

Theory of Interpersonal Behaviour (TIB)

The theory of interpersonal behaviour (TIB) was proposed by Harry Triandis in 1977. Like TPB, attitude is defined in TIB as the individual's overall positive or negative feelings about performing the behaviour in question, which may be measured as an aggregation of one's beliefs regarding the diverse consequences of that behaviour, weighted by the desirability of consequences (Bhattacherjee, 2012). In the TIB, social factors include subjective norms, social roles, and self-concept, while affective factors are emotional responses to the behaviour. TIB suggests that, besides these determinants of intention, habit mediates the relationship of intentions on behaviour. For instance, out of habit a person who intends to walk may end up driving. Moreover, the TIB submits that enabling conditions moderates the influence of intentions and habit such that someone may end up driving instead of walking because they must carry goods.

Applying TIB to travel behaviour research, Domarchi, Tudela, and Gonzáles (2008) used multinomial logit model to find significant effects of attitudes, habits, and affective (emotional) appraisal on car and public transit use. Also, using structural equations modelling and discrete choice modelling with latent variables, Galdames, Tudela, and Carrasco (2011) concluded that including attitudes significantly improved the model's explanatory power of the mode choice.

Empirical Literature Review

The conclusions from transport expenditure studies are necessary for transport policies. However, the questions of what factors drive participation and consumption decision of households in the transport fuel market, as well as the choice of mode of transport for workers, have not been conclusive in the empirical literature. Several studies identified variables that govern an individual's choice of mode based on which the individual maximises their preferences (e.g., Abane, 1993; Fiagborlo & Kyeremeh, 2016). Some of these studies highlighted a set of mobility practices among workers and unveiled attributes of the traveler, attributes of the journey as factors that impact choice of mode (Paulley *et al*., 2006; van der Waerden, Timmermans & Bérénos, 2008) This section reviews empirical literature on transport expenditures, mode choice from the stance of Ghana and elsewhere, drawing lessons based on the drivers of transport fuel expenditure and mode choice.

Transport Mode Choice and Effective Factors

Prior research on mode of transport provides evidence of the importance of attributes of the traveler, attributes of the journey and attributes of the transport modes in the choice of mode. Abane (1993) used the multinomial logit (MLOGIT) model to analyse the mode choice for the origin-destination among a cross-section of workers in the formal sector of Accra. Using altogether 126 employment centers consisting of 55 services and 71 firms, the study suggested that origin-destination behaviour of the sector was influenced mainly by perceive service quality of the commercial commuter vehicles and the personal circumstances of employees rather than by conventional transport characteristics such as access, waiting or in-vehicle times. Among other factors, gender roles, age differences, disposable incomes relative to travel cost as well as the reliability of schedules by the individual modes were the most important factors workers considered in choosing their modes.

Likewise, Abane (2011) examined the travel behaviour of residents in the four metropolitan areas in Ghana and observed that mini-buses (trotro) operating under the umbrella of the Ghana Private Road Transport Union (GPRTU) were still the most preferred mode for trips in major cities of the country. The study further indicated that while non-transport costs consumed a large chunk of respondents' disposable incomes, their expectation was to pay less than they were doing for commuting in the area. Even though the findings may be useful for policy decisions, they cannot be generalised because the study used cross-sectional data and sampled respondents from a particular region of Ghana. A comprehensive research that is based on multiple waves of cross-sectional data, thus, is likely to provide a more general policy appreciation towards the travel behaviour of residents in Ghana.

Similarly, Birago *et al*. (2017) explored the reasons behind commuters' nonpreference of Metro Mass Transit (MMT) for intra-city commuting in Accra. The study sought to understand the reasons behind commuters' nonpreference and perception of the level of service quality (LOV) delivery of the MMT, by using revealed preference method to elicit information from 134 commuters. It was found that though MMT fare was 20 percent cheaper, commuters did not prefer it due to non-adherence to time schedule, long in-vehicle time, perception of not getting access to seats, non-availability of bus at respondents' origins and destinations, accessibility of alternative modes and long waiting time for buses among others.

While the study recommended improvement in service attributes especially in-vehicle time, waiting time comfort, reliability and accessibility as means of increasing its modal share, including other attributes relating to car choice (the network, parking space, parking cost, reliability, ownership cost, fuel cost, toll frequency, toll cost, travelling time and traffic) in a more quantitative, utilitarian framework would have enhanced policy that guarantee shifting people from the use of unsustainable modes to the use of efficient high capacity public bus systems.

Fiagborlo and Kyeremeh (2016) used a discriminant model to examine factors that determine choice of modes of intra-city spare parts dealers in Accra and estimated specific and overall predictions of the model. While the study sampled only two hundred spare parts dealers, the researchers observed that individual characteristics as well as mode choice attributes determined the choice of mode of spare parts dealers. The study further correctly predicted more than two-third of the original private car users, while predicting over three-quarters of the original buses users. Moreover, the study over predicted the original trotro users with almost all original taxi users predicted. Though the discriminant model was successful in classifying about 67 percent of the original spare parts dealers, the findings are not applicable to the entire working population of Ghana. This thesis filled this gap, using NHTS to analyse the drivers of transport mode choice of workers in Ghana.

Amoh-Gyimah and Aidoo (2013a) determined alternative and individual specific factors that influence mode choice for trip by government workers in

Kumasi Metropolis. The study applied conditional logit regression to primary data of government workers in the Kumasi metropolis. Among the significant determinants of the choice of transport by government workers were family size, education, income, home-to-work distance and marital status. Also, the study observed that about 25 percent of government workers did not use public transport, while over 81 percent of those who used personal means of transport were unwilling to shift to an institutionally arranged large bus services. However, the study was limited in terms of its context and sample size, requiring a large scale analysis of the determinants of mode choice in Ghana to provide sustainable transport policy.

Agyemang (2017) explored mode choice for long distance trips in the Greater Accra Metropolitan Area (GAMA). While using both formal and informal sector workers, the study employed MLOGIT to analyse personal characteristics of trip makers including the car ownership status of trip makers as well as other mode-specific attributes that determine mode choice in Accra. Specifically, the study considered the current residential locations where trip makers who visited the CBD to work or shop traveled from as well as the transport modes they used. The results indicated that age, education and car ownership status of the trip makers and their perception of service quality impacted mostly on mode choice. Evidence also show that visitors to the Central Business District (CBD) were mostly peri-urban residence, who mostly used motorised transport for their trips (Agyemang, 2017).

Palma and Rochat (2000) examined the household's joint automobile ownership and usage of car for work-trips in Geneva, Switzerland. Employing an integrated logit approach, the findings indicated that contextual and individual factors, besides mode specific characteristics (travel time, cost and comfort), were the important determinants of mode choice. Meanwhile, the study indicated that car ownership mostly related to income levels of households, contextual and locational issues. The study finally highlighted public transportation inadequacy for commuters' needs, especially for sub-urban dwellers across the border with France.

Buehler (2011) similarly used a comparable national travel surveys to investigate determinants of travel mode choice in Germany and the USA. The results indicated that higher population density, a greater mix of land use, household proximity to public transport and fewer car per households negatively influenced trips by automobile. However, accounting for the differences in socio-economic factors and land-use showed that Germans were more likely to walk, cycle and use public transport, while Americans living in dense, mixed-used areas, and close to public transport were more likely to drive than Germans living in lower density areas, with more limited mix of land-use and farther from public transport. The study, consequently, recommended that transport policy differences that make car travel slower, more expensive, less convenient and alternative to the automobile more attractive in Germany should help account for the remaining differences.

Yang (2016) used a hierarchical structure and heuristic rules to modify travel mode choice function. The basic constructs in the function were utilities, constraints, attitudes and habits. The framework exhibited several dynamic processes, including the perception process on the environment, attitude formation process, habit formation process, interactions among an individual's own behaviours, interactions among travelers, feedback from travel to the built and social environments and feedback from other behaviours to the built and social environments. The study concluded that the framework might contribute to the study design, data collection, adoption of new research methods and provided indications for policy interventions, when it comes to utilitarian walking. Previously, Chiu Chuen *et al*. (2014) assessed the possible mode shift of travelers towards using public transport, given the usefulness of available transport modes.

Hasnine, Lin, Weiss and Habib (2018) investigated mode choice behaviour of post-secondary students in Toronto. Using a large-scale web-based travel diary survey of students of four universities (seven campuses), the study employed multinomial logit (MNLOGIT), nested logit (NLOGIT) and cross-nested (CNLOGIT). The study showed that CNLOGIT outperformed the MNLOGIT and NLOGIT models. The results showed that mode choice of female students who traveled to downtown campuses differed significantly from those of sub-urban campuses. The study again showed that female students who traveled towards downtown were more transit and active mode oriented than those who traveled towards outside of downtown. The study concluded that transit pass, car and bike ownerships and age groups influenced mode choice of student. But, using the CNLOGIT model showed larger changes in travel time for public transit users.

Jamal, Habib and Khan (2017) investigated the impact of smartphone on travel outcomes. The study applied a latent class modelling (LCM) to a web-based survey data conducted in Halifax Region Municipality, Nova Scotia in 2015. Specifically, the study analysed the changes in vehicle kilometers travelled (VKT) as an influence of smartphone use and how this differentiated among varied sociodemographic groups, residential locations and life-style strata. VKT was examined in three choice contexts: smartphone use had (i) reduced VKT (ii) no impact on VKT and (iii) increased VKT. The results revealed higher use of smartphones for online shopping, active transportation as primary mode, home to work school distance and pro-environment attitude as determinants that can decrease VKT.

Geng, Long, Chen, Yue, Li and Li (2017) examined the effects of multiple motivations, government measures and demographic characteristics on residents' travel mode choice behaviours. Using 1,244 urban residents in Jiangsu Province in China, the study employed multinomial logistic regression model. The results showed that against car use, pro-environmental motivation played a significant positive role in urging green travel mode choices (walking, bicycling and using public transport), though this green behaviour dominated self-interested motivation than the pro-environmental motivation. Additionally, the study revealed significant different effects among travel mode choices given gender, age, income, vehicle ownership, travel distance and government instruments. Finally, it concluded that tailored policy interventions should be directed to specific groups that have different principal motivations to guarantee sustainable urban transportation.

Relatedly, Ding, Chen, Duan, Lu, and Cui (2017) examined the impact of attitudes to walking and cycling on commute mode choice. Using the survey data collected in China, the study applied integrated discrete choice model and structural equation model. The results showed not only the role played by the latent attitude in travel mode choice, but it also identified the indirect effects of social factors on travel mode choice. The study finally showed that an integrated discrete choice model outperforms the traditional model. Besides Zahabi, Chang, Miranda-Moreno and Patterson (2016) investigated the link between evolution of urban cycling and built environment indicators and bicycle infrastructure accessibility in Montreal, Canada. The study used automobile and bicycle trip survey for the year 1998, 2003 and 2008. Using logistic and simultaneous equations, the study found significant increase in the likelihood of urban cycle across built environment types over time.

Additionally, the study showed significant differences of bicycle ridership across neighbourhoods, while controlling for other factors. Zahabi *et al*. (2016) also noted that for household level characteristics, individuals that live in a household with private vehicles had a decreased likelihood of cycling to work than those living in a household with no cars. In terms of an association between the index of bicycle infrastructure accessibility and bike mode choice, the study revealed a statistically significant outcome. Based on the results, and in combination with a GHG inventory at the trip level, the study again used a basic scenario to explore the potential impact of planned cycling infrastructure. The result revealed a negative relationship between the length of the bicycle network and GHG emissions. This means improving bicycle network will reduce car usage and GHG emissions.

Likewise, Heinen, Panter, Mackett and Ogilvie (2015) analysed how new transport infrastructure promotes the use of active travel. The study used quasi-experimental investigation nested within a cohort of 470 working adults in Cambridge, UK. The experiment began with the opening of a guided busway with walking and cycling paths in 2011. Exposure to the intervention was conceptualised as the negative of the square root of the shortest distance from home to busway.

The dependent variables were changes in commute mode share and number of commute trips before the intervention in 2009 and after the intervention in 2012 and changes in the extents of trips (i) involving any active travel, (ii) involving any public transport and (iii) made entirely by car. The study used multinomial model.

After controlling for mode and personal specific characteristics, residential settlement size and life events, the study revealed that nearness to the busway predicted an increased likelihood of a greater than 30 percent increase in the share of commute trips involving any active travel and greater than 30 percent decrease in the share of trips made entirely by car. However, the study showed a lower likelihood of a less than 30 percent reduction in the share of trips involving any active travel without considering any association of changes in the share of commute trips involving any public transport, the number of commute trips and commute distance. The result implies that new infrastructure promotes commute trips involving active travel and decrease in the share of trips made entirely by car.

Recently, Heinen, Harshfield, Panter, Mackett and Ogilvie (2017) investigated the link between exposure to the intervention and specific modal shifts and pattern of change, along with individual mode choice patterns between 2009 and 2012. Methodically, adult commuters working in Cambridge (UK) were used. The results indicated: (1) no change, (2) a full modal shift, (3) a partial modal shift, (4) non-stable but patterned behaviour and (5) complicated or random patterns. Though no significant link between exposure to the intervention and specific modal shifts or patterns of change was found, the study revealed a large diversity or change in travel behaviour patterns over time and showed that the intervention did not result in one specific pattern of behaviour change or produce only full modal shifts.

Alpizar and Carlsson (2003) studied a group of policies aimed at improving the attractiveness of the bus to promote the use of private transportation during peak hours. The study used a choice experiment constructed to find the answer to the following basic question: Given fixed house-to-work structures and no working hour flexibility, by how much is the choice of travel mode for commuters to work sensitive to changes in travel time, changes in costs for each mode and other service attributes? The outcomes provided information for identifying the most suitable combination of policies dealing with air pollution and congestion in the typical developing country context of metropolitan Costa Rica. The estimates of the value of travel time measure the potential benefits gained from reduced congestion.

Shen, Chen and Pan (2016) examined the effects of rail transit-supported urban expansion in four Shanghai suburban neighbourhoods, including three located near metro stations. Travel survey data collected from residents were used. The study employed binary logit model for car ownership and nested logit model for the commuting mode choice. The outcomes showed that: (1) proximity to metro stations has a significant positive association with the choice of rail transit mode as well as car ownership; (2) income, job status and transportation subsidy were also positively associated with the probabilities of owning car and driving it to work; (3) higher population density at work location related positively to the likelihood of commuting by the metro, but no significant relationship with car ownership.

Furthermore, the results showed that: (4) longer commuting distance was strongly associated with higher probability of riding the metro, rather than driving a car to work; (5) consideration of money, time, comfort and safety also appeared to exert quantifiable influences on car ownership and mode choice, while intention to ride the metro for commuting was reflected in its actual use as primary mode for journey to work. These results suggested that rail transit-supported urban expansion could produce important positive outcomes, and that this strategic approach could be facilitated by transportation policies and land use plans, as well as complemented by timely provision of highly excellent rail transit service to suburban residents.

Pooley and Turnbull (2000) investigated modal choice amongst commuters in Britain. Life histories of 1,834 individuals and 90 in-depth interviews were used. The study revealed that the reasons for using particular forms of transport had been quite stable over time. Moreover, the study revealed some long-established differences between men and women. This result suggests some trends that should have significant implications for the formation of present-day transport policy. Besides, Pazy, Salomon and Pintzov (1996) considered the relationship between women's willingness to extend their commuting trips in exchange for career gains. In the study, career gains were demarcated to include whatever the individual woman viewed as desirable improvement in her work situation. Three categories of variables were examined: career factors, family factors as well as commute factors.

In the Tel-Aviv metropolitan area, 162 working women in computer-related professions were used for the study. The results revealed that majority of respondents expressed willingness to extend their journey to work for a career improvement. Generally, commute duration and distance were the major determinants of such willingness. In particular, the longer the present commute, the more reluctant were women to further lengthen it. Regarding career orientation, the study indicated a positive association with willingness to increase commute, whereas education level, rank and weakly working hours did not have a significant influence. The study also confirmed higher willingness among women of weaker career orientation, when their job was incongruent with their career aspirations.

The study concluded that while mothers of young children were less inclined to travel more, those that depended on public transport showed a greater sensitivity to the presence of young child in their inclination to increase commute travel time than women who used private car. Commins and Nolan (2011) investigated travel for journey to work in the Greater Dublin Area. The data used were working individuals from the 2006 population census. The study analysed the influence of travel, supply-side factors, demographic, and socioeconomic factors on the choice of modes of transport. The study revealed that among other things, the household compositions, public transport availability, journey time and work location were significant in explaining the choice of mode of transport to work.

Examining the reasons for increasing use of private automobiles, Grdzelishvili and Sathre (2011) used dada on Tbilisi car drivers (n=159) and public transport users (n=163). The study considered the perceive strengths, weaknesses and potentials of the public transport system. The results showed that most respondents preferred to use a private car and avoided the use of public transport. Time issues (schedules and frequency), comfort and safety issues were identified to be particularly important. Thus, the study concluded that Tbilisi residents valued their time and wanted to use it efficiently. The study suggested effective urban policy, including incentives to encourage greater use of public transport in Tbilisi.

van der Waerden and van der Waerden (2018) investigated travelers' transport mode choice behaviour in the context of medium-and long-distance trips, controlling for attributes of train access modes. The study sought to provide insight into the contribution of both access and travel-mode attributes to the travelers' choice of car or the train for medium-and long-distance trips. Stated choice experiment was used. The study applied a mixed logit model to 32 attributes of the main transport modes (train and car) and access modes. The results revealed that time and cost-related attributes significantly contributed to the attractiveness of transport modes. Nonetheless, these effects differed considerably between the investigated modes. The results also indicated that safety-related attributes, chance of delay and transfer time from access mode to train platform played a major role.

Shaw, Blakely, Atkinson and Woodward (2020) examined the association between mode of travel to work and mortality. Methodically, the authors created cohort of New Zealand working population based on 1996, 2001 and 2006 mortality data. Mode of travel to work was reported on census day and causes of mortality were linked to ischaemic heart disease and injury. The study employed Poisson regression model, controlling for sociodemographics. The researchers conducted sensitivity analysis adjusting for smoking in the 1996 and 2006 cohorts, and a bias analysis about non-differential misclassification of cycling versus car use. The results showed uncommon walking (5 percent) and cycling (3 percent) to work.

The results further showed that those cycling to work had a reduced all-cause mortality (ACM) in the sociodemographic adjusted models compared to people reported using motor vehicles to work. The study indicated, moreover, that those walking and taking public transport had no substantive difference in ACM. Regarding cause-specific mortality, the result showed that no mode of transport was associated with detectable statistically significant reductions. The sensitivity analysis found weaker associations when smoking was adjusted for, while stronger associations was shown correcting for likely non-deferential misclassification of cycling. The study concluded that while large cohort was required for an association between cycling to work and reduced ACM, no association was found for walking or using public transport as well as inaccurate cause-specific mortality patterns.

Using a state-wide travel survey from California and taking advantage of a new comprehensive historical archive of regional real-time multi-modal transportation system data, Chakrabarti (2017) explored contexts in which persons belonging to households that owned car used transit for their commute within Los Angeles County. The researcher observed lack of access to the household vehicle(s) as the reason for choosing transit. Additionally, the results showed strong correlation of car-owners' transit mode choice with fast (relative to car), frequent and reliable transit service along with fewer transfer requirements, while rare evidence existed of discretionary transit use (or transit use by choice). The study further noted that among other critical facilitators of transit use were the home and workplace neighborhood density, proximity to transit stop and availability of rail.

According to the study, even if observed effects were due to self-selection, there were important lessons for transit planners. The results particularly suggested that transit-to-auto travel time ratio, headway and standard deviation of schedule deviation had negative effects on transit mode choice. The study identified effective plans for ameliorating transit's competitiveness relative to auto and hence attracting people out of their cars. It was observed that planners should invest in key areas of bus service quality, such as speed, frequency and reliability, while continuing with the rail network improvement programs and transit-oriented development efforts across U.S. cities. Finally, the study suggested that careful planning could promote discretionary transit use by attracting existing latent demand and by creating new demand that raises government interest in transit and growing traffic congestion.

Studies that considered value of travel time reliability in travel related context are enormous. Carrion and Levinson (2012) provided a review of work estimating the value of travel time reliability. This study provided a brief overview of some of these studies here. Small (2012) noted that there was a depth of research analysing the impact of travel time uncertainty on the relative attractiveness of driving a private vehicle. Besides, Small (2012) observed that the relative lack of revealed preference (RP) analysis on the effect of travel time uncertainty in public transport was tangled to unavailability of data on reliability of transit vehicles.

Gao Kun, Sun Lijun, Tu Huizhao and Li Hao (2018) carried out stated preference (SP) surveys to investigate commuters' mode choice behavior in multimodal networks. The study employed random parameter logit (RPL) models to estimate commuters' willingness to pay (WTP) and explored preference heterogeneity. Regarding potential factors yielding heterogeneity in valuation of travel time reliability (TTR) and in-vehicle crowding, the results indicated large heterogeneities in WTP for TTR improvement and in-vehicle crowding reduction. The study identified demographic attributes, commuting distance and time schedule variables (flexible work time and departure time constraints) as factors that explained travelers' heterogeneity in WTP for TTR. Age, gender, income and education were also found to influence WTP for reducing in-vehicle crowding.

Bhat and Sardesai (2006) also estimated a commute mode choice model, using RP and SP data collected from a web-based commuter survey in Austin, Texas. This model considered weekly and daily commute and midday stop-making behaviour, as well as travel time reliability. The technique employed was a mixed logit framework. Whilst the results highlighted the effects of commute and midday stop-making on commute mode choice, the result indicated that travel time reliability was an important variable in commute mode choice. The results were applied to predict the potential mode usage of a proposed commuter rail option as well as to examine the impact of highway tolls. Categorically, the study did not impugn the application of the mode choice model to examine a comprehensive range of travel mode-related policy actions for the Austin metropolitan region.

de Donnea (1972) investigated the extent of contribution of micro-economic theory in consumptive sphere to the understanding of the nature of the travel decisions of individuals. The study determined the possible contribution of micro-economic theory to our understanding of the value of travel time savings. It considered the problem of allocation of travel time among various activities in the consumer's utility function. The models innovatively distinguished between the utility of time as an input in the production of a given consumption activity and the (dis)satisfaction which resulted from the circumstances under which the time required to produce that given activity must be spent. While the study clearly provided information on the three main travel decisions of individuals (trip production, trip distribution and modal choice), it focused its recommendation on the information the models yielded about the modal choice and its determinants.

Koster and Koster (2013) examined the contribution of traffic condition to longer travel time variability. Using data from a stated choice experiment, the study used a semiparametric estimation approach to analyse observed and unobserved heterogeneity in the value of travel time and reliability. The result showed substantial heterogeneity in the willingness to pay for fast and reliable travel. In particular, the study observed that 5-25 percent of the heterogeneity in the value of time and reliability was attributable to observed characteristics of individuals, suggesting that unobserved heterogeneity was much more important than heterogeneity related to observable characteristics. The result moreover showed that schedule delay costs were averagely 24 percent of the costs of travel delays.

To estimate value of time and value of reliability, Nam, Park and Khamkongkhun (2005) employed the Multinomial Logit and Nested Logit models. The outcomes indicated that reliability was an important factor affecting mode choice decisions. Besides, elasticity estimates were used to assess the effects of the diverse policies and system augmentations for water transportation mode. This suggested that among these policies, decision makers could assess and select the best alternative by performing the benefit and cost analysis based on a new market share, the value of time and the value of reliability. Finally, the study suggested a set of promising policies and system improvement of the water transportation.

Analogously, in a systematic review of the current state of research in travel time reliability, Carrion and Levinson (2012) highlighted travel time reliability as a fundamental factor in travel behavior. The researchers observed that travel time reliability represents the temporal uncertainty experienced by travelers in their movement between any two nodes in a network. Carrion and Levinson (2012) hinted that the importance of time reliability depends on the penalties incurred by travelers. For example, in road networks, travelers considered the existence of a trip travel time uncertainty in different choice situations (departure time, route, mode, and others). The review, moreover, covered a meta-analysis, which was performed to determine the reasons behind the discrepancy among the reliability estimates.

By the same token, Hauer and Greenough (1982) estimated the distribution of the value of time in the population from which the subjects were sampled. On the basis of 824 cash offers made to Toronto subway riders, the study obtained distribution of the value of time for a variety of conditions and factors. The factors considered were time of day, duration of delay, age, gender, income, time budget and trip purpose. The results were enlightening, but the exploratory nature of the study limited any definitive statements. Even though it remains unclear whether the subjects decided to accept or reject the cash offer mainly on the basis of time versus money trade-off, this limitation did not blur the consistency of the results obtained.

The study thus highlighted the conceptual clarity of the method and its ability to conduct near scientific inquiries in terms of experimental design and accurateness.

Comparably, Cirillo and Axhausen (2006) investigated the distribution of the values of travel time savings, using a series of multinomial and mixed logit models. The results showed that after incorporating a number of time budget related variables, an infinitesimal, but relevant share of the respondents did not value time savings, or would rather have extended their journey. According to the researchers, the findings were consistent with results from other studies. Thus, a series of models that employed only time and costs to explain choices have resulted in even more than 10 percent shares depending precisely on the a-priori assumptions about the distributions of the parameters (normal, log-normal, normal, but censored at zero).

In cost-benefit analysis of cycling investments, Börjesson and Eliasson (2012) similarly estimated the value of time savings, value of different cycling environments and value of additional benefits. The results indicated that cyclists' value of travel time savings was higher than the value of time savings on alternative modes. The results also indicated that cyclists valued improvements in different bicycle lanes highly. Regarding additional benefits of cycling improvements in the area of health and reduced car traffic, the results did not support the notion that these additional benefits would be a significant part in a cost-benefit analysis. The study showed that bicyclists appeared to take health largely into account when making their travel choices, suggesting that it would be double-counting to add total health benefits to the analysis once the consumer surplus had been accounted for.

Concerning reductions in car traffic, the results revealed that the cross-elasticity between car and cycle was low. This implies that benefits from traffic reductions would be small even if there is cycling improvements. Notwithstanding that, the valuations of improved cycling speeds and comfort were so high implying that improvements for cyclists were cost-effective compared to many other types of investments, without having to invoke second-order indirect effects. The study concluded that bicycle should be appreciated as a competitive mode of travel rather than primarily as a means to accomplish improved health or decrease car traffic.

Transport Expenditure and Effective Factors

This section considers the existing literature on transportation expenditure. Bardazzi and Pazienza (2018) analysed the use of fuel for private mobility in Italy, focusing on the drivers of transport expenditure. The study used several waves of the Italian Household Budget Survey. The double-hurdle model was applied to data in the study and augmented by age and cohort effects. The result indicated that baby booms exhibited a positive cohort effect. Therefore, their transport fuel expenditure was significantly higher compared to younger generations. Apart from age, other socio-economic variables such as total household expenditure, gender and employment status were positively associated with energy expenditure. The study also indicated that having a motorbike decreases transport fuel expenditure. The results of the study, thus, confirmed evolving generational energy culture towards a sustainable transport system, while speeding up the decarbonisation process.

Gandelman, Serebrisky and Suárez-Alemán (2019) used income and expenditure survey to estimate Engel curve between spending and changes in household income in 12 Latin America and the Caribbean (LAC) countries. The estimates indicated heterogeneity in transport. The Engel curves also led to two simultaneous challenges. That is the need to develop an urban transport strategy following a two-pronged approach (i.e., two methods used to get the same result). Moreover, the estimates showed that frequent users of public transport in the low income population, faced an affordability problem. Yet, besides the growth of the middle class in the region, there is high income elasticity of private transport supporting an increasing private car ownership. The study suggested the use of demand side subsidies to address affordability of public transport, while warning against the use of taxes and charges to sway the dimensions of private transport.

Anowar *et al*. (2018) developed an econometric model of household budget allocations, focusing on transportation expenditure. The study employed the public-use micro-data extracted from Survey of Household Spending (SHS) for the years 1997-2009. The econometric model used was multiple discrete continuous extreme value model (MDCEV) framework. The analysis showed that the scaled version of the MDCEV model outperformed its other counterparts. The results from the study indicated that a host of household socioeconomic and demographic attributes along with the residential location characteristics affected the apportioning of income to various expenditure categories. Meanwhile, the study indicated a fairly stable transportation spending behaviour over time. Finally, the study concluded that further policy analysis should be done where increased in health expenditures and policy reduction in savings resulted in adjustments in all expenditure categories.

Eakins (2016) examined the determinants of household petrol and diesel expenditures. Using a large micro data set of Irish households, the study employed the double hurdle econometric methodology due to zero in the dependent variable. The results showed larger probability for households who participated in the diesel market compared with the petrol market as income rises. Also, households living in urban areas, those that spent money on public transport and those that did not possess a car would spend less on both petrol and diesel. Conversely, households with higher number of cars, those with more occupants working and those with higher spending level spent more on petrol and diesel. The study concluded that as the Irish economy recovers and average household income increases, these findings have implications for the design of policy towards reducing transport emission.

Diaz Olvera, Plat, and Pochet (2008b) analysed case studies on Dar es Salaam, Niamey and Ouagadougou. The estimates revealed that travel expenditure were partially conditioned by survey data collection methodologies and by choice of equivalence scales used to compare the standard of living of households. Regarding consumption and expenditure survey data, the analysis showed a positive correlation between amount spent on transport and household expenditure. Conversely, transport share decreased with increased income in travel survey. Moreover, using equivalence scales, the analysis tested for sensitivity for the share of travel expenditure by household budget quintile. The study also tested for the concentration indices for public and private household transport expenditure and average monthly expenditure per person on public and private transport. The analysis concluded that there were substantial inequalities among households and that poor populations could not afford a consistent use of motorised transport.

Christoffel Venter (2011) reviewed evidence on transport expenditure and affordability in South Africa. The study focused on low-income and mobility constrained persons. The results indicated that a person's location along the urban-rural continuum significantly affected both their transport expenditure levels and the perceived severity of their transport affordability problems. It was also observed that public transport users in displaced urban settlements and isolated deep rural locations and medium-income car commuters in suburbs and urban township faced the highest transport expenditures and affordability problems. Disabled and elderly people were found to have similar expenditure patterns and perceptions as travelers at large. The study proposed that spatially targeted interventions in transport supply and land use be used to address transport affordability problems in South Africa.

Similarly, Venter and Behrens (n.d.) reviewed the ideas of affordability within the policy framework of the 1996 White Paper. The objective of the 1996 White Paper was that less than 10 percent of commuters' disposable income should be spent on transport. However, considering its original intent, conceptual problems and methodological issues, Venter and Behrens (n.d.) found that the 10 percent benchmark in 1996 White Paper appeared to be misapplied in South Africa. An empirical evidence from recent data supported their conclusion. Venter and Behrens (n.d.) concluded that there was the need for a more nuanced understanding of the notion of affordability from the user's point of view to enhance precision and policy relevance of the transport expenditure indicators being used in South Africa.

Blumenberg and Agrawal (2014) explored how low income households managed their mobility needs. The study used qualitative data from interviews with 73 low income people who lived in and around San Jose, California. The study unveiled how low income families were ingenious and irrepressible in managing their transportation costs. Blumenberg and Agrawal (2014) observed that low income families adopted transportation survival strategies that came at a high price (i.e., fewer miles traveled), and thus reduced their access to opportunities that might lift them out of poverty. Sanchez *et al*. (2006) examined neighbourhood housing and transportation choices available to working households in 28 US metropolitan areas. The study analysed household physiognomies at the census travel level. First the study described the trends in transportation costs by household income levels.

Sanchez *et al*. (2006) noted a trade-off between housing and transportation cost (H+T). Based on microeconomic theory, the observation of the researchers suggested that as households choose residential location, transport cost burdens should not be considered separately from housing costs. A cluster analysis performed also showed that low income households were significantly burdened by combination of housing and transportation costs and that these households and their neighbourhoods potentially experienced other social and economic burdens that remove them from the possibility of home ownership and wealth accumulation.

Leung, Burke, Cui, and Perl (2019) tried to understand emerging research focus on issues of transport equity including effects of fuel prices. The study reviewed 45 years (1972-2017) of articles about fuel price impact, transport equity and urban context. These publications were drawn from Web of science. The results of bibliographic citation analysis showed eight key research clusters with a set of inter-city relative studies. Moreover, the context analysis was based on historical evolution, geographical trends, research methods and main themes. The results from the context analysis thus highlight the need for extra researches in transport energy and land use interaction, with a particular attention on transport equity.

Fan and Huang (2011) proposed a contextualised transportation affordability analysis framework that differentiates population groups based upon their sociodemographics, the built environment, and the policy environment. The framework was necessary because traditional measures failed to consider the wide variation in households' transportation needs and locational settings. The necessity of such a context-sensitive framework was demonstrated through a case study of the Twin Cities metropolitan area. The outcomes showed heterogeneity among different population groups on the basis of transportation needs and resource availability. There were also dilemmas associated with transportation affordability.

For example, though socioeconomically deprived group had the least auto ownership rate, their transportation needs were better served by automobiles. The framework, for instance, showed that automobiles reduced transportation hardship for the socioeconomically disadvantaged. However, the existence of auto oriented urban landscape required extra travel for access to destinations, which led to higher transportation costs (Fan & Huang, 2011). The study concluded that there was a need for a multi-modal transportation solution. Particularly, reducing societal auto dependence and providing financial subsidies for car access among disadvantaged groups were necessary to improve transportation affordability and social welfare.

Transportation and Effect of Telecommunication

The increasing penetration of ICT and the often increasing costs of transportation have given rise to claims that information-intensive activities have the potential to limit mobility of people. Hence, understanding of the interaction between ICT and transportation has become a major area of research with practical application in economics, geography and sociology. As the economy of Ghana and average household income improves, policy makers may want to leverage on ICT potential of the country towards reducing some of the direct and indirect externalities such as traffic congestion, air pollution, road accidents and transport costs that characterised the transport sector. This section considers a few relevant literatures on the relationship between transportation and telecommunication.

A large body of research revealed substitution and complementarity interactions between telecommunication and transportation. For example, Salomon (1986) analysed the applications of telecommunication technology to remote work, teleconferencing, teleservices, mobile communications and electronic mail transfer. The analysis was an objective review of the knowledge on the relationships between telecommunication and transportation. The analysis highlighted the importance of evaluating future changes of travel while focusing on the promises of substitution. However, the assessment methods used revealed some conceptual issues. Accordingly, a further research was required (Salomon,1986). Mokhtarian and Salomon (2001) also observed that information communication technology is repeatedly used as substitute for travel towards urban congestion management.

Salomon and Schofer (1991) investigated the interaction of costs of distance with telecommunications and transportation, emphasising the effects of geographical scale. Using data from Israel, the study demonstrated that the costs of distance were persistent even in telecommunications systems. Result also showed that transportation costs were not higher than telecommunications costs for short distances or small regions. And that pricing of telecommunications service by governments often did not reflect the costs of providing the services. This research only demonstrated context specific nature of actual interaction cost and hence no overall model was framed. The study concluded that decision-makers should utilise an accounting procedure instead of considering (re)location in specific contexts.

To understand the emission impacts of telecommuting, Sampath *et al*. (1991) examined the potential telecommuting as a strategy for managing travel demand. The study used data acquired from the state of California Telecommuting Pilot Project. The results indicated that emission-related findings comprised substantial reduction in the number of cold stats (60 percent fewer), emissions of organic gases (64 percent lower), carbon monoxide (63 percent lower), and oxides of nitrogen (73 percent lower) on telecommuting days. These reductions, according to the study, were almost related to the decrease in distance traveled by auto (76 percent). A further work was proposed to extend the analysis of emissions impacts.

Some evidence exists about the impact of telecommunications on travel (Mokhtarian & Salomon, 2001; Mokhtarian, 1993, 2002). Particularly, Mokhtarian

(1993) examined the impact of telecommunications technology on travel and urban form. The study identified three potential impacts. First, that telecommunications technology substituted for travel; second, that telecommunications technology stimulated new travel, and third, that telecommunications technology made travel more efficient or rearranged travel. The researcher contended that all of these three types of effects could then have an impact on urban form. As a result, the researcher concluded that telecommunications would lead to increase decentralisation, and thus create greater urban sprawl. However, this study did not display how telecommunication could be leveraged to decrease transport fuel expenditure.

Focusing primarily on passenger travel, but considering movement of goods, Mokhtarian (2002) examined the conceptual, theoretical and empirical evidence relative to the impact of telecommunications on travel. The study provided limited evidence about the extent of true causality between telecommunications and travel, requiring more research in that area. For example, the study concluded that empirical evidence for net complementarity was substantial, but not definitive, while net substitution was virtually nonexistent.

Choo and Mokhtarian (2007) examined causal relationships among travel, telecommunications, land use, economic activity and sociodemographics. They used national time series data spanning 1950-2000 in US. Employing structural equation modeling, the study focused on number of telephone calls as the measure of telecommunications, and passenger vehicle-miles traveled as the measure of transportation. The results revealed strong support for the hypothesis that telecommunications and travel were complementary. That is, telecommunications demand increase positively with increases in travel demand and the reverse is true. These results will be valuable for developing transportation or telecommunications strategies to diminish traffic congestion, air pollution and energy consumption.

Aguiléra *et al*. (2012) analysed the debate between complementarity and substitution from the standpoint of interactions with the spatiotemporal organisation of daily activities, the size and maintenance of social networks, and finally, perception of travel and spaces. The discussions undressed several issues that merited further exploration. Pawlak, Polak and Sivakumar (2017) recently developed PPS framework that incorporated the joint modelling of in-travel activity type, activity duration and productivity behaviour. The framework used copulas to provide a flexible link between a discrete choice model of activity type choice, a hazard-based model for activity duration and a log-linear model of productivity.

The researchers used data from the 2008 UK Study of Productive Use of Rail Travel-time. The outcomes revealed how the PPS framework freely responded to estimation. Specifically, the PPS captured how journey, respondent's attitude and ICT-related factors were related to expected in-travel time allocation to work, non-work activities and the associated productivity. This was the first framework that both captured the effects of different factors on activity choice, duration and productivity and modeled links between these aspects of behaviour. The framework produced parameters that provided convenient interpretation of results in semi-elasticities. The semi-elasticities thus enabled comparison of effects associated with the presence of on-board facilities (e.g., workspace, connectivity) or equipment use. This guarantees the application of the model outputs in applied perspectives.

Bris *et al*. (2017) analysed household transport expenditure as a function of the available variables, emphasising ICT. The analysis used cross-sectional dataset from 2010 involving information on 33 countries. The variables that were considered included: average household expenditure; ICT, represented by the percentage of households with internet access at home; and a number of contextual macroeconomic and infrastructural variables. Using a log-log model, the study demonstrated that household transport expenditure was negatively associated with internet penetration with an elasticity of -0.394. The result implies that, a 100 percentage increase in internet penetration would result in a less than 100 percent (39.4 percent) decrease in household transport expenditure. It also affirmed the substitution relationship between transport expenditure and ICT. After controlling for endogeneity of ICT, the estimated effects were consistent with existing research.

Okyere *et al*. (2018) examined the relationship between transport and telecommunication in developing countries within the broader concept of Smart Cities. Using Ghana as a case study and drawing principally on secondary data and few institutional surveys, the researchers carried out Spearman's rank correlation analysis and the results indicated that telegraph and telephone facilities, as well as new fiber optic network were greatly dependent on right-of-way of roads and railways in Ghana, just as it was shown in the progressive nations. Additionally, the study revealed that at the macro level, the nature of the relationship between telecommunication and transport tended to support the complementary role of telecommunication rather than substitution role. The study thus concluded by suggesting that further studies should be done at micro level to unravel the dilemma in the link between telecommunication and transport to enlighten public policy.

Chapter Summary

This chapter reviewed the relevant literature on the study. The first part reviewed the theoretical literature. The second part considered the empirical literature on transport mode choice and related expenditures from the perspective of Ghana. Undoubtedly, the literature on transport mode choice and related expenditures points to a variety of factors of potential importance. Some of the studies highlighted a set of mobility practices among workers and revealed attributes of the traveler, attributes of the journey as factors that impact choice of mode. The literature reviews also provided the basis for the substitution and complementarity hypothesis about how ICT impacts transportation expenditure.

However, while most of the studies used rigorous statistical technique, their focus was limited to sample size from urban areas. This dampened their generalisability. It was also noticed that scholarships did not exist on the lost labour productivity of travel time to work. Again, transport fuel expenditure has been studied at macro level with limited information at the micro level. This study fills these gaps by identifying the drivers of transport fuel expenditure and mode choice of respondents in Ghana. The theoretical construction of the study is discussed next.

CHAPTER FOUR

THEORETICAL FRAMEWORK

Introduction

The previous chapter reviewed the relevant literature on the study. This chapter considers the theoretical framework of the study. It also covers the analytical framework employed to estimate and evaluate the set objectives of the study. Theories are systematic explanations of the underlying phenomenon or behaviour. However, the chapter commences with an overview of the general linear model (GLM). It proceeds with the theoretical and analytical models for analysing the effect of ICT expenditures on in transport fuel market participation and consumption decisions of households; examining the effect of real value of travel time on transport mode choice of workers in Ghana; and assessing how the effect of ICT expenditure of households on transport fuel intensity differentiates demographic attribute (sex) of households, using disaggregated data form Ghana.

Overview of General Linear Model

It is a known knowledge that inferential statistical procedures in social science research are derived from a general family of statistical models called the general linear model (GLM). A model is an estimated mathematical representation of a set of data, and linear refers to a straight line. Hence, a GLM is a system of equations that can be used to represent linear patterns of relationships in observed data. The simplest type of GLM is a two-variable linear model that examines the relationship between one independent variable (the cause or predictor) and one dependent variable (the effect or outcome). The GLM is represented formally as:

$$y = \beta_0 + \beta_1 x_1 + \varepsilon \qquad (1)$$

Where β_0 is the intercept term, β_1 is the slope and ε is the error term. The error term (i.e., ε) represents the deviation of actual observations from their estimated values.

The GLM for n predictor variables is specified as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n + \varepsilon \qquad (2)$$

Where predictor variables x_1 may represent independent variables or covariates (control variables). Covariates are variables that are not of theoretical interest but may have some impact on the dependent variable y and should be controlled, so that the residual effects of the independent variables of interest are detected more precisely. Covariates capture systematic errors in a regression equation while the error term (ε) captures random errors. The GLM is not one single statistical technique, but a family of methods that can be used to conduct sophisticated analysis with different types and quantities of predictor and outcome variables.

Hence, GLM is a very powerful statistical tool for analysing data. Some of the GLM methods are: Analysis of Variance (ANOVA), which researchers use to assess the effects of binary independent variable on the outcome variable. However, if the researcher seeks to control for the effects of one or more covariate in ANOVA, the appropriate technique is an Analysis of Covariance (ANCOVA). If the interest of the researcher, moreover, is to model ANOVA or ANCOVA with multiple outcome variables, then the correct estimator to utilise is a multivariate ANOVA (MANOVA) or multivariate ANCOVA (MANCOVA), respectively.

Theoretical Model for the First Objective

The first objective of this study was to analyse the effect of ICT expenditure of households on transport fuel market participation and consumption decisions of households. When variables to be explained has a lot of observations at zero, estimating the model using OLS procedure may result in biased and inconsistent estimated parameters (Humphreys, 2013; Amemiya, 1984). Besides, logging the dependent variable may also not be an option, since the log of zero is undefined and would culminates in a missing observation. Meanwhile, there could be valuable information enshrined in the zero observation that could effectively not be captured.

Tobin (1958) developed a model to deal with data with lot of zeros yielding a censored dependent variable. The model allows the inclusion of all observations including those censored at zero without considering the sources of the zeros. Tobin's model has a number of assumptions. First assumption is that the same explanatory variables affect the likelihood of a non-zero observation (the participation decision) and the level of a positive observation (the consumption decision) and more so with the same sign. Second assumption is that the zeros in the data are because of economic (income and price) reasons and that the zeros are purely due to corner solutions. Consequently, households that do not participate in the market do so because they are restrained by relative prices and their incomes.

The Tobin's assumptions were questioned to be too restrictive as zeros may come from the household's deliberate choice to abstain from consuming a good. For example, this study assumed that household may decide to walk or bike for the benefits of active modes. Additionally, advancement in mobile telecommunication could leverage travel and number of trips of households and hence their transport fuel expenditure (Aguiléra *et al*., 2012). Furthermore, granted that higher income households are more likely to spend more on transport, if they have a choice and can therefore substitute for more expensive mode, their transport fuel expenditure is likely to be less. Therefore, this study expected a positive effect of income on the probability of transport fuel market participation and a negative effect of income on consumption decisions of households. These two conflicting effects imply that Tobit regression model may be ineffective in accounting for zeros in a survey data.

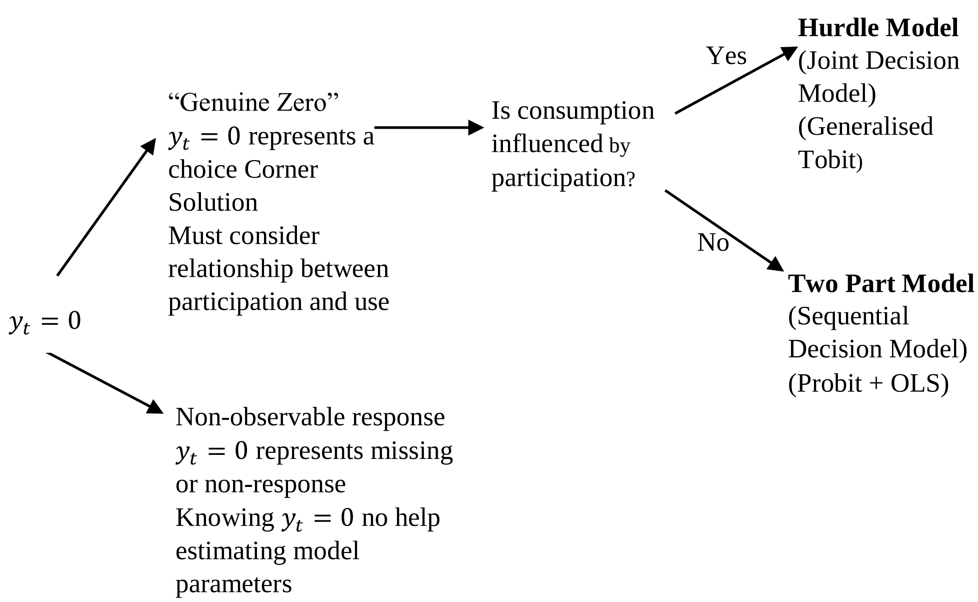


Figure 1: Summaries of the appropriate methods for dealing with zeros in data.

Source: Humphreys (2013).

Following Humphreys (2013), this study used methodology that recognises that the dependent variable, in this case, transport fuel expenditure of households contains zero. Accordingly, a household may decide not to spend any money on transport fuel directly or indirectly during the survey period. Figure 1 shows summaries of the appropriate methodologies for dealing with zeros in survey data.

When zeros are present on the outcome variable y_i, it is appropriate first to determine the reasons for the zeros in the data (Humphreys, 2013). The three plausible reasons are: (1) that the zeros are "genuine" and occurred due to the choices made by the households in the survey; (2) that the presence of the zeros could be due to the inability of the households to have control over the decision, and (3) that the possibility that the zeros could be due to missing or non-response outcomes. According to Humphreys (2013), if the zeros were due to the reasons (1) and (2), then the Tobit model must be used. If the Tobit fails to fit the data, consideration should be given to either double-hurdle or Two-part models for the analysis. If the zeros in the data resulted from the third reason (i.e., missing or non-response outcomes), then Heckman sample selection model should be appropriate.

Heckman (1979) argued, however, that an estimation on subsample due to missing or non-response outcomes could result in sample selection bias, and therefore proposed a two-step estimation procedure known as heckit. Heckman's model regarded the zero observations to arise mostly from self-selection or choice (Heckman, 1979). There is a difference between heckit and Tobit. Heckit observes the process in a two-step decision and allows the use of different sets of explanatory variables in both stages of estimations, while Tobit uses a one-step procedure and assumes that factors affecting the decision to participate in the market and the consumption are the same. Heckit is a "generalised" version of the Tobit model.

Likewise, Cragg (1971) also removed the restrictive assumptions in Tobit model to generalise it. Cragg (1971) argued that the double-hurdle model would be appropriate to account for zeros in data and give special treatment to the participation decision. According to Cragg (1971), two hurdles had to be overcome to observe positive values of expenditure. So, regarding demand of durable goods, Cragg (1971) asserted that households first of all had to desire positive amount, and then desire the factors that influence these positive expenditures on the goods. Following this argument, I assumed that the decision to spend or not is the first hurdle and the second hurdle depended on the amount to spend on transport fuel.

From the forgoing, it appears there is some buddy connection between heckit and double hurdle models. The two models have rules that preside over the discrete outcomes as zero and positive, which are determined by the participation and the level of consumption decisions. Both models also allow for the possibilities of variation in the explanatory variables used at the different stages. However, while the heckit assumes that there will be no zero observations at the second stage, once the first stage is passed, the double hurdle stresses the possibility of zero observation that may arise from the individual's choice or random circumstances.

Literature (Humphreys, 2013; Amemiya, 1984) indicated that because of the restriction that Tobit model placed on the zero inflated data, using OLS regressions would lead to biased results. Generally, household expenditure and transport expenditure data in all the rounds of the GLSS are replete with zero values (GSS, 2014). Following Adusah-Poku and Takeuchi (2019), this study contended that the zeros in the GLSS datasets resulted from (1) the inability or unwillingness of the respondents to respond to a particular question; (2) failure on the part of the data entry officers for a given question, or (3) a non-applicability of the question. The first and second reasons for the zeros in the data were in sync with those suggested by Humphreys (2013). That is, the zeros are ‘‘genuine” (Figure1). Consequently, this study adopted the Cragg’s double-hurdle model because it is held that the decision to spend depends on participation decision of the consumer.

The Double Hurdle Model (Cragg, 1971)

This study considered the double hurdle model to analyse the first objective. The broad aim of objective one was to analyse the effect of ICT expenditure on transport fuel market participation and consumption decisions of households in Ghana. Multiple waves of micro level data from the living standard surveys of households in Ghana were used to analyse the transport fuel expenditure of households. The transport fuel expenditure of households is a sum of direct and indirect fuel expenditure by households on public and private transport in Ghana. Hurdle models are appropriate when the zeros in the data are genuine. This means that the decision of the economic agent to purchase transport fuel depends on their decision whether to participate in the transport fuel market or not to participate. That is, when agent makes participation and consumption decisions concurrently.

The hurdle model is also based on the preposition that individuals must pass two separate hurdles before they are observed with a positive level of consumption. The initial hurdle is to determine factors affecting participation decision in the market for the good, and second is to determine the level of actual amount of the good consumed. This study chose Cragg’s double-hurdle technique to analyse the data to ensure consistency in the outcomes of our results. Adusah-Poku and

Takeuchi (2019); Bardazzi and Pazienza (2018); Eakins (2016) have applied the Cragg's double hurdle econometric model specification to analyse transport fuel.

Several other studies that applied double hurdle model in various areas are Newman, Henchion and Matthews (2003), who applied it to household expenditure on prepared food; Fabiosa (2006), who applied it to wheat consumption; Aristei and Pieroni (2008), who applied it to alcohol consumption; Akinbode and Dipeolu (2012), who applied it to fresh fish consumption; and Njogu, Olweny and Njeru (2018), who applied it to the link between farm production capacity and agricultural credit access from banks. This shows how systematically the double hurdle model has become a useful extension of the univariate Tobit model, and allows for two separate stochastic process for market participation decision (whether to buy or not) and consumption decision (how much to buy). The analytical framework of the double hurdle model is subsequently defined for the first objective of this study.

Analytical Framework for Double Hurdle Model: Objective 1

Following Adusah-Poku and Takeuchi (2019); Bardazzi and Pazienza (2018); and Eakins (2016), the analytical hurdle framework is specified as follows:

$y*_{i1} = w_i\alpha + u_i$ Participation Decision (3a)

$y*_{i2} = z_i\gamma + v_i$ Consumption Decision (3b)

$y_i = x_i\beta + v_i$ if $y*_{i1}$>0 and if $y*_{i2}$>0 (3c)

$y_i = 0$ Otherwise (3d)

where y^*_{i1} is a latent endogenous variable indicating households participation decision, y^*_{i2} is a latent endogenous variable indicating households consumption decision, y_i is the observed dependent variable (household transport fuel expenditure), w_i is a set of characteristic variables explaining the participation decision, z_i is a vector of variables explaining the consumption decision and; u_i and v_i are independent, homoscedastic, normally distributed random error terms.

The double hurdle model assumes that the residuals of the hurdle equation(s) and the outcome equation are uncorrelated. For this assumption to be plausible, the model typically must assume that it is different people who align themselves between the possible alternative situations. For instance, as in this study, if households who decide to participate or otherwise in the transport fuel market are different from those who decide to spend on transport fuel, then their market participation and consumption decisions are two clear separable decisions.

Besides, the double hurdle model produces estimates for α and γ in (3a) and (3b). However, the estimates of the coefficients of the independent variable in (3a) and (3b) are difficult to interpret because the dependent variable is in latent or unobserved form. Thus, according to Eakins (2016), the estimates are always presented as discrete effects and elasticities. The discrete effects represent the absolute change in the overall level of y_i (including the zero values) when the value of the independent variable shifts from zero to one. The elasticities, on the other hand, represent the percentage change in the overall level of y_i for a percentage change in the explanatory variable. For continuous variables, elasticities are computed at the sample means. For categorical variables, the delta method is used to obtain the marginal effects (Adusah-Poku & Takeuchi, 2019; Eakins, 2016).

In the Cragg's double hurdle model, the overall effect on the dependent variable, that is, the expected value of y_i for values of the explanatory variables, x, is written as $E[y_i | x]$, which is more commonly known as the unconditional expectation (or unconditional mean) of y_i. It is called the unconditional expectation because it is based on all values of y_i rather than a subset of positive values, for example. The unconditional expectation is decomposed into two parts: the conditional expectation $E[y_i | x, y_i > 0]$, which is the expected value of y_i for values of the explanatory variables, *x*, conditional on $y_i > 0$ and the probability of a positive value of y_i for values of the explanatory variables, x, $P[y_i > 0 | x]$.

The decomposition of the unconditional expectation into the probability of participation and the conditional expectation followed the work of McDonald and Moffitt (1980) in their decomposition of the unconditional mean of the dependent variable in the Tobit model and is summarised by the following equation (4):

$$E[y_i | x] = P[y_i > 0 | x] * E[y_i | x, y_i > 0] \tag{4}$$

Courtesy equation (4), and with a little mathematical manipulation, it can be shown that the elasticity on the probability of participation and the elasticity on the conditional level of y_i will amount to the overall elasticity on the unconditional level of y_i. Thus, the relative contribution from either participation or consumption to the overall effect can be ascertained. Following Eakins (2016), the probability of transport fuel market participation and consumption decisions conditional on participation are determined in the double hurdle model used in this study as follow:

$$\mathrm{P}[\mathrm{y_i} > 0 \mid \mathrm{x}] = \Phi(w_i\alpha)\Phi\left(\frac{x_i\beta}{\sigma_i}\right) \tag{5}$$

$$\mathrm{E}[\mathrm{y_i} \mid \mathrm{y_i} > 0, \mathrm{x}] = x_i\beta + \sigma_i\left(\frac{\phi\left(\frac{x_i\beta}{\sigma_i}\right)}{\Phi\left(\frac{x_i\beta}{\sigma_i}\right)}\right) \tag{6}$$

Where $\Phi(.)$ and $\phi(.)$ are the cumulative distribution function for a standard normal random variable and standard normal probability density functions (cdf and pdf), respectively. Marginal effects can be calculated by differentiating each of the above equations with respect to each explanatory variable. The following differential equations are credited to Eakins (2016) and Adusah-Poku and Takeuchi (2019).

$$\frac{\partial \mathrm{p}[\mathrm{y_i} > 0 \mid \mathrm{x}]}{\partial \mathrm{x_j}} = \alpha_j\phi(w_i\alpha)\Phi\left(\frac{x_i\beta}{\sigma_i}\right) + \Phi(w_i\alpha)\phi\left(\frac{x_i\beta}{\sigma_i}\right) \tag{7}$$

$$\frac{\partial \mathrm{E}[\mathrm{y_i} \mid \mathrm{y_i} > 0, \mathrm{x}]}{\partial \mathrm{x_j}} = \beta_j - \beta_j\left(\frac{\phi\left(\frac{x_i\beta}{\sigma_i}\right)}{\Phi\left(\frac{x_i\beta}{\sigma_i}\right)}\right)\left[\frac{x_i\beta}{\sigma_i} + \left(\frac{\phi\left(\frac{x_i\beta}{\sigma_i}\right)}{\Phi\left(\frac{x_i\beta}{\sigma_i}\right)}\right)\right] \tag{8}$$

Where α_j and β_j are the coefficient on the explanatory variable $\mathrm{x_j}$ from the participation and consumption equations (3a and 3b) respectively. For the discrete explanatory variables, the marginal effects represent the absolute change in the probability of a positive value, the conditional expectation and the unconditional expectation when the value of the variable shifts from zero to one, all else equal.

Applying the product rule to differentiate Eq. (4) gives rise to the marginal effect for the unconditional expectation as defined in the following Eq. (9) as:

$$\frac{\partial E[y_i \mid x]}{\partial x_j} = \frac{\partial p[y_i > 0 \mid x]}{\partial x_j} E[y_i \mid y_i > 0, x] + \frac{\partial E[y_i \mid y_i > 0, x]}{\partial x_j} p\,[y_i > 0 \mid x] \qquad (9)$$

Equation (9) indicates that the marginal effect of the unconditional expectation equals the marginal effect of the probability of a positive value times the conditional expectation plus the marginal effect of the conditional expectation times the probability of a positive value or participation. Again, following Eakins (2016), the marginal effects (elasticities) for the probability of a positive expenditure, conditional expenditure and unconditional expenditure for the continuous explanatory variables such as household income, ICT expenditure of households, size of households and age of household heads etcetera are calculated as follows:

$$e_j^p = \frac{\partial p[y_i > 0 \mid x]}{\partial x_j} X \frac{x_j}{p\,[y_i > 0 \mid x]} \qquad (10)$$

$$e\frac{cc}{j} = \frac{\partial E[y_i \mid y_i > 0, x]}{\partial x_j} X \frac{x_j}{E[y_i \mid y_i > 0, x]} \qquad (11)$$

$$e_j = \frac{\partial E[y_i \mid x]}{\partial x_j} X \frac{x_j}{E[y_i \mid x]} = e_j^p + e\frac{cc}{j} \qquad (12)$$

Where the last equation states that the elasticity on the unconditional level of expenditure is the summation of the elasticity of the probability of participation and the elasticity of the conditional level of expenditure. This holds because of equation (4) and (6). For the discrete explanatory variables, e_j^p, e_j^{cc} and e_j represent the proportional change in the probability of a positive value, the conditional expectation and unconditional expectation when the value of the variable shifts from zero to one, holding all other variables constant in the model.

Following Eakins (2016) the model could be modified to allow for heteroscedasticity by specifying the variance of the errors as a function of a set of continuous variables as follows: $\sigma_i = \exp(z_i h)$ (13)

Where z_i represents the continuous variables in x_i, the set of variables explaining the expenditure decision. Normally, the exponential form is used because it allows for the property that the standard deviation σ_i is strictly positive (Eakins, 2016).

Reiteratively, the Cragg's double hurdle model specified in equations (3a) and (3b) produces different coefficients (α and γ). There are also different sets of variables (w_i and z_i) in the equations (3a) and (3b) of the model. Generally, to choose Tobit over Cragg's model, it is assumed that the coefficients for the participation and consumption equations or decisions are the same ($\gamma = \alpha$).The assumption is tested using likelihood ratio test because Cragg' model nests Tobit model. The test starts by performing separate estimations for Tobit, Probit and truncated regression (Greene, 2000) and obtaining their log likelihoods. These computed likelihoods are then used to reckon likelihood ratios statistics as follows:

$$\lambda_{R+1} = 2*(LL_{probit} + LL_{truncreg} - LL_{tobit}) \quad (14)$$

Where the test statistic follows chi-square distribution with R+1 degrees of freedom equal to the number of independent variables (including an intercept) between Tobit model and the Cragg's double hurdle model. If λ_{R+1} exceeds the appropriate chi-square critical value, the Cragg's double hurdle model is accepted over Tobit. Equations (3a and 3b) are empirically specified in Chapter Six to aid estimation.

Theoretical Model for Transport Mode Choice: Objective 2

This section of the study considers the theoretical model for transport mode choice. The theoretical model for analysing the second objective is the discrete choice models (DCMs). For many years, researchers in variety of disciplines have developed interest in discrete choice problems. For example, the original application of discrete choice model can be traced to mathematical psychology (e.g., see Tversky, 1972). Meanwhile, Cox (1970) also applied the models in biometric analysis. In the area of econometric application, McFadden (1980); Manski and McFadden (1981) popularised the discrete choice model. The initial scholarly implementation of the discrete choice models in transportation analysis was limited to binary choice for travel mode (see Warner, 1962; Watson, 1974).

The binary choice model was largely used to estimate "value of time," which is the trade-off between travel time and travel cost implied in travel demand model. This value was used to assign a monetary value to the travel time savings in the evaluation of alternative transportation projects (e.g., see Bruzelius, 1979). However, while there was an improvement in the binary choice model, years later, there was a complete change in orientation towards mode choice models with two or more alternatives and application to other travel-related choices such as trip destination (Westin & Gillen, 1978), trip frequency (Jacobson, 1983), car ownership, residential location and housing (Ben-Akiva & Lerman, 1975; Ben-

Akiva, 1973). Some other researchers (Daly & Zachary, 1979; Train, 1976) have also considered choice of mode for travel to work. Moreover, Koppelman (1983) econometrically predicted transit ridership in response to transit service changes.

Generally, researchers are inclined to express individual behaviours in the form of aggregate quantities such as the market demand for a commodity or a service. But aggregate behaviour is an amalgam of individual decisions. Therefore, the expected outcomes of all predictive models of aggregate behaviour is achieved through explicit or implicit modeling of individual behaviour. Thus, travel mode choice within the context of disaggregate models have also received much attention compared to aggregate models. Xiong, Chen, He, Guo and Zhang (2015) employed theory of random utility maximisation to study travel mode behaviour. They assumed that individual's choice is determined by indirect utility of each alternative, and the individual can choose the one that maximises their utility level.

Meanwhile, a choice is an outcome which involves a sequence of decision-making process. This process begins with the definition of the choice problem. This is followed by the determination of alternatives, through evaluation of attributes of the alternatives and selection and implementation of the alternative. For example, a choice problem could be the decision of a traveler to work. Normally, the traveler's environment and the supply of transportation services determine the availability of the alternative modes for the trip. Assuming the traveler is considering car, bus and walking as alternative modes. Following the decision-making process, the traveler evaluates or gathers information about the attributes of every alternative mode. Assuming there are three relevant attributes, say, travel time, travel cost and comfort. The traveler then has to process all available information about these attributes in order to arrive at a choice of travel mode.

Usually, the traveler will arrive at this choice by applying certain decision rule. This rule is a specific sequence of processes that lead to the selection of the fastest mode that costs less than, say, a Ghana cedi irrespective of comfort. The final step in this decision process is obviously the trip to work itself, using the chosen mode. This is the reason specific theory of choice is a collection of procedures that define such elements as the decision maker, the alternatives, the attributes of the alternatives and the decision rule. It is emphasised at this point that not all observed choice behaviour is an outcome of such an explicit decision making process. For example, some people make decision based on their intuition or imitate others and in the process form habit which then becomes conventional behaviour. Even this conventional behaviour of the individuals sometimes can still be modeled following a choice process, albeit the decision maker generates only one alternative.

There are challenges with the specification and estimation of a discrete choice model to predict a chosen alternative by all individuals. To overcome these challenges, Thurston (1927) applied the concept of random utility, which was first employed in the field of psychology. The true utility of alternatives was assumed to be random variables. This is to make the chance of choosing an alternative depends on the probability that an alternative has the greatest utility among the available alternatives (Thurston,1927). Nonetheless, because people rarely make choices in economically rational ways, past travel behaviour theories also drawn on and adapted a number of alternative behavioural theories. These are theories of planned behaviour and interpersonal behaviour (Ajzen, 1991; Triandis, 1977).

Following Ben-Akiva and Lerman (1985), who originally applied random utility theory of consumer choice behaviour in economics, this study adopted mode choice model based on random utility theory. The essence of the random utility theory was to provide a framework for our analysis, like a demand function, which expresses the action of a consumer under given circumstances. While encouraging readers to consult any advanced microeconomic textbooks for more information on consumer choice theory (Jehle & Reny, 2011; Nicholson & Snyder, 2014), this study proceed with the belief that mode choice behaviour is actually a consumer choice behaviour. In this study, mode choice implies available means of transport from home to work. The thesis considered four possible alternative modes of transport from home to work, which mainly makes it different from the private and public transport modes classification adopted by Ortuzar and Willumsen (2005).

Analytical Framework of the MNLOGIT Model: Objective 2

The analytical framework for estimating the multinomial logit (MNLGT) is considered here. The MNLGT framework has been the most commonly used framework for analysing discrete choice data (Cameron & Trivedi, 2010; Green, 2000). The framework captures different continuous latent variables for each choice. These variables are like evaluation scores of each individual for each choice. The higher the score, the more likely the individual will choose that alternative. Following Train (2009), this thesis assumed that an individual i has a choice among four alternative modes $j = 1, 2, \ldots k$ with certain attributes, and the alternatives used by workers are small public transport (SPT), large public transport (LPT), private motorised transport (PMT) and non-motorised transport (NMT).

Thus, k=4. Letting U_{ij} be the utility of an individual i for alternative mode j, where $j = 1, 2 \ldots k$, the study assumed that utility followed the functional form as:

$$U_{ij} = u(V_{ij}) \tag{15}$$

Suppose V_{ij} represents the part of U_{ij} that represents the systematic, deterministic or observed component of each choice j and individual i, and V_{ij} is a function of the vector of exogenous variables, X_i, and the vector of the respective parameters, β_j, then the systematic, deterministic or observed component equation is given as:

$$V_{ij} = f\left(X_i, \beta_j\right) = \beta_j X_i \tag{16}$$

Following from (15), it is further assumed the utility is a function of observed component, random component and the intercept. The random utility takes the form

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \delta_j + \beta_j X_i + \varepsilon_{ij} \tag{17}$$

Where $\beta_j X_i$ is the inner-product of the predictors and their coefficients for choice j, and ε_{ij} is independent and identically distributed by the type 1 extreme value distribution. It represents the component that is hidden, unknown or unobserved. Since ε_{ij} is hidden, unknown or unobserved, it represents the random component of the utility. Since $\varepsilon_{ij} = U_{ij} - V_{ij}$, then ε_{ij} is highly dependent on how the study would represent the observed part of the utility in equation (17). Hence, several utility equations can be developed, but they may or may not give the same choice probabilities. The empirical equation for estimating choice probability of a transport mode is developed in Chapter Seven of this study. Meanwhile, the discussion here proceeds with the features of the predictors in MNLGT model.

In MNLGT model, the predictors are fixed across choices, but the coefficients vary across choices. The effect of predictors being fixed across choices is that the mean value of the predictors remains constant no matter which choice is being considered. For example, while individual specific attributes like age, gender and income remain fixed across choices in a mode choice analysis, their coefficients vary no matter which choice is being considered. However, variables like travel time, waiting time, convenience, comfort, flexibility of schedule and distance et cetera, vary across choices. The conditional logit (CLGT) model has been developed to account for such variation of variables across choices by focusing on the set of alternatives for each individual. But, where the explanatory variables are characteristics of those alternatives, CLGT model is not different from MNLGT in all respect, except for the linear structure of the latent variable (Kropko, 2008).

Also unlike MNLGT, where a predictor is fixed across the choices with the effect of the predictor being different for each choice, the CLGT model was designed to ensure that variables that are different for each choice have the same effect across choices. For example, if distance from home to work is an important predictor of an individual's mode choices, then distance is an equally important consideration irrespective of whether the car, bus, or walking are being considered, in the case of CLGT model. For MNLGT model, an attribute of individuals may be an important consideration of individuals when they evaluate the car mode, but that may not be of importance when the individuals evaluate the alternative modes.

To remove variations of variables across choices, statisticians have simply hybridised MNLGT and CLGT models to form a hybrid MNLGT (HMNLGT). The HMNLGT has a structure and latent variables that take the form that do not have space in this thesis. The intention of HMNLGT approach was to merge behavioural model with predictive choice models, with the random utility maximisation as its theoretical basis (Kropko, 2008; Walker & Ben-Akiva, 2011; Hoffman & Duncan, 1988). The real value of travel time and distance considered in this study are generic. In this regard, these variables are assumed not to assume different values for an alternative under certain restrictive condition, but their impacts do change across alternative modes. This assumption is to ensure that a one Ghana cedis per hour increases in the real value of travel time or a unit increase in kilometric distance of travel do not have similar impact on modal utility for alternative modes.

From equation (17), given a set of alternative modes, individual i is likely to choose mode j over alternatives k if $\mathrm{U_{ij}} > \mathrm{U_{ik}}\ \forall_j \neq \mathrm{k}$. But, it has been noted that nobody observes or measures utilities directly. And that many of the attributes that influence individual's utilities cannot be observed or measured and must be treated as random variables. This implies that utilities themselves in models are random, and as a consequence, choice models can give only probability with which alternatives are chosen, not the choice itself. Therefore, using the implied probability of observed outcome, the choice probability model is specified as:

$$p_i\left(j \middle| X_i\right) = p\left(U_{ij} > U_{ik}\right), \forall j \neq k$$

$$= p\left(U_{ij} > U_{ik}\right) = p(V_{ij} - V_{ij} > \varepsilon_{ik} - \varepsilon_{ij}) \tag{18}$$

Assuming the probability that i^{th} individual chooses mode j over alternatives k is denoted by P_{ij}, with $j = 1$ if individual chooses the first mode, $j = 2$ if individual chooses the second mode, and $j = 3$ if individual chooses the third mode, et cetera.

The general probability model for alternative modes is formulated as:

$$P_{ij} = \frac{e^{(\beta x_{ij})}}{\sum_{j=1}^{3} e^{(\beta x_{ij})}} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \ldots + \beta_n x_{ni} \tag{19}$$

Where $\beta_0, \beta_1, \beta_2, \ldots, \beta_n$ are the parameters to be estimated and x_{ni} is a vector of explanatory variables expected to influence the choice of modes. These coefficients describe the relative probability of a choice to a base category. Setting arbitrarily $\beta_0 = \beta_1 = \beta_2 = \ldots = \beta_n = 0$ for the base category in any statistical package like Stata, the conditional probability of an i^{th} individual choosing a mode j over alternatives k given the vector of X explanatory variables can be expressed as follows:

$$P(j = \frac{1}{x_i}) = \frac{1}{\sum_{j=1}^{3} e^{(\alpha x_{ij})}} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \ldots + \beta_n x_{ni} \tag{20}$$

and $P(j \geq \frac{2}{x_i}) = \frac{e^{(\alpha x_{ij})}}{\sum_{j=2}^{3} e^{(\alpha x_{ij})}} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \ldots + \beta_n x_{ni}$ (21)

Expansion of equation (21) to include factors affecting individual's choice of transport mode, gives the empirical model estimated in Chapter Seven of this thesis.

The MNLGT model as stated early on is the most commonly used regression model for nominal dependent variables in social sciences. However, researchers have raised concerns about the implicit assumption of independence of irrelevant alternatives (IIA) that underpins the MNLGT model. Theoretically, the IIA assumes independence of the errors in the evaluation functions. But, an important effect of this assumption is that the odds ratios are fixed when other choices are added or deleted. Thus, the IIA is in action when no change to any other choice coefficients will change the odds ratio. When IIA assumption is violated, the estimates of MNLGT models are biased and inconsistent. The Hausman-McFadden (1984) and Small-Hsiao (1985) tests are commonly used to test for IIA.

Both tests work with the same general approach. However, if they are not supported, there are two alternative models that can be used. One is the conditional probit model, which allows for multivariate normal correlated error terms. The other is the nested logit model (Small & Hsiao,1985; Hausman & McFadden, 1984) in which the choice process is viewed as a set of nested choices. This approach retains the computational advantages of the logit form but selectively relaxes the independence assumption and thereby allows for variety of response patterns to a change in the characteristics of one alternative. The independence of the errors terms in the MNLGT has been later tested in Chapter Seven of this study. The next section considers the theoretic model for analysing the third objective of this thesis.

Theoretical Model for Transport Fuel Intensity: Objective 3

The essence of this section is to consider the theoretical model for the third objective. The third objective was to access how the effect of ICT expenditure of households on transport fuel intensity of households differentiates demographic attribute (sex) of households, using disaggregated data from Ghana. The theoretical model for the third objective was the binary response analysis, which is undertaken when a phenomenon to be explained is qualitative in nature. Theoretically, binary response models assume that there is an unobserved or latent continuous outcome variable. However, two states are observed on latent variable: 0 and 1. Thus, lower values on the latent continuous variable are observed as 0, and higher values on the latent continuous variables are observed as 1. The regions of the latent variable that are observed as 0 and 1 are separated by a point called threshold or cutoff point.

In many of the applications of these models, it is assumed that an economic agent makes a choice between two alternatives. In this study, it is assumed for example that an economic agent chooses to spend more or less on a given good that they consume, constrained by market conditions. Another example is when a job seeker in the labour market decides to accept an offer or not, given the market conditions. These scenarios of spending more on a good and accepting an offer are seen as successes or correspond to $Y=1$, and spending less on a good and not accepting an offer are seen as failures or correspond to $Y=0$. The binary response model thus gives the probability that $Y=1$, given a set of explanatory variables.

In the case of spending more or less on a good for example, the common explanatory variables may include: the price of the good in question, income of the decision maker, age of the decision maker and what have you. For labour market outcomes, some plausible explanatory variables are: wage rate, nature of the job, education and experience of the job seeker, et cetera. The preoccupation of the econometrician is to estimate the conditional probability that $Y=1$ considered as a function of the explanatory variables. Functionally, the conditional probability that Y=1, which is considered as a function of the explanatory variables is specified as:

$$E[y_i \mid x_i] = p(y_i = 1 \mid x_i) = F(x_i\beta) \qquad (22)$$

Analytical Framework of Logistic Regression: Objective 3

The previous section considered the theoretical model for transport fuel intensity. In equation (22), the conditional probability assumes a linear probability model (LPM) form when $F(.)$ is a linear function of $x_i\beta$. To estimate β, which is a vector of unknown parameters, Ordinary Least Square (OLS) regression can be used. The challenge, however, is that the error or residual from linear probability violates the homoskedasticity and normality of error assumption of OLS regression. This could result in invalid standard error and hypothesis tests, unless $F(.)$ is approximately linear over the values in x_i (Long, Long & Freese, 2006). Other framework in use is Hotelling's T^2 where the dichotomous outcome could be turned into grouping variable and predictors turned into outcome variables. Hotelling's T^2 produces an overall test of significance. But, it does not produce coefficient for each variable and so cannot show the effects of other predictors (Long *et al*., 2006).

For this reason, logit and probit models have been used to estimate equation (22) in most leading journals (Horowitz & Savin, 2001; Wooldridge, 2010). This study adopted the logit framework for assessing how the effect of ICT on transport fuel intensity differentiates demographic attribute (sex) of households, using disaggregated data from Ghana because its estimates are easily interpretable. Transport fuel intensity denotes annual household fuel expenditure on transport in

Ghana cedis above or below the mean annual household fuel expenditure on transport. The logit and probit frameworks are nonlinear models, and are motivated by an expression regarding latent variable. From the definition of transport fuel intensity, the decision to spend above or below the mean annual household transport fuel expenditure can be expressed as latent variable (y_i*). Although y_i* cannot be observed, its observed variable (y_i) is implicitly expressed functionally as follows:

$$y_i = \begin{cases} 1 \text{ if } y_i*>0 \\ 0 \text{ if } y_i* \leq 0 \end{cases} \quad (23)$$

Additionally, logit and probit models assume that the latent variable y_i* is related to a set of observable predictor variables (x_i) that explain variation in the latent variable according to an expression, which functional form is stated as:

$$y_i* = x_i\beta + \mu_i \quad (24)$$

Where β is as stated before and μ_i is an error term that is independent of x_i and captures all other factors that affect y_i*. For a symmetrically distributed error term about zero, the distribution function is defined by $F(.)$. Where $F(.)$ is a function that takes on values strictly between zero and one. The probability of observing a binary response variable y_i equals to one (i.e., decision to spend below the mean annual household transport fuel expenditure) is functionally expressed as follow:

$$p(y_i = 1 | x_i) = p(y_i* > 0 | x_i) = p(\mu_i > -x_i\beta | x_i) \quad (25)$$

From equation (24) and given that the error is symmetrically distributed about zero, equation (25) will imply that $p(x_i\beta + \mu_i > 0)$, which further implies that $1 - F(-x_i\beta) \Rightarrow F(x_i\beta)$, which is the same as the expression stated in equation (22).

In other words, equation (25) expresses the probability that the error term realised is larger than negative of the value of the observable part, $\mu_i > -x_i\beta$. From equation (25), the probability of observing a decision to spend above the mean annual household transport fuel expenditure can also be deduced and expressed as:

$$p(y_i = 0 \mid x_i) = 1 - p(y_i = 1 \mid x_i) = 1 - F(x_i\beta).$$

Usually, to avoid compromising the probabilities of the (0,1) range, which are always associated with binary variables, it is assumed that the probability is a sigmoid (S-shaped) function of z, $F(z)$. Where z is the function of the explanatory variables. There are several mathematical functions that are sigmoid in nature. The logistic function is one of such. It is functionally expressed as follows:

$$F(z) = \Lambda(z) = \frac{1}{1+e^{-z}} = \frac{e^z}{1+e^z} \qquad (26)$$

Where $Z = x_i\beta$

From (26), it can be shown that if z approaches positive infinity, e^{-z} goes to 0 and p goes to 1 (but cannot exceed 1), and as z approaches negative infinity, e^{-z} goes to infinity and p goes to 0 (but cannot be below zero). Again, the slope of the logistic function in equation (26) is expressed as follows:

$$f(z) = F'(z) = \lambda(z) = \frac{e^z}{(1+e^z)^2} \qquad (27)$$

Combining equations (25 & 27) gives rise to the definition of marginal effect of the continuous variables on the response probability. The marginal effect is stated as:

$$\frac{\partial p(y_i = 1 \mid x_i)}{\partial x_i} = f(z)\beta_j = \frac{e^z}{(1+e^z)^2}\beta_j \qquad (28)$$

From equation (28), it can be seen that the marginal effect is not constant. This is because it depends on the value of z, which in turn depends on the values of the explanatory variables. Clearly, the marginal effect also has the same sign as β_j. It is evaluated at the sample means of the explanatory variables (Wooldridge, 2010).

Apart from the logit, another commonly used distribution is the probit. The sigmoid function for probit model is the cumulative standard normal distribution.

$$F(z) = \Phi(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{\frac{1}{2}z^2}$$

$$f(z) = \phi(z) = \frac{1}{\sqrt{2\pi}} e^{\frac{1}{2}z^2}$$

$$\frac{\partial p(y_i = 1)}{\partial x_i} = f(z)\beta_j = \phi(z)\beta_j$$

Likewise, the marginal effects of the probit regression vary with z. Although, the logistic distribution has slightly flatter tails, the outcomes of the probit and logistic regression models are quite similar. While the variance of the probit is 1 (standard normal distribution), that for the logit is $\frac{\pi}{\sqrt{3}}$. Also, the probit and logistic models relate similarly as: $\beta_{probit} = 0.625\beta_{\log it} and \beta_{\log it} = 1.6\beta_{probit}$ (Amemiya,1984).

It is, however, noteworthy that the nonlinear nature of the logit and probit models also makes OLS inept for estimating their parameters. Hence, maximum likelihood estimation (MLE) is employed to estimate their parameters. This ensures that the heteroskedasticity in var(y|x) is automatically accounted for (Wooldridge, 2010). To illustrate MLE, let assume a random sample of size n of the binary variable y .Supposed the probability of the decision to spend below the mean annual household transport fuel expenditure is the same for all observations, $p(y_i = 1 | x_i) = p$, then the probability distribution for i-th observation is given by:

$$p^{y_i}(1-p)^{1-y_i} \tag{29}$$

If the observations are mutually independent, the likelihood function is given by:

$$L(p) = \prod_{i=1}^{n} p^{y_i}(1-p)^{1-y_i} \tag{30}$$

Taking the log of (30) produces the log-likelihood function in the following form:

$$\begin{aligned} \log(L(p)) &= \sum_{\{i;y_i=1\}} \log(p) + \sum_{\{i;y_i=0\}} \log(1-p) \\ &\sum_{i=1}^{n} y_i \log(p) + \sum_{i=1}^{n} (1-y_i)\log(1-p) \end{aligned} \tag{31}$$

Now assume that y observations are mutually independent but allow the probability of decision to spend below the mean annual household transport fuel expenditure to differ among the observations. Earlier, the $F(x_i, \beta)$ was deduced using the latent variable framework. Clearly, all observations follow the same function, but there are differences in the values of the explanatory variables. In this case, y_i follows a Bernoulli distribution with probability function specified as:

$$p_i = P[y_i = 1 | x_i] = F(x_i, \beta) \tag{32}$$

The probability distribution is given by:

$$p(y_i) = p_i^{y_i}(1-p)^{1-y_i}$$

While the log-likelihood function is given as:

$$
\begin{aligned}
\log(L(\beta)) &= \sum_{i=1}^{n} y_i \log(p_i) + \sum_{i=1}^{n} (1-y_i)\log(1-p_i) \\
&= \sum_{i=1}^{n} y_i \log(F(x_i\beta)) + \sum_{i=1}^{n} (1-y_i)\log(1-F(x_i\beta)) \\
&= \sum_{\{i;y_i=1\}}^{n} y_i \log(F(x_i\beta)) + \sum_{\{i;y_i=0\}}^{n} \log(1-F(x_i\beta))
\end{aligned}
$$

From equation (26), $F(z) = \Lambda(z) = \dfrac{e^z}{1+e^z}$. Therefore, the log-likelihood function for the logit model estimated in this study is expressed mathematically as:

$$
\begin{aligned}
\log(L(\beta)) &= \sum_{i=1}^{n} y_i \log(\Lambda(Z)) + \sum_{i=1}^{n} (1-y_i)\log(1-\Lambda(Z)) \\
&= \sum_{i=1}^{n} y_i \log\left(\frac{e^z}{1+e^z}\right) + \sum_{i=1}^{n} (1-y_i)\log\left(1-\frac{e^z}{1+e^z}\right) \qquad (34) \\
&= \sum_{\{i;y_i=1\}}^{n} \log\left(\frac{e^z}{1+e^z}\right) + \sum_{\{i;y_i=0\}}^{n} \log\left(1-\frac{e^z}{1+e^z}\right)
\end{aligned}
$$

In Chapter Eight, the thesis considers the logistic regression equation for assessing how the effect of ICT expenditure on transport fuel intensity differentiates the demographic attribute (sex) of households, using disaggregated data from Ghana.

Chapter Summary

This chapter gave extensive attention to the theoretical framework of the study. It commenced with an overview of general linear models, which are systems of equations that can be used to represent linear patterns of relationships in observed data. Specifically, the chapter touched on ANOVA, ANCOVA, MANOVA and MANCOVA, which are all within the family of the generalised models. The chapter continued with the discussion on the theoretical models for the set objectives of the study. In particular, the chapter focused on the double hurdle model for analysing transport fuel market participation and consumption decisions, followed by MNLOGIT for analysing the transport mode choice of workers, and highlighted the binary logistic regression model for analysing transport fuel intensity in Ghana.

Also, the chapter considered the analytical frameworks, which allowed for the transformation of the theoretical models into empirical equations. These frameworks were used in analysing the effect of ICT expenditure on transport fuel market participation and consumption decisions of households; examining the effect of real value of travel time on transport mode choice of workers in Ghana; and assessing how the effect of ICT expenditure on transport fuel intensity of households differentiates demographic attribute (sex) of households, using disaggregated data from Ghana. The following chapter focuses on the methodology used in this thesis to achieve the three set objectives and hypotheses of the study.

CHAPTER FIVE

RESEARCH METHODS

Introduction

This chapter presents the methodologies of the study. The chapter discusses the research design, paying attention to the secondary data because of the stated objectives and the specific hypotheses of the study. This is followed by operationalisation of variables used, data sources and management of the data used in the study. The next section commences with the philosophical issues in the study.

Philosophy of the Study

The general goal of this thesis is analogous to travel demand, which refers to the amount and type of mobility that people make in a particular situation. This reflects commuters' ability and decision to spend and, therefore, the value they attach to specific travel activity such as a particular trip or mode. Values attach to travel activity may not be stable. This is because of the variance of importance people attach to trips. Some trips such as commuting and visiting to healthcare services are important, and so people will take them even if it cost them so much. There are others such as impulse shopping and some recreational trips that are of lower value to commuters, and will only attract many people if they are cheaper.

The decisions regarding how to spend scarce resource and time on transport reflect not only mobility needs of people but also their options and preferences. This is what the economists call demand, which refers to the amount and type of goods and services people and business are willing and able to consume under specified conditions. Given an endowment of income, people are expected to make rational decisions after evaluating the cost of different options they have to meet for a particular need, in this case commuting travel and cost. This travel behaviour will not only reflect their personal economic evaluation, but also their preferences.

Since the focus of this study was to identify the drivers of transport fuel expenditure and mode choice in Ghana, it resonates with utilitarian philosophy. The two philosophers who wrote about utilitarianism were Jeremy Bentham (1748–1832) and John Stuart Mill (1808–1873). The fundamental perspective of utilitarian precepts is that rightful behaviours are those produced by one's actions, where the total positive outcomes are greater than the total negative outcomes. For this school of thought, the primary focus of ethical analysis is the consequence of our behaviour. According to Mill, behaviours that maximise happiness should be selected against those minimising suffering. Thus, actions that create the greatest happiness for most people are the correct behaviours from utilitarian perspective.

Research Design

This study adopted secondary data analysis to accomplish the three objectives and test the research hypotheses. This is because the research hypotheses were all related to the identification of drivers of household transport fuel expenditure and mode choice behaviours. Like the two key observable drivers of interest (ICT expenditure and Real Value of Travel Time), the choice of secondary data analysis enabled establishment of correlations between all other observable variables and the outcome variables. The choice of secondary data does not allow for control over the selection of respondent and the measurement technique employed in the data collection process. Nevertheless, fortunately the results could be generalised because of the validity and reliability of the study process. The next sections of the chapter consider measurement and operationalisation of variables used in the study; the datasets and sources, followed by how the data is managed.

Operationalisation of Variables used in the Study

This section considers measurement and operationalisation of relevant drivers of transport fuel expenditure and mode choice. Variables are concepts that are generalisable properties of phenomenon, while construct is an abstract concept that is specifically chosen to explain a given phenomenon. Scientific research requires operationalisation of constructs in terms of how they will be empirically measured. This thesis developed three representative models for the three specific objectives, with total transport fuel expenditure of households, main mode of transport of workers and transport fuel intensity of households as the main objective variables. In particular, the dependent variable for the first objective was fuel expenditure on public and private transport, respectively. The second dependent variable was the main mode of transport used from home to work. The main mode of transport was further categorised into small public transport (SPT); large public transport (LPT); private transport (PMT) and non-motorised transport (NMT).

While the first objective sought to model transport fuel market participation and consumption decisions of households, the third dependent variable helped in assessing how the effect of ICT expenditure of households on transport fuel intensity differentiates demographic attribute (sex) of households, using disaggregated data from Ghana. Though ICTs can range from cutting edge internet-based technologies and other tools that have been around for long, such as radio, telephones, mobile phones, television and satellites, these have been proxied with their expenditures in this study. Following Mraihi (2012), this study conceptualised transport fuel intensity (TFI) as an average annual household fuel expenditure on transport in Ghana cedis above or below the mean annual transport fuel expenditure threshold. As already noted in Chapter Four, TFI is binary variable (1/0), which has been coded and measured as less fuel intensive (LFI) or more fuel intensive (MFI).

There are several indicators of energy demand and gas pollutants emissions. These are transport energy intensity, transport intensity, transport energy emission intensity, vehicle intensity and vehicle energy intensity (Mraihi, 2012). Others are modal mix (road, rail, air, and water shares), energy mix for every mode (gasoline, diesel, liquefied petroleum gas (LPG), electricity or other fuel types, such as bio-carburant), rate of motorisation, transport energy consumption share and annual growth of vehicle park (Mraihi, 2012). Beyond these intensities, economic, demographic, urban and technological factors were also identified as influencing factors of energy demand and gas pollutants (Mraihi, 2012). Evidence also exists of other factors such as average travelling distance, vehicle types share (personal cars, bus, heavy and light trucks), average vehicle age, driving condition, urbanisation, urbanised kilometers as well as national road network (Mraihi, 2012).

The effects of these factors on energy consumption and gas pollutants production derived from road transport activities. This is because majority of goods and passengers are transported annually by road mode, which is considered an important source of fossil fuels consumption and gas emission (IEA, 2012). While previous studies employed economic approaches to study causal relationship between economic growth, transport activities and environmental impacts and their driving factors (Tanczos & Torok, 2007), others adopted the ecologic approach to investigate the correlation between economic growth and transport activity and transport energy consumption. Some focused on the coupling phenomena between economic growth and transport activity and transport energy consumption, while measuring and analysing energy consumption and gas emissions (Mraihi, 2012).

Pongthanaisawan and Sorapipatana (2010), for example, considered the impacts of the use of motorcycle and car ownerships on fuel consumption and greenhouse gas emissions. Recent evidence also highlighted energy indicator and different associated influencing factors (technological, technical, regulatory, fiscal and economic) that ameliorate the negative effects of energy consumption and gas emissions of the transport sector (Mraihi, 2012). While information exists about the effects of demographic factors on energy intensity (Mraihi, 2012), little is known about the influence of ICT expenditure on transport fuel intensity of households and how this influence is differentiated by demographic (sex) within the context of disaggregated data from Ghana. Anowar *et al*. (2018) and Diaz Olvera *et al*. (2008a) revealed factors that influence household transport expenditure, while (Abrahamse *et al*., 2009; McCarthy, Delbosc, Currie & Molloy, 2017; Shen *et al.*, 2016; Tyrinopoulos & Antoniou, 2013) shown causes of transport mode choice.

The current study leveraged on the existing gap in the literature to control for drivers of TFE of households, transport modes choice and TFI based on their testability and data availability. For example, the study considered the relationship between dependent variables and household mean telecommunication expenditure (hictexp, log transformed), size of the household (hsize, log transformed), age of household head codified as age. Age is a continuous variable measured in years. Notably, the normalisation of some variables was necessary to ensure that they were normally distributed. Additionally, household expenditure was used as a proxy for household income (hinc). Household expenditure is a continuous variable in terms of mean annual income. Understandably, expenditure provides stable and permanent measure of income than total income (Mathur & Morris, 2014; Poterba, 1991; Rice, 2004). See theory of permanent income hypothesis (Friedman, 1957).

The study included location of household, sex of household head, whether household head is a single adult without children or without adult member 64 years and more, level of education of household head (heduc). Level of education was included to ascertain its influence on the objective variables of the models used in this study. The level of education is an indicator variable, with 4 indicating tertiary level education and 1 indicating no level of education. The values (1&4) are not in ranking order. Based on these values, level of education was dummy coded so that subgroups on it could be compared. For instance, "no education" was used as the reference category, and each other three subcategories was treated as a dichotomous variable against "no education". In this process, the four categories became three dichotomous variables – basic education (1) vs. no education (0); secondary education (1) vs. no education (0) and tertiary education (1) vs. no education (0).

This shows that the use of dummy coding converts any independent categorical variables with n categories into a series of n-1 dichotomous variables (Fiagborlo & Kyeremeh, 2016). This study used this approach to convert all categorical variables such as location of household, sex of household head, whether household head is a single adult without children or without adult member 64 years and more. For instance, location of household has two categories (1= urban; 0 otherwise), sex of household head (1= male-headed households; 0 otherwise), whether household head is a single adult without children or without adult member 64 years and more is an indicator variable, with 1 representing whether household head is a single adult without children or without adult member 64 years and more and 0 otherwise. The study included interaction between location of households and ICT expenditure of households to allow ICT effect on transport fuel expenditures to vary with location of households individually and collectively.

Other variables that require operationalisation and measurement are: RVTT; distance; per capita private motorised assets (ppcma); per capita commercial motorised assets (pcma). While RVTT (lost labour hours in transit) measures hours spent in transit one-way trip from home to work as a product of national minimum wage in Ghana, distance covered from home to work is measured in kilometres per hour. The ppma and pcma of respondents indicate the proportion of private and commercial cars that are accessible to individuals in their respective households. Further details about all the variables hypothesised to influence participation and consumption decisions of households, as well as mode choice and transport fuel intensity are presented in Chapters Six, Seven and Eight.

Data and Sources

The data for this study were extracted from the Ghana Living Standards Survey (GLSSs) and National Household and Transport Survey ([NHTS], 2012). In particular, five rounds of the GLSSs and one round of the NHTS were utilised. For instance, this study used rounds three, four, five, six, and seven of the GLSSs and NHTS (2012) for executing the three objectives. These two datasets were employed because each one independently could not provide the information needed to execute the objectives of this study. Factually, travel surveys do not provide the information on household transportation expenditures, and consumer expenditure surveys do not also provide information about travel behaviour (Blumenberg & Agrawal, 2014).The latest round of the GLSS is round seven (GLSS7). But, at the time of treating the data for this study, there was limited evidence from the survey about income items, which were also not stable at times for analysis. Hence, income was proxied with household expenditure in this study.

Like GLSS3, GLSS4 provided information about patterns of household consumption and expenditure on food and non-food items on a particular household. The GLSS4 was conducted between April 1998 and March 1999. The total sample in the GLSS3 and GLSS4 were 4,521 and 5,998 households, respectively. Likewise, the rounds five, six and seven of GLSS are also nationwide surveys with the round six covering a representative sample of 18,000 households in 1,200 enumeration areas. Out of 18,000 households, 16,772 were successfully enumerated given a response rate of 93.2 percent. Like previous rounds, the GLSS6 considered demographic characteristics of households, education, health, employment, migration and tourism, housing conditions, household agriculture, household expenditure, income and their components and access to financial services and credit and assets. In this study, the focus was on total transport expenditure, which includes fuel expenditure for private cars and public transport.

The NHTS (2012) focused on the household as the socioeconomic unit, but collected information on individuals within the household and on the communities in which the households were identified. The data captured information on household members aged three (3) years and older on the use of transport services to school. They also captured information on access and use of transport services to health facilities, their economic activities and the use of transport services; their access and use of modes of transport (GSS, 2014). In all, the NHTS (2012) data contains 6,000 households with 23,238 individual members. Out of the 23,238 household members, 7,308 worked during the past 12 months before the survey. After sorting the data for this study, 7,262 workers, out of 7,308 who worked, were observed to use the same means of transport from home to work. It was also noted that individuals and households chose travel modes on the basis of their socio-economic characteristics and the attributes of the available transportation options.

Data Management

This section considers the data management, after having elucidated on data and their sources in the previous section. Data management and exploration are necessary in research to ascertain patterns within the data and to look for casual pathways and connections. In this study, Stata version14 was employed to explore the data. By the nature of the measurement scales deployed in the collection of the data, this study employed statistical techniques to determine whether the variables of interest were evenly distributed across all categories or whether responses were skewed towards one end of the rating scales. The summary results also enabled description of the data with numerical indices and checked for missing responses.

Again, data management and exploration ensured that all internal consistency protocols or procedures were applied to ensure the reliability of scores, since the data collection process made it impossible to have control over the selection of respondent and the measurement technique employed. Thus, cross tabulation of frequencies and tables were employed to analyse the demographic characteristics of households and other factors that influence the objective variables of interest. The independent variables were correlated to determine their true independence. This helped to avoid the multicollinearity among variables. Further discussions about frequencies and multicollinearity are found in the next chapters.

Chapter Summary

While some of the information about the data are spread among the subsequent chapters, this chapter discussed the methodologies of the study. The chapter discussed the research design and payed attention to the secondary data because of the stated objectives and the specific hypotheses of the study. This was followed by operationalisation of variables used in the study, data source and their management. The chapter commenced with the philosophical issues in the study.

CHAPTER SIX

DRIVERS OF TRANSPORT FUEL EXPENDITURE

Introduction

This chapter considers the drivers of transport fuel market participation and consumption decisions of households. The chapter begins with the empirical double hurdle model, while the next section presents the summary statistics of the variables used in the study. This is followed by the multicollinearity and likelihood-ratio tests. The parameters of the maximum likelihood estimates of the Cragg's double hurdle model are discussed next. The chapter continues with the presentation of the marginal effects of income; ICT expenditure; household size; age; location; sex; life-cycle; and education on fuel market participation and consumption decisions of households. The last section conclusively provides the summary to the chapter.

Empirical Double Hurdle Model

From Chapter Four of this study, the analytical equations (3a) and (3b) identified participation and consumption decisions of households in transport fuel market. This section of the study specified the empirical double hurdle regression equations, which are premised on the analytical hurdle equations (3a) and (3b) as:

$$\begin{aligned} PAT_i = {} & \alpha_0 + \alpha_1 \ln hict\exp + \alpha_2 \ln hsize_i + + \alpha_3 urban_i + \alpha_4 \text{age}_i + \alpha_5 \text{agesq}_i \\ & + \alpha_6 male_i + \alpha_7 sadult_i + \alpha_8 beduc_i + \alpha_9 seduc_i + \alpha_{10} teduc_i + \varepsilon_i \end{aligned} \tag{35.1}$$

$$\begin{aligned} CON_i = {} & \lambda_0 + \lambda_1 \ln hict\exp + \lambda_2 \ln hinc_i + \lambda_3 \ln hsize_i + \lambda_4 urban_i + \lambda_5 \text{age}_i \\ & + \lambda_6 \text{agesq}_i + \lambda_7 male_i + \lambda_8 sadult_i + \lambda_9 beduc_i + \lambda_{10} seduc_i + \lambda_{11} teduc_i + \varepsilon_i \end{aligned} \tag{35.2}$$

Where *PAT* and *CON* represent the decision of a household head to participate in the transport fuel mark or not and how much they spend if they decided to participate, respectively; ln*hictexp* is the normalised household mean telecommunication expenditure; ln*hinc* is the normalised household income proxied by mean household expenditure in Ghana cedis; ln*hsize* is the normalised household size; *urban* is a dummy of the location of household; *age* is the age of the head of household; *male* is a dummy for sex of the head of household; *sadult* is a dummy for whether household head is a single adult without children or without adult member 64 years and more; *beduc* is a dummy for basic level of education of household head; *seduc* is a dummy for secondary level of education of household head; and *teduc* is a dummy for tertiary level of education of household head.

Detailed definitions and measurements of all the variables hypothesised to influence participation and consumption decisions of households are presented in Table 1. In Table 1, the expectation was that on average, normalised ICT expenditure of households would have both positive or diminutive effect on transport fuel market participation as well as consumption decisions of households. Bris *et al*. (2017) found a negative association of transport expenditure of households with internet penetration for the reason that ICT reduces mobility of households as it offers opportunity for people to conduct some remote activities online, hence circumventing the need to travel. Moreover, ICT can help in finding less onerous travel possibilities (destinations, modes, routes, time of day) through easier access to up-to-date, repeatedly real-time, information (Bris *et al.*, 2017).

ICT enables access to information which would enable households, particularly, those in the lower extreme of income to shift towards less expensive ways of accessing activities. For example, in the case of travel cost, ICT may create

Table 1: Variables hypothesised to influence transport fuel expenditure and consumption decision of households in Ghana

Variable descriptions		1st	2nd
Dependent variable		Exp. Sign	
tfe	Annual household transport fuel expenditure in Ghana cedis		
Independent variable			
Continuous			
lnhictexp	Natural log of household mean telecommunication expenditure	-/+	-/+
lnhinc	Natural log of household income proxied by mean household expenditure in Ghana cedis	+	+
lnhsize	Natural log of household size	+	-
age	Age of head of household in years	+/-	+/-
Discrete			
urban	1=Urban household 0=Rural household	+/-	+/-
sex	0=Female head of household 1=Male head of household	-	-
sadult	Single2 =1 for single adult household head without children or without adults >64 years, 0 otherwise	+/-	+/-
education	Education level of household head. Coded:0=no education, 1=basic education 1= secondary education and 1=tertiary education. No education is the reference category	+	+
*loc*lnictexp*	Interaction between household location and mean telecommunication expenditure	+/-	+/-

Source: Fiagborlo (2019).

awareness of the less expensive choices among destinations, modes, routes, time of day. These decisions may include joint or shared option such as ad-hoc vehicle pooling and sharing, which are facilitated by the proliferation in ICT. Furthermore, ICT penetration could offer more opportunities for utilising online mechanisms such as seller-to-seller platforms and transactions, online auctions, or price comparison tools for purchases of vehicle. This may reduce the cost of transport as transport expenditure of households also includes the cost of vehicle ownership.

Other studies (Okyere *et al*., 2018; Choo & Mokhtarian, 2007; Mokhtarian & Tal, 2013) found positive or negative relationships between telecommunication and transport. In particular, Okyere *et al*., 2018 noted that ICT has helped developed countries to minimise travel time and expenditures, because its infrastructure has made possible interaction and interconnectivity between and across homes, office buildings and transportation systems. Choo and Mokhtarian (2007), however, reported a bidirectional relationship between telecommunication and transport, suggesting a reverse causality between them. Similarly, Mokhtarian and Tal (2013) found substitution and complementary relationships between telecommunication and transport, where decrease in price of one of the commodities, reduces the demand for the other, and where the demand curve for one commodity shifts to the right as consumers move downwards along the existing demand curve of the other.

Table 1 also indicates that a proportionate increase in the income of the households is expected to increase proportionately the participation in the transport fuel market as well as the consumption by households, conditional on participation in the transport fuel market. Similarly, it is expected that a proportionate increase in the household size would increase proportionately transport fuel market participation of households, while proportionately decreasing the level of transport fuel consumption, when the decision to participate is made by the households. The positive effect reflects the greater transport fuel expenditure associated with increase size of the households and their additional needs for mobility. Whereas the negative effects on consumption shows scale effects (Bardazzi & Pazienza, 2018), whereby larger households share traveling cost by sharing and pooling cars thereby reducing the component of private transport cost relative to smaller households.

While literature almost universally predicted that an aging population was responsible for reducing transport expenditure because the aged often stays at home for a larger portion of the day (Bardazzi & Pazienza, 2018), it is expected that age of the household heads will exert positive or negative effect on transport fuel market participation and consumption of households. This effect is expected because of the anticipated quadratic relationship between age and transport fuel expenditure. Thus, there is the tendency to be less active in social and economic space as one grows older, hampering fuel market participation and consumption decisions of household heads. It is also expected that location of households would have positive or negative influence on transport fuel market participation and consumption decisions of households, because location influences the distance people endure in their travels, which distance is a key determinant of transport fuel expenditure.

For example, it is expected that those households that are closer to economic centres would spend less on transport fuel, while those that live farther away would spend more. Although past research (Eakins, 2016) showed ambiguous differences in transport fuel expenditure between urban and rural areas, Bris *et al*. (2017) found a positive association between urbanization and transport expenditure due to more opportunities for activities provided in urban areas. Sex of the head of households is another important determinant of transport fuel expenditure decision of households. This is because of the different roles and responsibilities discharge towards livelihood generation and home management by men and women as heads of households. Anecdotally, women travel more compared to their counterpart; while male headed households tend to have the higher inclination to generate financial resources for the household compared to the female headed households.

This study, therefore, expected to establish a negative relationship between male headed households and transport fuel market participation and consumption decision. Evidence is also anticipated of life-cycle effect in market participation and consumption decision. Thus, the study expected that having household heads who are single, have no children, and have no aged member beyond the age of 64 years should have negative effect on market participation and positive or negative effect on the level of consumption (Table 1). The expected indeterminate effect on the level of consumption is based on the fact that depending on the occupation and location of the single adult household heads, their transport fuel expenditure could be high or less conditional on the probability of transport fuel market participation.

This study also controlled for level of education of head of the households to test for the effect of human capital on the probability of market participation and level of transport fuel expenditure. It is expected that household heads with higher level of education will have higher participation in the transport fuel market and level of consumption, conditional on market participation (Table 1). The trust is that highly literate household heads would be more receptive to technology use and also be more mobile than their counterparts who have no education. Higher levels of education also imply higher human capital and higher income of the household heads. The higher income generates higher trip rates and higher levels of participation in all activities including probability of participation in the transport fuel market for educated household heads relative to uneducated household heads.

Finally, as part of the control variables, this study assesses the effect of interaction of location of households with ICT expenditure on transport fuel expenditure. It is expected that probability of market participation and consumption decisions of households would increase otherwise with the joint presence of location and ICT expenditure of households. Thus, the study expected urban households who spend more or less on ICT to be less or more likely to participate in the fuel market, and also spend less or more on transport fuel, conditional on participation in the fuel market than rural households. The subsequent section of the analysis focuses on the summary statistics of the variables utilised in the study.

Summary Statistics of Variables used in the Study

The analysis of the summary statistics begins in Figure 2, which presents the percentage of households with zero TFE reported in the GLSS 3-7 datasets. Figure 2 demonstrates that more than two-fifths (43%) of the households in Ghana reported zero expenditure on transport fuel in 1991; and this figure (43%) declined to more than one-third (33%) in 2017. Although the drop appears to be substantial, the 1998 transport fuel expenditure revealed over one-quarter (26%) change in the zeros reported by the households. Recent studies (Adusah-Poku & Takeuchi, 2019; Eakins, 2016; Humphreys, 2013) have assigned a number of reasons to zeros in data. In particular, Humphreys (2013) noted three main reasons for zeros in data.

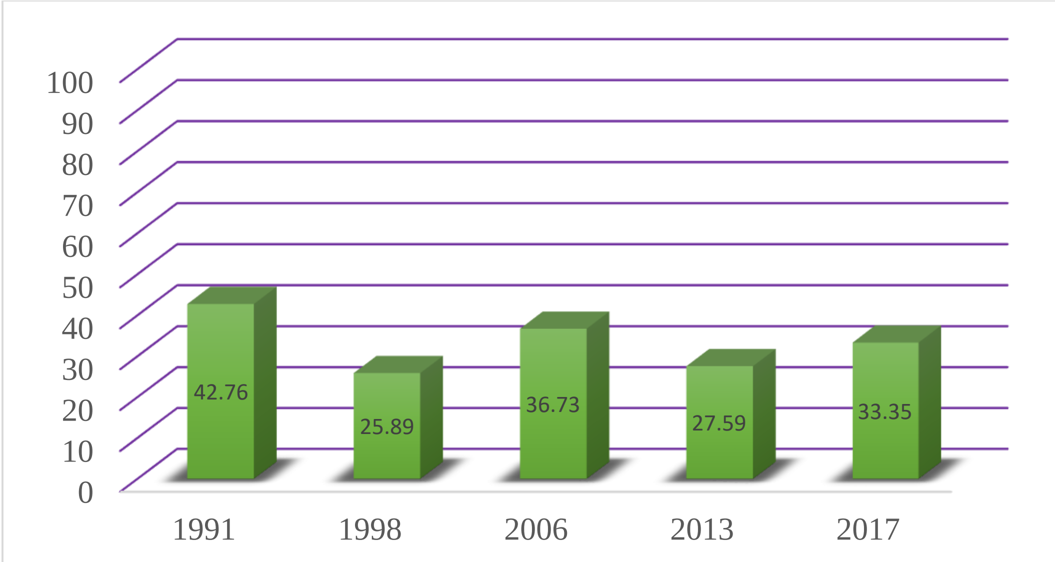


Figure 2: percentage of households with zero transport fuel expenditure, 1991-2017

Source: Fiagborlo (2019).

First, that the zeros may occur genuinely due to market constraints i.e., income and price. Second, that zeros may occur for some durable commodities resulting from their infrequent purchases. Finally, that the zeros are explained by other factors than infrequent demand and market constraints. While Adusah-Poku and Takeuchi (2019) disagreed with the first and second reasons, their recent paper affirmed the third reason of Humphreys (2013) that zeros are due to other factors than market constraints and infrequent purchase of commodities. It could be argued that transport fuel is durable and may not be consumed often. Some households may travel by walking to appreciate the aestheticism of the environment, while others may walk to derive health benefits. Again, advancement in ICT may make households not to travel often to access social and economic services. These may be the reasons for zero transport fuel expenditure for some households in this study.

Table 2a, b & c present the summary statistics of variables used in the study.

Concentrating on Table 2a, the average transport fuel expenditure of households in GLSS3/1991 was GH¢ 5.484. Interestingly, this figure had increased over the years with the mean transport fuel expenditure of households standing at GH¢ 14.856 in GLSS4/1998 (Table 2a). From Table 2a, the average income in GLSS3/1991 was GH¢ 61.300 and this had increased to GH¢ 362.096 in GLSS4/1998, while changing over the years up to 2017, when the new GLSS7 data was outdoored. For instance, even though in GLSS6/2006 (Table 2b) the income of households was GH¢ 8105.183, this had increased to about GH¢ 10441.27 from GLSS5 to GLSS7.

The average household size across all waves was about 4 persons per households. This can either have positive consequences on market participation and negative or positive effect on the level of transport fuel expenditure, conditional on market participation. This positive or negative effects on consumption is due to the predisposition of members to car-pool and share transport cost, resulting in scale effect (Bardazzi & Pazienza, 2018). The average ICT expenditure of households in 1991 was GH¢ 0.035; this rose to GH ¢ 287.452 in 2017, with an average minimum and maximum age of the household heads standing at 17 and 98 years, respectively.

While an average of 0.40 percent [(0.349+0.444)/2] of the households lived in urban areas against 0.60 percent of rural residents, majority (0.69 percent) of the heads of the households on average were men with 0.31 percent representing women. Moreover, there were also about 0.34 percent of the household heads who were single adult without children and have no members whose age was 64 years and above compared to household heads who were matrimonially engaged with children and adult members who are below 64 years across all waves (see Table 2).

Table 2a: Sample summary statistics, GLSS3 1990/1991 and GLSS4 1997/1998

GLSS3 1990/1991					GLSS4 1997/1998				
Variable	Mean	Std. Dev	Min.	Max.	Variable	Mean	Std. Dev	Min.	Max.
transport fuel expenditure	5.484	8.154	0	184.2069	transport fuel expenditure	14.85607	17.5013	0	325.9322
household income	61.29974	49.21281	1.5695	1000.239	household income	362.0956	475.671	6.387619	10228.74
household size	4.478655	2.831093	1	30	household size	4.403301	2.631292	1	21
household ICT expenditure	0.035383	0.409205	0	18.25	household ICT expenditure	0.98969	5.925171	0	141.4375
location of household	0.349	0.477	0	1	location of household	.3666222	.4819223	0	1
household location*ICT exp	0.023	0.385	0	18.25	household location*ICT exp	0.792493	5.608259	0	141.4375
age of household head	44.282	15.327	15	98	age of household head	45.82911	15.36921	18	98
agesq of household head	2195.787	1524.808	225	9604	agesq of household head	2336.481	1562.87	324	9604
sex of household head	0.678	0.467	0	1	sex of household head	.6637212	.4724749	0	1
single adult household	0.260	0.439	0	1	single adult household	.2652551	.4415057	0	1
basic education of h head	0.259	0.438	0	1	basic education of h head	.5295098	.49917	0	1
secondary education h head	0.348	0.476	0	1	secondary education h head	.0348449	.1834023	0	1
tertiary education h head	0.025	0.157	0	1	tertiary education h head	.0453484	.2080846	0	1

Source: Fiagborlo (2019).

Table 2b: Sample summary statistics, GLSS5 2005/2006 and GLSS6 2012/2013

GLSS5 2005/2006					GLSS6 2012/2013				
Variable	Mean	Std. Dev	Min.	Max.	Variable	Mean	Std. Dev	Min.	Max.
transport fuel expenditure	40.64904	159.5113	0	13776.98	transport fuel expenditure	91.00956	116.22	0	1506.47
household income	5672.09	109790.8	8	7302980	household income	8105.183	7582.376	31.2	146345.4
household size	4.276832	2.870468	1	29	household size	4.264429	2.783572	1	29
household ICT expenditure	565.8653	40209.49	0	3650380	household ICT expenditure	312.8615	515.601	0	15755.4
location of household	.4120644	.4120644	0	1	location of household	.4438946	.496857	0	1
household location*ICT_exp	459.9037	39278.44	0	3650380	household location*ICT_exp	203.5938	471.8215	0	15755.4
age of household head	45.35464	15.62679	15	98	age of household head	45.83884	15.89259	15	98
agesq of household head	2301.211	1591.147	225	9604	agesq of household head	2353.759	1640.027	225	9604
sex of household head	0.720736	.4486633	0	1	sex of household head	.718042	.4499664	0	1
single adult household	0.318282	.4658365	0	1	single adult household	.3175531	.4655384	0	1
basic education of h head	0.36622	.4817971	0	1	basic education of h head	.5327331	.4989423	0	1
secondary education h head	0.28633	.4520699	0	1	secondary education h head	.0815049	.2736171	0	1
tertiary education h head	0.05453	.2270792	0	1	tertiary education h head	.1015383	.3020492	0	1

Source: Fiagborlo (2019).

Table 2c: Sample summary statistics, GLSS7 2016/2017

Variable	Mean	Std. Dev	Min.	Max.
transport fuel expenditure	108.2657	138.6481	0	3820.995
household income	10441.27	10302.21	81.1	232614.7
household size	4.210165	2.865758	1	28
household ICT expenditure	287.4517	585.4764	0	30352
location of household	.4277039	.4947635	0	1
household location*ICTexp	188.5023	572.178	0	30352
age of household head	46.24682	15.91249	15	99
agesq of household head	2391.957	1636.375	225	9801
sex of household head	.6882591	.4632214	0	1
single adult household	.4237999	.4941773	0	1
basic education of h head	.5261712	.4993326	0	1
secondary education h head	.082345	.2749	0	1
tertiary education h head	.1182765	.3229469	0	1

Source: Fiagborlo (2019).

Collinearity Diagnostic Test

The previous section considered the distribution of variables used in this study. According to Garson (2013), multicollinearity creates issues of validity in econometric analysis. For instance, it affects the validity of the statistical tests by inflating the standard errors of the regression coefficients. Consequently, this section aims to ascertain the level of multicollinearity among the independent variables used in the model. Specifically, the tolerance value for each independent variable was estimated using multicollinearity diagnostic test. As a rule of thumb, higher variance inflation factor (VIF) value of more than 10 designates a problem of multicollinearity (Pallant, 2020). Therefore, whenever a variable has a tolerance value approaching zero, those variables ought to be dropped and utilised in Pearson's correlation analysis to test for significant relationship between the outcome variable as well as the independent variables (Cameron & Trivedi, 2010).

Table 3 reports the estimated variance inflation factor for the variables used in the Cragg's double hurdle model. In particular, Table 3 reports that all the independent variables passed the tolerant test and so the data did not violate the multicollinearity assumption. For example, the tolerance value of each independent

Table 3: Estimated variance inflation factors for the variables used in the Cragg's double hurdle model.

Variable	VIF	1/VIF
household income	1.49	0.6696
household size	2.66	0.3764
household ICT expenditure	1.50	0.6688
age of household head	1.18	0.8483
location of household	1.28	0.7790
sex of household head	1.12	0.8951
single2 adult household	2.34	0.4269
basic education of household head	1.65	0.6073
secondary education of household head	1.49	0.6790
tertiary education of household head	1.70	0.5895

Mean VIF=1.64

Source: Fiagborlo (2019).

variable ranges between 0.3764 and 0.8951, which exceeded the benchmark value of below 0.10 suggested by Pallant (2007). Although condition number was not included in this analysis, lack of multicollinearity among the independent variables was further confirmed by the overall mean VIF value of 1.64, which was also below the cut-off value of 10 (Adwere-Boamah,2011). Similarly, the likelihood-ratio test, following Schmidt and Lin (1984), is presented in the ensuing section of the study.

Likelihood-Ratio Test

What the likelihood-ratio test does is to compare the fit of two models. From equation (14) of Chapter Four, the test was meant to help choose the best model between two nested models with the ultimate goal of having a model that best fit our data. It is significant to explain that two models are nested when one is a special case of the other. The likelihood-ratio test tests whether Cragg's double hurdle model is significantly different from the Tobit model (Schmidt & Lin, 1984). The Tobit model is usually tested against Cragg’s model by estimating a probit, a truncated regression and a Tobit model (Greene, 2000) with the same independent variables and computing the likelihood ratio statistic. The null hypothesis is that the Tobit is appropriate for analysing the data. While the Tobit model is endorsed when the chi-square statistic is larger compared to Cragg’s double hurdle model, the Cragg’s double hurdle framework is selected if the null hypothesis is rejected.

But the use of chi-square statistics as a measure of fit has been criticised on the ground that when sample sizes are larger, it is much easier to accept or reject more complex model. Also, the chi-square test statistics are designed to detect any departure between a model and observed data. Consequently, likelihood-ratio tests often lead to the rejection of acceptable model because the models are less parsimonious than they ought to be. In this study, following Schwarz (1978), the Bayesian Information Criterion (BIC) was used to choose between the suitability of the Tobit and the Cragg's double hurdle models. The BIC assesses the overall fit of a model and allows for the comparison of both nested and non-nested models. While the Tobit model was assumed to be appropriate for analysing the data, the BIC statistic indicates that the Cragg's double hurdle model is more appropriate for the data as the BIC is smaller for the Cragg's double hurdle relative to the Tobit's.

Appendix A reports the Akaike's information criterion (AIC) and the BIC statistics. Appendix A also considered the log-likelihoods that helps determined the optimal iterative values of the estimated coefficients in the double hurdle models. The BIC statistic is described by Stata as $BIC_{stata} = DEV_m + \ln(N)*P$. Where P is the number of parameters estimated (including the constant), N is the number of observations and DEV_m is the deviance of the model. The succeeding subsection of the chapter discusses the results of the empirical maximum likelihood estimations of the Cragg's double hurdle regression model for the effect of ICT expenditure on the transport fuel market participation and consumption decisions of households.

Maximum Likelihood Estimates of the Cragg's Double Hurdle Model

The results of the econometric estimation of the Cragg's double hurdle model are discussed in this subsection. Granted that only non-economic factors influence market participation decisions of households, this study excluded income from the market participation equation (35.1), but included it in the consumption equation (35.2). This helps ascertain the effect of income on transport fuel expenditure, conditional on transport fuel market participation of households. To make easy comparison of the estimated elasticities across waves, this study used same explanatory variables in the market participation and consumption equations.

The Cragg's double hurdle model was estimated by maximising the logarithm of likelihood function. Appendix B presents the results of the maximum likelihood parameter estimates for the Cragg's double hurdle model for transport fuel expenditure of households. For the participation and consumption equations, the analysis started with normalized income, normalized household size, normalized household mean ICT expenditure, age of the head of household measured in years. The dummy variables are location of household head, sex of household head, whether household head is a single adult without children or without adult member 64 years and above, level of education of household head and interaction between location of households as well as mean ICT expenditure.

The results reveal some unique features of the parameter estimates in this study. These features are the conflicting effects of the independent variables on the dependent variable. For instance, normalized household size, normalized household mean ICT expenditure of households, location of households, interaction between location of household and mean telecommunication expenditure of households, and sex of household heads have all had conflicting signs in participation and the consumption equations across the GLSS3-GLSS7. Although some variables have the same signs, age of household heads and being single adult without children and without adult member 64 years and above, are significant only in the consumption equation but not in the participation equation (see Appendix B).

These conflicting effects of the independent variables disguise the effects of the independent variables on the probability of participation and consumption, conditional and unconditional on participation in the transport fuel market. Obviously, this makes the effects of these variables more complicated to be handled with Tobit model. This further reaffirms our resolve to employ the Cragg's double hurdle model in this study (Adusah-Poku & Takeuchi, 2019; Ibrahim & Srinivasan, 2013). Appendix B reveals the effect and significance of the rest of the independent variables on market participation and consumption of transport fuel in this study.

For example, Appendix B shows that the coefficients of income in the consumption equation are positive and significant at 1 percent across all waves of data. These results show that transport fuel consumption expenditure of households increases with income, indicating that transport fuel is a normal good. But whether transport fuel demand is a necessary or luxurious goods depends on income elasticities, which are assessed subsequently in this study. For all waves (GLSS3-GLSS7), household size has a positive and significant effect on transport fuel market participation of households, except for GLSS5 and GLSS7 where the result is not significant. This result implies that larger households are more likely to participate in transport fuel market. Deaton and Paxson (1998) and Eakins (2016) found similar relation between household size and food and transport expenditures.

Regarding consumption equation, the results show a significant negative coefficient of household size at 5 percent and 1 percent levels for GLSS3 and

GLSS7, respectively. Whereas, the analysis shows a significant positive coefficient of household size at 10 percent level only for GLSS5. The results show that while an additional person to the household decreases the conditional consumption of transport fuel for households in GLSS3 and GLSS7, it increases the conditional consumption of transport fuel in GLSS5. While the reduction in the conditional consumption of transport fuel in GLSS3 and GLSS7 may be due to joint travel decision and spread of travel cost amongst members, it appears an additional member to the household may raise average travel fuel cost relative to GLSS4,5&6.

ICT has the potential to reduce mobility of households as it offers opportunity for people to conduct some remote activities online (Aguiléra *et al.*, 2012; Bris *et al.*, 2017). Appendix B reports a negative coefficient of ICT expenditure of households in the participation equation for GLSS3, confirming that a rise in ICT expenditure decreases participation in the transport fuel market. Nonetheless, the results are positive and significant at 1 percent for GLSS4-GLSS7, implying that an increase in ICT expenditure increases the probability of participation in the transport fuel market for households. The results confirm intuition and existing literature (Bris *et al.*, 2017; Choo & Mokhtarian, 2007; Mokhtarian & Tal, 2013; Okyere *et al.*, 2018). In particular, Mokhtarian and Tal, 2013 highlighted the complex roles of ICT noting that a net outcome of travel substitution or complementarity results from multiple impacts of ICT expenditure.

For location variable, the coefficient is positive and significant in the participation equation for all waves, except for GLSS6 and GLSS7 where the coefficient is not significant. This reveals that transport fuel market participation of urban households is more likely to be higher than that of the rural households. This result consistently agrees with the expectation and the finding of Bris *et al.*(2017). Regarding consumption equation, the coefficient for location variable is negative and significant for GLSS3,6&7. However, except for GLSS5 where the coefficient for location variable is negatively insignificant, the coefficient is significantly positive for GLSS4.The implication of the result is that conditional transport fuel expenditure declines for being in urban households than being in rural households, except for GLSS4 where the coefficient is significantly positive. This result is consistent with the expectation and also confirms the finding of Bris *et al*.(2017).

For interaction between location and ICT expenditure of households, the coefficients show conflicting signs for all the waves in the participation equations. For instance, while the coefficients in the participation equation are statistically significant for GLSS5 and GLSS7, respectively, they are not significant for GLSS3, GLSS4 and GLSS6. Appendix B reveals a negative coefficient of the interaction term for GLSS5, implying that transport fuel market participation decreases for urban households than rural households, given ICT expenditure of households. However, the positive coefficient for the interaction term for GLSS7 implies that transport fuel market participation increases for urban households compared to being in rural households, given ICT expenditure of households. The results show that though ICT reduces mobility (Bris *et al*., 2017), its influence on participation differs in the transport fuel market for urban households than rural households. The finding of Eakins (2016) has remained protected by the conclusion from this study.

Focusing on the consumption equations, the results show positive and statistically significant coefficients on the interaction term across GLSS5, GLSS6 and GLSS7, respectively. However, the coefficient is statistically negative at 10 percent level of significant for GLSS3. These results show that for GLSS5,6&7, transport fuel expenditure of households increases for being in urban households compared to being in rural households, given ICT expenditure of households. However, for GLSS3, the result suggests that transport fuel consumption expenditure declines for urban households compared to rural households, given ICT expenditure. The implication of these findings is that ICT expenditure widens transport fuel expenditure gap between urban and rural residence in the case of GLSS5, GLSS6 and GLSS7, but the opposite effect is observed relative to GLSS3.

Differentiating equations (35.1 & 35.2) with respect to age of the household heads and substituting for their coefficients highlight the quadratic effects. From Appendix B, the probability of transport fuel market participation decisions of household heads optimised at ages 37 years, 44 years, 45 years, 53 years and 52 years, respectively, for all the waves in the GLSS data. Thus, household heads are less likely to participate in the transport fuel market after the ages 37 years, 44 years, 45 years, 53 years, and 52 years across GLSS3-GLSS7. A significant relationship (1 percent-10 percent) between age square and transport fuel expenditure of households has been established across all waves, indicating parabolic relationship between consumption as well as age of the household heads.

The finding implies that the older the household heads, the higher their level of transport fuel consumption to meet increasing economic and social opportunities than the younger household heads. However, the level of transport fuel expenditure starts decreasing after the household heads attain certain age due to the decline in economic and social opportunities. Again, from Appendix B the result shows that the parabolic curve peaks in the consumption equation at ages 51 and 33, respectively. This suggests that beyond ages 51 and 33 of the head of households, their level of transport fuel consumption will decline, considering the GLSS3 and GLSS7. This result is consistent with the study of Bardazzi and Pazienza (2018).

Relative to the life-cycle effect, the results reflect a positive life-cycle effect on the participation equation when the household heads are single adult without a child or an adult 64 years and above than married household heads with a child and an adult less than 64 years for GLSS3 and GLSS4, except for GLSS5-GLSS7 where the result shows a negative life-cycle effect. It is also noted that the life-cycle effect on the participation equation is only significant for GLSS5. Nonetheless, the result implies that a single adult household heads without a child or an adult 64 years and above were more or less likely to participate in the transport fuel market in the GLSS3/GLSS4 and GLSS5-GLSS7, respectively, compared to their counterparts with different characterisation. The result shows that whether the household heads are single adult without a child or without adults 64 years and above, the influence on transport fuel consumption is positive and significant across the entire waves.

Results from the participation equation show a negative coefficient for sex of household heads, indicating that male-headed households are less likely to participate in the transport fuel market than female-headed households. The consumption equation, however, shows positive coefficients for sex of household head across all waves, indicating that level of consumption of transport fuel increases with male-headed than female-headed households. The difference in their participation and consumption decisions could be explained by their gendered roles and difference in their travel patterns. Women travel often than their male counterparts using public transport (Elias, Benjamin & Shiftan, 2015), and as such show desires to participate in the transport fuel market than their male counterparts.

In the consumption equation, the result agrees with the intuition that male-headed households tend to spend more on transport fuel than female-headed households, because men tend to have inclination to generate financial resources for the family. What is not clear is whether the differences in the results for the participation and consumption decisions are solely due to differences in gendered role, or are there other latent characteristics? While the answer to this question is beyond this chapter, the third objective of this study attempts to assess how the effect of ICT expenditure on transport fuel intensity differentiates demographic (sex) attribute of household heads, using disaggregated data from Ghanaian society.

Finally, the coefficients of the level of education for household heads are positive and significant at 1 percent for all waves in the participation equation, demonstrating that probability of transport fuel market participation increases with the level of education. Particularly, the results show that as household heads move from basic to tertiary levels of education, the probability of transport fuel market participation increases for all waves. Appendix B reports that conditional transport fuel consumption of households positively and significantly increases with level of education of household heads. Intuitively, education implicates higher income, which generates higher trip rates and higher levels of participation in all activities including transport fuel market participation. Hence, the result suggests that level of education of head of households is imperative in transport fuel market participation decisions. The subsequent subsection discusses the elasticities of the explanatory variables over time in the participation and consumption equations.

Marginal Effect

In the previous section, the parameter estimates of the Cragg's double hurdle model provided no information than statistical significance and the sign of the influence for each explanatory variable. This section discusses the elasticities of the explanatory variables over time in the participation and consumption equations. For continuous explanatory variables, the elasticities or marginal effects were calculated at the sample means. While for the discrete or categorical variables, the effects were calculated as percentage changes in the dependent variable when it shifts from zero to one, holding other independent variables equal. Following Eakins (2016), the effects of the explanatory variables were decomposed into effect on the probability of transport fuel market participation, effect on transport fuel expenditure, conditional and unconditional on transport fuel market participation, and differentiated these components with respect to every explanatory variables.

It is instructive to note that the effect on the probability of participation indicates how a variable affects the likelihood (probability) to participate in transport fuel market, while the conditional marginal effect or elasticity measures how a variable affects the transport fuel expenditure of the households, conditional on participation (i.e., given that a decision has been made to participate in the transport fuel market). Also, the unconditional marginal effect or elasticity indicates the overall responsiveness of transport fuel expenditure to a change in a variable of the households. The significance levels of these elasticities and discrete effects are also based on the significance levels of their underlying marginal effects.

Appendix C presents the elasticity estimates of the explanatory variables and their associated standard errors and shows the breakdown of the estimates into probability of participation (EPP), conditional (ECP) and unconditional (EUCp) estimates, respectively, for the Cragg's double hurdle model. These elasticities help measure the effects of the explanatory variables on transport fuel expenditure. For purposes of simple representation, figures are used to show the elasticities effects of the various independent variables on transport fuel expenditure in this analysis. The comparison of the estimated elasticities (EPP, ECP and EUCp) across every waves was made possible because these elasticity estimates are proportional change in the dependent variable. The next section considers the elasticities of income on probability of transport fuel market participation and transport fuel expenditure, conditional and unconditional on the level of participation in transport fuel market.

Income and Transport Fuel Expenditure

First, since income was excluded from the participation equation, the result show that the extent of probability of transport fuel market participation is zero. Figure 3 reports income elasticities on the level of transport fuel expenditure, conditional and unconditional on transport fuel market participation. The degree of responsiveness of transport fuel expenditure to income, conditional and unconditional on transport fuel market participation is positive and statistically significant at 1 percent levels across all waves (see Appendix C). In Figure 3, the level of transport fuel expenditure increases positively with the level of income.

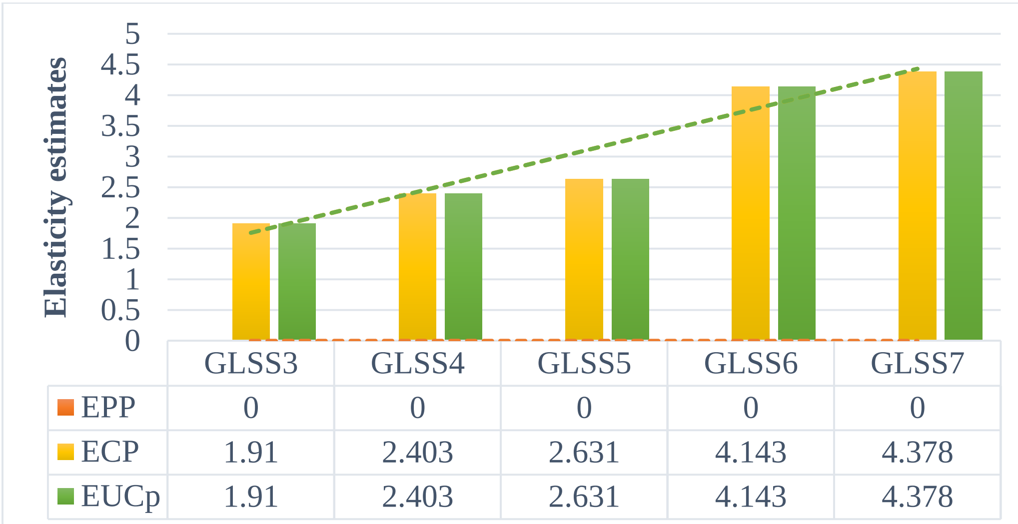


Figure 3: Effect of income on transport fuel expenditure (1991-2017

Source: Fiagborlo (2019).

For instance, the income elasticity estimates on ECP and EUCp of level of transport fuel expenditure in respect of each wave are 1.910, 2.403, 2.631, 4.143 and 4.378. This implies that transport fuel expenditure, conditional and unconditional on participation in transport fuel market, is income elastic across all wave. Therefore, a 100 percent increase in income will cause the level of transport fuel expenditure, conditional and unconditional on transport fuel market participation to increase by more than 100 percent in respect of each wave, say, 1.91 percent, 2.40 percent, 2.63 percent, 4.14 percent, and 4.38 percent. The result is a testament that transport fuel is a normal good for all households considered in this study, reflecting the expectations of this study and previous finding of Eakins

(2016; 2011). This suggests that income is an economic variable that influences taste and preferences of people and mainly their level of transport fuel expenditures.

Household Size and Transport Fuel Expenditure

From the analysis, estimated elasticities of participation and consumption to household size are positive and significant across all waves (see Appendix C). However, the study reveals negative elasticity estimates of participation and consumption to household size for households considered in GLSS3 and GLSS7, respectively. Furthermore, there was no evidence of statistical significance for conditional elasticity and elasticity of probability of transport fuel market participation in GLSS4, GLSS6 and GLSS5, respectively (see Appendix C). The results imply that elasticity estimates of probability of participation and overall level of transport fuel expenditure increase significantly with household size for each wave. Whereas, conditional and unconditional on participation in the transport fuel market, the elasticity estimates of the level of transport fuel expenditure reduce significantly with the household size variable in GLSS3 and GLSS7, respectively.

Figure 4 reports effect of household size on participation and consumption of transport fuel. Mainly, Figure 4 reveals that elasticity estimates of participation in the transport market for household size are 0.179, 0.089, 0.018, 0.050 and 0.014, respectively. While, conditional and unconditional on participation in the transport fuel market, the elasticity estimates for household size are -0.070, 0.108, 0.0267, 0.116, 0.052, 0.070, 0.013, -0.064 and -0.050, respectively. Considering GLSS3, these results demonstrate that a 100 percent rise in the size of households increases

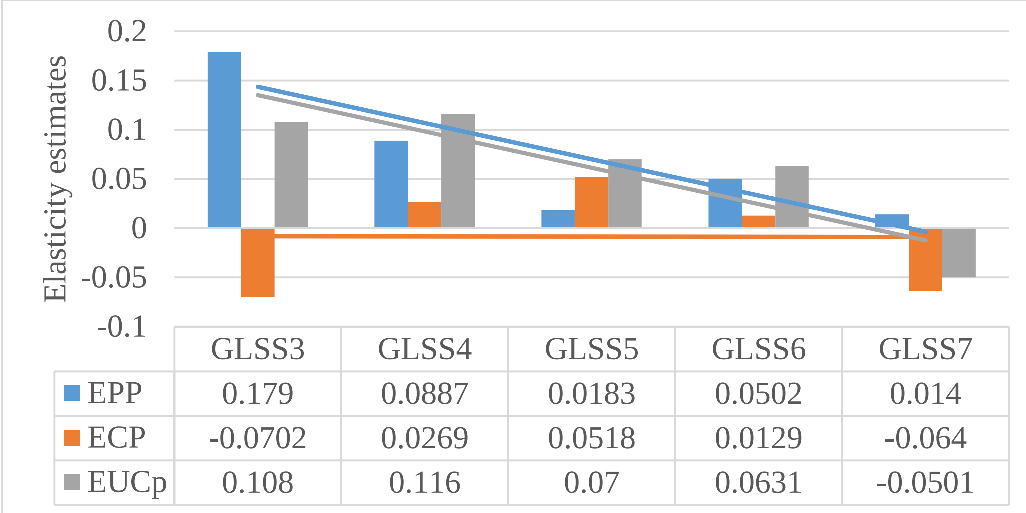


Figure 4: Effect of household size on transport fuel expenditure (1991-2017)

Source: Fiagborlo (2019).

the probability of transport fuel market participation by 0.179 percent, decreases transport fuel consumption of households by 0.070 percent, conditional on fuel market participation, while increasing the unconditional level of transport fuel consumption of households in transport fuel market by degree of 0.108 percent.

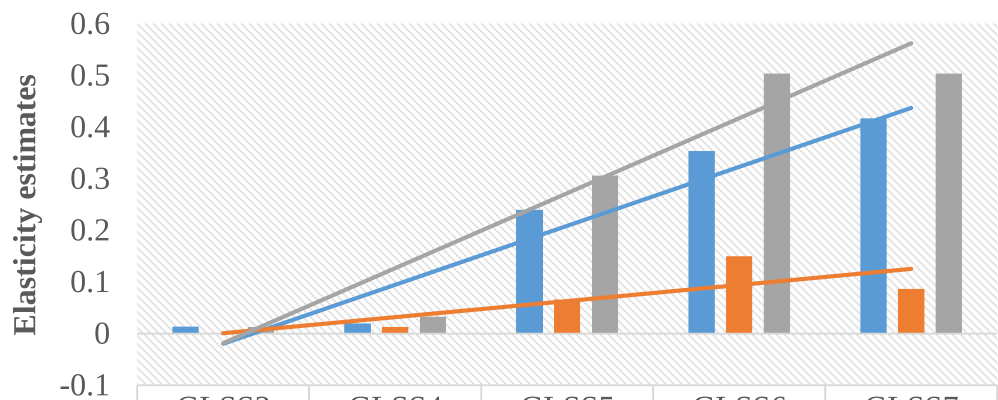
To further ascertain the effect of household size on transport fuel expenditure, the elasticity estimates (EPP, ECP and EUCp) were compared across all waves. In Figure 4, the results show that the impacts of household size on probability of participation (EPP) and unconditional intensity of transport fuel consumption (EUCp) have declined from 18 percent and 11 percent to 1 percent and -5 percent, respectively, over time across all waves. This outcome shows that even though probability of participation (EPP) and overall level of transport fuel consumption unconditional on transport fuel market participation (EUCp) increase with household size in respect of each wave, these effects diminish over time with the rate of decline in level of transport fuel consumption unconditional on transport fuel market participation (EUCp) outstripping the former (EPP) across all waves.

Interestingly, the sharper decline in the overall levels of the transport fuel expenditure than the probability of participation could be explained by the fairly constant conditional consumption of transport fuel by households over time. Other plausible reason for these outcomes is that as the household size increases over time due to population dynamics, members of the households might most likely make joint decision to travel, in which case, they might share cars and the cost of travel. This might have resulted in the decline of the decision to participate in the fuel market and unconditional level of transport fuel market participation of households over time, other things being equal. The result is consistent with the existing literature about the relationship between household size and transport fuel expenditure (Bardazzi & Pazienza, 2018; Eakins, 2016; Deaton & Paxson, 1998).

ICT and Transport Fuel Expenditure

One of the objectives of this study was to analyse the effect of ICT expenditure on transport fuel market participation and consumption decisions of households. This subsection presents the results of the effect of ICT on transport fuel market participation and consumption decisions of households. Appendix C shows that conditional elasticity is negative and significant for ICT expenditure variable in GLSS3, while both probability and unconditional elasticities are positive and significant for the ICT expenditure for each wave. The positive elasticity of participation and unconditional elasticity appear strange. However, this reflects a case where households with less access to ICT spend more on transport fuel than those with more access, regardless of fuel market participation decision.

Figure 5 reports the comparison of the elasticity estimates (EPP, ECP and EUCp) for the impacts of ICT expenditure across all waves. In respect of GLSS3,



	GLSS3	GLSS4	GLSS5	GLSS6	GLSS7
EPP	0.0135	0.0197	0.24	0.354	0.417
ECP	-0.000458	0.0132	0.0665	0.15	0.0865
EUCp	0.013	0.0329	0.306	0.504	0.504

Figure 5: Effect of ICT expenditure on transport fuel expenditure (1991-2017)

Source: Fiagborlo (2019).

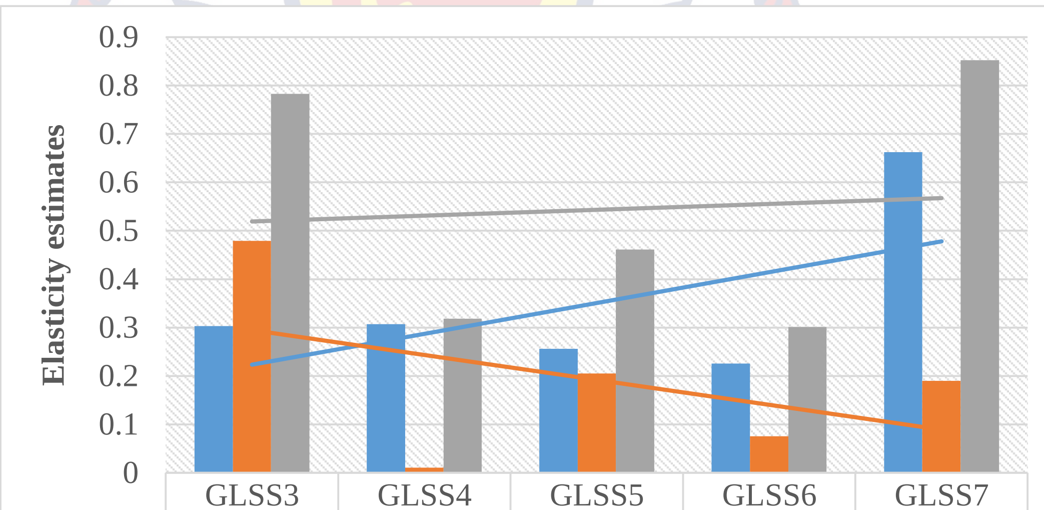
Figure 5 reveals that a proportionate increase in ICT expenditure significantly reduces the levels of transport fuel expenditure conditional on participation in the transport fuel market (ECP). However, these decreasing conditional elasticities have been dominated by the positive elasticity of probability on participation in the transport fuel market (EPP), culminating into positive overall effects on the level of transport fuel expenditure, unconditional on participation in the transport fuel market (EUCp) across all waves. For instance, the result shows that a proportionate increase in ICT expenditure proportionately increases the overall level of transport fuel expenditure significantly unconditional at 1 percent level on participation in the transport fuel market for households in each wave, all other things being equal.

It is expected that on average, ICT expenditure would have both positive or diminutive effect on both participation decision and level of consumption of transport fuel, conditional or unconditional on participation in the transport fuel market. As already noted, ICT has the potential to reduce mobility of households; ICT offers opportunity for people to conduct some activities remotely online (Bris *et al.*, 2017). It may create awareness of the less expensive choices among destinations, modes, routes and time of day. This may reduce travel costs of households. Thus, the negative conditional elasticity estimate for ICT variable, in respect of GLSS3, is deemed to confirm expectation. However, the results reveal positive and statistically significant elasticity estimates for ICT expenditure variable for each wave, implying increasing effect of ICT expenditure on participation, conditional and unconditional on transport fuel market participation.

While the negative conditional elasticity estimate for ICT variable confirms expectation and the finding of Bris *et al*, (2017), the results generally suggest substitution and complementary relationships between ICT and transport fuel expenditure, corroborating existing studies (Okyere *et al.*, 2018; Mokhtarian & Tal, 2013; Choo & Mokhtarian, 2007) that found similar results. It is expected that these findings will highlight the need to pay a closer attention to the cost of ICT and its ramification for associated economic burden for transport expenditure; and provide support for the need for maintaining cheaper digitisation among the top policy measures aimed at improving social welfare of households in Ghana. This may, however, require a more longitudinal analysis of the relationship between ICT expenditure and transport fuel expenditure, which does not have space in this thesis.

Age and Transport Fuel Expenditure

This part of the study focuses on the effect of age on transport fuel market participation and consumption decision of households. Figures 6 and 7 show the comparison of the elasticity estimates (EPP, ECP and EUCp) for age across all waves. The results show that age of household heads has quadratic effects on transport fuel expenditure across all waves. Thus, age elasticities of household heads are positive (Figure 6) and negative (Figure 7) for probability of participation, conditional and unconditional level of transport fuel expenditure, suggesting that conditional on transport fuel market participation, as household heads age, their transport fuel expenditure increases and declines later, all other things being equal.

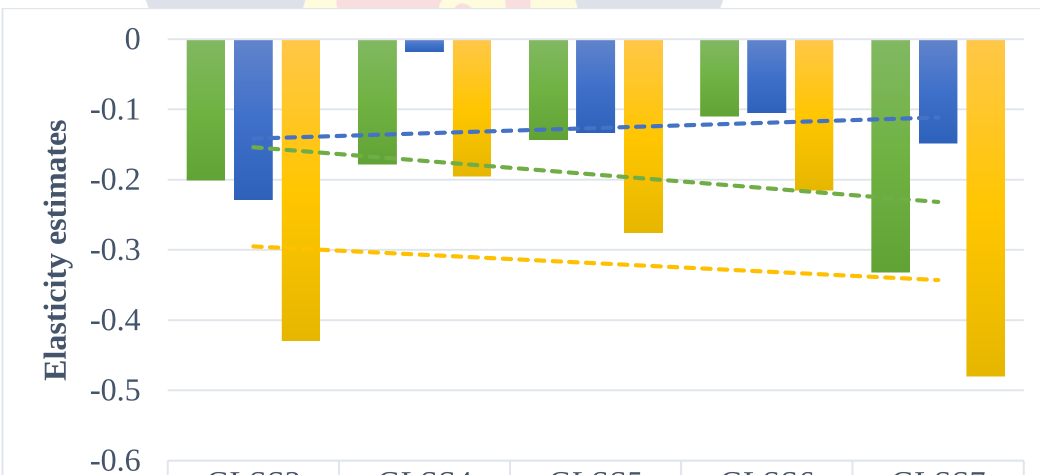


	GLSS3	GLSS4	GLSS5	GLSS6	GLSS7
EPP	0.303	0.307	0.256	0.226	0.662
ECP	0.479	0.0109	0.205	0.0755	0.19
EUCp	0.783	0.318	0.461	0.301	0.852

Figure 6: Effect of age of HoH on transport fuel expenditure (1991-2017)

Source: Fiagborlo (2019).

Specifically, Figure 6 reveals that a proportionate increase in the age of the head of the households insignificantly proportionately increases the probability of participation in the transport fuel market by 30 percent in respect of GLSS3. But, this effect only significantly reduces proportionately the probability of participation in the fuel market by 20 percent beyond 51 years of age (Figure 7). Regarding the level of transport fuel consumption (ECP), the result shows that a proportionate increase in the age of household heads increases conditional level of transport fuel expenditure by 48 percent (Figure 6). This, however, decreases by 23 percent after 33 years of age of the household heads, in respect of GLSS3 (Figure7), other things being equal. These inverse outcomes might be owing to the fact that economic and social needs of older household heads start waning after a certain age in their lives, reducing their mobility needs and transport fuel expenditure, all else being equal.



	GLSS3	GLSS4	GLSS5	GLSS6	GLSS7
EPP	-0.201	-0.178	-0.143	-0.11	-0.332
ECP	-0.229	-0.0178	-0.133	-0.105	-0.148
EUCp	-0.43	-0.195	-0.276	-0.215	-0.48

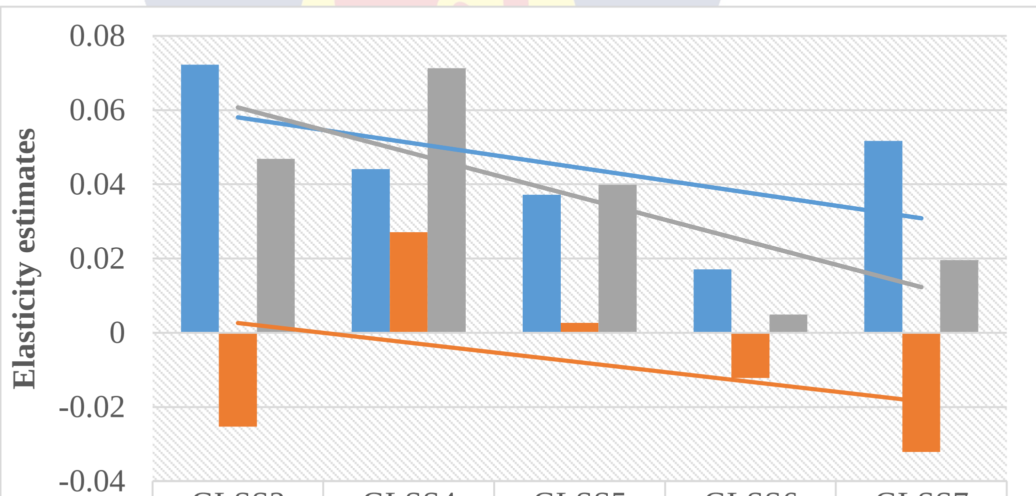
Figure 7: Effect of Agesq of HoH on transport fuel expenditure (1991-2017)

Source: Fiagborlo (2019).

While readers are urged to consult Appendix C for the rests of the effects of a proportionate change in the age of household heads and its elasticities effects on participation and consumption for each of the GLSS data used in this analysis, it is emphasised that previous study (Bardazzi & Pazienza, 2018) predicted increasing effect of aging on transport expenditure as the aged often stays at home for a larger portion of the day. The finding in this study does not depart from the previous study.

Location and Transport Fuel Expenditure

Location influences the distance people endure in their travels and ultimately influences their transport fuel expenditure. This subsection considers the effect of urbanisation on participation and consumption of transport fuel. Figure 8 shows the urban effect on participation and consumption of transport fuel. It was



	GLSS3	GLSS4	GLSS5	GLSS6	GLSS7
EPP	0.0722	0.0441	0.0372	0.0171	0.0517
ECP	-0.0253	0.0271	0.00265	-0.0122	-0.0321
EUCp	0.0469	0.0713	0.0399	0.0049	0.0196

Figure 8: Urban effect on participation and consumption of transport fuel

Source: Fiagborlo (2019).

expected that location of households would influence transport fuel market participation and consumption decisions either positively or negatively. From Figure 8, this study observes that the elasticity on probability of participation (EPP) and overall level of transport fuel expenditure (EUCp), unconditional on participation for location variable over time is positive and significant for all waves. This advocates that dwelling in urban areas by households significantly increases participation and overall level of transport fuel expenditure of households, unconditional on participation in transport fuel market compared to rural dwelling.

Regarding conditional elasticities (ECP), the result shows significant urban effects for urban households than rural households (Appendix C). For instance, the result shows decreasing transport fuel expenditure, conditional on transport fuel market participation among urban households than rural households in respect of GLSS3, GLSS6 and GLSS7. But, the urban effect is positive and significant conditionally on transport fuel market participation among households dwelling in urban area compared to households dwelling in rural area in respect of GLSS4 and GLSS5 (Appendix C). Comparing the elasticities (EPP, ECP and EUCp) across all waves (Figure 8), this study reveals that moving into urban area from rural area has a waning urban effect on transport fuel expenditure across waves.This urban elasticity effect on transport fuel expendtire perhaps is because living in urban than rural areas promotes access to jobs and socioeconomic services without traveling.

The decrease in the size of the elasticity (EPP, ECP and EUCp) of the urban variable across all waves could also be hypothetically attributed to improved dualisation on some urban corridors, which ensures efficient travel time and economies of fuel usage resulting in the decline in transport fuel expenditure among urban commuters than rural ones. Interestingly, the analysis demonstrates that dwelling in urban area does not only decrease unconditionally total expenditure on transport fuel among urban households relative to the reference category over time, but also the elasticity estimates on probability of participation as well as level of transport fuel expenditure, conditional on participation in transport fuel market.

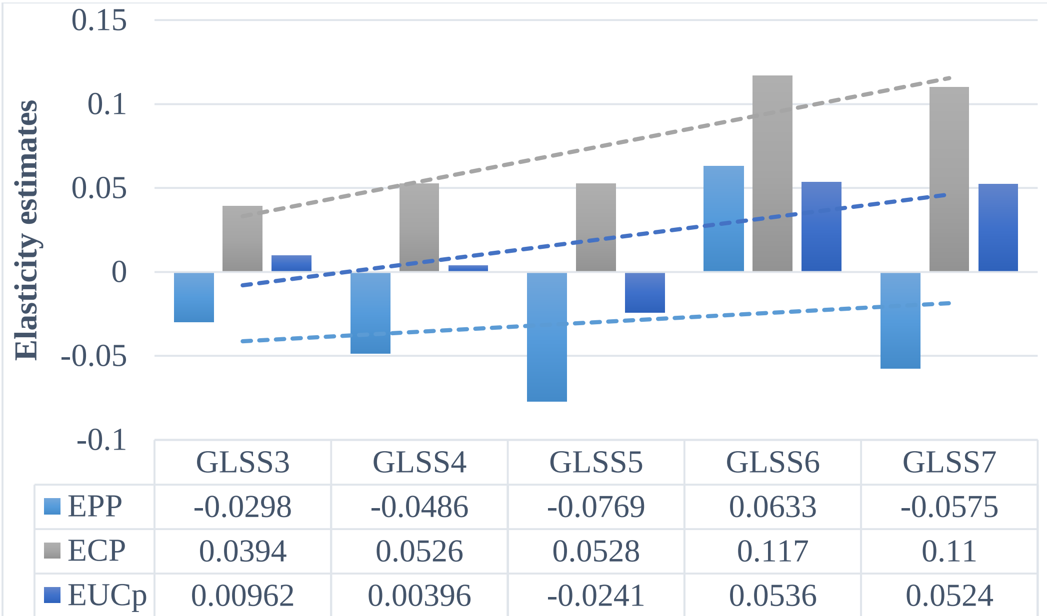
In particular, this study indicates that while elasticity estimates on probability of participation decreases on average about 4 percent over time for households dwelling in urban areas compared to rural dwellers, conditional on participation in the transport fuel market, the urban effect on the level of transport fuel demand decreases on average about 2 percent for households dwelling in urban areas compared to those dwelling in rural areas. This indicates that even though urbanisation has a diminishing effects over time on probability of participation and transport fuel demand, conditional on participation in transport fuel market, the decreasing urban effect is higher for the later than the former, and the overall level of transport fuel expenditure, unconditional on participation in transport market.

Generally, the results imply that dwelling in urban areas increases the probability of participation and level of transport fuel expenditure, unconditional on transport fuel market participation among urban households than rural households, in respect of each sample used. Clearly, conditional on transport fuel market participation, the level of expenditure on transport fuel declines in respect of GGLSS3, GLSS6 and GLSS7 for households dwelling in urban areas than rural areas. However, the results show increases in transport fuel consumption for households living in urban areas than those in rural areas in respect of GLSS4&5. The result reveals the importance of location in determining market participation and consumption decision of urban households versus rural households in Ghana.

The trend in the elasticity estimates over time also show that probability of participation in transport fuel market, level of consumption as well as overall transport fuel expenditure have become less and less for urban households than rural households. This, therefore, has implication for urban planning policies in terms of transport infrastructure, housing and distribution of socioeconomic service centres as these may influence choice of travel modes, participation and level of transport fuel expenditure, conditional and unconditional on participation in the transport fuel market. Of course, the outcome of this study is consistent with expectation and findings of some existing studies that similarly found association between urbanisation and transport expenditure (Bris *et al.*, 2017; Eakins, 2016).

Sex and Transport Fuel Expenditure

The different roles and responsibilities discharge towards livelihood generation and home management by men and women as heads of households tend to have implication for their transport fuel expenditure decision. Figure 9 presents the effect of sex on market participation and consumption of transport fuel. Based on anecdotal evidence, this study expected a negative relationship between male-headed households and transport fuel market participation and consumption decision compared to female-headed households. From Figure 9, the result shows that sex of household heads has negative effects on the probability of transport fuel



	GLSS3	GLSS4	GLSS5	GLSS6	GLSS7
EPP	-0.0298	-0.0486	-0.0769	0.0633	-0.0575
ECP	0.0394	0.0526	0.0528	0.117	0.11
EUCp	0.00962	0.00396	-0.0241	0.0536	0.0524

Figure 9: Effect of male HoH on transport fuel expenditure (1991-2017)

Source: Fiagborlo (2019).

market participation (EPP) in respect of GLSS3, GLSS4, GLSS5 and GLSS7, except for GLSS6. However, the result shows positive conditional (ECP) and unconditional (EUCp) effects on participation in the fuel market, except for the case of unconditional (EUCp) where sex has negative consequence in respect of GLSS5.

This outcome implies that male-headed households are virtually less likely to participate in the transport fuel market, but once the decision to participate has been made, their transport fuel expenditure increases more than female-headed households. This is evidenced across all waves, except for GLSS5, where regardless of the decision to participate in the transport fuel market, the overall transport fuel expenditure of male-headed households tends to reduce compared to female-headed households. The result further heightens the need to employ an appropriate technique in analysing the effect of sex on transport fuel expenditure.

This is because sex is seen to exert conflicting effects on participation as well as consumption decisions, conditional on participation in the transport fuel market.

Additionally, the elasticity estimates (EPP, ECP and EUCp) were compared across all waves over time for the variable male head of households. Figure 9 reveals a trend in the elasticity esimates, showing values that are moving in the same direction with ECP on average increasing in size over time more than EPP and EUCp, respectively. Specifically, the evidence shows that the ECP for male-headed households is proportionately greater on transport fuel expenditure in respect of GLSS7 relative to GLSS3 than EPP and EUCp. This implies that male-headed households over time have increasing transport fuel consumption, given participation in the transport fuel market against the probability of participation in the marlet and unconditional level of transport fuel than fenale-headed households.

The result shows that even though within GLSS6 male-headed households have a positve elasticity estimates on ptobabiltiy of participation (EPP), these estimates show an increasing negative impact over time, indicating that male-headed households have a decreasing degree of probability of participation in the transport fuel market than female-headed ones. What is more interesting, moreover, is that the aggregate elasticity estimates (EPP and ECP) over time give rise to moderately increasing proportional effects on the overall transport fuel expenditure, unconditional on particiaption in the transport fuel market (EUCp). The EUCp is clearly sandwiched between EPP and ECP (Figure 9). In other words, the results show that even though transport fuel consumption over time intensifies for male household heads, the proportional increase in unconditional transport fuel expenditure is relatively lesser than conditional level of transport fuel expenditure.

The result implies that actual transport fuel expenditure is higher than total expenditure on transport fuel expenditure and the probability of participation in the transport fuel market for male-headed households than female-headed households. The decrecrasing proportional probability of participation in the transport fuel market for male-headed households is likely as fuel may be infrequently purchased, while women were found to travel often than their male counterparts with bus and may show more interest in the transport fuel market. However, the proportional rise in the levels of transport fuel expenditure, conditional and unconditional on transport fuel market participation may intuitively depend on the inclination of male-headed households to frequently move to work in order to generate financial resources to keep up their family. This may have explained the rising transport fuel expenditure for male-headed households relative to the female-headed households.

Karimu, Mensah and Adu (2016) also found evidence that female-headed households in Ghana were more likely to adopt LPG than male-headed households. They opined that the negative relationship reflects the differences in the decision making by female-headed and male-headed households in terms of preferences, welfare, and opportunity cost of time. These findings also sync with the results of Adusah-Poku and Takeuchi (2019), who found that having male-headed household decreases the probability of participating in the LPG market. What is not clear in the case of this thesis is whether the differences in the effects on the probability of participation and level of transport fuel expenditure, conditional and unconditional on participation in the transport fuel market are solely attributable to gendered role, or there are additional latent socioeconomic explanations? Subsequently, Chapter Eight of this study endeavours to provide some empirical answers to this question.

Life-Cycle and Transport Fuel Expenditure

This subsection looks at the life-cycle effect on transport fuel market participation and consumption decisions of households in Ghana. It was anticipated that having household heads who are single, have no children, and have no aged member beyond 64 years should have negative effect on transport fuel market participation and positive or negative effect on the level of transport fuel consumption (Sanchez *et al*., 2006). Figure 10 presents the effect of life-cycle on TFE. The evidence is that the life-cycle transpires and its effect on the participation

	GLSS3	GLSS4	GLSS5	GLSS6	GLSS7
EPP	0.0185	0.00958	-0.0168	-0.00149	-0.000851
ECP	0.0232	0.0273	0.0286	0.0384	0.0433
EUCp	0.0416	0.0368	0.0118	0.0369	0.0425

Figure 10: Effect of Life-cycle on transport fuel expenditure (1991-2017)

Source: Fiagborlo (2019).

in the transport fuel market is positive in respect of GLSS3 and GLSS4. On the contrary, life-cycle has negative effect on participation in the transport fuel market in respect of GLSS5 through GLSS7, when the head of households is a single adult without a child or an adult member 64 years of age and above compared to single adult head of households with a child and adult member less than 64 years of age.

In terms of significance, Appendix C indicates that the life-cycle effect only significantly influenced participation in transport fuel market at 1 percent level in GLSS5. However, apart from GLSS3 and GLSS4, the life-cycle effect in GLSS5-GLSS7 shows that head of households that is single without a child or an adult member 64 years and above is less likely to participate in transport fuel market than their counterparts with different characterisation. The result also shows that being a single head of households without a child or an adult member of 64 years and above increases the level of transport fuel consumption significantly, conditional on participation in transport fuel market for each of the samples used in this study.

However, a comparison of the elasticity estimates (EPP, ECP and EUCp) over time reveals a trend in the effect of life-cycle on transport fuel expenditure (Figure 10). The result shows that the estimate of elasticities (EPP and ECP) move in opposite direction with the former declining over time in spite of its original significant positive effects across a section of the households in respect of GLSS3 and GLSS4. The result implies long term effect where household heads who are single without a child or an adult member who is 64 years and above over time become disinterested in the participation in transport fuel market, conditional on participation in transport fuel market, while the level of transport fuel expenditure for a single adult household heads increases steadily over time compared to single adult households with either a child or an adult member who is less than 64 years.

Paradoxically, the result also indicates that the elasticity estimates (EUCp) on the overall level of transport fuel expenditure, unconditional on participation in the transport fuel market, have declined over time, while conditional on the transport fuel market participation, the effect of life-cycle on the level of transport fuel expenditure increases. The significance of this finding is that while the estimates (ECP) for a single adult household heads without a child and an adult member over 64 years show increasing trend in transport fuel consumption, the elasticity estimates (EUCp) on overall level of transport fuel expenditure, unconditional on the participation in the transport fuel market have been trending negatively for the life-cycle compared to single adult households with a child or an adult member who is less than 64 years. These has implications for government fiscal financing instruments, and funding for transport within the context of Ghana.

Education and Transport Fuel Expenditure

This section considers the effect of level of education on transport fuel expenditure. It is expected that household heads with higher level of education compared to no education will have higher participation in the transport fuel market and level of fuel consumption, conditional and unconditional on market participation. Appendix B presents the coefficients of the level of education for all waves in the participation equation. Specifically, the results show that as household heads move from basic level to tertiary level of education compared to no education, the probability of transport fuel market participation significantly increases for all waves. The finding shows that education of heads of households in each wave in the consumption equation significantly increases with the level of transport fuel expenditure, conditional on the transport fuel market participation.

Moreover, consistent with expectations, the result indicates that as the head of households moves from basic level of education to tertiary level of education, compared to no education, the effects on the probability of participation in transport fuel market increase, and so is the level of transport fuel, conditional and unconditional on transport fuel market participation for all household heads in respect of GLSS3&4. The finding also reveals a negative conditional effects of level of education for household heads within GLSS5-GLSS6. The probability of participation and unconditional level of transport fuel expenditure of household heads for all levels of education, compared to no education, moreover, remain positive within every waves with the exception of GLSS7 where the unconditional level of transport fuel expenditure declines with the level secondary education.

The results imply that since higher education could increase the desire for higher income activities of households, this could generate higher trip rates and higher levels of participation in all forms of activities, including participation in the transport fuel market among educated household heads. Readers should consult Appendix B for details on the path and significance of the level of education of household heads on the probability of participation, conditional and unconditional level of transport fuel expenditure. The next subsection adopts the graphical approach to compare the degree of elasticities of probability of participation and level of transport fuel expenditure, conditional and unconditional on participation in the transport fuel market to the specific level of education of the household heads.

Basic Education Versus No Education and Transport Fuel Expenditure

This section of the study considers the effects of basic level education of household heads on the probability of participation in the transport fuel market and the level of fuel consumption, conditional and unconditional on participation in the transport fuel market. The esimates (EPP, ECP and EUCp) on the variables representing the basic education of household heads are represented in Figure 11.

	GLSS3	GLSS4	GLSS5	GLSS6	GLSS7
EPP	0.0364	0.119	0.0759	0.0805	0.0933
ECP	0.0207	0.0562	-0.00574	-0.0621	-0.0508
EUCp	0.0571	0.175	0.0701	0.0184	0.0425

Figure 11: Effect of basic education on transport fuel expenditure (1991-2017)

Source: Fiagborlo (2019).

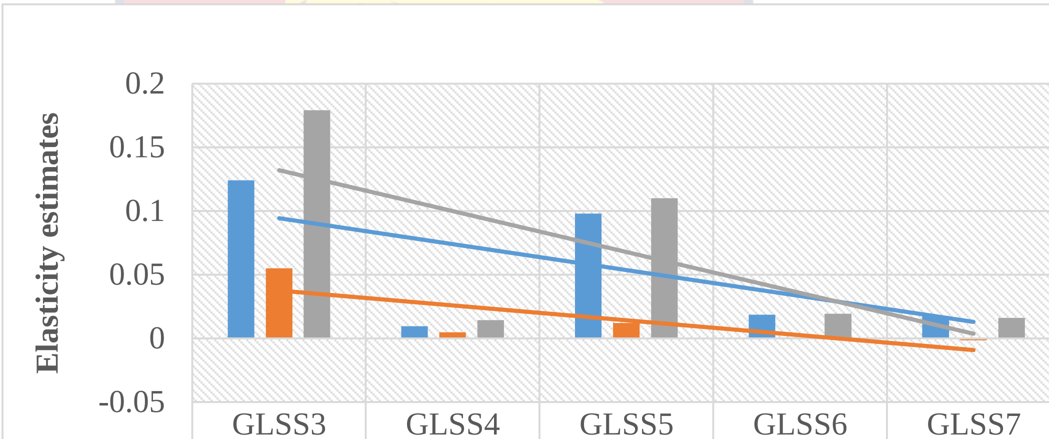
The results in Figure 11 strikingly show that the EPP and ECP values are moving in opposite directions with the former on average increasing in size over time with the later decreasing in size over time in same manner. This suggests that there are two competing effects taking place; the first being a greater ease with which household heads access the transport fuel market, possibly because of impovements in their level of education from no education, which enhances their ability to earn more incomes, travel more, and also intensify participation in transport fuel market.

The second competing effects taking place is perhaps a consequence of recession in the economy or that people are much informed about physio-environmental effects of commuting on motorised transport, which reduces their level of consumption of transport fuel. It is also noticed that the increasing effects of the probability of participation in the transport fuel market of households has been dominated by the decreasing conditional elasticiy of consumption of transport fuel, which ultimately decays over time the overall level of transport fuel expenditure, unconditional on participation in the transport fuel market for hnousehold heads with basic level of education compared to no education in Ghana.

This finding implies that over time, household heads that attained basic level education may spend less on transport fuel than those with no education at all. Households heads with basic level education compared to non-educated ones may desire for higher income activities and generate higher trip rates that requires higher propensity to participate in transport fuel market. But, the awareness of the environmental efffects of using motorised transport through basic level education than no education, may lessen over time the level of transport fuel expendiuture of households, conditional and unconditional on participation in transport fuel market.

Secondary Education Versus No Education and Transport Fuel Expenditure

This section looks at the specific elasticity estimates of secondary education over time on probability of participation in the fuel market, level of fuel consumption, conditional and unconditional on participation in the transport fuel market. Figure 12 shows the effect/elasticity estimates of secondary education on participation and consumption of transport fuel. From Figure 12, the elasticity estimates (EPP, ECP and EUCp) of secondary education are positive across all samples with the exception of ECP, in respect of GLSS7, where the estimate of elasticity is negative. Moreover, the result shows that the estimates (EPP, ECP and EUCp) of secondary education over time diminish even though the rates of decline



	GLSS3	GLSS4	GLSS5	GLSS6	GLSS7
EPP	0.124	0.00956	0.0978	0.0186	0.0176
ECP	0.055	0.00467	0.0121	0.000587	-0.00154
EUCp	0.179	0.0142	0.11	0.0192	0.0161

Figure 12: Effect of secondary education on transport fuel expenditure (1991-2017)

Source: Fiagborlo (2019).

are higher on ECP than EPP and EUCp. This means that EPP and EUCp are higher for household heads with secondary level education than those with no education.

However, this study observes that EPP, ECP and EUCp over time have become asymptotically closer to the extent where EUCp lies between EPP and ECP. From the results, it appears that household heads with education up to seconary level are more likely to participate in transport fuel market and spend more on transport fuel, unconditional on the participation in the short-run than those with no education. Whereas in the long-run, household heads with secondary level of education are less likely to participate in transport fuel market and spend less on transport fuel, conditionally and unconditonally than those with no education. Besides, the observed difference over time between EPP and ECP, conditional on participation in transport fuel market, implies that household heads with secondary level of education comapered to those with no education may spend less on transport fuel, conditional on participation than probability of market participation.

Tertiary Education versus No Education and Transport Fuel Expenditure

This section discuses the effect of elasticity estimates on probability of participation (EPP) of the level of tertiary education, level of transport fuel expenditure, conditional (ECP) and unconditional (EUCp) on participation in the transport fuel market. Figure 13 shows comparison of the elasticity estimates (EPP, ECP and EUCp) for tertiary level of education of head of households over time. Education of household heads up to tertiary level increases probaility of particiaption in transport fuel market, level of transport fuel expenditure, conditional and unconditional on participation in the transport fuel market. This is because Figure 13 demonstrates a positive elasticity estimates (EPP, ECP and EUCp) on all the components of transport fuel expenditure over time. This result indicates an increasing effects of tertiary level of education of hosehold heads than no education on trnapsort fuel expenditure across all the waves used in this study.

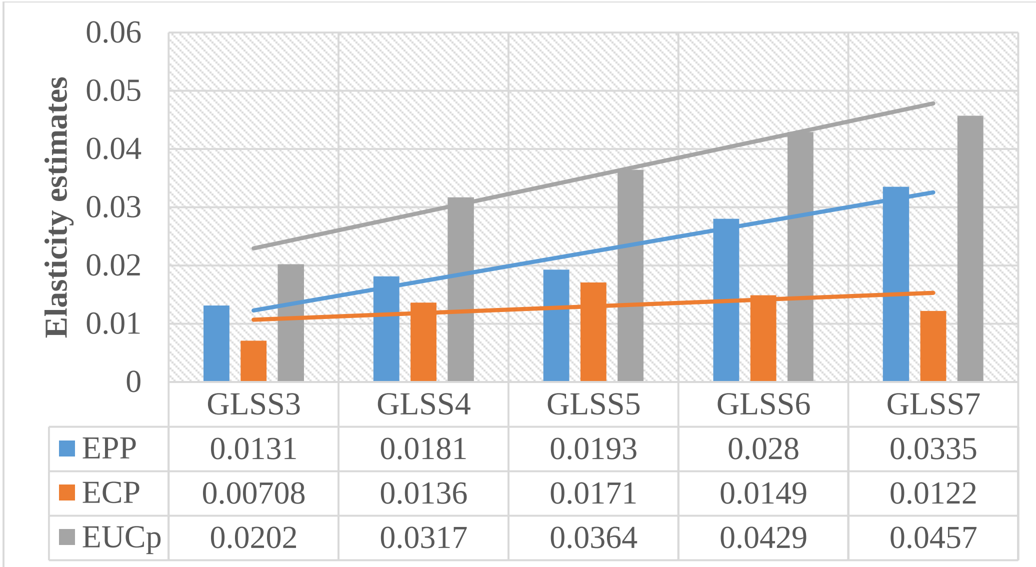


Figure 13: Effect of tertiary education on transport fuel expenditure (1991-2017)

Source: Fiagborlo (2019).

Specifically, the outcome from Figure 13 shows that with an initial 1 percent proportional increase in transport fuel market participation, 1 percent and 2 percent proportional increase in the level of transport fuel consumption, conditional and unconditional on participation in the transport fuel market for heads of household who attain tertiary level of education from no educaton, the effects on probability of participation, level of transport fuel consumption, conditional and unconditional on transport fuel market participation over time have increased to 3 percent, 2 percent and 5 percent, respectively, for household heads with tertiary level of education from no education. Comparing the level of transport fuel market participation and intensity of consumption, conditional and unconditional on transport fuel market participation, this analysis shows a difference between levels of intensities and participation, over time, across the elasticity estimates on EPP, ECP and EUCp for household heads with tertiary level of education, respectively.

For instance, the elasticity estimates for household heads with tertiary level of educaton on EPP and ECP increase steadily, albeit the estimates on EPP shows a higher level of paricipation in the transport fuel market over time than the estimates on ECP. The effect aso reveals a lower level of transport fuel market participation (EPP) relative to the elasticity estimates on EUCp. This implies that household heads with education up to tertiary level show higher perobability of paricipation in the transport fuel market than they exhibit for the level of transport fuel expenditure, conditional on the participation in the tranport fuel market over tiime. However, the estimates for the overall level of transport fuel expenditure (EUCp) is higher than the likelihood of participation in the transport fuel market for heads of households with tertiary level education than those with no education.

Chapter Summary

This chapter analysed the drivers of transport fuel market participation and consumption decisions of households, using the double hurdle regression model The evidence showed that ICT expenditure wields a significant positive impact on households' market participation and transport fuel consumption. The results showed that both probability and conditional elasticities were positive and statistically significant for ICT expenditure in each wave. These results were consistent with other studies, implying complementary connection between ICT expenditure and households' transport fuel market participation and consumption. The results also reveal accessibility effect of ICT whereby households with lesser access to ICT than those with greater access tend to spend more on transport fuel, conditional on transport fuel market participation. The results indirectly support the substitution hypothesis that availability of ICT decreases the necessity to travel.

Additionally, the study found that households' transport fuel consumption expenditure increases with income, indicating that transport fuel is a normal good for all households considered in this study, reflecting our expectations and the findings in previous studies. It further suggests that income is such a key economic variable that may influence tastes and preferences of people and consequently their level of transport fuel expenditures. This study revealed that transport fuel expenditure, conditional and unconditional on participation in transport fuel market were income elastic across all wave. In particular, these results mean that a proportionate increase in households' income will increase transport fuel expenditure more than proportionately. This result has implications for long term transport fuel consumption for growing economies, and so should form the basis for the design of effective transport policy towards plummeting GHG emissions.

Further, the result revealed that household size has a significant positive effect in the participation equation, but negative effect in the consumption equation. However, even though the probability of participation (EPP) and the overall level of transport fuel consumption (EUCp) showed positive trends with household size, the faster decline in unconditional level of transport fuel expenditure is possible because larger households are inclined to making joint travel decision, sharing cars and travel costs, which perhaps manifested in the reduction in the transport fuel market participation and the overall level of transport fuel expenditure, other things remaining the same. While results are consistent with existing literature, further study is needed to confirm the assertion about joint travel decision and travel costs.

Moreover, male household heads were found to have a consistent negative desires for transport fuel market participation, albeit, this did not reduce their transport fuel consumption compared to female-headed households. Meanwhile, even though transport fuel consumption over time intensified for male household heads, the proportional increase in unconditional transport fuel expenditure was rather smaller relative to the conditional level of transport fuel expenditure. This decreasing probability of participation in the transport fuel market for male-headed households appears to be consistent with literature where women were found to travel often than their male counterparts and spent more on transport. It is also possible that the inclination of male-headed households to work and generate financial resources to support the family, might have increased their mobility, and for that matter, transport fuel expenditure compared to female-headed households.

Adding to the preceding results, this study showed that location had positive influence on transport fuel market participation, but inconsistent effects on the level of transport fuel expenditure. In spite of this inconsistency, the negative trend over time in the probability of participation in transport fuel market, level of consumption and overall transport fuel expenditure for urban households than rural households, suggests intensed urban effects as urban households accessed jobs and socioeconomic services without travels; hence spent less or nothing on transport fuel. The decreasing trend is also possible perhaps due to improved dualisation on some urban corridors, ensuring efficient travel time and economies of fuel usage.

The result has implication for policy on urban infrastructure as housing and distribution of socioeconomic service centres may influence choice of travel modes and transport fuel market participation and level of transport fuel consumption.

More so, the results provide interesting implications for public policy and perhaps explain why carbon and congestion pricing, are not considered options for government's fiscal financing instruments for transport in Ghana. For instance, the result showed evidence that single household head without a child or a member 64 years and above significantly increased their level of transport fuel consumption, conditional on participation in transport fuel market, irrespective of whichever wave was used. The result signifies long term effect where household heads who are single without a child or an adult member 64 years and above over time became disinterested in the participation in transport fuel market, conditional on participation in transport fuel market, while the level of transport fuel expenditure for a single adult household heads increased steadily over time compared with single adult households with a child or an adult member who is less than 64 years.

Again, level of education of household heads constitutes one of the significant drivers of transport fuel market participation and level of transport fuel expenditure, conditional and unconditional on transport fuel market participation. Basic level of education versus no education of household heads showed two competing effects by intensifying participation in transport fuel market while reducing level of consumption of transport fuel. The increased participation may be induced by greater ease with which household heads access transport fuel market, possibly due to impovements in their level of education, which enhances their ability to earn more incomes and travel more. The reduction in the level of transport fuel consumption may also be as a result of recession in the economy or that household heads with basic education were much informed about physio-environmental effects of commuting on motorised transport than no education.

The analysis indicated that household heads with education up to seconary school were more likely to participate in transport fuel market and also spent more on transport fuel, unconditional on the participation in the transport fuel market in the short-run than those with no education. However, the results showed that in the long-run household heads with secondary level of education than those with no education would less likely participate in transport fuel market and spend less on transport fuel conditionally and unconditonally.This suggests that secondary level of education of household heads could be potentially used to minimise the environmental impact of fuel energy consumption. Finally, education of household heads up to the tertiary level compared to no education augmented the probaility of transport fuel market particiaption and level of transport fuel expenditure, conditional and unconditional on transport fuel market participation of households.

CHAPTER SEVEN

DRIVERS OF TRANSPORT MODE CHOICE

Introduction

This chapter analyses the drivers of transport mode choice of workers in Ghana. It is organised into eight sections. The first section states the empirical MNLOGIT regression equation. Section two discusses the issue of multicollinearity, while focusing later on the LR test in the third section. The fourth section examines the distribution of mode of transport by workers. The chapter continues with section five, discussing the frequency of mode of transport by sociodemographic variables of respondents, while section six deliberates on the conditional distribution of the mode of transport. Section seven highlights the empirical results. Finally, section eight presents the summary of the whole chapter.

Empirical MNLOGIT Regression Equation

The analytical framework for examining the effect of RVTT on transport mode choice of workers was specified in equation (21) of Chapter Four. To explain the effects of RVTT and assess the relative risks and sensitivity of drivers on choice of mode of transport to work and general travel behaviour of workers, this section of the thesis expands the analytical equation (21) of Chapter Four to accommodate factors that affect individual's choice of mode of transport to give rise to the full empirical MNLOGIT regression equation. This study applied an MNLOGIT model to home-to-work data generated from the NHTS (2012) data of individual workers in Ghana. The empirical MNLOGIT regression equation is specified as follows:

$$TMC_{ij} = \alpha_0 + \alpha_{1i} rvtt_j + \alpha_{2i} distance_j + \alpha_{3i} age_j + \alpha_{4i} agesq_j + \alpha_{5i} \text{pc\_pma}_j \\ + \alpha_{6i} \text{pc\_cma}_j + \alpha_{7i} urban_j + \alpha_{8i} male_j + \alpha_{9i} married_j + v_i \quad (36)$$

Where TMC_{ij} denotes the alternative mode j, which was used by individual i from home to work. These alternatives are small public transport (SPT); large public transport (LPT); private transport (PMT) and non-motorised transport (NMT). Taxi, trotro and mini-bus were combined to get small public transport because they share similar characteristics. Similarly, MMT bus, ferry and train were combined to form large public transport. Regarding private transport, the study combined private car with motor-cycle. For non-motorised transport, the combination was in respect of walking and bicycling as means of transport. It is acknowledged that those who do not own private transport have access to the most expensive mode of small and large public transport. It is a fact that small, large and private modes of transport compete each other among travelers in Ghana. Particularly so, where there is long distance and non-motorised modes are not an option for trip to work. The non-motorised transport was used as the base category against which all other modes were assessed. Consequently, the estimated parameters in the model are expressed relative to non-motorised transport mode.

From the literature and on the basis of intuition, this study identified that personal characteristics, attributes of the households and the characteristics of the location where people live and work have a strong association with modal choice (Agyemang, 2017; Tyrinopoulos & Antoniou, 2013; Abane, 2011). Therefore, equation (36) shows a functional relationship between transport mode choice and real value of travel time from home to work (*RVTT*); distance from home to work (*distance*); age of respondents (*age*); age squared of respondents (*agesq*); per capita private motorised assets of respondents (*pc_pma*); per capita commercial motorised assets of respondents (*pc_cma*); location of respondents (*urban*); sex of respondents (*male*); and marital status of respondents (*married*). One of the most imperative variables in the studies of travel behaviour, the income of individuals, has not been included in this regression model. It is anticipated that its inclusion will collinear with the recalibrated travel time, RVTT, which is also measured in monetary terms.

Table 4 contains the definitions and measurements of the variables hypothesised to influence the choice of transport of individuals from home to work.

Table 4: Variables hypothesised to influence individual's choice of mode of

Variable	Descriptions	Expectation
Dependent Variable:		
TMC	Main means of transport by respondent from home to work	
Independent Variable:		
Continuous		
RVTT	Real value of travel time measured as a product of national minimum wage in Ghana and hours spent in transit from home to work.	+/-
Distance	One way trip distance covered from home to work measured in kilometres.	+/-
age	Age of respondent measured in years.	+/-
agesq	Age square of respondent measured in years.	+/-
pc_pma	Per capita private motorised assets ownership of respondent.	+/-
pc_cma	Per capita commercial motorised assets ownership of respondent.	+/-
Discrete		
urban	1= urban respondent, 0 otherwise	+/-
male	1= male respondent, 0 otherwise	+/-
married	1 = married respondent, 0 otherwise	+/-

Source: Fiagborlo (2019).

This study stresses that real value of travel time and distance, which represent mode related attributes, are generic in the model. This was to ensure that an increase of one Ghana Cedis of RVTT per hour or a unit increase in the kilometric distance per hour of travel has the same effect on utility for all modes. From Table 4, it is expected that, all else equal, a faster mode of travel is more likely to reduce RVTT and positively influence its effect on choice of transport than a slower mode (Börjesson & Eliasson, 2012). As a result, in this study, RVTT is expected to have a positive or negative effect on the choice of mode of transport from home to work. Distance is one-way trip from home to work measured in kilometres per hour. It is expected that the longer the distance covered by a traveler, the more expensive the mode of transport is likely to be for that trip, and the more likely the less expensive mode should be chosen for that trip over the more expensive one; hence, distance was expected to take on positive or negative value.

Another variable that was controlled for in the model and measured in years of respondents was the age and age squared. Age squared was included to account for possible non-linearity in the regression model and also to calculate the age beyond which individual is likely to switch from one mode to the other. The expectation was that as individual ages, their desire to travel on public transport should decline because of psychological factors such as perceptions, attitudes and habits that older people might formed. Fiagborlo and Kyeremeh (2016) found that older people preferred to use private car to younger travelers because of status symbols of private car. Thus, age was expected to take positive and negative value.

Per capita private motorised assets ownership of respondent is one of the independent variables in the analysis. Per capita private motorised assets ownership is defined as total private motorised assets divided by the size of household. In other words, per capita private motorised assets ownership is the number of private motorised assets available to an individual respondent. It was included to ascertain the effect of availability of asset ownership on travel behaviour of workers. It was expected that per capita private motorised assets ownership should have positive or negative effect on main mode of transport from home to work. The implication is that the higher the per capita private motorised assets ownership the more likely an individual is to use private mode for travel from home to work than alternative modes, other things being equal. The opposite is that the lower the per capita private motorised assets ownership the less likely an individual is to utilise private mode for travel from home to work than alternative modes, all other things being equal.

Similarly, per capita commercial motorised assets ownership of respondent, which measures the number of commercial motorised assets available to individuals was expected to have a positive or negative effect on the main mode of transport from home to work. This is likely to occur if the increase in the per capita commercial motorised assets ownership is due to a fall or rise in the size of households or an increase in the commercial assets of individuals. The implication is that the higher the per capita commercial motorised assets ownership, the more likely is the individual to choose public mode of transport than non-motorised transport, other things being equal. On the other hand, the lower the per capita commercial motorised assets ownership, the less likely is the individual to choose public mode of transport than non-motorised transport, other things being equal. Singleton (2000) found availability of vehicle as condition for using a vehicle.

Table 4 further shows the signs of location, gender and marital status. These variables were included to measure their discrete effects on the probability of choosing one mode of transport over the other. For example, urban was a dummy variable with one for individual who lives in urban area and zero otherwise. While we expected existence of locational differences between urban and rural individuals regarding their work mode choice, we equally expected that individuals in rural setting should prefer non-motorised means of transport to work to other alternative modes than those in urban settings, holding other factors constant. The opposite hypothesis is that individuals in rural settings are less likely to utilise non-motorised means of transport to work compared to alternative transport modes than those individuals living in urban settings, other things remaining the same. Therefore, this study expected the sign on the urban variable to be positive or negative value.

As noted already, in explaining the mode choice behaviour of travelers, (Amoh-Gyimah & Aidoo, 2013b; Plaut, 2005) used gender among other socioeconomic characteristics. Carrion *et al.* (2011) used travelers' characteristics in mode choice models to control for observed heterogeneity. Sex was included to assess gender differences relative to the choice of mode of transport from home to work in Ghana. Sex variable takes one if individual was a male and zero otherwise, where female was used as the reference category. Female individuals were expected to have higher proclivity to use public transport compared to male individuals, generating higher probability of using public transport for females than male respondents. Fiagborlo and Kyeremeh (2016) established that women spare parts dealers used public transport more than men. Similarly, Amoh-Gyimah and Aidoo (2013) found that most working women in Kumasi used public transport to work.

Test of Collinearity

This section considers the issue of multicollinearity. The descriptive statistics of the variables were looked at. The tolerance value for each independent variable in the model were estimated. This collinearity diagnostic test was done to guard against matrix ill-conditioning or multicollinearity. As a rule of thumb, higher variance inflation factor (VIF) value and condition number above 10 suggest a problem of multicollinearity. Generally, when variables are almost completely redundant, the tolerance value for those variables approach zero and those variables are dropped and used in Pearson's correlation analysis to test for significant relationship between the outcome variable and the independent variables. Table 5 demonstrates the estimated VIF and condition number for the independent variables utilised in the MNLOGIT model of transport mode choice of Ghanaian workers.

Table 5: Estimated VIF for the variables used in the MNLOGIT model

Variable	VIF	SQ VIF	Tolerance	R-Squared	Eigenvalue	Cond Index
RVTT	1.05	1.02	0.9546	0.0454	5.2990	1.0000
distance	1.04	1.02	0.9589	0.0411	0.9480	2.3642
Sex	1.00	1.00	0.9965	0.0035	0.5881	3.0017
Age	1.02	1.01	0.9841	0.0159	0.4892	3.2913
urban	1.02	1.01	0.9792	0.0208	0.4122	3.5855
PC_PMA	1.11	1.05	0.9035	0.0965	0.1461	6.0221
PC_MMA	1.10	1.05	0.9110	0.0890	0.0830	7.9926
Mean VIF 1.05				Condition Number		7.9926

Source: Fiagborlo (2019).

From Table 5, it has been observed that all the independent variables passed the tolerant test and so the data did not violate the multicollinearity assumption. For example, the tolerance value of each independent variable ranges between 0.9035 and 0.9965 which exceeded the benchmark value of below 0.10 suggested by Pallant (2007). From Table 5, the overall mean VIF value of 1.05 and condition number of 7.9926, which were below the cut-off value of 10 further confirm lack of multicollinearity among the independent variables (Adwere-Boamah, 2011).

Likelihood-Ratio Test

The likelihood-ratio (LR) test is one of the three classical approaches to hypothesis testing. Together with the Lagrange multiplier and the Wald test, LR test helps to test for one or several constraints on parameter values in a regression model. Beyond the description and the test for tolerance for each independent variable, this section of the study conducts LR test for measure of fit for the transport mode choice. What the LR test basically does is to compare the fit of two models. It is significant to explain that two models are nested when one is a special case of the other. The null hypothesis is that the parsimonious model is the best model. The parsimonious model is only rejected when the test statistic is large. In other words, if the null hypothesis is rejected, then the unrestricted model is a significant improvement over the parsimonious one. Ultimately, the LR test helps to choose the best model between two nested models to fit the data in this study.

Table 6 presents the LR test for measure of fit for MNLOGIT model of transport mode choice. From Table 6, it is observed that the difference in BIC value of 22.986 provides strong support for the current model. Thus, the MNLOGIT analysis showed that the full model, which considered together all the independent variables was significant at p<0.000 with chi-squared value of 2216.376, df=24, N = 7,262. This implies that the odds of choosing an alternative mode given the referenced mode relates significantly to all the explanatory variables in the model. The "pseudo" R estimates also indicate that the model explained between 26 percent (Cox & Snell R Squared) and 60 percent (Nagel kerke R Squared), respectively, of the variation in the choice of mode of transport (TMC) to work.

Table 6: Likelihood-ratio test for measure of fit for MNLOGIT model

Fit	Restricted model	Saved model	Difference
Log-Lik Intercept Only:	-2064.657	-2064.657	0.000
D(df=7235):	1909.253	1909.253	3.685
McFadden's R^2	0.537	0.538	-0.001
ML/ (Cox-Snell) R^2	0.263	0.263	-0.000
Count R^2	0.969	0.969	-0.000
AIC:	1966.938	1969.253	-2.315
BIC (df=27):	2175.965	2175.965	-22.986

Fit	Full t model	Saved model	difference
Log-Lik Full Model:	-956.469	-954.626	-1.843
LR(df=24):	2216.376	2220.061	-3.685
Prob > LR:	0.000	0.000	0.298
McFaggen's Adj R^2:	0.524	0.523	0.001
Cragg-Uhler Nagelkerke) R^2:	0.606	0.607	-0.001
Adj Count R^2:	0.491	0.493	-0.002
AIC*n:	0.271	0.271	-0.000
BIC (df=27):	2175.965	2175.965	-22.986

Source: Fiagborlo (2019).

Indeed, the LR statistics indicate that all the variables significantly predict the choice of mode by respondents in Ghana. From Table 6, the LR statistics value of 2216.376 and p<0.000 also implies that the whole regression model is statistically significant and therefore provide a good fit for the level of explanation.

Distribution of mode of transport by respondents

This section examines the distribution of mode of transport by the socioeconomic characteristics and attributes of alternative transport options that influence the choice of transport modes of respondents. Table 7 presents the distribution of the transport modes by respondents, who used the same modes of transport from home to work. The total number of respondents considered for this

Table 7: Distribution of mode of transport by respondents

Main mode of transport	Frequency	Percent
Small public transport (*taxi, trotro and mini-bus*)	271	3.7
Large public transport (*MMT bus, ferry and train*)	63	0.9
Private transport (*private car and motor-cycle*)	106	1.5
Non-motorised transport (*walking and bi-cycling*)	6822	93.9
Total	7,262	100

Source: Fiagborlo (2019).

study was 7,262 workers, who used the same means of transport from home to work during the referenced period. It is revealed that out of 7,262 respondents who used the same modes of transport, 6,822 respondents, representing majority (94 percent), used non-motorised transport (walking and bi-cycling) mode from home to work within the referenced period, while 271, representing about 4 percent, traveled from home to work utilising small public transport mode (taxi, trotro and mini-bus).

Table 7 further shows that out of these 7,262 workers who used the same means of transport from home to work,169 respondents, representing 2 percent, used large public transport (MMT bus, ferry and train) and private transport (private car and motor-cycle) modes, respectively. The result indicates that more workers in Ghana combined walking and bicycling as a means of mobility to work. This contradicts the study of Agyeman (2017) as well as the work of Abane (2011) plausibly because of the size of the data used in this analysis. This study included all workers (formal and informal) and covered Ghana, while Abane (2011) excluded informal sector workers and used limited sample that covered only Accra. Interestingly, of the 2 percent of the respondents that used large public transport and private transport modes, only 0.9 percent combined MMT bus, ferry and train to work, while the rest combined private cars and motor-cycle to work from home.

The statistics have implications for the BRT policy that envisaged moving at least 80 percent of passengers through the mass transport by 2023. The outcome also does not acquiesce with the finding of Fiagborlo and Kyeremeh (2016), who found that about 9.1 percent of business people in Accra used public bus from home to work. This is obviously perhaps for the difference in the sample sizes and data used in this study. From Table 7, the distribution of transport modes also shows no pervasive dominance of private car as a mobility means and calls for a possible policy attention towards non-motorised transport modes (walking and bi-cycling) as many respondents are becoming more amenable to using this mode of transport.

Transport Mode Choice and Sociodemographic Characteristics of Workers

Several studies provide useful information about factors that influence transport mode choice (Ortuzar & Willumsen, 2005; Abane, 2011; Fiagborlo & Kyeremeh,2016; Birago *et al*.,2016; Carrion *et al*., 2011). Some of these factors are attributes of the traveler, attributes of the journey, characteristics of the transport facility and psychological factors such as perceptions, attitudes and habits. Having

Table 8: Frequency of mode of transport by socio-demographic variables of respondents

	Main mode of transport								
	Small public transport		Large public transport		Private transport		Non-motorised transport		Ghana
Sex	Frequency	%	Frequency	%	Frequency	%	Frequency	%	%
Male	140	51.7	35	55.6	71	67.0	3215	47	47.7
Female	131	48.3	28	44.4	35	33.0	3607	53	52.3
Total	271	100	63	100	106	100	6822	100	100
Marital Status:									
Not married	53	19.6	26	41.3	19	17.9	2191	32.1	31.5
Married	218	80.4	37	58.7	87	82.1	4631	67.9	68.5
Total	271	100	63	100	106	100	6822	100	100
Location									
Urban	156	57.6	36	57.1	47	44.3	2656	38.9	39.9
Rural	115	42.4	27	42.9	59	55.7	4166	61.1	60.1
Total	271	100	63	100	106	100	6822	100	100
Sector of employment:									
Private	8	3.0	0	0.0	4	3.8	8	0.1	0.3
Public	260	95.9	63	100.0	99	93.4	6792	99.6	99.3
NGos	3	1.1	0	0.0	3	2.8	22	0.3	0.4
Total	271	100	63	100	106	100	6822	100	100

	Main mode of transport								
	Small public transport		Large public transport		Private transport		Non-motorised transport		Ghana
Time unit	Frequency	%	Frequency	%	Frequency	%	Frequency	%	%
Daily	163	60.2	9	14.3	90	84.9	5789	84.9	83.3
Monthly	94	34.7	46	73.0	13	12.3	967	14.2	15.4
Weekly	14	5.2	8	12.7	3	2.8	66	1.0	1.3
Total	271	100	63	100	106	100	6822	100	100
Availability of transport:									
Morning	1	0.4	1	1.6	1	0.9	47	0.7	0.7
Afternoon	14	5.2	0	0.0	9	8.5	171	2.5	2.7
Evening	36	13.3	3	4.8	1	0.9	377	5.5	5.7
Night	109	40.2	48	76.2	29	27.4	1314	19.3	20.7
All day	11	4.1	2	3.2	16	15.1	3215	47.1	44.7
Always available	100	36.9	9	14.3	50	47.2	1698	24.9	25.6
Total	271	100	63	100	106	100	6822	100	100
Reliability of transport:									
Reliable	129	47.6	7	11.1	52	49.1	2043	30.0	30.7
Reliable sometimes	68	25.1	8	12.7	26	24.5	1250	18.3	18.6
Not reliable	74	27.3	48	76.2	28	26.4	3529	51.7	50.7
Total	271	100	63	100	106	100	6822	100	100

Source: Fiagborlo (2019).

considered the distribution of the transport modes by respondents, this section discusses the frequency of mode of transport by socio-demographic variables of respondents. Specifically, this section of the study considers gender, marital status, geographic location, sector of employment, status of employment, time unit of the day, availability and reliability in relation to small public transport, large public transport, private transport and non-motorised transport, respectively. Table 8 and (Appendix F) present the frequency of mode of transport by sociodemographic attributes of respondents and the chi square test of independence. The results provide general behavioural trends in mode choice of workers from home to work.

While the result in Appendix F shows the importance of sex as a determinant of transport mode, Table 8 presents the frequency of small public transport (taxi, trotro and mini-bus), large public transport (MMT bus, ferry and train), private transport (private car and motor-cycle) and non-motorised transport (walking and bi-cycling) by sex of respondents. Concentrating on the sex of workers, this study observes that sex plays significant role in the choice of transport. This observation is affirmed by a χ^2 value of 19.953 with its associated p-value of 0.000 (Appendix F). According to Pallant (2001), for a test to be significant the p-value must be equal to or less than 0.05. Thus, the initial proposition that sex has no significant influence on the choice of transport has been rejected with certainty.

In particular, Table 8 shows that out of 47.7 percent of male workers, two-third (67 percent) of them frequently used a combination of private cars and motor-cycle to work than women; regarding non-motorised transport, the result indicates that of the 52.3 percent of female workers, more than half (53 percent) of them frequently used a combination of walking and biking to work than men. The results indicate that more men than women used motorised transport to work, while more women than men used non-motorised transport to work. The results suggest policy decisions that promote walking or biking among men. The differences in the use of motorised means and non-motorised mode by men and women could be explained by reasons such as avoiding traffic, difficulty of obtaining a mode, accessibility and availability of mode and location of respondents adduced by Birago *et al.* (2017). Similarly, Pooley and Turnbull (2000) observed differences in cycling to work by men and women and attributed the result to men who reported laziness on their part and the need to look smart for work, while women reporting fear of urban traffic as the reason for not bicycling to work from home. The disparity may also be due to the difference between men and women relative to occupation and access to economic power (Uteng, 2012). While women participation in economic space is high, and almost equal to that of men, women tend to participate more in informal sectors of the economy and remain poorer than men. Accordingly, ownership of assets (private cars) remain the preserve of men. Study (Peters, 2013) on percentage of men and women who own cars, trucks, motorcycles and scooters showed that, 9 percent of car owners in Ghana were men and 2 percent of the women own car.

The result is not different from the global trend whereby, even though, car ownership is a status symbol and is used as a measure of economic improvement and employment, and as an enabler of independence and mobility, ownership of car is skewed in favour of men with women walking, biking and using public transport more than men (Adom-Asamoah, Amoako, & Adarkwa, 2020). Moreover, a preliminary analysis of marital status of workers relative to their mode choice shows that workers were married or not married. For instance, Table 8 reveals that of all workers who commuted from home to work, less than one-third (32 percent) were not married meanwhile a little more than two-third (68 percent) were married.

When the relationship was further interrogated between the indicators of the marital status and the frequency of transport mode choice, the result indicates that over three-quarters (80.4 percent) of all married workers were users of small public transport (taxi, trotro and mini-bus), whereas less than one-fifth (19.6 percent) of small public transport (taxi, trotro and mini-bus) users were not married. The result also shows that over three-quarters (82.1 percent) of the private transport (private car and motor-cycle) users were married whereas less than one-fifth (19.6 percent) of the private transport (private car and motor-cycle) users were not married. Regarding non-motorised transport (walking and bi-cycling), the result shows that over two-third (67.9 percent) of the users were married, while a little less than one-third (32.1 percent) were not married. For large public transport (MMT bus, ferry and train) users to work, the result reveals that more than two-fifth (41.3 percent) users were not married, meanwhile less than two-third (58.7 percent) were married.

Several reasons may be at play in these results. Marriage comes with benefit of pooling resources together, and cost of being vulnerable because of children. As such, married people normally turn to travel with more comfortable but expensive modes of transport to avoid walking and bicycling than unmarried people. The present evidence confirms this assertion. It is generally observed that respondents who were married frequently used motorised modes of transport to work compared to non-married respondents. Pooley and Turnbull (2000) accordingly noted that the need for married women to travel to work often over considerable distance has been a major factor in explaining the use of car by women in the late twentieth-century.

To assess the importance of marital status in the choice of transport to work, we also conducted a chi-square test of independence. Result in Appendix F shows a χ^2 value of 30.944, with its associated p-value of 0.000, indicating that there is a significant association between marital status and the choice of transport mode. The results imply that matrimonial relationship is vital in transport choice decision of workers as shown in the frequencies of the mode of transport by married and not married workers in this study. This study assessed geographical difference among workers and its implication for transport mode choice. Table 8 reports that about 60 percent and 40 percent of workers live in rural and urban areas, respectively. The implication is that more respondents lived in urban areas than rural areas. The analysis shows that more than half (57.6 and 57.1 percent) of the frequent users of small public transport (taxi, trotro and mini-bus) and large public transport (MMT bus, ferry and train) were urban dwellers, while the reverse were also rural dwellers.

It is further observed that except for small public transport (taxi, trotro and mini-bus) and large public transport (MMT bus, ferry and train) users, about 56 and 62 percent, respectively, of the frequent users of private transport (private car and motor-cycle) and non-motorised transport (walking and bi-cycling) from home to work were rural dwellers. The result is a manifestation that urban dwellers prefer to travel to work frequently on taxi, trotro, mini-bus, MMT bus, ferry and train, while rural residents prefer to frequently go to work, using private car, motor-cycle, walking and bicycling. This current finding reflects the nature of urban planning in Ghana, where people live on the periphery of the city and also depend on private means of transport to access economic centres because of lack of public transport.

The analysis also looked at the significance of the relationship between geographical location and transport mode of respondents. Appendix F reveals the result of a χ^2 value of 46.617, with its associated p-value of 0.000, indicating that there exists a significant association between geographical location and the choice of transport mode for workers in Ghana. Following Bardazzi and Pazienza (2018), Readers are referred to Tables 8 and Appendix F, respectively, for details of the rest of the results. A number of reasons could explain the difference in the choice of transport mode amid rural and urban dwellers. These reasons may be economic, demographic, technical, distance, vehicle age, driving condition and national road network (Mraihi, 2012). Diaz Olvera *et al*. (2008b); Gannon and Liu (1997) noted that due to location, people depend on public transport irrespective of its high fares.

Christoffel Venter (2011) also argued that because origins and destinations across nations were becoming farther apart due to sprawling urban development, poorer households pay more for using public transport for trips than their richer counterparts. Manaugh *et al*. (2010) opined that if transport policies incorporates land use mix and population densification, it would encourage changes in spatial organisation of activities, increasing accessibility to social and economic centres, which would reduce travels in the long-round. The outcomes of this study may have social and economic implications for travelers and are therefore imperative for transport and urban planning policies. For example, this study reveals that more dwellers in rural areas walk to work than urban dwellers, and urban dwellers prefer to use taxi and buses to work relative to rural dwellers. Therefore, the outcomes from this study provide reference point for effective BRT implementation in Ghana.

Birago *et al.* (2017) and Abane (2011) showed that sector of employment influenced transport mode decisions of workers in Accra. In this regard, it is paramount to analyse how sector of employment of respondents influences their choice of mode of transport to work in Ghana. The sector of employment indicator has been categorised into three subsectors, including: private, public and non-governmental (NGO) sectors, respectively. Result shows that almost every worker (99 percent) was a public sector worker, leaving nearly one percent for the private and NGO sector workers, respectively. The statistics in Table 8 further indicate that over three-quarters (96 percent) of small public transport (taxi, trotro and mini-bus) users were public sector employees, whereas only three percent of small public transport (taxi, trotro and mini-bus) users to work were private sector employees.

Again, this study finds a rare use of taxi, trotro and mini-bus, as only one percent of NGO sector workers chose to go to work on small public transport (taxi, trotro and mini-bus). The results reflect public sector worker's domination in the use of taxi, trotro and mini-bus from home to work in Ghana. Similarly, the result shows a 100 percent patronage of large public transport (MMT bus, ferry and train) among public sector workers, while no worker (private and NGO) used large public transport (MMT bus, ferry and train) from home to work within the referenced period. Across all modes, the result, therefore, implies that public sector employees often use taxi, trotro and mini-bus as well as MMT bus, ferry and train from home to work compare to private sector, in addition to NGO sector workers, respectively.

Considering the private transport mode, the outcome shows that about 93 percent, 4 percent and 3 percent, respectively, of public, private and NGO sector workers were users of private transport mode (private car and motor-cycle) (Table 8). Regarding non-motorised transport (walking and bi-cycling), the analysis shows that nearly all users (99 percent) were public sector employees, with virtually none (1 percent) of the other sector workers using non-motorised transport (walking and bicycling) from home to work. The high proclivity of public sector workers to use various transport modes from home to work could plausibly be due to availability of these modes at the public sector works' origin, accessibility of alternative modes, less waiting times for the modes et cetera. In their recent publication, Birago *et al*. (2017) asserted that low income earners who were self-employed in the informal sector commuted frequently using MMT buses because of the relatively low fares.

This assertion is corroborated by these findings even though the two studies are incomparable. While the work of Birago *et al*. (2017) covered only respondents in Accra, the present study used a nationwide data for its analysis. While the difference in the conclusions calls for a further enquiry into the reason for the low patronage of all modes by private and NGO sector workers, the current analysis examines the significance of the association between sector of employment and transport mode choice, using a chi-square test of independence. Appendix F reveals a χ^2 value of 145.728, with its associated p-value of 0.000, indicating that a significant association exists between sector of employment and transport modes.

This result implies that sector of employment of respondents should be included in any transport analysis to determine its influence on the choice of transport modes.

Time unit has been included in the analysis of transport mode choice. The aim was to understand how it influences transport modes of respondents. In this analysis, time unit has been segregated into daily, weekly and monthly units. Foremost, a chi-square test of independence was conducted to assess whether there is any significant association between time unit and transport modes. The result as presented in Appendix F shows that there is a significant association between time unit and transport mode choice of respondents because of the χ^2 value of 369.256, with its associated p-value of 0.000. This confirms our instinct about the significant role that time unit plays in the transport mode choice decisions of Ghanaian workers. Regardless of the overall significance of time in the transport mode choice of respondents, a further assessment of the distribution of the transport mode choice in terms of daily, weekly and monthly time units discloses important information.

From Table 8, the findings show that of all respondents who frequently used small public transport (taxi, trotro and mini-bus) from home to work within the referenced period, six out of ten (60 percent) were daily users, while one out of twenty (5 percent) were monthly users. Considering all respondents who frequently used large public transport (MMT bus, ferry and train) from home to work within the referenced time, the results indicate that almost three-quarters (73 percent) were weekly users, with a little over one-fourth (27 percent) as daily and monthly users, respectively. It is also, further, found that over three-quarters (85 percent) of all the private transport (private car and motor-cycle) users from home to work were daily users, but only 3 percent out of all private transport users were monthly users. The study also discloses that close to ninety out of hundred (85 percent) of respondents were using daily non-motorised transport to work, meanwhile only 15 percent of the respondents weekly and monthly used combined walking and bicycling to work.

Availability was a major factor influencing the use of car (Palma & Rochat, 2000). However, the current study sought to understand how non-availability of transport influences transport modes choice of workers. To start, non-availability of transport was classified into morning, afternoon, evening, night, all days and always non-availability. This was to determine the association of these indicators with small public transport (taxi, trotro and mini-bus), large public transport (MMT bus, ferry and train), private transport (private car and motor-cycle) and non-motorised transport (walking and bi-cycling). A chi-square test of independence was conducted to determine significant association between non-availability of transport and mode choice. Appendix F shows a χ^2 value of 399.770 with its related p-value of 0.000, indicating a significant character of non-availability of transport in the decisions of workers to use alternative means of transport to work in Ghana.

Having determined the overall significance of non-availability of transport in the choice of transport mode by workers, the study further assessed the frequency distribution of the transport modes conditioned on such non-availability indicators as morning, afternoon, evening, night, all days and always non-availability. Table 8 shows that, of all workers who frequently used transport from home to work, 0.7 percent reported that non-availability of transport from home to work was a challenge in the morning; 2.7 percent reported that transport non-availability was a challenge in the afternoon; 5.7 percent reported that transport was unavailable in the evening; 20.7 percent reported that the challenge of transport availability was at night; 44.7 reported that transport was always unavailable; while a little over one-quarter (25.6 percent) also reported no challenge at all about transport availability.

The result shows that of all workers who frequently used small public transport (taxi, trotro and mini-bus) to work within the referenced period, a little over two-fifth (40.2 percent) reported this mode of transport to be a challenge at night, while only (0.4 percent) of the users of small public transport (taxi, trotro and mini-bus) reported that this mode of transport was unavailable in the morning. The result further shows that for those who used small public transport (taxi, trotro and mini-bus) from home to work, about 40 percent reported of not having any transport problem. Considering all respondents who frequently used large public transport (MMT bus, ferry and train) from home to work within the period, the result discloses that a little over three-quarters (76 percent) of users of this mode reported that availability of this mode of transport was a challenge at night, while no worker at all reported that MMT bus, ferry and train were unavailable in the afternoon.

For all those who went to work combining MMT bus, ferry and train, the result indicates that about 14 percent of them reported that there was no challenge regarding availability of MMT bus, ferry and train. Regarding those who used private transport (private car and motor-cycle) from home to work, the finding manifests that while almost half (47 percent) of the private transport (private car and motor-cycle) users reported no challenge of this mode at all, close to 2 percent of workers who combined private car and motor-cycle to work reported that these modes were unavailable in the morning and evening, respectively. It is also observed that while about 0.7 percent of all those who used non-motorised transport (walking and bi-cycling) reported that walking and bicycling were challenging in the morning, about one-fourth (24 percent) of the workers who used non-motorised transport (walking and bi-cycling) reported this mode was not challenging at all.

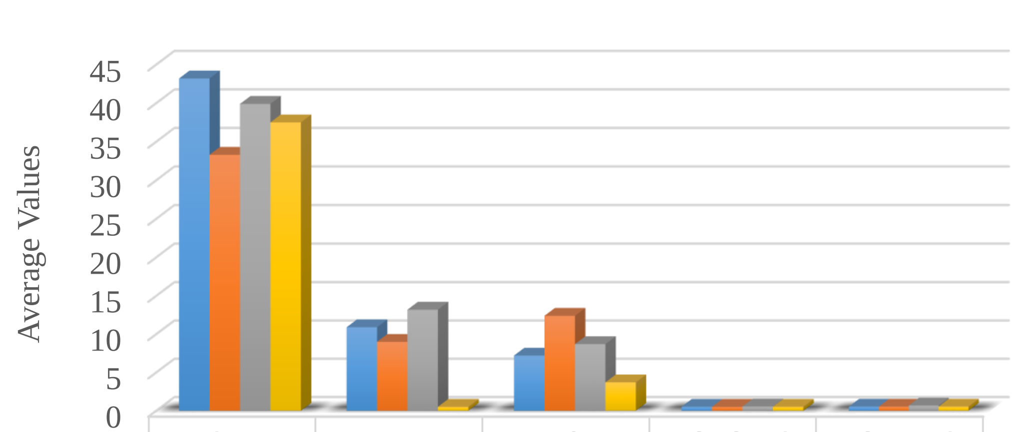
Unavailability of non-motorised transport (walking and bi-cycling) was a problem to almost half (47 percent) of the workers who used this mode of transport to their work places within the referenced period. This present result has implication for planning and transport policy. Some of the plausible reasons for unavailability of non-motorised mode may be unsafe nature of routes to work, discomfiture in walking or biking from home to work because of social status, and the length of the routs to work as well. Another level of service attributes that commuters consider when choosing a mode of travel is reliability of transport (Birago *et al.*, 2017; Tyrinopoulos & Antoniou, 2013; Redman *et al*., 2013). Consequently, this study sought to also unpack the accusation of reliability of transport with transport modes of workers in Ghana. Principally, this study segregated transport reliability into indicators including reliable, sometimes reliable as well as unreliable, respectively.

Initially, the overall association of reliability of transport with transport mode was assessed by testing the original conjecture that reliability of transport attracts commuters away from other alternatives modes. A chi-square test of independence was employed and the result shows a χ^2 value of 106.666, with its associated p-value of 0.000, confirming the instinct about the significant role that reliability plays in the transport mode choice decisions of Ghanaian workers

(Appendix F). Considering how reliability indicators are loaded on transport mode choice, this study reveals that of all workers who traveled to work within the period, a little over half (51 percent) of them saw transport to be unreliable, while less than one-fifth (19 percent) of them saw reliability as an occasional issue. In Table 8, over three-quarters of all workers who saw reliability as a challenge of transport used a combination of MMT bus, ferry and train to work, while those who saw MMT bus, ferry as well as train mode of transport as reliable were about 11 percent.

Within the same period of the study, the analysis shows that nearly half (48 percent) of all workers who used small public transport (taxi, trotro and mini-bus) from home to work considered this mode of transport as reliable, with one-quarter (25 percent) viewing this mode (taxi, trotro and mini-bus) of transport as occasionally reliable. It is further observed that, while nearly half (49 percent) of private transport (private car and motor-cycle) users saw this transport mode to be reliable, almost one-quarter (24 percent) of this mode users reported it to be occasionally reliable. In terms of all respondents who frequently used non-motorised transport (walking and bi-cycling) from home to work, the study finds that a little over half (51 percent) of the workers reported unreliability of this mode, with almost one-fifth (18 percent) workers reporting that non-motorised transport (walking and bi-cycling) from home to work were seldom reliable (see Table 8).

Before discussing the effects of the relative risks and sensitivity of the drivers on choice of mode of transport, the study presents the distribution of mean age, RVTT, distance, PC_CMA and PC_PMA by main modes of transport in Figure 14. The results indicate that workers who traveled to work on small public transport (taxi, trotro and mini-bus) have the highest mean age (43.2 years), whilst the lowest mean age (33 years) represents those who traveled to work on large public transport (MMT bus, ferry and train). This result suggests that older respondents used small public transport, while relatively young people used large public transport from home to work. The result shows how relevant age is in the choice of transport mode.



	Age	RVTT	DIST	PC_CMA	PC_PMA
SPT	43.2	10.9	7.2	0.51	0.52
LPT	33.3	9	12.4	0.5	0.52
PMT	39.9	13.2	8.7	0.54	0.66
NMT	37.5	0.5	3.7	0.51	0.53

Figure 14: Distribution of mean age, RVTT, distance, pc_cma and pc_pma by main mode of transport.

Source: Fiagborlo (2019).

Abane (1993) and Birago *et al.* (2017) found age rather than transport characteristics (access, in-vehicle time) to influence travel-to-work behaviour of employees in Accra. Amoh-Gyimah and Aidoo (2013) asserted that as people get older, the use of public transport decreases whereas the use of private car increases. Palma and Rochat (2000) also concluded that younger commuters were more likely to use their cars to work, whereas older people tended to be more committed to public transport. Amoh-Gyimah and Aidoo (2013) claimed that as people get older, they get good jobs, save money and become financially capable of purchasing private cars. These studies provided basis for the current finding, albeit some past results are inconclusive and lacked generalisation due to their limited scope. Surely, Abane (1993) and Birago *et al.* (2017) studied respondents in Accra, while Amoh-Gyimah and Aidoo (2013b) basically covered government employees in Kumasi.

The result further discloses that whilst all private transport (private car and motor-cycle) users have the highest RVTT of 13.2 Ghana Cedis per hour, the lowest RVTT of 0.5 Ghana Cedis per hour represents all those who used non-motorised transport (walking and bi-cycling) from home to work (Figure 14). This means that much labour hours is being lost, using private car and motor-cycle than walking and bicycling to work in Ghana. Regarding distance from home to work, the result shows that workers who traveled to work on large public transport (MMT bus, ferry and train) endured the highest mean distance of 12.4 kilometers per hour compared to the lowest distance of 3.7 kilometers per hour endured by those who walked and biked to work from home. The analysis also reveals a marginal difference between large public transport (MMT bus, ferry and train) users and private transport (private car and motor-cycle) users when it comes to assets ownership (Figure 14).

For example, Figure 14 reports that while those who used private transport (private car and motor-cycle) from home to work have the highest mean (0.54) per capita commercial assets ownership, the lowest mean (0.50) per capita commercial assets ownership is reported for those who journeyed on large public transport (MMT bus, ferry and train) from home to work. Similarly, we observe marginal difference between small public transport (taxi, trotro and mini-bus) and private transport (private car and motor-cycle) users in terms of their per capita private assets ownership. For instance, while Figure 14 shows that the mean per capita private assets ownership is highest (0.66) for those who used private car and motor-cycle to work, the lowest (0.52) mean per capita private assets ownership is reported for respondents who went to work using large public transport (MMT bus, ferry and train) as well as small public transport (taxi, trotro and mini-bus), respectively.

Conditional Distribution of Choice of Mode of Transport

While the analysis at this point may suggest duplicity of results, it is imperative not to discuss the results of the multinomial regression that would only communicate information to readers about the probability of choosing a mode to work over alternatives, given the explanatory variables. Consequently, this study conditioned the distribution of the main mode of transport by mean age, RVTT, distance, ownership of per capita commercial and private assets (pc_cma and pc_pma) on sex of respondents across their location, using a graphical approach. The highest number of workers, as noted, were users of non-motorised transport (walking and bi-cycling) to work, whilst the lowest number of workers were large public transport (MMT bus, ferry and train) users. It has been established that more men than women went to work from home using private mode (private car and motor-cycle), and that more workers lived in rural areas than urban areas (Table 8).

However, the study did not account for age-gender-location relationship with main mode of transport from home to work. For instance, what transport mode will a female or male worker use to work, conditional on their age and geographical context? Figure 15 presents the answers by showing the distribution of main modes of transport by mean age as well as sex of respondents across geographical location.

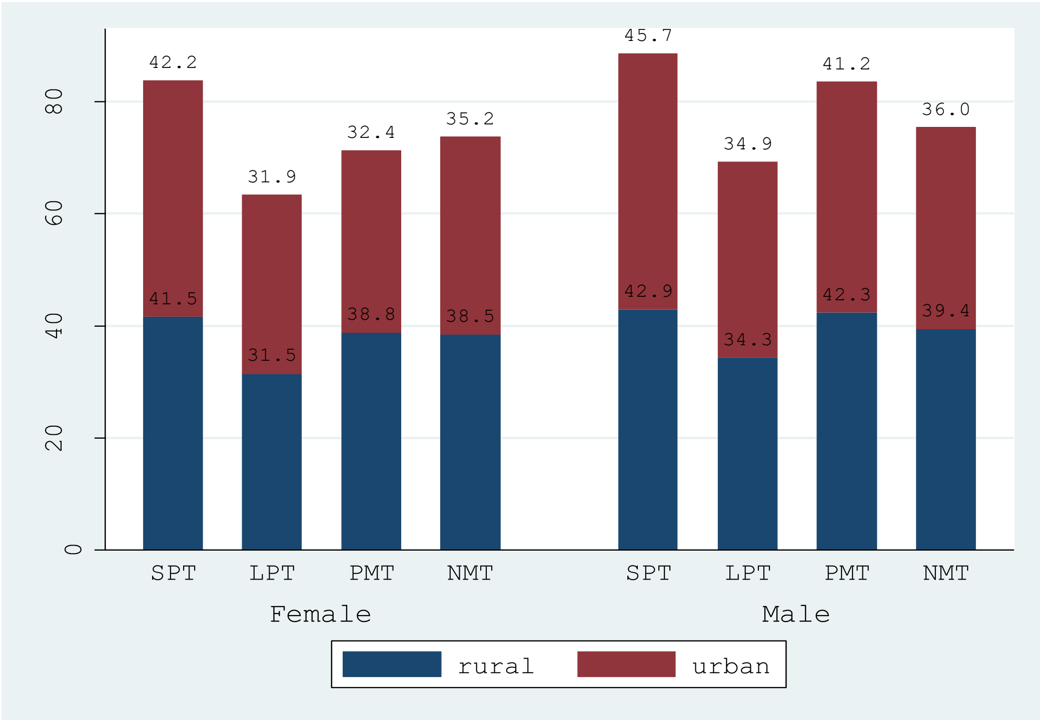


Figure 15: Distribution of main mode of transport by mean age of respondents and sex across location

Source: Fiagborlo (2019).

It is observed that for all small public transport (taxi, trotro and mini-bus) users from home to work, the mean age of urban men was (46 years), whilst that of urban women was (42 years). Regarding rural location, the result similarly shows that for all small public transport (taxi, trotro and mini-bus) users from home to work, the mean age of rural men was (43 years), whilst that of rural women was (42 years).

This result is interesting because, while older urban or rural men were using taxi, trotro and mini-bus to work from home compared to urban or rural women, the finding reveals that the mean age of rural men equals that of the national average for all workers who were small public transport (taxi, trotro and mini-bus) users from home to work (Figures 14 & 15). Comparing the influence of mean age of male workers on transport modes within urban or rural settings to the mean age of female workers, we conclude that older urban or rural men than urban or rural women were utilising small public transport (taxi, trotro and mini-bus) to work.

Another interesting results from Figure 15 is that the mean age of urban men and urban women who used large public transport (MMT bus, ferry and train) from home to work were (35 years) and (32 years), respectively. Considering rural dwelling, the study shows a similar effect for all large public transport (MMT bus, ferry and train) users from home to work. Thus, the mean age of rural men was (34 years), whilst that of rural women was (32 years). This result implies that older men than women are shuttling on large public transport (MMT bus, ferry and train) from home to work in urban and rural areas. Again, the results indicate the importance of age in the choice of transport and so confirm the findings in the extant literature (Birago *et al.*, 2017; Amoh-Gyimah & Aidoo, 2013b; Palma & Rochat, 2000; Abane, 1993). The next paragraph considers the role of RVTT in the decision of men or women to go to work, whether living in urban or rural areas, using transport.

Figure 16 reports the distribution of main mode of transport by mean RVTT of respondents and sex across location. The national mean RVTT for all workers who used private transport (private car and motor-cycle) from home to work was 13 Ghana Cedis per hour. Yet, conditional on sex and location, the result shows the mean RVTT for urban women to be 23 Ghana Cedis per hour relative to 13 Ghana

Cedis for urban men. This result is not surprising because of the different gendered

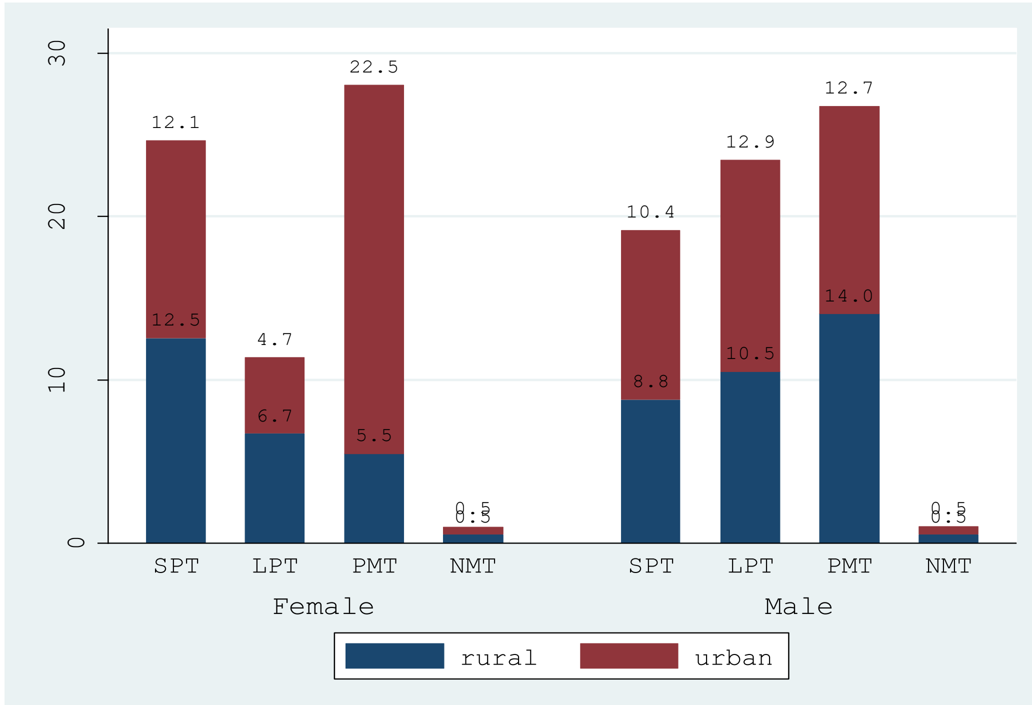


Figure 16: Distribution of main mode of transport by mean RVTT of respondents and sex across location

Source: Fiagborlo (2019).

roles between urban women and men. While urban women perform lots of chores, including dropping of kids at school, before continuing to work later in the morning when traffic already builds up, most urban men drive straight to work from home resulting in the observed difference in the mean RVTT between the two groups in this study. The result shows that traffic congestions in urban environment does not impose only increasing emissions and decreasing speed of travel (Alpizar & Carlsson, 2003), but higher value of travel time for women than men in urban areas.

Regarding rural dwelling, the mean RVTT for rural men was 14 Ghana Cedis per hour, a little over the national mean RVTT of 13 Ghana Cedis per hour for all workers, while women in rural areas had mean RVTT of 6 Ghana Cedis per hour, for using private car and motor-cycle to work. This outcome also reflects the dichotomous occupational role between rural women and men. In the 1930s and 1940s, majority of women did not work or worked closer to home (Pooley & Turnbull, 2000). In Ghana, anecdotal evidence suggests that most rural women do not constitute significant proportion of the working class (48 percent) as evidenced in the data used for this study. Moreover, due to childcare obligations, women also often work closer to home and do not commute for long hours to work like men, explaining the plausibility of higher mean RVTT for rural men than rural women.

While it is discovered that urban women who used private transport (private car and motor-cycle) from home to work spent more mean RVTT than urban men, the outcome for all non-motorised transport (walking and bi-cycling) users from home to work is rather interestingly different. For example, Figure 16 demonstrates that across location, for all non-motorised transport (walking and bi-cycling) users to work, the mean RVTT for women and men remains the same and coincides with the national mean RVTT of 0.5 Ghana Cedis per hour, respectively. It is, however, noted that although majority of men were more likely than women to use private transport (private car and motor-cycle) from home to work (Table 8), it appears within the context of location and mean RVTT, more urban women are enduring longer hours driving to work; hence spending more RVTT on average than men. This finding has implications for the workers, the environment and the employers.

Distance and transport modes have been examined in literature (Birago *et al.*, 2017; Pooley & Turnbull, 2000; Abane, 1993). Figure 17 presents the distribution of transport mode by mean distance as well as gender across location.

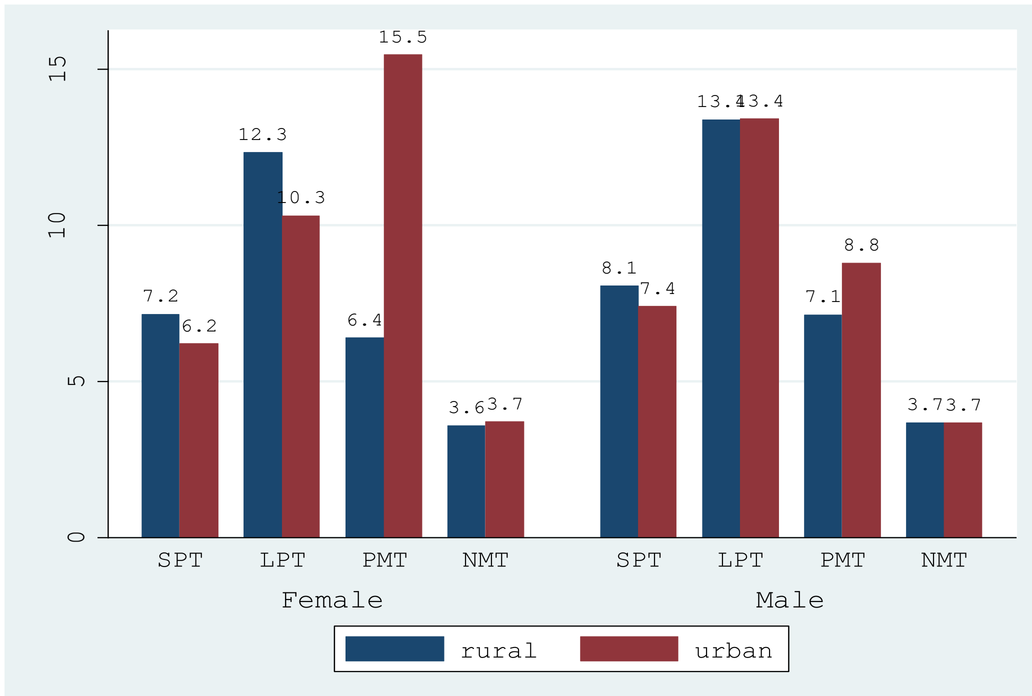


Figure 17: Distribution of main mode of transport by mean distance of respondents and sex across location

Source: Fiagborlo (2019).

Accordingly, where people live was found to change their journey to work distances, route of journey and transport mode (Pooley & Turnbull, 2000). So, this study expected that all workers in Ghana will choose transport mode options which best satisfy their travel-to-work needs, conditional on the mean distance they have to endure, their sex and where they live. Reiteratively, more men than women used private mode (private car and motor-cycle) from home to work, whilst more workers lived in rural areas than urban areas (Table 8). This study also indicated that those who used large public transport (MMT bus, ferry and train) to work endured longer average distance (12.4 km) than those who walked as well as biked.

Figure 17 reports that, conditional on the mean distance, sex and location, the mean distance for urban women, who used private transport (private car and motor-cycle) from home to work was 16 km per hour compared to 9 km per hour for urban men. What this result means is that, women in urban areas are enduring longer distances from home to work than urban men, and this, according to Abane (1993), may arise from poor land-use arrangement. The plausible reason women endure longer distances to work than urban men may also be as a result of women performing multiple domestic tasks, including dropping of kids at school, before getting to work from home than most men, who drive straight to work from home.

Comparing rural men and women, who used private car and motor-cycle in terms of distances covered from home to work, this study finds that rural men were enduring longer mean distance (7 km) from home to work than the 6 km per hour mean distance of rural women, even though the longer distance by rural men is lower than the 9 km per hour mean distance for all workers in Ghana, who used private transport (private car and motor-cycle) to work from home (Figure 14). Pooley and Turnbull (2000) found that majority of women in the 1930s and 1940s did not work or worked closer to home. Anecdotal evidence in Ghana suggest that women do constitute significant proportion of the working population. This study finds more than half (52 percent) of the workers to be women. Meanwhile women tend to work closer to their home, with rural men commuting long distance to work.

The analysis further indicates that women in urban areas traveled longer distance to work than rural women, while there is no substantial difference between the distance endured by rural working men and urban working men, who used private cars and motor-cycles to work from home. Considering the large public transport (MMT bus, ferry and train) users from home to work, the result shows that mean distance for urban men was 12.4 km per hour, while that of urban women was 10.3 km per hour for all workers who traveled to work by MMT bus, ferry and train. Regarding rural men and women, Figure 17 shows that rural men endured longer distance (13.4 km per hour) to work from home than rural women (12.3 km per hour). The finding suggests that urban women who traveled to work from home, using the large public transport (MMT bus, ferry and train), endured longer distances (12.3 km per hour) than did rural working women (10.3 km per hour).

Interestingly, this study ostensibly finds no difference between the mean distances for rural and urban men, who used large public transport (MMT bus, ferry and train) to work from home. In particular, whilst the mean distance was 12.4 km per hour for urban men, who used large public transport (MMT bus, ferry and train) to work from home, that for rural men was 13.4 km per hour. The result implies that older working women in urban areas are traveling longer distances on large public transport (MMT bus, ferry and train) from home to work than rural working women, but we do not find any ostensible difference between the distance covered by urban working men and rural working men in the choice of mode of transport for travel to work from home. The outcome is consistent with the result of Birago *et al.* (2017) that distance is a significant variable in the choice of transport mode.

Pooley and Turnbull (2000) established that awareness of the environmental issues makes people to bike to work rather than use cars. Meanwhile the benefits of using bike such as low cost, relative speed (especially the ability to undertake complex cross-town journeys quickly to cut through standing traffic and avoid waiting for public transport), and enjoyment of exercise, have been documented. This paragraph establishes the connection between mean distance and non-motorised transport (walking and bi-cycling) within the context of location and gender. Figure 17 shows that of all those who combined walking and bicycling to work from home, the mean distance to work was quite proportionally distributed between rural working women and urban working men, respectively. While urban women endured 3.7 km per hour combining walking and biking to work, urban men similarly endured 3.7 km per hour combining walking in addition to biking to work.

Again, Figure 17 reveals that whilst rural women who were participating in the labour market endured 3.6 km per hour walking and biking from home to work, the men in the rural areas who were participating similarly endured a slightly higher mean distance of (3.7 km per hour) from home to work. The result shows that though women were more likely to combine walking and biking from home to work (Table 8), regarding mean distance, sex and location, there is no substantial difference between either rural working men and urban working women. The extent to which distance influences the probability of the choice of transport mode is considered in the subsequent subsection under the multinomial regression analysis.

Previous section of this thesis showed that private transport (private car and motor-cycle) users have the highest mean (0.54) per capita commercial assets ownership, whilst the lowest mean (0.50) per capita commercial assets ownership was reported for large public transport (MMT bus, ferry and train). Similarly, Figure 14 showed that the mean per capita private assets ownership was highest (0.66) for users of private car and motor-cycle to work from home, whilst the lowest (0.52) mean per capita private assets ownership was reported for users of large public transport (MMT bus, ferry and train) and small public transport (taxi, trotro and mini-bus), respectively. The next paragraphs discuss how accessibility to private and commercial motorised assets influences transport mode choice of respondents from home to work within the framework of gender as well as location.

Aforementioned study (Curl *et al.*, 2018) identified residential location among other demographic factors to influence the level of car ownership change.

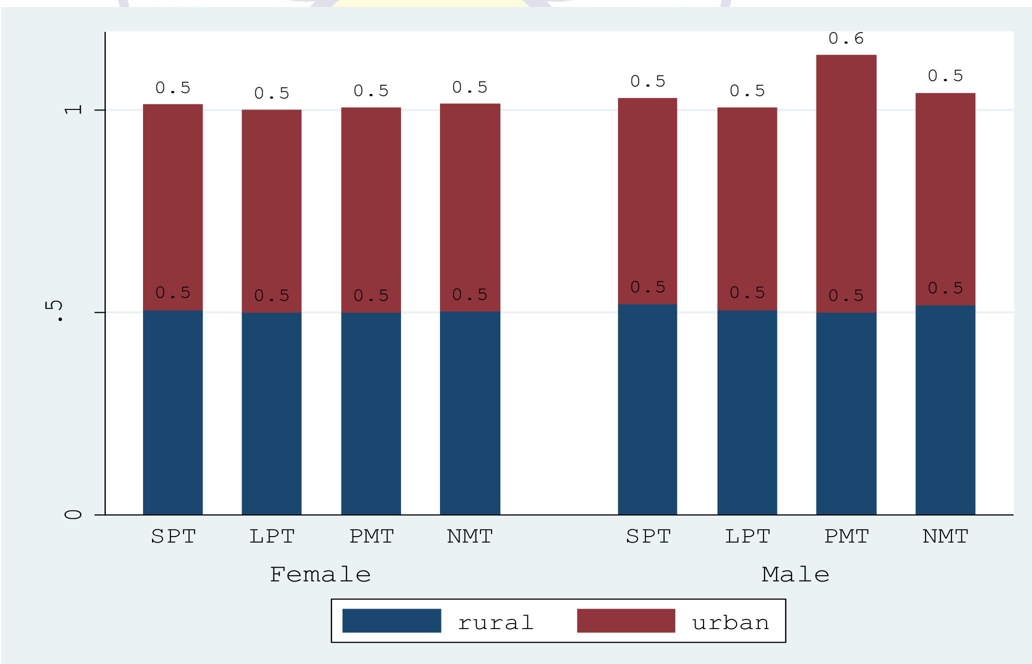


Figure 18: Distribution of main mode of transport by mean pc_cma of respondents and sex across location

Source: Fiagborlo (2019).

Figures 18 & 19 present the distribution of main mode of transport from home to work by mean per capita commercial and private motorised assets of respondents across sex and location. The finding shows that urban male workers, who traveled to work, using private transport (private car and motor-cycle), have the highest access to commercial motorised assets compared to rural men (Figure 18). For other modes, the result shows that male or female workers in rural or urban areas have equal access to commercial motorised assets (Figure 18). Regarding respondents' access to private motorised assets, the result in Figure 19 indicates that rural as well as urban men, who commuted on private transport (private car and motor-cycle) to work from home, have the dominant access to private motorised assets than women.

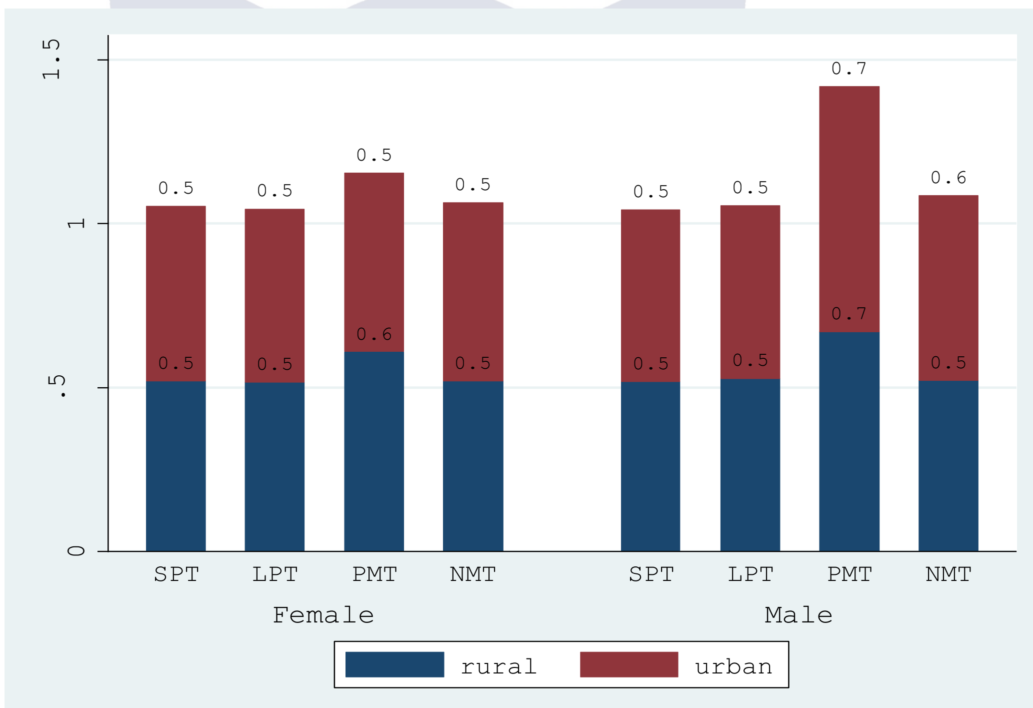


Figure 19: Distribution of main mode of transport by mean pc_pma of respondents and sex across location

Source: Fiagborlo (2019).

Moreover, the result shows that urban and rural male workers, who used private transport (private car and motor-cycle) from home to work, have equal access to per capita private assets. Whilst rural women, who used private transport (private car and motor-cycle) to work from home, have higher access to per capita private motorised assets, Figure 19 shows that urban men, who used private transport (private car and motor-cycle) to work, have higher access to per capita private motorised assets than urban women, who used private car and motor-cycle.

Again, even though rural women, who were private transport (private car and motor-cycle) users to work from home, have higher access to per capita private motorised assets compared to urban women, the result reveals that rural men, who were private transport (private car and motor-cycle) users to wok, have dominant access to per capita private motorised assets across genders (Figure 19). The result discloses that urban men have higher access to per capita private motorised assets compared to rural men who walked or biked (Figure 19), whilst urban or rural male or female workers have equal access to per capita commercial motorised assets (Figure18). The next paragraph discusses home-work trip frequency relative to transport mode choice, conditional on sex and location. It is believed that if business activities are conglomerated in an area, congestion may result from trips to work into that area; hence, frequency of trip to work may impact the choice of transport.

Figure 20 displays the distribution of main mode of transport from home to work by mean trips frequency of respondents and sex across location. According to Figure 20, the mean trip frequency for rural male workers, who used private transport (private car and motor-cycle) to work from home, was higher than rural female workers, who used same transport mode to work from home. Within gender, the results indicate that while rural and urban female workers, who used private transport (private car and motor-cycle) to work from home, have the same average trip frequency, the rural and urban male workers, who commuted on same mode of transport to work from home, have different trip frequencies. Figure 20 also shows that more trip frequency was made by urban male workers who used private transport (private car and motor-cycle) to work from home than rural male workers.

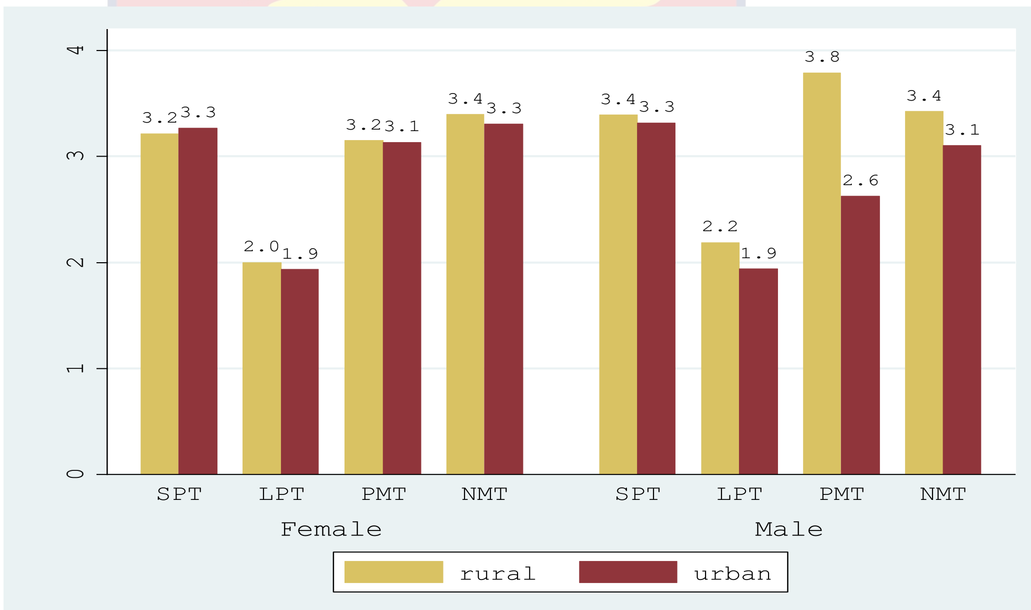


Figure 20: Distribution of main mode of transport by mean trips frequency of respondents and sex across location

Source: Fiagborlo (2019).

The result, however, shows a marginal difference between the mean trip frequency for urban and rural female workers, who commuted on large public transport (MMT bus, ferry and train) from home to work. For instance, it is noted that while the average frequency trips for rural women was 2.0, that for urban women, who used the same means of transport from home to work, was marginally 1.9. For male workers, who used large public transport (MMT bus, ferry and train) to work, the result indicates that the mean trip frequency for rural male workers was higher (2.2) than urban male (1.9) workers, who used large public transport (MMT bus, ferry and train) from home to work (Figure 20). This result, therefore, signifies a marginal dominance of mean trip frequency of rural male and female workers, who used large public transport (MMT bus, ferry and train) from home to work.

Empirical Results of the MNLOGIT Model of Transport Mode Choice

The results of the multinomial logistic regression of transport mode choice by workers in Ghana are presented and discussed under this section. Table 6 reveals that the model explained between 26 percent (Cox & Snell R Squared) and 60 percent (Nagel kerke R Squared) variation in the choice of main mode of transport. Thus, the odds of an individual choosing an alternative mode given the referenced mode relate significantly to the explanatory variables in this model. Since MNLOGIT is a non-linear model, there are two options for interpreting the coefficients. One, is to compute the marginal effects, which approximate on additive scale how much the dependent variable is expected to change for a unit change in the explanatory variable. Two, is to exponentiate the coefficients to get the relative risk ratio on multiplicative scale by which extent the dependent variable changes for one unit change in an explanatory variable (see Long & Freese, 2006).

Tables 9 reports the results of the relative risk ratios (RRR) and maximum likelihood estimates (MLE) for MNLOGIT model of mode of transport by workers from home to work. From Table 9, the result indicates that the relative risk ratio for a unit increase in the variable RVTT is 7.644 (exp (2.034)) for using small public transport (taxi, trotro and mini-bus) to work from home, compared to non-motorised transport (walking and bicycling), other variables being held constant.

Table 9: Relative Risk Ratio and MLE for MLOGIT model of mode of transport

Variables	Small public transport		Large public transport		Private transport	
	RRR	MLE	RRR	MLE	RRR	MLE
RVTT	7.644***	2.034***	7.573***	2.025***	7.700***	2.041***
	(1.911)	(0.250)	(1.898)	(0.251)	(1.926)	(0.250)
distance	1.069***	0.067***	1.124***	0.117***	1.091***	0.086***
	(0.018)	(0.017)	(0.022)	(0.019)	(0.019)	(0.018)
age	1.138***	0.130***	0.900**	-0.105**	1.040	0.039
	(0.044)	(0.038)	(0.042)	(0.047)	(0.053)	(0.051)
agesq	0.999***	-0.001***	1.001	0.001	1.000	-0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
pc_pma	0.132	-2.024	0.440	-1.411	7.588***	2.027***
	(0.167)	(1.268)	(0.440)	(1.805)	(2.788)	(0.367)
pc_cma	0.587	-0.533	0.000	-8.168	0.035***	-3.361***
	(0.467)	(0.795)	(0.002)	(5.700)	(0.042)	(1.214)
male	1.427**	0.356**	1.735	0.551	2.632***	0.968***
	(0.259)	(0.181)	(0.636)	(0.367)	(0.712)	(0.271)
urban	1.609***	0.476***	1.894*	0.639*	0.875	-0.133
	(0.293)	(0.182)	(0.706)	(0.373)	(0.227)	(0.259)
constant	0.000***	-7.888***	0.658	-0.418	0.001***	-7.545***
	(0.000)	(0.991)	(2.181)	(3.313)	(0.001)	(1.251)
observations	7,262		7,262		7,262	

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Fiagborlo (2019).

That is to say, the expected risk is 7.644 times higher for individual whose RVTT increases by a unit for using small public transport mode to work from home compared to using non-motorised transport (walking and bicycling), all else equal.

As to large public transport, the result indicates that the risk of combining MMT bus, ferry and train is 7.573 (exp (2.025)) times higher for a unit increase in the variable RVTT than walking and bicycling to work, holding other variables in the model constant. For private transport (private car and motor-cycle), the expected risk is 7.700 (exp (2.041)) times higher for combining private car and motor-cycle than walking and bicycling to work, other things being equal. Distance is very significant in the choice of transport from home to work (Birago *et al.*, 2017). In particular, the result shows that the relative risk for a unit increase in the distance variable is 1.069 (exp (0.067)) times higher for using small public transport to work relative to walking and bicycling, all else equal. Simply put, for an extra kilometer per hour, an individual is more likely to use small public transport mode to work relative to using non-motorised transport to work, other things being equal.

For large public transport (MMT bus, ferry and train) users, the result indicates that the relative risk is 1.124(exp (0.117)) times higher for workers who spent a kilometre per hour more to work from home combining MMT bus, ferry and train than workers walking and bicycling, other things being equal. Moreover, the study finds that when an individual decides to travel to work combining private car and motor-cycle, the relative risk is 1.091(exp (0.086)) times higher compared to walking and bicycling, holding other variables in the model constant. Previous study found age to be significant in transport mode choice (Alpizar & Carlsson, 2003). In this analysis, age of workers is significant at 1 percent in the choice of taxi, trotro as well as mini-bus users. It is also significant at 5 percent in the choice of large public transport (MMT bus, ferry and train) to work from home, whilst insignificant in the choice of private transport (private car as well as motor-cycle).

Concerning relative risk, the results in Table 9 show that while an additional year for a worker who used small public transport (taxi, trotro and mini-bus) to work increases the expected risk by 1.138 (exp (0.130)) times higher relative to non-motorised transport (walking and bicycling), other things being equal, the expected risk was, however, 0.900 (exp (-0.105)) times lower for a worker who used large public transport to work than using non-motorised transport (walking and bicycling), all else equal. Age squared was included in the model to test for its quadratic effect on the choice of mode of transport. Table 9 reports that age has quadratic effect on the small public transport (taxi, trotro and mini-bus). Specifically, age has significant inverted U-shaped effect on the choice of small public transport (taxi, trotro and mini-bus). The implication is that the use of small public transport (taxi, trotro and mini-bus) to work rises with age, but declines later.

Moreover, the result shows insignificant inverted U-shaped and U-shaped effects of age on the choice of private transport (private car and motor-cycle) and large public transport (MMT bus, ferry and train) to work, respectively. The implication is that the use of private transport (private car and motor-cycle) increase with age, but decline beyond tipping point, while the insignificant U-shaped effect implies that the use of large public transport (MMT bus, ferry and train) decreases with increasing age, and increases later with the rising age of the individual.

Focusing on the relative risk ratio in Table 9, and accounting for the significant quadratic effect of age, the result shows that an additional year for workers beyond the tipping point, decreases the expected risk by 0.999 (exp (-0.001)) times more for using small public transport (taxi, trotro and mini-bus) to work than using non-motorised transport (walking as well as biking) to work, other things being equal.

The previous section graphically examined how accessibility to private and commercial motorised assets influences transport mode choice of workers within the context of gender and location. While Curl *et al.* (2018) found residential location among other factors to influence the level of car ownership change, Oakil, Manting and Nijland (2016) showed that car ownership determines car use. Accordingly, this study explored the effects of per capita private and per capita commercial motorised assets on transport mode choice of workers. Table 9 reports interesting associations between per capita private and per capita commercial motorised assets and transport mode choice of workers. Particularly, it is noted that even though per capita private and per capita commercial motorised assets have no significant associations with transport mode choice, an increase in access to these assets was found to decrease the likelihood of using small public transport (taxi, trotro and mini-bus) and large public transport (MMT bus, ferry and train) to work.

However, the result provides evidence of a significant association between private transport (private car and motor-cycle) use and per capita private as well as per capita commercial motorised assets. Factually, increasing access to these assets will increase but decrease the likelihood of using combination of private car and motor-cycle to work from home. Concentrating on the private car and motor-cycle, the result shows that a unit increase in access to per capita private assets increases the expected risk by 7.588 (exp (2.027)) times higher for using private transport (private car and motor-cycle) to work than using non-motorised transport (walking and bicycling) to work, other thing being equal. Besides, a unit increase in access to per capita commercial motorised assets decreases the relative risk by 0.035(exp (-3.361)) times higher for those who used private transport to work relative to those who used non-motorised transport to work, all other variables being held constant.

The results suggest that ownership of motorised assets, whether private or commercial, has no significant influence on the choice of small public transport (taxi, trotro and mini-bus) and large public transport (MMT bus, ferry and train) to work, but assets ownership (car) relates significantly to the utilisation of private transport (private car and motor-cycle) to work, supporting the finding of Oakil *et al*. (2016). Several studies (Birago *et al*., 2017; Amoh-Gyimah & Aidoo, 2013a; Okoko, 2007; Abane, 1993) found sex to be significant in the analysis of transport mode choice in developing countries. This thesis controlled for the association between gender and choice of transport mode. Table 9 reports that sex was significant at 5 percent in determining the choice of small public transport (taxi, trotro and mini-bus) from home to work, but effect the choice of private transport (private car and motor-cycle) from home to work at 1 percent level of significance.

However, the result did not show significant evidence of sex determining the choice of large public transport (MMT bus, ferry and train) from home to work. The insignificance of sex in the large public transport model implies that there is no significant mean difference effect between male and female workers relative to their choice of MMT bus, ferry and train form home to work. Meanwhile, sex has a positive sign in all the transport mode models signifying that men were more likely to use alternative modes from home to work than women. The result further shows that the expected risk was 1.427(exp (0.356)) higher for male workers than female workers for using small public transport from home to work, compared to using non-motorised transport (walking and bicycling), other things being equal, confirming that women were more likely to walk as well as bike to work than men.

It is also evident in literature (Pooley & Turnbull, 2000) that where people live changes their journey to work distances, as well as their route of journey and transport modes. Although this study principally established that about 60 percent and 40 percent, respectively, of workers lived in rural and urban areas, it further explores the response of transport modes from the effects of locational differences between urban and rural workers. Notably, an individual in rural setting rather than urban settings was expected to prefer non-motorised means of transport to work from home to alternative modes, holding all other factors in the model constant. The reverse was expected, where an individual in rural settings rather than urban settings exhibits less likelihood to use non-motorised means of transport to work in the presence of alternative modes, holding all other factors in the model constant.

Table 9 specifically reports that living in urban area than rural area increases the likelihood of picking small public transport (taxi, trotro and mini-bus) to work at 1 percent level of significance, compared to using non-motorised transport (walking and bicycling), but only increases the likelihood of using large public transport (MMT bus, ferry and train) to work at 10 percent level of significance, compared to using non-motorised transport (walking and bicycling) to work. While no evidence is found suggesting any significant effect of living in urban area than rural area on private transport (private car and motor-cycle), the result indicates that living in urban area compared to rural area decreases the likelihood of using private transport (private car and motor-cycle) to work from home, compared to using non-motorised transport (walking and bicycling) to work, all other things being equal.

The insignificance of the urban variable in the private transport model manifests no significant mean difference effect between urban and rural workers on their choice of private transport (private car and motor-cycle) to work. Regarding relative risk, the result indicates that being in urban area than rural area increases the expected risk by 1.609 (exp (0.476)) times more for using small public transport (taxi, trotro and mini-bus) to work than using non-motorised transport to work, holding other factors in the model constant. Likewise, being in urban area compared to rural area increases the relative risk by 1.894 (exp (0.639)) times more for using large public transport to work relative to using non-motorised transport, holding other factors in the model constant. The result implies that being in urban area than rural area increases the relative risk less for using small public transport to work than using large public transport (MMT bus, ferry and train) to work, compared to using non-motorised transport, holding all other variables constant.

Chapter Summary

The thrust of this chapter was to examine the drivers of transport mode choice of workers. Specifically, it examined the relative risks of RVTT on main mode of transport within the general context of travel behaviour of workers in Ghana. To realise this objective, an MNLOGIT model was fitted to home-to-work data. Consistent with our expectation and the extant literature, the results indicated that RVTT and distance travel by a worker significantly influenced the choice of transport modes, and an increase in the RVTT and distance per hour increase the expected risk for using PMT and LPT for individuals compared to those walking and bicycling to work from home. Further, while being a male worker significantly explained workers' choice of SPT and PMT, no significant evidence was found of gender effecting the choice of MMT bus, ferry and train from home to work. This implies that there is no significant mean difference effect between male and female workers relative to their choice of MMT bus, ferry and train to work from home.

Meanwhile, gender has a positive sign in all the transport mode models signifying that men were more likely to use alternative modes from home to work than women. For the relative risk, the result showed that the expected risk was higher for male workers than female workers for using SPT from home to work, relative to walking and bicycling, confirming that women were walking and biking to work than men. Additionally, the result showed that living in urban area against rural area increased the likelihood of picking SPT and LPT to work, compared to walking and bicycling. Though no evidence of a significant effect was found of living in urban area versus rural area on the choice of PMT, the result indicated that living in urban area versus rural area decreased the likelihood of using PMT to work, compared to walking and bicycling to work, manifesting no significant mean difference effect between urban and rural workers on their choice of PMT to work.

It was also noticed that even though per capita private and commercial motorised assets had no significant associations with transport mode choice, an increase in access to assets was found to decrease the likelihood of using SPT and LPT to work from home, other things being equal. There was, however, an evidence of a significant association between PMT use and per capita private as well as per capita commercial motorised assets. Thus, as individual's access to these assets increases, their likelihood of using combination of private car and motor-cycle to work from home increases in respect of the positive coefficient on the per capita private asset, and decreases based on the negative coefficient on the per capita commercial motorised assets. Across all modes, the result revealed that a unit increase in access to per capita private asset increases the relative risk of individual using private car and motor-cycle to work higher than walking and biking to work.

In addition to the preceding results, this study found that while age of workers was significant in the choice of taxi, trotro and mini-bus and MMT bus, ferry and train to work from home, it was insignificant in the choice of private car and motor-cycle to work. Thus, additional year to the age of a worker who used taxi, trotro and mini-bus to work increases the expected risk higher than walking and bicycling, while decreasing the expected risk more for a worker who used large public transport (MMT bus, ferry and train) from home to work compared to non-motorised transport (walking and bicycling). The next chapter of the study addresses the third specific objective, which aimed to understand whether (or) not the effect of ICT expenditure of households on transport fuel intensity differentiates demographic attribute (sex) of households, using disaggregated data from Ghana.

CHAPTER EIGHT

DRIVERS OF TRANSPORT FUEL INTENSITY

Introduction

Generally, this thesis sought to identify the drivers of transport fuel expenditure and mode choice in Ghana. This chapter addresses the third specific objective, which aimed at assessing how the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of households, using disaggregated data from Ghana. There are five sections in this chapter. The first section provides introduction to this chapter. The second section presents the empirical model of the study, and this is followed by a brief recaps of the data used as well as the descriptive statistics. Section four considers the VIF and LR tests of the variables used in the study. The penultimate section discusses the results and the findings of the study. The final section considers the summary of Chapter Eight.

Fuel intensity (Logistic regression equations)

Chapter Four of this study specified the log-likelihood framework for the logit equation (34) for assessing how the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of households, using disaggregated data from Ghana. The empirical logistic regression equations (37) is specified under this section. The independent variable is less fuel intensive (LFI). The empirical logistic regression equation is functionally specified as follows:

$$LFI_i = \beta_0 + \beta_1 h\exp_i^{ict} + \beta_2 h\exp_i^{ictsq} + \beta_3 hsize_i + \beta_4 hinc_i + \beta_5 urban_i + \beta_6 male_i + \beta_7 married_i + \beta_8 aged_i + \beta_9 owntype_i + \beta_{10} worker_i + \varepsilon_i \qquad (37)$$

Where the predictor variables are the amount of household mean ICT expenditure ($hexp^{ict}$); the squared of the amount of household mean ICT expenditure ($hexp^{ictsq}$) and household size (*hsize*). The rest are: dummy of the income of household proxied with mean household expenditure in Ghana cedis (*hinc*); dummy of the location of households (*urban*); dummy of sex of the head of households (*male*); dummy of the marital status of the head of households (*married*); dummy of whether households have members above age 65 years or otherwise (*aged)*; dummy of whether the household head has own type of house or otherwise (*owntype*); dummy of whether the household has more workers than the average number of workers in households (*worker*). Every other parameter in the empirical equation (37) is as explained elsewhere in the aforementioned chapters.

It is imperative, moreover, to note that the logistic regression equations (37) was set up to satisfy two purposes. Of interest are the household model and the gender models. The outcome and all the control variables remain the same in these models, except for the gender models where gender was dropped. Table 10 reports the variables hypothesised to impact TFI in the household and gender models, and their definitions, measurements and expected signs. In Table 10, it is expected that an increase in mean ICT expenditure of households would have quadratic effect on TFI, other things being equal. Similarly, it is expected that an increase in household size would decrease TFI because of scale effects (Bardazzi & Pazienza, 2018). However, it is expected that dwelling in urban area, being male household heads, being married household heads, having a member of the household aged above 65 years, owning a house, and having more than one-third of the household members working, should all have positive or negative effects on transport fuel intensity.

Table 10: Variables hypothesised to impact household, women and men TFI

Dependent variable	Description of variables	Sign
TFI	Transport fuel intensity, which denotes annual household fuel expenditure on transport in Ghana cedis above or below the mean annual household fuel expenditure on transport. It is therefore a binary variable with 1= less fuel intensive (LFI) expenditure, 0= more fuel intensive (MFI) expenditure	
Independent variable		
Continuous:		
hictexp	Household mean telecommunication expenditure in Ghana cedis	+/-
hictexpsq	Squared household mean telecommunication expenditure in Ghana cedis	+/-
hsize	Measured as total number of residents excluding household help	-
Discrete:		
hinc	Quintile of mean household income proxied by mean household expenditure in Ghana cedis	+/-
urban	1=urban respondent, 0 otherwise	+/-
male	1=male headed household, 0 otherwise	+/-
married	1 =married household head, 0 otherwise	+/-
aged	1=age of household members above 65 years, 0 otherwise	+/-
owntype	1 =head of household in own house, 0 otherwise	+/-
worker	1=household has more workers than average # of workers, 0 otherwise	+/-
SEX# INCQ	Interaction between sex and quintile of mean income of household / ICT expenditure	+/-

Source: Fiagborlo (2019).

It is, furthermore, expected that male headed households should be more likely to be LFI compared to their female counterpart because, male headed households tend to have more access to their own means of transport and are also capable of generating financial resources for the family than female headed households. This study applied logistic regression to the transport fuel intensity data, which were extracted from the GLSS7 data of households in Ghana. The following subsection describes briefly the data used for executing objective three.

Data used in the Study

This subsection highlights the GLSS7 data of households in Ghana. This data is the latest consumer expenditure survey in Ghana. Although it does not generally provide information on travel behaviour, the GLSS7 includes sufficient information on household transportation expenditures to aid the analysis. It is noted that the GLSS7 data on the transport fuel expenditure includes purchases of gasoline for private vehicles, but precludes fuel expenditure on public transport. Again, like other surveys considered in Chapter Five, the GLSS7 also includes items such as expenditures on food, education, water, electricity and garbage disposal, remittances, miscellaneous expenditure and rental payments (GSS, 2017). This study used 14009 sample for the household model and a disaggregated sample of 4366 for women and 9643 for men models, respectively. The descriptive statistics of the factors affecting transport fuel intensity are discussed in the subsequent section to help determine the sanctity of the data used for the analysis.

Descriptive Statistics of Factors affecting TFI (all sample)

While the previous section highlighted the data used for the study, this section considers the statistics of the factors affecting TFI. The process involves testing of household data to ascertain whether there is significant difference between LFI and MFI on the basis of some predictive characteristics. Student t-test was engaged to analyse the continuous variables such as ICT expenditure and household size. The categorical variables were analysed using the Pearson's chi-square distribution test. The null hypothesis was that there is no difference between LFI and MFI differentiated on the basis of the various predictive variables in the regression models. On the other hand, the alternative hypothesis was that there is difference between LFI and MFI differentiated on the basis of the predictive variables in the regression models. Table 11 reports the descriptive statistics of variables used for the regressions as well as test of difference for household sample.

From Table 11, it is observed that the student t-test of the difference in the mean ICT expenditure for LFI households and MFI household was statistically equal to zero. This imply that mean ICT expenditure differs between households that were LFI and those that were MFI. Similarly, Table 11 reports significant difference between the LFI and MFI on the basis of household size. Therefore, the null hypothesis that there is no difference between LFI and MFI differentiated on the basis of household size could not be accepted at 1 percent level of significance. The implication of the result is that household size is significant in the decision of households to LFI or MFI. Likewise, the result reveals that income of the households is significant in the determination of whether to be LFI or MFI. This is

Table 11: Descriptive statistics of variables used for the regressions and test of difference for sub-sample (household sample)

	Sample (14009)		MFI		LFI		
Variable	Prop/M	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Sig. level
hictexp	284.867	582.641	579.584	1100.457	253.25	85.558	***
hsize	4.200	2.867	5.466	3.634	4.065	2.738	***
Incgroup	3.000	1.414	3.897	1.201	2.904	1.402	***
urban	0.430	0.495	0.427	0.495	0.430	0.495	***
male	0.688	0.463	0.936	0.245	0.662	0.473	***
married	0.552	0.497	0.808	0.394	0.524	0.500	***
owntype	0.480	0.500	0.391	0.488	0.490	0.500	***
aged	0.149	0.356	0.066	0.249	0.158	0.365	***
worker	0.310	0.463	0.397	0.489	0.301	0.459	***

Note: ∗∗∗implies the means of the corresponding variables for those who are LFI and MFI are significantly different at 1%

Source: Fiagborlo (2019).

because, the null hypothesis that there is no difference between LFI and MFI based on households' income could not be accepted at 1 percent level of significance.

Explicitly, this study aims at assessing how the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of household heads, using disaggregated data from Ghana. Consequently, a test has been done to test the hypothesis that being a male head of households or otherwise significantly differentiates between decision to be LFI or MFI. Table 11 reveals a significant difference between LFI and MFI on the basis of sex. Thus, the assertion that being a male head of households or otherwise did not matter in the decision to spend less or more on transport fuel was not accepted at 1 percent level of significance. This test result confirms the finding of (Elias *et al.*, 2015). Regarding whether urban or rural dwelling affects TFI of households, the initial conjecture of no significant difference between LFI and MFI groups on the bases of households' dwelling was not accepted at 1 percent level of significance. This is because Table 11 reveals a significant difference between LFI and MFI groups based on household's dwelling.

Based on the t-test in Table 11, this study also fails to accept the null hypothesis at 1 percent level of significance about the equality between the LFI and MFI groups on the basis of marital status of the head of households. The reason is that marital status of household heads significantly differentiates between LFI and MFI groups. Considering age and working members of households, Table 11 reveals a significant evidence against the null hypothesis that there is no difference between LFI and MFI groups differentiated on the basis of having a member of the household aged above 65 years or otherwise, and having more than one-third of the household members working or otherwise. For instance, the test results show that there is a significant difference at 1 percent level of significance between LFI and MFI groups differentiated on the basis of having aged 65 years and above and having number of working members beyond the mean threshold in the household.

Descriptive Statistics of Factors affecting TFI (women and men sample)

Sex is one of the critical sociodemographics that can determine travel behaviour (Uteng, 2012), but often times its influence on transport activities are least examined. Preceding section of this study recalled the objective of assessing how the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of household heads, using disaggregated data from

Ghana. Appreciating the influence of ICT on transport fuel expenditure from sociodemographic (sex) perspective is imperative to help policy makers design policies that are gender sensitive, efficient and equitable. Some evidence (Uteng, 2012) exists about how women in most cities who intended to travel shorter distances preferred more public transport and taxi services to private car than men.

More often than not, women perform multiple tasks and activities as a reflection of their gendered role in society. They segmentise their travels into non-work related trips such as dropping of kids at school, going to the market, the shops and the hospital et cetera, sometimes often at odd hours using an unorthodox, expensive modes of transport. According to Village Level Transport Travel Survey (VLTTS), women versus men spent three times as much on transport activities. GSS (2014) likewise reports a rising trend in average transport expenditures per household from GH¢ 624 million to GH¢ 3649 million. Coupled with the global fuel price increases and the multiplicity of daily travel patterns of women, would the burden of transportation costs arising from fuel price increases affect men and women differently? Could the burdens be ameliorated through ICT use to release time and energy of women for socially and environmentally productive activities?

Meanwhile, the complexity of transport needs of women compared to men warrants adequate critical policy responses to transport needs of women through ICT to increase their contribution to economic productivity and social welfare. Furthermore, studies (Jamal *et al*., 2017; Mokhtarian & Tal, 2013; Polydoropoulou & Tsirimpa, 2012) show that electronic shopping, working from home or long-distance learning reduce the possibility of daily travels that an individual make. For example, Polydoropoulou and Tsirimpa (2012) asserted that ICT offers potential to contribute to new opportunities for residential and teleworking and women are expected to leverage from such opportunities if they have access to information usage. ICT has also been found to increase access to finance through mobile money (Asongu, 2013), as well as overcame mobility restrictions and savings and transport costs in real time according to Food and Agriculture Organization([FAO], 2018).

While there is huge body of information about substitution and or complementary effects of ICT on e-activities (Salomon, 1986), these effects are varied among studies (Mokhtarian & Tal, 2013) and their impact on mobility conditions of people is still unclear. Although some efforts have been made to determine how women during typical weekday allocate their time and explore the role of ICT on the way these activities were done (Polydoropoulou & Tsirimpa, 2012), the issues whether (or) not the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of households has received less attention. The articulation of the significance of transportation in meeting economic and social needs of people is well documented, and as a result this study acknowledges the interaction between transport energy consumption and efficient energy use of vehicles, as well as how vehicle design improves fuel efficiency.

However, given the preceding background and the existence of large scale effects of transport related activities on energy consumption, the environment and climate, scientific research is required. The present study aimed at assessing how the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of household heads, using disaggregated data from Ghana. The motivation is to determine how ICT expenditure could ameliorate or bridge the transport fuel intensity gap between female-headed households and male-headed households. Specifically, assessing how the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of households, using disaggregated data, will help appreciate how the effect of transport fuel intensity derives from gendered roles of female as well as male household heads in Ghana.

To realise this goal, the subsequent paragraphs were dedicated to discuss the descriptive statistics of factors affecting TFI from women and men samples. The means of all variables for the LFI and MFI of gendered household heads were computed to determine whether the means of these variables were statistically different from each other. The means were compared using an independent t-test to ascertain whether the difference between the two groups (women and men) was statistically different. The null hypothesis postulates that the difference in the population mean of the two groups (female-headed households and male-headed households) is statistically equal to zero and the alternative hypothesis states that the difference in the population mean of the two independent groups (female-headed households and male-headed households) is statistically not equal to zero.

Considering the sample size of the different gender groups, differentiated by TFI in Table 12, the study shows that at all levels of fuel intensity, the dominance of male-headed households was pronounced. For instance, while 4,279 female-headed households spent less than the average transport fuel expenditure, 8,373 male-headed households made similar transport fuel expenditure within the study period. Regarding those who spent beyond the average transport fuel expenditure,

Table 12: The sample size of gender groups differentiated by TFI

TFI	WOMEN	MEN	TOTAL
MFI	87	1,270	1,357
LFI	4,279	8,373	12,652
TOTAL	4,366	9,643	14,009

Source: Fiagborlo (2019).

the statistics indicate that 87 of the households headed by women spent more on TFI, while 1270 male-headed households spent more on TFI (Table 12). This distribution implies that male-headed households were MFI and LFI than female-headed households. But, is the difference in the TFI between female-headed and male-headed households significant? What factors will significantly explain the observed difference between female-headed as well as male-headed households?

Table 13 reports the analysis of the continuous variables such as ICT expenditure and household size, using student t-test, while using Pearson's chi-square distribution test for the categorical variables. The results indicate that the difference in the mean ICT expenditure for female-headed and male-headed households for less fuel intensive and more fuel intensive group is statistically different from zero. This is a significant proof that mean ICT expenditure for female-headed and male-headed households differentiates between their transport fuel intensity. However, the extent of the difference of ICT expenditure for female-headed households and their male-headed counterparts for the LFI and MFI groups can be appreciated in the regression Table 15 in the next subsection of this chapter.

Table 13: Descriptive statistics of variables used for the regressions and test of difference for sub-sample (women group)

Female Sample (4,366)			MFI		LFI		
Variable	Prop/M	Std. Dev.	Prop/M	Std. Dev.	Prop/M	Std. Dev.	Sig. level
hictexp	218.050	575.940	709.063	886.077	208.066	563.619	***
hsize	3.398	2.147	4.069	2.401	3.384	2.139	***
Incgroup	2.836	1.387	4.103	1.182	2.810	1.379	***
urban	0.486	0.500	0.586	0.495	0.484	0.500	***
married	0.209	0.407	0.402	0.493	0.205	0.404	***
owntype	0.555	0.497	0.402	0.493	0.558	0.497	***
aged	0.207	0.405	0.138	0.347	0.208	0.406	***
worker	0.217	0.412	0.483	0.503	0.211	0.408	***
Male sample (9,643)							
hictexp	315.120	583.168	570.714	1113.37	276.352	438.597	***
hsize	4.564	3.071	5.561	3.685	4.412	2.938	***
Incgroup	3.074	1.420	3.883	1.201	2.951	1.411	***
urban	0.404	0.491	0.417	0.493	0.402	0.490	***
married	0.707	0.455	0.836	0.370	0.687	0.464	***
owntype	0.447	0.497	0.391	0.488	0.455	0.498	***
aged	0.123	0.328	0.061	0.240	0.132	0.339	***
worker	0.352	0.478	0.391	0.489	0.346	0.476	***

Note: ***implies the means of the corresponding variables for those who are more fuel intensive and less fuel intensive are significantly different at 1%

Source: Fiagborlo (2019).

Distribution of transport fuel intensity by variables used in the study

The previous sections tested household data disaggregated into female and male data to learn whether there was a significant difference between LFI and MFI on the basis of some predictive characteristics in our logistic regression. Generally, the results of logistic regression only communicate information to readers about the probability of choosing one category of an event over the other. Concerning the present study, the discussion of the logistic regression would only communicate to the readers the probability of being less fuel intensive compared to being more fuel intensive, given the presence of explanatory variables. Therefore, this section of the study considers the influence of social and economic variables on TFI, within the framework of gendered travel behaviour. Specifically, the section considers how income, mean ICT expenditure, housing-ownership type and marital status influence transport fuel intensity of female-headed and male-headed households.

The section begins with the relationship between gender and the transport fuel intensity (TFI), conditioned on income. This is to highlight how the effect of income on TFI changes given the gender of household heads. This study used xtile command in Stata to categorise income into lower income group (LIG), lower middle income group (LMIG), middle income group (MIG), upper middle income group (UMIG) and higher income group (HIG), respectively. Figure 21 reports the distribution of TFI by income group and gender. It is observed that from the lower income group to higher income group, more male-headed households than female-headed ones were LFI, compared to being more fuel intensive. In particular, the result shows that while a little over 12 percent of male-headed households were LFI

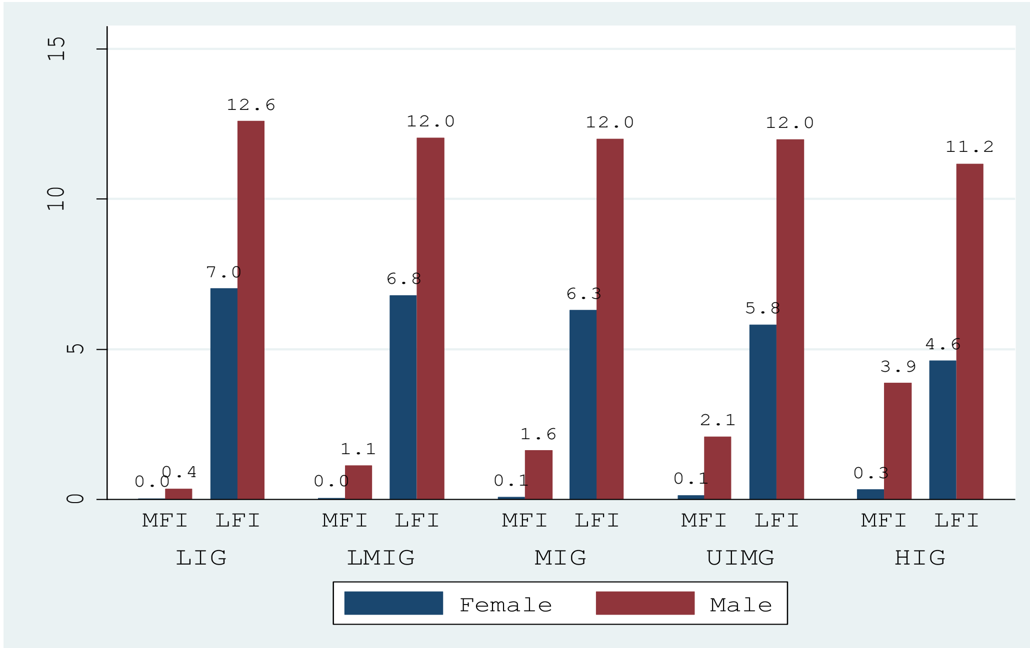


Figure 21: Distribution of TFI by income group and gender

Source: Fiagborlo (2019).

compared to 0.4 percent who were MFI in the LIG, only about 7 percent of the female-headed households were LFI compared to none that were MFI in the LIG.

The result implies that more male-headed than female-headed households in the LIG were LFI. Relative to the HIG, Figure 21 shows that higher proportion of male-headed than female-headed households were LFI. Figure 21 reports that in the HIG, over 10 percent of male-headed households were LFI against four percent that were MFI, while only five percent of female-headed households were LFI, compared to less than one percent that were MFI. Again, the result indicates that more male-headed households than female-headed households in the HIG were LFI in the same income group. Conditioning on location and mean ICT expenditure, Figure 22 reports the distribution of TFI by gender. The result shows much perceptible difference in transport fuel intensity between male-headed or female-headed rural as well as urban households, given their average expenditure on ICT.

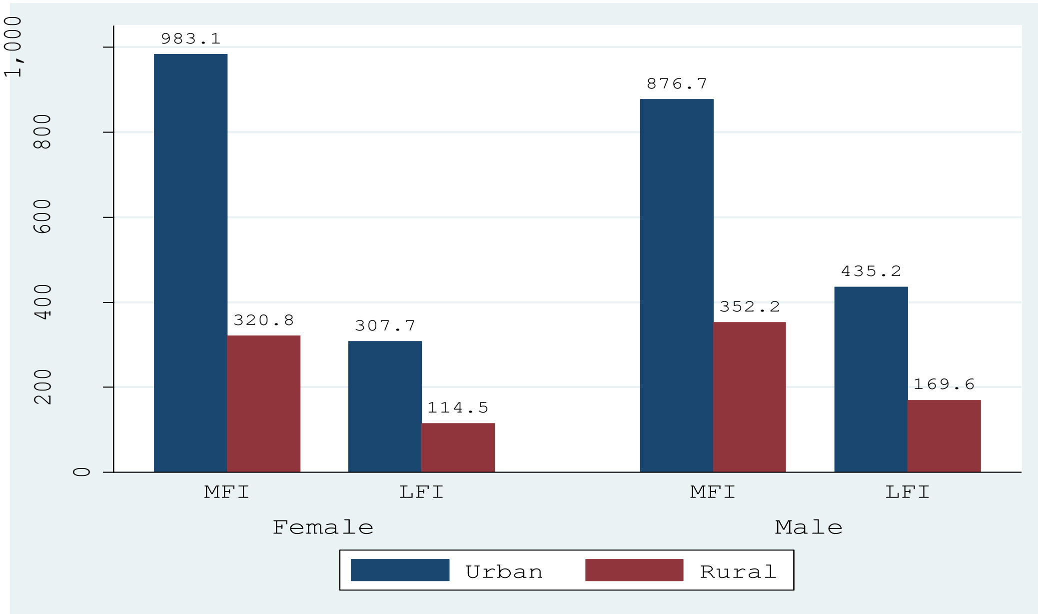


Figure 22: Distribution of TFI by mean HTCOME and gender across location

Source: Fiagborlo (2019).

For example, while female-headed urban households, who spent about GH¢ 1000 on average were MFI, those who spent a little over GH¢ 300 were LFI. Regarding female-headed rural households, the result indicates that those who spent about GH¢ 320 on average on ICT were MFI, whilst female-headed rural households, who spent a little over GH¢ 100 on average on ICT were LFI. The results indicate that female-headed urban households, who spent more on average on ICT were MFI and female-headed urban households, who spent less on average on ICT were LFI. Similarly, female-headed rural households, who spent more on average on ICT were MFI whilst female-headed rural households, who spent less on average on ICT were LFI. Clearly, the analysis shows that the choice of female-headed rural and female-headed urban households to be MFI or LFI is derived from the differences in the scale of the mean ICT expenditures between these clusters.

The finding, focusing on male-headed urban households, shows that those who spent a little over GH¢ 870 on average on ICT were MFI, and those who spent just below GH¢ 450 were LFI. Regarding male-headed rural households, Figure 22 indicates that those who spent less than GH¢ 350 on average on ICT were MFI, whilst male-headed rural households, who spent about GH¢ 170 on average on ICT were LFI. Again, there is no doubt that male-headed urban households, who spent more on average on ICT were MFI and male-headed urban households, who spent less on average on ICT were LFI. Also, male-headed rural households, who spent more on average on ICT were MFI whilst male-headed rural households, who spent less on average on ICT were LFI. Therefore, it appears that the decision of urban or rural male-headed households for being MFI or being LFI may be due to the different mean ICT expenditure between urban or rural male-headed households.

Housing ownership and its influence on transport expenditure has been a subject of research (Sanchez *et al*., 2006). The following discussion covers the difference in the intensity of transport fuel between owned-type household heads and rented-type household heads that were either male or female, conditional on how much was spent on average on ICT. Figure 23 reports the distribution of TFI by mean ICT expenditure and gender across housing type. While female-headed owned-type households, who spent above GH¢ 800 on average on ICT were MFI, female-headed owned-type households that spent below GH¢ 200 on average on ICT were LFI. Also, while female-headed rented-type households, who spent about

GH¢ 235 on average on ICT were observed to be LFI, those female-headed rented-type households, who spent a little over GH¢ 530 on average on ICT were MFI.

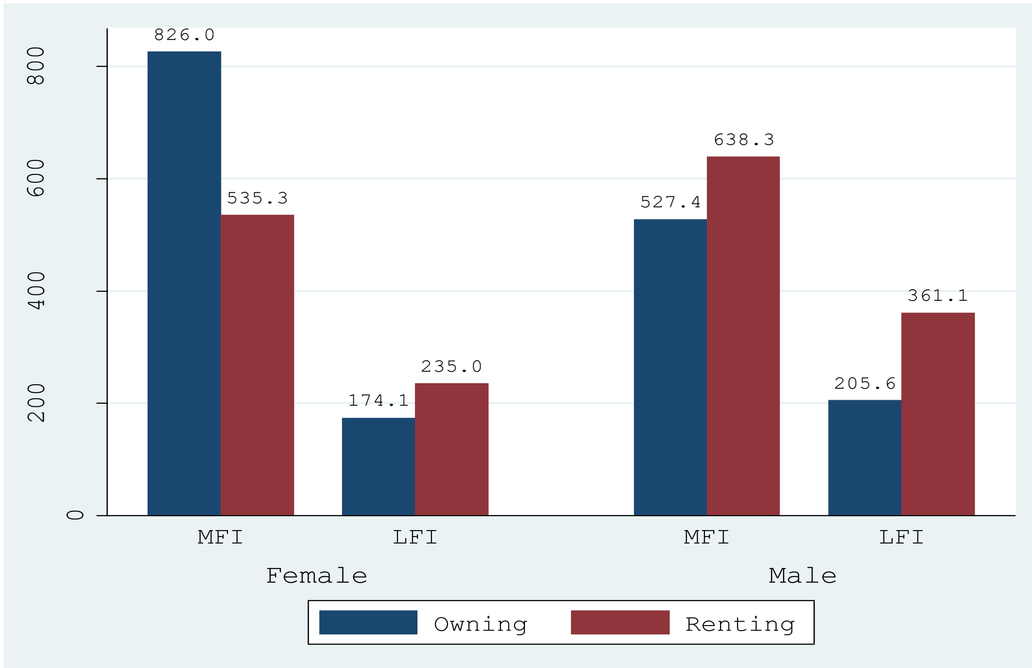


Figure 23: Distribution of TFI by mean HTCOME and gender across htype

Source: Fiagborlo (2019).

The results indicate that female-headed owned-type households, who spent more on average on ICT were MFI, whilst female-headed owned-type households who spent less on average on ICT were LFI. Similarly, female-headed rented-type households, who spent more on average on ICT were MFI and female-headed rented-type households, who spent less on average on ICT were LFI. From the aforesaid analysis, the difference in transport fuel intensity between female-headed households living in rented homes and those living in their own apartments is visibly a function of the extent of mean ICT expenditures between owned-type housing of female-headed households. The result, focusing on male-headed owned-type households, reveals that those who spent more than GH¢ 520 on average on ICT were MFI, whilst those who spent less GH¢ 200 on average on ICT were LFI.

Figure 23 further reveals that male-headed households who lived in rented apartments and spent above GH¢ 630 on average on ICT were MFI, whilst those who spent about GH¢ 360 on average on ICT were LFI. The results indicate that male-headed households in rented homes, who spent more on average on ICT were MFI compared to being LFI. Similarly, the results indicate that male-headed households in their own homes, who spent less on average on ICT were LFI than being MFI. The results further imply that while male and female headed households with similar housing ownership types, who spent less on average on ICT were LFI, male-headed and female-headed households with different housing ownership types, who spent more on average on ICT were MFI. The results imply that the difference in the scale of ICT expenditure and housing ownership type between female-headed and male-headed households may account for the difference in TFI.

This study reveals that about one-third of workers who travelled to work daily were not married, while over two-third were married (Table 8, p.194). There is no finding on which proportion of these marital indicators were male or female, and how much each category paid for any travel trips. However, Pooley and Turnbull (2000) noted that the need for most married women to travel to work over considerable distance has been a major factor in explaining car use by women in the late twentieth-century. While trying to assess the gendered role in intensity of transport fuel, this study determines how marital status combines with mean ICT expenditure to influence transport fuel intensity. So, Figure 24 reports the distribution of TFI by mean ICT expenditure and gender across marital status. While married female-headed households, who spent about GH¢ 860 on average on ICT were MFI, those who spent about GH¢ 250 on average on ICT were LFI.

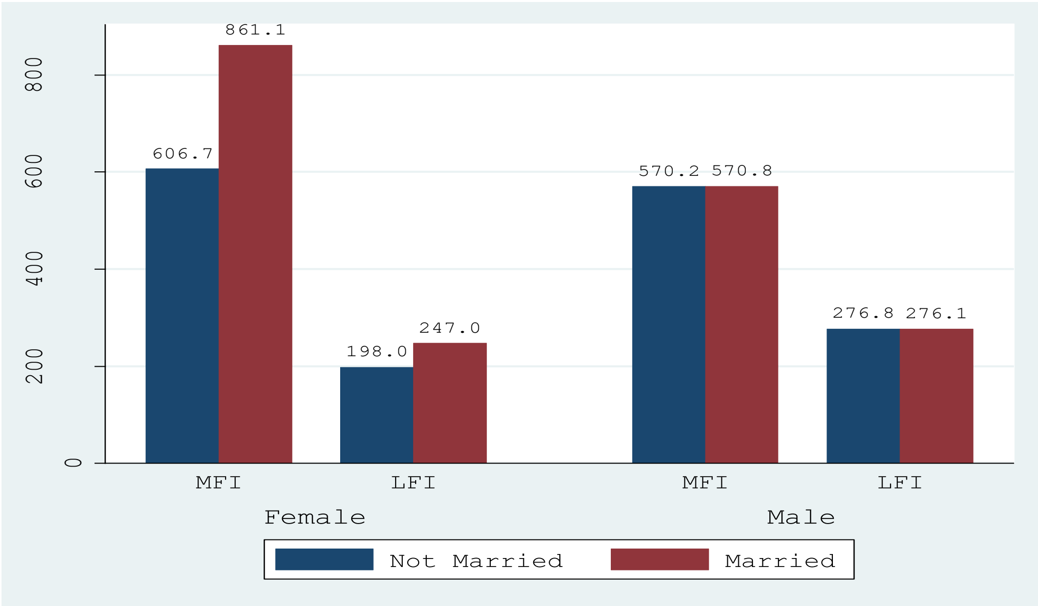


Figure 24: Distribution of TFI by mean HTCOME and gender across marital status

Source: Fiagborlo (2019).

Also, while unmarried female-headed households that spent about GH¢ 700 on average on ICT were more MFI, those that spent below GH¢ 200 on average on ICT were lees LFI. Figure 24, however, reveals no difference between MFI and LFI for unmarried male-headed and married male-headed households, conditional on their mean ICT expenditure. For instance, while unmarried male-headed households that spent about GH¢ 570 were MFI, married male-headed households who spent similar amount on average on ICT were MFI. Likewise, married and unmarried male-headed households that spent about GH¢ 276 were, respectively, LFI. This results imply that the difference in the TFI may arise from the difference in the scale of mean ICT expenditure for married or unmarried female-headed households, while there is no difference of being MFI or LFI for married or unmarried male-headed households, considering their average ICT expenditure.

Economic factors cannot be divorced from the decision to spend more or less on transport fuel. It was observed that from lower income group to higher income group, more male-headed households than female-headed households were LFI, compared to being MFI (Figure 21). However, the issue of whether a female-headed or male-headed households at any levels of income, conditional on their level of ICT expenditure, would be LFI or otherwise has not been addressed. Figure 25 presents the distribution of TFI by mean ICT expenditure and gender across income groups. This study shows a difference in TFI between female-headed and male-headed households, conditional on their mean ICT expenditure across income groups. While female-headed households in the HIG, who spent at least GH¢ 1,130 on average on ICT were MFI, those that spent a little over GH¢ 600 were also LFI.

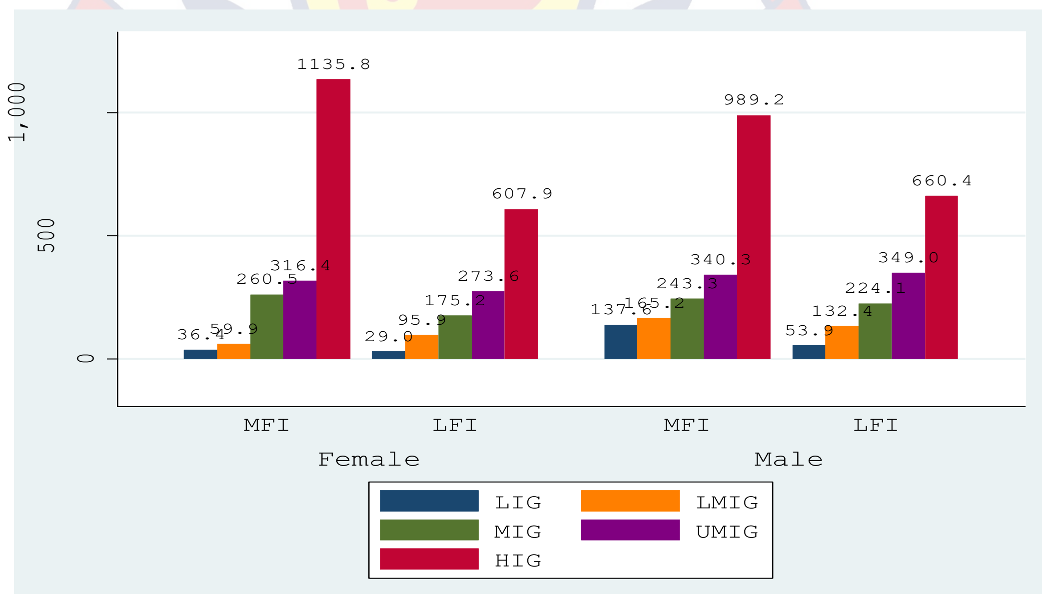


Figure 25: Distribution of TFI by mean HTCOME and gender across income group

Source: Fiagborlo (2019).

Focusing on male-headed households in the HIG, the study shows that those who spent about GH¢ 990 on average on ICT were MFI, whilst those who spent about GH¢ 660 on average on ICT were LFI. The results show that female-headed or male-headed counterparts in the HIG, whose mean ICT expenditure is fairly high were MFI, whilst those whose mean ICT expenditure is relatively low were LFI. It is also observed that female-headed households in the HIG were less LFI, compared to male counterparts in the same income bracket. Similarly, Figure 25 reports that female-headed households in the HIG were more MFI, compared to male counterparts in the same income bracket. Conversely, Figure 25 shows that female-headed households in the LIG were less MFI, compared to male counterparts in the same income bracket. Again, female-headed households in the LIG were less LFI, compared to male counterparts in the same income bracket. This results suggest that across income group the choice of being MFI or LFI by female or male-headed households depends on the extent of different mean ICT expenditure of households.

Test of Collinearity and Likelihood-Ratio

The previous section discussed the distribution of transport fuel intensity by variables used in the study. However, like every econometrician does, this section considers the estimates of the tolerance value for each independent variable in the models. This test was to assess whether the independent variables are truly independent and whether there were no issues of matrix ill-conditioning. As already noted, matrix ill-conditioning implies problems of multicollinearity. The rule of thumb is that higher variance inflation factor (VIF) value and condition number of more than 10 confirm the presence of multicollinearity. Generally, multicollinearity occurs when tolerance value for variables approaches zero rendering the variables insignificant for regression analysis (Pallant, 2020; Cameron & Trivedi, 2010).

Multicollinearity among independent variables in logistic regression creates problems for the validity of the model. Particularly, it affects the validity of the statistical tests of the regression coefficients by inflating the standard errors of the coefficients (Garson, 2013). Table 14 presents the variance inflation factor and condition number for the various variables used in the logistic regression model.

Table 14: Estimated variance inflation factors for the variables used in the logistic regression model

Variable	VIF	Sq.VIF	Tolerance	R-Squared	Eigenvalue	Con.Index
hictexp	1.19	1.09	0.8374	0.1626	5.8675	1.0000
hsize	1.49	1.22	0.6712	0.3288	1.0676	2.3444
incgroup	1.54	1.24	0.6475	0.3525	0.8326	2.6547
urban	1.39	1.18	0.7192	0.2808	0.6973	2.9007
male	1.32	1.15	0.7576	0.2424	0.5364	3.3073
married	1.54	1.24	0.6479	0.3521	0.3456	4.1202
owntype	1.07	1.04	0.9320	0.0680	0.2770	4.6026
aged	1.34	1.16	0.7445	0.2555	0.1967	5.4619
worker	1.15	1.07	0.8703	0.1297	0.1109	7.2743
Mean VIF 1.34				Condition Number	7.2743	

Source: Fiagborlo (2019).

Table 14 demonstrates that the data did not violate the multicollinearity assumption. The tolerance value of each independent variable ranges between 0.6475 and 0.9320, which exceeded the suggested criteria of below 0.10 (Pallant, 2020). The overall mean VIF value of 1.34 as well as condition number of 7.2743, which were both below the cut-off value of 10, further equally amplified lack of multicollinearity amongst the independent variables (Adwere-Boamah, 2011).

Following from the tolerance test for each independent variable, the likelihood-ratio test was also conducted for the overall fitness of the model. The test is one of three classical approaches to hypothesis testing, and together with the Lagrange Multiplier and the Wald test, the likelihood-ratio test helps to test for one or several constraints on parameter values in a regression model. This study conducted the L-R test to help choose the best model between two nested models with the ultimate desire of having a model that best fit our data. We underscore that two models are nested if one is a special case of the other. After Stata allows us to compare the fit statistics of these models, what the LR test basically does is to guide us choose the most appropriate model for the analysis. The null hypothesis is that the parsimonious model is the best model. The parsimonious model is only rejected if the unrestricted model is a significant improvement over the parsimonious one.

The results of the L-R test are exhibited in Appendix D. From Appendix D, the difference of 6.654 in Bayesian Information Criterion (BIC) provides strong support for the current model. In other words, the analysis shows that the full model, which considered together all the independent variables is significant at $p<0.000$ with chi-squared value of 997.128, df=12, N=14009. These statistics imply that the odds of TFI for households relate significantly to all the explanatory variables that were considered in the logistic regression model. It is further observed that the models correctly classified approximately 90.29% of the household cases, 97.98%

and 86.81% of the women and men cases, respectively. For supplementary appreciation of model classification, readers should see Appendix D for details.

Meanwhile, Appendix D reports the model "pseudo" R that explains between 10% (Cox & Snell R Squared) and 20% (Nagel kerke R Squared) of the variance in the household TFI. Similarly, the "pseudo" R explains between 3% (Cox & Snell R Squared) and 18% (Nagel kerke R Squared) and 8% (Cox & Snell R Squared) and 16% (Nagel kerke R Squared) of the variances in TFIs for men and women models, respectively (Appendix D). The Wald statistics indicate that the variables significantly predict the TFIs of overall households and the disaggregated (women headed and men headed) households. From Appendix D, the Wald statistics value of 997.128 and p-value, which equals to 0.000 for household model implies that the whole model statistically, significantly provides a respectable level of explanation. Similarly, regarding the female-headed and male-headed models, the Wald statistics value of 155.91 and 599.70 with p-value equals to 0.000 imply that the general models statistically, significantly provide a virtuous explanation.

Logistic Regression Results

This section assesses how the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of household heads, using disaggregated data from Ghana. The study first estimated full household model, including the demographic attribute (sex) of household heads; followed by separate models for female-headed and male-headed households; and obtained coefficients for each model. This helps improve the understanding of the drivers of transport fuel intensity within the context of disaggregated data. Table 15 presents the summary of the raw coefficients, odds ratios [(Exp (B)] of the three sets of the binary logistic regressions along with their robust standard errors in parentheses.

Table 15: Estimated Logistic coefficient and odds ratio for household, women and men of transport fuel intensity

VARIABLES	Model a	Model b	Model c	(EXP(B))[a]	(EXP(B))[b]	(EXP(B))[c]
hictexp	-0.001***	-0.001**	-0.001***	0.999***	0.999**	0.999***
	(7.34e-05)	(0.000)	(7.61e-05)	(0.000)	(0.000)	(0.000)
hictexpsq	2.21e-08***	4.20e-08	2.05e-08***	1***	1	1***
	(3.50e-09)	(1.24e-07)	(3.63e-09)	(3.50e-09)	(1.24e-07)	(3.63e-09)
hsize	-0.028**	0.091*	-0.033***	0.972**	1.096*	0.968***
	(0.012)	(0.052)	(0.012)	(0.011)	(0.057)	(0.012)
income: lig	2.183***	2.409***	2.187***	8.870***	11.126***	8.908***
	(0.162)	(0.564)	(0.169)	(1.439)	(6.279)	(1.509)
income: lmig	1.055***	1.718***	1.024***	2.871***	5.571***	2.784***
	(0.110)	(0.429)	(0.114)	(0.315)	(2.390)	(0.317)
income: mig	0.673***	1.268***	0.639***	1.959***	3.554***	1.895***
	(0.0952)	(0.358)	(0.099)	(0.187)	(1.272)	(0.188)
income: umig	0.499***	0.678**	0.488***	1.647***	1.971**	1.629***
	(0.0841)	(0.296)	(0.088)	(0.138)	(0.583)	(0.143)
urban	0.372***	0.454*	0.367***	1.451***	1.575*	1.444***
	(0.074)	(0.253)	(0.078)	(0.108)	(0.398)	(0.113)
male	-1.557***			0.211***		
	(0.121)			(0.026)		
married	0.468***	0.651***	0.451***	1.600 ***	1.918***	1.569***
	(0.084)	(0.237)	(0.088)	(0.133)	(0.455)	(0.139)
owntype	-0.356***	-0.786***	-0.303***	0.700***	0.456 ***	0.739***
	(0.072)	(0.247)	(0.075)	(0.051)	(0.113)	(0.056)
aged	0.806***	-0.041	0.887***	2.239***	0.960	2.427***
	(0.117)	(0.330)	(0.123)	(0.261)	(0.317)	(0.300)
worker	0.028	-0.855***	0.0991	1.029	0.425***	1.104
	(0.067)	(0.242)	(0.069)	(0.069)	(0.103)	(0.077)
constant	3.044***	2.968***	1.447***	20.987***	19.458***	4.252***
	(0.167)	(0.415)	(0.131)	(3.512)	(8.075)	(0.555)
observations	14,009	4,366	9,643	14,009	4,366	9,643

Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

NB: a=household model; b=women model and c=men model

Source: Fiagborlo (2019).

From Table 15, the result shows a significant relationship between mean ICT expenditure and transport fuel intensity. This is because ICT expenditure is statistically significant at 1 percent in the three regression models. The negative coefficient for the mean ICT expenditure suggests that a unit increase in the mean ICT expenditure reduces the likelihood of spending less on transport fuel compared to spending more on transport fuel, all else equal, in the aggregated, male-headed and female-headed household models. In particular, the results indicate that a unit decrease in mean ICT expenditure increases the odd by a factor of 0.999 of being LFI compared to being MFI in the aggregated, female-headed and male-headed household models, respectively. This result is in line with expectation, while implying complementarity of ICT to transport fuel intensity. Thus, it implies that a rise in ICT expenditure will increase expenditure on transport fuel, all else equal.

Mokhtarian and Tal (2013); Mokhtarian (2002) also found complementary relationships between telecommunication and transportation. However, while it was established that ICT reduces the rate of mobility of people (Salomon, 1986) and so on average expected to decrease transport fuel expenditure, the complementarity established in this study reflects an ineffectiveness of transport systems. This is because inefficiency of transport systems that results from a serious congestion, nullifies how much households spend on ICT, and thus their spending on transport fuel are less likely to fall. Consistent with Mokhtarian and Tal (2013) and Mokhtarian (2002), the probability of being LFI may require a complete elimination of travel possibilities facilitated by availability of high quality interactions made possible through teleconferencing, telecommuting, teleshopping, telebanking and telemedicine at efficient costs among digitally literate households.

Table 15 also reports a positive relationship between income and transport fuel intensity. This means that at every level of income, the households that were headed by males or females were more likely to be LFI compared to being MFI, other thing being equal. However, this study reveals that as income moves from the lower category to the higher category, the magnitude of the effects on transport fuel intensity declines. The decline is an indication that transport fuel is a normal good, with households and those headed by females or males being less LFI compared to being MFI as income level rises, all else equal. The result synchronises with economic theory, in which case income relates positively with goods or services. Regarding income effect, the lower income female headed households were more LFI, whiles there is no substantial difference between the effects of income on TFI for lower income male-headed households as well as the aggregated households.

Particularly, the result shows that being in the lower income category versus the higher income category increases the log odds by a factor of 11.126 of being LFI than being MFI for households headed by females, while increasing the log odds by a factor of 8.87 and 8.91, respectively, for being LFI than being MFI for households in the full model and those headed by males, holding other factors the same. This shows that female-headed households in lower income bracket were sensitively LFI than being MFI relative to the full and male-headed household models. This finding confirms the less resourcefulness of women compared to men resulting from an irreconcilable participation of women and men in the labour market due to their gendered role differences, reflecting in the different outcome of transport fuel intensity among the various categories of household in the models.

Also of particular significance is the observation that being in the upper middle income category compared to the higher income category increases the log odds of being LFI by a factor of 1.971 than being MFI for female-headed households, other things being equal. However, compared with the lower income category, the magnitude of being LFI than being MFI for female-headed households in the upper middle income category, absolutely declined from 11.126 to 1.971. Additionally, Table 15 reports that being in the upper middle income category compared to the higher income category increases the log odds by a factor of 1.647 and 1.629, respectively, of being LFI than being MFI for the full households and disaggregated male-headed households, indicating an absolute decline in the magnitude from 8.870 and 8.908 to 1.647 and 1.629, respectively. Clearly, female-headed households were more likely to be LFI than male heads.

Besides, while size of the households is less likely to cause less expenditure on transport fuel by the households in the full model and those headed by males, it is more likely to cause female-headed households to be more LFI than being MFI. Principally, a unit increase in the size of female-headed households, other things being equal, induces the log odds of being LFI by a factor of 1.096 relative to being MFI. Also, a unit increase in the size of the households, including those headed by males, other things being equal, decreases the log odds of being LFI by a factor of 0.972 and 0.968, respectively, compared to being MFI. This is an evidence of scale effects (Bardazzi & Pazienza, 2018) whereby an additional member to the households increases the possibility to share and pool cars among female-headed households to become LFI, while the impossibility of sharing and pooling cars may decrease the possibility of being LFI among male and aggregated households.

The dummy variable for location has a slightly different interpretation. For example, dwelling in urban areas compared to rural areas increases the log odds of being LFI by factor of 1.451, 1.575 and 1.444, respectively, in the aggregated, female-headed and male-headed models, other things being equal. The results indicate that female-headed urban households, on average, were more likely to be less fuel intensive than being more fuel intensive compared to the aggregated and male-headed households. However, regarding the extent of the reduction in the intensity of transport fuel expenditure, the results show that the male-headed urban households have the least effect relative to the aggregated and female-headed households. While reasons are hesitantly assigned to these results, there is an evidence that women often trip-chain travel than men (Elias, *et al.*, 2015), making participation in transport fuel market possible for men than female counterparts.

Interestingly, gender was also represented in the full model to account for the effects of the presence of the male heads relative to female heads on TFI. The result indicates that the presence of male heads in the household is significant in explaining the households' susceptibility of being LFI compared to being MFI. Specifically, the result suggests that having a male head present in the household than female head decreases the log odds of being LFI compared to being MFI by a factor of 0.211, holding other factors the same (Table 15). This finding is consistent with the intuition that male heads of households are inclined to work to generate financial resources for the livelihood of the family, increasing their frequent mobility demand and transport fuel expenditure than female heads of households.

Table 15 further reports that being married compared to being unmarried increases the log odds of being LFI than being MFI by factor of 1.600, 1.918 and 1.569, respectively, considering the full model, female and male household models. Specifically, the result shows that being married versus unmarried increases the likelihood of being LFI than being MFI in the female model, all else being equal. Also, being married against unmarried increases the likelihood of being LFI than being MFI in the male and the aggregated household models, other things being equal. However, considering the extent of marital status across all models, the result shows that its effect is greater in the female household model than male and the aggregated household models. Marriage may produce children and occasion the use of expensive modes of transport to shun walking and biking, albeit marriage comes with the benefits of pooling resources and the possibility to pool and share cars; hence increasing the likelihood of being more LFI in the female household model.

The link between house-ownership and TFI is considered in this study. Table 15 reports that being a house owner versus being a renter decreases the chance of being LFI than being MFI. Particularly, being in own apartment versus rented one decreases the log odds of being LFI by factor of 0.700, 0.456 and 0.739, respectively, in the aggregated, female and male household models, holding other factors constant. Across all the models, we observe that being in own apartment versus rented one decreases the odds of being LFI in the male model compared to the aggregated and female models. However, while the extent of being LFI is greater in the male model for home-owners compared to renters, the effect is lesser among home-owners versus renters in the aggregated and male models, all else equal. It appears from the data that home-ownership serves as a proxy for life-cycle state, picking up some of the effects of household size that is separately less significant, and reflecting the small home-ownership effect in the female model.

While the dummy variable for aged has a slightly different interpretation, it was expected that having a member of the household aged above 65 years should have positive or negative effects on TFI. Table 15 establishes that having a member of the household aged above 65 years or otherwise increases the log odds by factor of 2.239 and 2.427 but decreases it by factor of 0.960, respectively, of being LFI than being MFI in respect of the aggregated, male and female household models. Focusing on the extent of the effect of age on TFI across male-headed and the aggregated models, the analysis shows that though there is no significant difference between the positive effect of the odds of being LFI in the male-headed versus the aggregated models, the result implies that having a member of the household aged above 65 years reduces TFI. Whilst this finding supports the result of Bardazzi and Pazienza (2018), the small negative effect in the female model suggests otherwise.

Adding to the preceding results, this study again expected that having more than one-third of the household members working should have positive or negative effect on TFI. Table 15 confirms that while employment status of household members has no significant positive influence on TFI, it decreases significantly the log odds of being LFI versus MFI by a factor of 0.425 in the female household model, other things being equal, suggesting a direct link between employment status and transport fuel intensity. Whilst Bardazzi and Pazienza (2018) also found employment status exerting positively on energy expenditure, Eakins (2016) observed that households with higher number of occupants working spent more on energy. As the economy of developing countries recovers and employment opportunities improve, this result provides an impeccable basis for the design of an effective transport policy towards reducing GHG emissions that threaten the SDG7.

Chapter Summary

This chapter addressed the third specific objective of this study. The idea was to assess how the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of households, using disaggregated data from Ghana. Three logistic regression equations were estimated for household, female-headed and male-headed household models. The result showed complementary nexus between ICT and TFI, implying that a rise in ICT expenditure will increase transport fuel intensity, all else equal. This highlights an ineffectiveness of the transport systems as no matter how much households spent on ICT, spending on transport fuel will rise. Consistent with literature, the finding suggests that probability of reducing transport fuel intensity requires a complete elimination of travel possibilities facilitated by availability of high quality interactions made possible through teleconferencing, telecommuting, teleshopping, telebanking and telemedicine at a reduced cost among digitally literate households.

Additionally, the result showed that across income group the choice of female or male-headed households for being MFI or LFI depends on the extent of different mean ICT expenditure, and that irrespective of income category, female-headed households were more LFI than being MFI compared to male-headed households and the aggregated models, all else equal. Besides, the results revealed that the choice of female-headed rural and urban households to be MFI or LFI was derived from the differences in the scale of the mean ICT expenditures between these clusters. Likewise, there was a perceptible difference in TFI between male-headed or female-headed rural and urban households, given their different average transport fuel expenditure. Interestingly, the result suggested that female-headed urban households were more likely to be LFI than being MFI in respect of the aggregated and male-headed households, conceding to the fact that women often travel more than men due to their gendered roles and spend more in the process.

Considering the extent of the effect of age on TFI, no significant difference was found between the positive effect of the odds of being LFI in the male-headed versus the aggregated models. However, the result implies that having a member of the households aged above 65 years increases the possibility of spending less on transport fuel, holding other factors constant. Meanwhile, the minimal negative effect of being LFI in the female household model indicates that having an aged in female households decreases the probability of spending less on transport fuel, all else equal, corroborating the existing literature. Furthermore, if the size of households is increased across the three households, the result showed that female-headed households were more LFI than being MFI, other factors being held equal.

In addition to the preceding findings, this study also established that the difference in the scale of ICT expenditure and housing ownership type between female-headed and male-headed households might account for the difference in TFI. Regarding matrimonial status of household heads, the results showed that the difference in TFI might have arisen from the differences in the scale of mean ICT expenditure for married or unmarried female-headed households, albeit there was no finding of any difference of being transport fuel intensive for married or unmarried male-headed households, as well as their mean ICT expenditure. Moreover, there was a direct association between employment status and transport fuel intensity, consistent with the finding that households with higher number of working members spent more on energy. These results, provide an impeccable basis for the design of an effective transport policy towards reducing GHG emissions that threaten the SDG7. The summary, conclusions, policy recommendations, as well as the limitations of the entire study are considered in the proceeding Chapter Nine.

CHAPTER NINE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Introduction

Chapter Nine concludes the study. It has four main sections, which first provides a brief summary of the entire thesis, detailing the objectives of the study, the theoretical underpinning, while highlighting the theoretical and empirical literature as well as the analytical frameworks of the study. It also covers the summary of the methodologies including the empirical models used. The second section of the chapter considers the conclusions of the study based on the key results. Section three outlines the policy recommendations based on the conclusions of the study. While it finally gives some direction for future research, section four discusses the key contributions of the study to knowledge as well as the limitations.

Summary

The main objective of this study was to identify the drivers of transport fuel expenditure and mode choice in Ghana. The theoretical underpinning of this study was the random utility maximisation theory where economic agents were assumed to choose among alternatives to maximize their utility. Chapter Two presented an overview of the transport sector in Ghana. It highlighted the abstract definition of transportation in general. In Chapter Three, the study stressed the theoretical and empirical literature on drivers of transport fuel expenditure and mode choice, reviewing scholarly works of transport economists and transport practitioners. The fourth chapter provided detailed information on the theoretical models, as well as the analytical frameworks that informed the empirical equations that were estimated and evaluated. Chapter Five discussed the research methodology, while focusing on the secondary data because of the stated objectives and the hypotheses.

Chapter Six considered the effect of ICT expenditure and other sociodemographic characteristics on households' transport fuel market participation and consumption decisions. The study applied the double hurdle model to five waves of the Ghana Living Standard Surveys to accomplish the first objective. The double hurdle model specified a probit model for zeros in the data (i.e., participation or no participation) and truncated regression for the positive values in the data (i.e., consumption of transport fuel), conditional on transport fuel market participation. The positive values were observed once hurdles were cleared.

Chapter Seven examined the drivers of transport mode choice of workers. Specifically, it examined the relative risks of RVTT and other capability variables on mode of transport within the context of travel behaviour of workers. To realise objective two, an MNLOGIT model was applied to home-to-work data, which were extracted from the NHTS (2012) data of individual workers in Ghana. Finally, the eighth chapter addressed the third specific objective of the study. The idea of the third objective was to assess how the effect of ICT expenditure on transport fuel intensity differentiates demographic attribute (sex) of households, using disaggregated data from Ghana. Three logistic equations were estimated for households, female-headed and male-headed household models. The next section of the summary reflects on the conclusions derived from the results from this study.

Conclusions

The empirical evidence suggested that normalized ICT expenditure wields a significant positive impact on households' transport fuel market participation and consumption. The results of the estimated elasticities showed that both probability and conditional elasticities were positive and statistically significant for the ICT expenditure variable for each wave. While these results appeared strange at first, they are consistent with other studies, implying complementary connection between ICT expenditure and households' transport fuel market participation and transport fuel consumption. The results may also reflect a hidden accessibility effect of ICT, such that, households that have lesser access to ICT than those with greater access tend to spend more on transport fuel, given their transport fuel market participation decision. The results further indirectly support the substitution hypothesis that availability of ICT diminishes the necessity to travel and travel cost.

Additionally, this study found that households' transport fuel consumption expenditure increases with income. This indicates that transport fuel is a normal good, reflecting the expectations and the findings in previous studies. It further suggests that income is a key economic variable that may influence travel decision and transport fuel expenditure. The estimated income elasticities showed that transport fuel expenditure, conditional and unconditional on transport fuel market participation were income elastic across all wave. These results mean that a proportionate increase in households' income will increase the level of transport fuel expenditure more than proportionately. This has implications for long term transport fuel consumption for growing economies, and thus should form the basis for the design of an effective transport policy towards reducing GHG emissions.

It was further observed that household size has a significant positive effect in the participation equation, but negative effect in the consumption equation. However, even though the probability of participation and the overall level of transport fuel consumption showed positive trends with household size, the faster decline in unconditional level of transport fuel expenditure is plausible because larger households are inclined to making joint travel decision, sharing cars and travel costs, which perhaps manifested in the reduction in the transport fuel market participation and the overall level of transport fuel expenditure, all else being equal. Although these results are consistent with literature, further research is necessary to confirm the assertion about the joint travel decision and sharing of travel costs.

Moreover, male household heads were found to have a consistent negative desires for transport fuel market participation, albeit this did not reduce their transport fuel consumption compared to female-headed households. Meanwhile, even though transport fuel consumption over time intensified for male household heads, the proportional increase in unconditional transport fuel expenditure was rather smaller relative to the conditional level of transport fuel expenditure. The decreasing probability of participation in the transport fuel market for male-headed households appears to be consistent with literature where women were found to travel often than their male counterparts and spent more on transport. It is also possible that the inclination of male-headed households to work and generate financial resources to support the family, might have increased their mobility, and for that matter, transport fuel expenditure compared to female-headed households.

Adding to the preceding results, this study found that location has positive influence on transport fuel market participation, but inconsistent effects on the level of transport fuel expenditure. In spite of this inconsistency, the negative trend over time in the probability of in transport fuel market participation, level of consumption and overall transport fuel expenditure for urban households than rural households, suggests intensed urban effects as urban households accessed jobs and socioeconomic services without travels; hence spent less or nothing on transport fuel. The decreasing trend is also possible perhaps due to improved dualisation on some urban corridors, ensuring efficient travel time and economies of fuel usage. The result has implication for policy on urban infrastructure as housing and distribution of socioeconomic service centres may influence choice of travel modes and transport fuel market participation and also level of transport fuel consumption.

More so, the results provide interesting implications for public policy and perhaps explain why carbon and congestion pricing are not considered options for government's fiscal financing instruments for transport in Ghana. For instance, the founding revealed that single household head without children or an adult member 64 years and above significantly increased their level of transport fuel consumption, conditional on participation in transport fuel market, irrespective of whichever sample is used. The result signifies long term effect where household heads who are single without children or an adult member 64 years and above over time became disinterested in the participation in transport fuel market, conditional on participation in transport fuel market, while the level of transport fuel expenditure for a single adult household heads increased steadily over time compared with single adult households with a child or an adult member who is less than 64 years.

Again, level of education of household heads constitutes one of the significant drivers of transport fuel market participation and level of transport fuel expenditure, conditional and unconditional on market participation. Yet, basic level education versus no education of household heads showed two competing effects by intensifying participation in transport fuel market while reducing consumption of transport fuel. The increased participation may be induced by greater ease with which household heads accessed transport fuel market, perhaps because of impovements in their level of education, which boosts their ability to earn more incomes and travel more. The reduction in the level of transport fuel consumption may possibly be as a consequence of recession in the economy or that household heads with basic education compared to no education were principally informed about negative physio-environmental effects of commuting on motorised transport.

This study found that household heads with education to seconary school versus those with no education were more likely to participate in transport fuel market and consmue more transport fuel, conditional and unconditional on transport fuel market participation in the short-run. However, in the long-run, household heads with secondary level education versus those with no education were found to be less likely to participate in the transport fuel market and consume less transport fuel conditionally and unconditonally.This suggests that education of household heads to secondary level could be used as a policy apparatus to minimise environmental impact of fuel energy consumption in Ghana. Further, education of household heads to tertiary level compared to no education increased the likelihood of particiaption in transport fuel market and the consumption of transport fuel, conditional as well as unconditional on the participation in transport fuel market.

Relating to empirical chapter seven, the result strikingly indicated that RVTT and distance travel significantly influenced the choice of transport modes, and an increase in the RVTT and distance per hour increase the expected risk for using PMT and LPT for individuals compared to those walking and bicycling to work from home. The result also showed that private transport (private car and motor-cycle) users have the highest RVTT with those using non-motorised transport (walking and bi-cycling) from home to work reflecting the lowest RVTT. Moreover, more urban women than men were enduring longer hours and spending more RVTT on average driving to work from home. The findings signify lost in labour productivity for private transport users and urban women than men. This has implications for wage negotiation among worker unions, firms and governments.

Further, while being a male worker significantly explained the choice of SPT and PMT, there was no significant evidence of sex determining the choice of MMT bus, ferry and train from home to work, implying that there is no significant mean difference effect between male and female workers relative to their use of MMT bus, ferry and train to work from home. Meanwhile, sex has a positive sign in all the transport mode models signifying that men were more likely to use alternative modes from home to work than women. For the relative risk, the result showed that the expected risk was higher for male workers than female workers for using SPT from home to work, relative to walking and bicycling, confirming that women were walking as well as biking to work than men. These results suggest that planners may need to consider elements of road designs such as street lights, pavements and stroller access to make streets and cities more walkable for women.

Additionally, the result showed that living in urban area against rural area increased the likelihood of picking SPT and LPT to work, compared to walking and biking. Though there was no evidence of a significant effect of living in urban area versus rural area on the choice of PMT, the result indicated that living in urban area versus rural area decreased the likelihood of using PMT to work, compared to walking and bicycling to work. This suggests that even though the results manifest no significant mean difference effect between urban and rural workers on their choice of PMT to work, it reflects the nature of urban planning in Ghana, where people live on the periphery of the city and depend on private means of transport to access economic centres due to lack of public transport. Meanwhile, urban men than women who have higher access to per capita private motorised assets than urban women were found to use private car and motor-cycle to work from home.

The study also discovered that even though per capita private and commercial motorised assets had no significant associations with transport mode choice, an increase in access to assets was found to decrease the likelihood of using SPT and LPT to work from home, other things being equal. There was, however, an evidence of a significant association between PMT use and per capita private as well as per capita commercial motorised assets. Thus, as individual's access to these assets increases, their likelihood of using combination of private car and motor-cycle to work from home increases in respect of the positive coefficient on the per capita private asset, and decreases based on negative coefficient on the per capita commercial motorised assets. Across all modes, the result showed that a unit increase in access to per capita private assets increases the relative risk of using private car and motor-cycle to work higher than walking as well as biking to work.

In addition to the preceding results, this study found that while age of workers was significant in the choice of taxi, trotro and mini-bus as well as MMT bus, ferry and train to work, it was insignificant in the choice of private car and motor-cycle to work. Thus, additional year to the age of a worker who used taxi, trotro and mini-bus to work increases the expected risk higher than walking and bicycling, while decreasing the expected risk more for a worker who used large public transport (MMT bus, ferry and train) to work, compared to non-motorised transport (walking and bicycling). The study further found that while women in urban areas were enduring longer distances to work than urban men, the older urban women were traveling longer distance from home to work using MMT bus, ferry and train than rural women. The study showed no ostensible difference between distance covered by older urban men and rural men in the choice of transport mode.

Besides, the results revealed the importance of matrimonial relationship in transport mode choice decision of workers as majority of the workers were married. A significant proportion of the married workers compared to non-married workers were frequent users of motorised transport to work than non-motorised transport. Consistent with literature, the results indicated a significant association between sector of employment and transport modes. Specifically, public sector employees were found often to use taxi, trotro and mini-bus as well as MMT bus, ferry and train from home to work compared to private sector and NGO sector workers. There was also a significant association between time unit and transport mode choice of respondents, with a significant number of respondents reporting that unavailability of transport occurs always, against a few who reported that non-availability of transport to work from home was often a problem in the morning hours of the day.

Also consistent with literature is the revelation that reliability plays significant role in the transport mode choice decisions of Ghanaian workers. Moreover, the estimated results of the third specific objective also yielded some conclusions. The results showed that a rise in ICT expenditure will increase transport fuel intensity, all else equal. This highlights an ineffectiveness of the transport systems such that no matter how much households spent on ICT, spending on transport fuel will rise. The results, therefore, imply a complementary nexus between ICT and transport fuel intensity. Consistent with literature, the finding suggests that probability of reducing transport fuel intensity requires a complete elimination of travel possibilities facilitated by availability of high quality interactions made possible through teleconferencing, telecommuting, teleshopping, telebanking and telemedicine at a reduced cost among digitally literate households.

Additionally, the result showed that across income group the choice of female or male-headed households for being MFI or LFI depends on the extent of different mean ICT expenditure, and that irrespective of income category, female-headed households were more LFI than being MFI compared to male-headed households and the aggregated models, all else equal. Besides, the results revealed that the choice of female-headed rural and urban households to be MFI or LFI was derived from the differences in the scale of the mean ICT expenditure between these clusters. Likewise, there was a perceptible difference in TFI between male-headed or female-headed rural and urban households, given their different average transport fuel expenditure. Interestingly, the result suggested that female-headed urban households were more likely to be LFI than being MFI in respect of the aggregated and male-headed households, conceding to the fact that women often chain travel than men due to their gendered roles and so spend less in the process.

Considering the extent of the effect of age on TFI, this thesis found no significant difference between positive effect of the odds of being LFI in the male-headed versus the aggregated models. However, the result implies that having a member of the household aged above 65 years increases the possibility of spending less on transport fuel, holding other factors constant. This result is possible because an aging population was found to depress transport expenditure because the aged often stays at home for a larger portion of the day. Meanwhile, the minimal negative effect of being LFI in the female-headed model indicates that having an aged in female households decreases the probability of spending less on transport fuel, all else equal, and thus corroborating the existing literature. Furthermore, if the size of households is increased across the three households, the result showed that female-headed households were more LFI than being MFI, other factors being held equal.

The thesis, in addition to the preceding findings, established that the difference in ICT expenditure and housing ownership type between female-headed and male-headed households might account for the difference in transport fuel intensity. Regarding matrimonial status of household heads, the results indicated that the difference in TFI arisen from the difference in the scale of mean ICT expenditure for married or unmarried female-headed households, albeit there was no difference of being transport fuel intensive for married or unmarried male-headed households, as well as their mean ICT expenditure. Moreover, the direct association between employment status and transport fuel intensity is consistent with the finding that households with higher number of working members spent more on energy. These results provide an impeccable basis for the design of an effective transport policy towards reducing GHG emissions that threaten the SDG7.

Policy Recommendations

The preceding section of this chapter presented the conclusions of the study based on the key results in the three empirical chapters. However, only a few of these conclusions were outstanding for our policy recommendations. The study revealed complementary connection between ICT expenditure and transport fuel market participation and consumption of households. This implies that households that have lesser access to ICT at a higher cost may spend more on transport fuel, given their decision to participate in the transport fuel market. Besides, the results also support the substitution hypothesis that availability of ICT at a cheaper cost to people may diminish the necessity to travel and hence transport fuel expenditure.

The conclusions bear out the evidence in the literature suggesting that the probability of reducing transport fuel intensity could be through a complete elimination of travel possibilities by facilitating availability of high quality interactions, which could be made possible through teleconferencing, telecommuting, teleshopping, telebanking and telemedicine at a reduced cost among digitally literate households. Mobile is the most economical way of ensuring increase digital inclusion in Ghana because it may help government realise its goals of intensifying ICT infrastructure and access, and promoting the use of ICT in all sectors of the economy. Regrettably, mobile is one of the heavily taxed sectors in Ghana, and its operators are subject to 14 different taxes and regulatory fees plus various one-off charges. Veritably, taxes account for almost a quarter of the cost of mobile ownership in Ghana, which is above the regional average (GSMA, 2015).

Thus, to ensure affordability and usage of ICT, the ministries overseeing Finance, Communication and Transport in Ghana should ensure abatement of the costs of ICT for households. The possibility is by eliminating Communication Service Tax (CST) on mobile data and removing customs duties on handsets and smartphones as captured in the 2015 budget. By doing so, the cost of ICT should reduce to ensure affordability and usage of ICT and discourage mobility. This may have revenue implications for government, but the net effect on the economy and the environment might be positive. The reduction in the cost of ICT should discourage mobility as high ICT industries and large companies in the country's congested central business districts (CBDs) would allow their staff flexible work schedules to work from home. All this will reduce mobility and transport fuel cost.

Additionally, the significant positive income elasticities have implications for long term transport fuel consumption for the growing economy, and should form the basis for the Ministry of Environment, Science Technology and Innovation and

Ministry of Road and Transport in designing an effective transport policy towards reducing GHG emissions to realise the SDG7 on transportation. Specifically, as government always seeks to improve household income directly through income subsidies or social interventions to offset the burden of other policy considerations, efforts should be made to decrease the need for spending on travel by encouraging jobs and service growth in or near high income communities. For example, the Land Use and Spatial Planning Authority (LUSPA) should enable a balance re-distribution of urban population to ensure increasing population density, land use mix and job density as diversified use of land offers potential opportunities for access to diverse activities by people and hence ensures decreasing need for travel.

Over the period, the finding shows that the overall expenditure on transport fuel decreases with increasing household size. This is possible because larger households are more inclined to making joint travel decision, sharing cars and travel costs in the process. Thus, efforts should be made by car renting and transport service providers to encourage larger households to petronise their services as this could present them with the opportunity to make joint travel decision and share travel costs. Specifically, transport service providers should offer free public bus tickets on selected days to larger households and also distribute free public bus tickets to selected larger households that frequently use their service among others.

Undoubtedly, the results also suggests intensed negative urban effects. This is evidenced by the negative trend in the probability of participation in transport fuel market, level of consumption and overall transport fuel expenditure for urban households against rural households. This trend is plausible because as more households become urbanised and can easily access jobs and socioeconomic services because of improved and dualised urban roads, as well as enforced traffic regulations, travel times will become more efficient. This may results in economies of fuel usage leading to reduce transport fuel market participation and consumption. Therefore, Ministry of Environment, Science Technology and Innovation (MESTI) through the Land Use and Spatial Planning Authority (LUSPA) should ensure that polices on urban infrastructural development contemplate the distribution of housing as well as socioeconomic service centres to facilitate urban agglomeration.

Also, policy initiatives and programmes that propel rural-urban migration should be encouraged together with the enforcement of traffic regulations by the Motor Traffic Unit of the Ghana Police Service to ensure free flow of traffic to minimise congestion in urban areas to warrant easy access to jobs and socioeconomic services. This will influence the choice of travel modes and the transport fuel market participation and consumption decisions of urban households. Furthermore, having the heads of the households married with children and an adult member aged 64 years and above ensure that there is a negative life-cycle effect on the consumption of transport fuel, conditional on the market participation in the short and long runs. Therefore, government through the Ministries of Education, Finance and Transport should intensify social intervention policies such as Free Education, Free Meals as well as Free School Ride for school children. These interventions would encourage heads of households to have additional dependants.

Also, government through the Ministry of Health and Social Security and National Insurance Trust (SSNIT) should ensure that the aged have the best of medical care and that workers have the best of working condition and pension payments to enable them live long, as growing old is a function of good health, which is derived from good social and economic policies of the day. This study also suggests that education of household heads to secondary level provides policy path to minimise fuel energy consumption and environmental impact. This is because educated household heads may be much informed about the effects of using motorised transport on the environment than uneducated and so reduce their level of transport fuel consumption. Therefore, government's free SHS policy should be sustained. More efforts should be directed towards ensuring that all barriers working against its implementation are removed. Perhaps, households that can afford should be made to pay to complement the resources of the state to guarantee its sustainability. Ministry of Education (MoE) should facilitate access to education at all levels by providing more educational infrastructure at all level of education.

The results also reveal that RVTT and distance travel significantly influence the choice of transport modes. This is evidenced by increases in the expected risk for using PMT and LPT for individuals compared to those walking and bicycling to work from home when there is an increase in the RVTT and distance per hour. Since RVTT is calibrated as the product of minimum wage and in-vehicle time to work, the finding suggests lost in labour productivity for private and large public transport users, which may have repercussions for tripartite wage negotiation among workers, employers and governments. It may also have implication for housing policy for all workers in Ghana. The result may also have implication for the BRT system that envisaged moving at least 80 percent of passengers in Ghana.

Therefore, combining the concept of minimum wage and integrating NMT into all public transport systems to improve accessibility might help to reduce the lost in labour productivity for users in the country. While many people may want to use private car as their income increases and they get older as this study indicates, prioritising modes that can carry larger numbers of passengers without exponential increase in road space requirements may help in reducing the dependence on car use. This may mean allocating road space to high-quality facilities for public transport and NMT. Also, increasing car purchasing cost by upgrading vehicle standards may keep the purchasing price up or prevent it from falling, which may contribute to the management of car purchase. Again, more stringent traffic safety regulations and initiating stronger enforcement against illegal driving behaviour might not only improve traffic safety but may help to restrain the growth of usage.

The result also found that more workers in Ghana combined walking and biking to work. This calls for policy towards walking and bicycling. Promoting walking and bicycling by eliminating tariffs on bicycle import to improve affordability will not only reduce the use of private mode of transport, but it will lessen energy consumption and greenhouse gas emissions. Women were found to be walking and biking than men suggesting that street lights, pavements access should be included in road design to make streets and cities walkable for women.

Contribution to Knowledge

This thesis had three specific objectives. The first objective analysed the effect of ICT expenditure and other sociodemographic characteristics of households on transport fuel market participation and consumption decisions of households. The second objective provided insight into the relative risks of RVTT and other capability variables on main mode of transport within the background of travel behaviour of workers, while finally assessing exactly how the effect of ICT expenditure of households on transport fuel intensity of households differentiates demographic attribute (sex) of households, using disaggregated data from Ghana.

The focus of traditional travel behaviour literature is on transportation related expenditure alone. There has been limited research to analyse transport fuel expenditure in conjunction with its driving characteristics, thus limiting the ability to investigate the potential substitution or complementarity role of ICT on transport fuel expenditure. Again, earlier studies have developed quantitative models almost exclusively with single year cross-sectional datasets. As a result, they were unable to provide the dynamic patterns of transport expenditure that reflect their evolution over time due to technological or temporal changes. A unique feature of this thesis is the use of multiple datasets, which allowed for the estimation of elasticities that capture the dynamic effects of the drivers of transport fuel expenditure. By realising objective one, this study provides policy information about the influence of ICT on transport fuel market participation as well as consumption decisions of households.

Additionally, despite the comprehensiveness of literature, there is no evidence of studies on mode choice in recent times that ensure that individuals have equal opportunity in making their mode choice decisions. For example, the application of such variable as real value of travel time that assumed that individuals have same income; and also that individuals face the same in-vehicle time has not been conceptually demonstrated. This thesis proposed real value of travel time as an exogenous factor to explain transport choice behaviour of Ghanaian workers. The real value of travel time was calibrated as the product of minimum wage and in-vehicle time. By attaining objective two, this study helps to understand how RVTT determines the choice of mode to work by individuals, and also the RVTT in travel behaviour of workers in developing country such as Ghana.

Also, by focusing on the effect of RVTT on transport modes choice, and controlling for other individual and mode specific factors, this study contributes to the current global debate about switching people from their personal car to alternative modes. It also contributes to the global strategy towards achieving targets 5.5 and 5.6 of the SDGs by assessing how the effect of ICT expenditure of households on TFI differentiates demographic attribute (sex) of households, using disaggregated data. Methodologically, this thesis contributes to the literature, updating the usual Tobit model with the novel application of the double hurdle technique to zero inflated transport fuel expenditure data in Ghana. Finally, this study apparently departs from the traditional classification of transport into private and public modes by classifying transport into small public transport; large public transport; private motorised transport and non-motorised transport, respectively.

Limitations to the Study

Regardless of the contributions of this study to the literature by bridging the gap for Ghana, the design and the nature of data used are not excepted from limitations. While some of these limitations are highlighted here, their combined effects did not conspire to annul the policy relevance of the findings of this study. To start with, although this study used multiple datasets which allowed for the estimation of elasticities that captured the dynamic effects of the drivers of transport fuel expenditure, using longitudinal data would have obviously allowed for a comprehensive modelling and tackling of the dynamic changes in transport fuel expenditure market participation and consumption decisions of households. Also, the multiple datasets used are consumption survey, which did not include transport characteristics that are usually found in travel survey. Consequently, variables such as vehicle engine capacity, vehicle miles travel and fuel prices, which could have enhanced the quality of the results of objective one, have been omitted in this study.

Although the extent of unavailability of these variables limit the study, other variables identified as relevant associates of transport fuel expenditure of households have been included in the study. Another limitation is the issue of retrospectivity of the data collection method. Transport fuel expenditure data was elicited from households who did the purchase in years preceding the data collection period. Difficulty of recollecting facts due to time lag, may lead to extreme values misreporting on the transport fuel expenditure. This might affect the reliability and strength of the results. For transport mode choice, people who preferred to walk or bike to work might have self-selected to live in neighbourhoods that assured them easy access to walk or bike to work than those who live far from their working setting. Thus, the distance endured by workers might not have a direct link with travel behaviour. Somewhat, it is the housing choice that defined the travel behaviour. So, an attitudinal data is needed to control for the self-selection issues.

Issues for Further Research

This study considered total transport fuel expenditure. Future researches need to be done to model transport fuel expenditure for only public transport. This will aid policies that guarantee resilient public transportation system, which should translate into a reduction in private car demand for fuel. Also, future study should use longitudinal data to provide a comprehensive modelling and tackling of the dynamic changes in transport fuel expenditure market participation and consumption decisions of households. Besides, variables such as vehicle engine capacity, vehicle miles travel and fuel prices should be included in future study to booster the quality of the research outcomes. Transport fuel expenditure data should be elicited from households in real time to circumvent issues of extreme values misreporting to guarantee reliability as well as strength of future research outcomes.

Future study could expand to embrace the share of workers in high-information and management industries such as media, finance, insurance, real estate, and scientific and technical services. This would ensure that digitally literate households are analysed to warrant robust outcomes. Finally, future studies should ensure the inclusion of attitudinal data or techniques to account for reasons people live in an area. This will curb the issues of self-selection bias in the future studies.

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APPENDICES

A: Comparing Tobit model versus Cragg model using AIC and BIC

	TOBIT Model		CRAGG Model	
DATA (N)	AIC	BIC	AIC	BIC
GLSS3 (4,521)	21980.63	22076.88	15668.24	15835.07
GLSS4 (5,998)	40779.65	40880.14	29667.65	29841.83
GLSS5 (8,637)	67936.01	68034.91	51421.9	51605.56
GLSS 6 (16,772)	156228.4	156344.3	126479.1	126680
GLSS7 (13,832)	124405.4	124518.4	102964	103159.9
	df = 15		df = 26	

df = Degree of freedom;

$AIC = -2 * \ln L + 2 * k$

$BIC = -2 * \ln L + 2 * \ln N * k$

AIC = Akaike's information criterion; BIC = Bayesian information criterion;

N = Number of observation; L = value of the likelihood

k = The estimated parameters

Note:

The model attaining the lowest BIC value is selected as the best model. Based on Raftery’s suggestion, two models with a BIC difference of less than 2 between them is barely worth mentioning. While a difference between 2 and 5 is positive, BIC difference of between 5 and 10 is strong. Moreover, two models with a BIC difference of more than 10 is very strong. Hence, Cragg is elected ahead of Tobit.

B: Maximum Likelihood Estimates of the Cragg's double hurdle model

	GLSS3 1990/1991		GLSS4 1997/1998		GLSS5 2006/2007	
VARIABLES	Main equation	Select equation	Main equation	Select equation	Main equation	Select equation
lnhinc	0.492***		0.430***		0.354***	
	(0.0210)		(0.0178)		(0.0312)	
lnhsize	-0.0564**	0.208***	0.0210	0.173***	0.0418*	0.0283
	(0.0273)	(0.0462)	(0.0209)	(0+-*.0441)	(0.0234)	(0.0364)
lnhictexp	0.0598*	-0.484***	0.0894***	0.381***	0.0234***	0.244***
	(0.0338)	(0.101)	(0.0243)	(0.0608)	(0.00794)	(0.0123)
urban	-0.0794***	0.312***	0.0726***	0.300***	-0.0447	0.218***
	(0.0226)	(0.0427)	(0.0179)	(0.0412)	(0.0273)	(0.0438)
urban*lnhictexp	-0.0852*	0.175	0.00931	-0.0363	0.0205**	-0.0335*
	(0.0439)	(0.135)	(0.0270)	(0.0910)	(0.00873)	(0.0175)
age	0.0107***	0.0101	0.000230	0.0166**	0.00452	0.0102*
	(0.00397)	(0.00730)	(0.00319)	(0.00697)	(0.00311)	(0.00562)
agesq	-0.000103**	-0.000136*	-7.51e-06	-0.000189***	-5.79e-05*	-0.000113**
	(4.04e-05)	(7.31e-05)	(3.21e-05)	(6.75e-05)	(3.17e-05)	(5.47e-05)
male	0.0586***	-0.0649	0.0792***	-0.182***	0.0732***	-0.192***
	(0.0223)	(0.0434)	(0.0171)	(0.0409)	(0.0167)	(0.0359)
Single	0.0877**	0.107	0.103***	0.0899	0.0881***	-0.0928*
	(0.0419)	(0.0749)	(0.0298)	(0.0683)	(0.0305)	(0.0558)
Basic education	0.0805***	0.207***	0.106***	0.557***	-0.0133	0.374***
	(0.0281)	(0.0513)	(0.0192)	(0.0421)	(0.0245)	(0.0377)
Secondary educ	0.159***	0.525***	0.134***	0.680***	0.0455*	0.616***
	(0.0273)	(0.0517)	(0.0402)	(0.113)	(0.0251)	(0.0434)
Tartary educ	0.277***	0.762***	0.299***	0.992***	0.313***	0.643***
	(0.0648)	(0.139)	(0.0404)	(0.120)	(0.0420)	(0.0881)
Constant	-0.255**	-0.585***	0.0841	-0.247	0.851***	-0.523***
	(0.117)	(0.177)	(0.111)	(0.176)	(0.211)	(0.142)
lnsigma		-0.668***		-0.663***		-0.543***
		(0.0159)		(0.0130)		(0.0186)
Observations	4,521	4,521	5,998	5,998	8,637	8,637

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix B, continued

	GLSS6 2012/2013		GLSS7 2016/2017	
Variables	Main eqn.	Select equation	Main eqn.	Select equation
lnhinc	0.475***		0.490***	
	(0.0120)		(0.0127)	
lnhsize	0.0107	0.0973***	-0.0544***	0.0224
	(0.0139)	(0.0271)	(0.0135)	(0.0254)
lnhictexp	0.0279***	0.188***	0.0155***	0.181***
	(0.00379)	(0.00630)	(0.00439)	(0.00689)
urban	-0.113***	0.0644	-0.145***	0.0434
	(0.0303)	(0.0523)	(0.0344)	(0.0591)
urban*lnhictexp	0.0171***	0.00610	0.0141**	0.0449***
	(0.00567)	(0.0105)	(0.00645)	(0.0120)
age	0.00151	0.0116***	0.00404*	0.0277***
	(0.00195)	(0.00395)	(0.00230)	(0.00443)
agesq	-4.37e-05**	-0.000110***	-6.17e-05***	-0.000269***
	(1.89e-05)	(3.77e-05)	(2.27e-05)	(4.30e-05)
male	0.161***	-0.209***	0.159***	-0.165***
	(0.0113)	(0.0266)	(0.0124)	(0.0273)
Single	0.120***	-0.0111	0.101***	-0.00418
	(0.0184)	(0.0398)	(0.0183)	(0.0372)
Basic education	-0.116***	0.357***	-0.0953***	0.348***
	(0.0143)	(0.0261)	(0.0170)	(0.0289)
Secondary education	0.00695	0.541***	-0.0189	0.412***
	(0.0229)	(0.0494)	(0.0259)	(0.0529)
Tertiary education	0.144***	0.651***	0.102***	0.544***
	(0.0221)	(0.0491)	(0.0241)	(0.0491)
Constant	0.115	-0.732***	0.220**	-1.208***
	(0.0982)	(0.102)	(0.112)	(0.118)
lnsigma		-0.553***		-0.579***
		(0.00688)		(0.00746)
Observations	16,772	16,772	13,832	13,832

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

C: Elasticity Estimates for the Cragg's double hurdle model

	GLSS3			GLSS4			GLSS5		
VARIABLES	Pr(y)	E(y*|Pr(y))	E(y|Zg>0)	Pr(y)	E(y*|Pr(y))	E(y|Zg>0)	Pr(y)	E(y*|Pr(y))	E(y|Zg>0)
lnhinc	-	1.910***	1.910***	-	2.403***	2.403***	-	2.631***	2.631***
		(0.0817)	(0.0817)		(0.0995)	(0.0995)		(0.231)	(0.231)
lnhsize	0.179***	-0.0702**	0.108**	0.0887***	0.0269	0.116***	0.0183	0.0518*	0.0700*
	(0.0398)	(0.0347)	(0.0530)	(0.0226)	(0.0266)	(0.0348)	(0.0242)	(0.0284)	(0.0375)
lnictexp	0.0135***	-0.000458	0.0130***	0.0197***	0.0132***	0.0329***	0.240***	0.0665***	0.306***
	(0.00242)	(0.00114)	(0.00276)	(0.00266)	(0.00163)	(0.00317)	(0.00968)	(0.0123)	(0.0158)
age	0.303	0.479***	0.783***	0.307**	0.0109	0.318	0.256*	0.205	0.461**
	(0.218)	(0.176)	(0.288)	(0.129)	(0.146)	(0.194)	(0.140)	(0.141)	(0.199)
agesq	-0.201*	-0.229***	-0.430***	-0.178***	-0.0178	-0.195**	-0.143**	-0.133*	-0.276***
	(0.108)	(0.0887)	(0.145)	(0.0636)	(0.0749)	(0.0978)	(0.0h693)	(0.0729)	(0.101)
urban	0.0722***	-0.0253***	0.0469***	0.0441***	0.0271***	0.0713***	0.0372***	0.00265	0.0399***
	(0.0100)	(0.00772)	(0.0126)	(0.00600)	(0.00637)	(0.00873)	(0.00760)	(0.00733)	(0.0105)
male	-0.0298	0.0394***	0.00962	-0.0486***	0.0526***	0.00396	-0.0769***	0.0528***	-0.0241
	(0.0199)	(0.0151)	(0.0250)	(0.0110)	(0.0113)	(0.0157)	(0.0142)	(0.0120)	(0.0186)
Single	0.0185	0.0232**	0.0416**	0.00958	0.0273***	0.0368***	-0.0168*	0.0286***	0.0118
	(0.0132)	(0.0109)	(0.0171)	(0.00731)	(0.00791)	(0.0108)	(0.00980)	(0.00973)	(0.0139)
Basic education	0.0364***	0.0207***	0.0571***	0.119***	0.0562***	0.175***	0.0759***	-0.00574	0.0701***
	(0.00899)	(0.00728)	(0.0115)	(0.00908)	(0.0101)	(0.0136)	(0.00767)	(0.00902)	(0.0120)
Secondary education	0.124***	0.0550***	0.179***	0.00956***	0.00467***	0.0142***	0.0978***	0.0121*	0.110***
	(0.0123)	(0.00950)	(0.0154)	(0.00159)	(0.00140)	(0.00211)	(0.00692)	(0.00719)	(0.00994)
Tertiary education	0.0131***	0.00708***	0.0202***	0.0181***	0.0136***	0.0317***	0.0193***	0.0171***	0.0364***
	(0.00240)	(0.00165)	(0.00286)	(0.00218)	(0.00183)	(0.00283)	(0.00266)	(0.00230)	(0.00348)
Observations	4,521	4,521	4,521	5,998	5,998	5,998	8,637	8,637	8,637

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix C, continued

	GLSS6			GLSS7		
VARIABLES	Pr(y)	E(y*|Pr(y))	E(y|Zg>0)	Pr(y)	E(y*|Pr(y))	E(y|Zg>0)
lnhinc	-	4.143***	4.143***	-	4.378***	4.378***
		(0.104)	(0.104)		(0.114)	(0.114)
lnhsize	0.0502***	0.0129	0.0631***	0.0140	-0.0640***	-0.0501**
	(0.0140)	(0.0169)	(0.0223)	(0.0155)	(0.0160)	(0.0225)
lnictexp	0.354***	0.150***	0.504***	0.417***	0.0865***	0.504***
	(0.0104)	(0.0143)	(0.0179)	(0.0135)	(0.0158)	(0.0209)
age	0.226***	0.0755	0.301**	0.662***	0.190*	0.852***
	(0.0765)	(0.0893)	(0.117)	(0.105)	(0.107)	(0.153)
agesq	-0.110***	-0.105**	-0.215***	-0.332***	-0.148***	-0.480***
	(0.0376)	(0.0446)	(0.0579)	(0.0528)	(0.0544)	(0.0774)
urban	0.0171***	-0.0122**	0.00491	0.0517***	-0.0321***	0.0196**
	(0.00465)	(0.00535)	(0.00704)	(0.00577)	(0.00573)	(0.00806)
male	-0.0633***	0.117***	0.0536***	-0.0575***	0.110***	0.0524***
	(0.00807)	(0.00809)	(0.0114)	(0.00960)	(0.00856)	(0.0128)
Single	-0.00149	0.0384***	0.0369***	-0.000851	0.0433***	0.0425***
	(0.00534)	(0.00585)	(0.00797)	(0.00806)	(0.00774)	(0.0112)
Basic education	0.0805***	-0.0621***	0.0184*	0.0933***	-0.0508***	0.0425***
	(0.00589)	(0.00760)	(0.00965)	(0.00786)	(0.00894)	(0.0119)
Secondary education	0.0186***	0.000587	0.0192***	0.0176***	-0.00154	0.0161***
	(0.00170)	(0.00187)	(0.00253)	(0.00222)	(0.00213)	(0.00310)
Tertiary education	0.0280***	0.0149***	0.0429***	0.0335***	0.0122***	0.0457***
	(0.00209)	(0.00225)	(0.00306)	(0.00296)	(0.00285)	(0.00407)
Observations	16,772	16,772	16,772	13,832	13,832	13,832

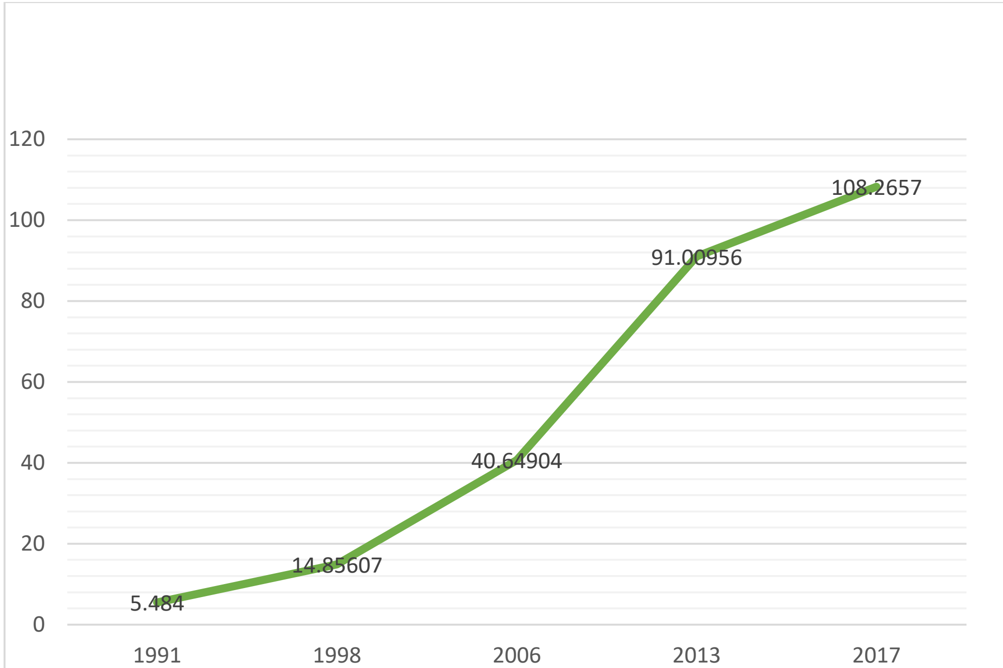
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0

D: Likelihood-ratio test for measure of fit for FILOGIT model

Fit	Current model	Saved model	Difference
Log-Lik Intercept Only:	-4456.858	-4456.858	0.000
D (df=13996/13991/5):	7509.207	7468.124	41.083
McFadden's R^2:	0.158	0.162	-0.005
Cox-Snell/ML R^2:	0.095	0.098	-0.003
McKelvey & Zavoina R^2:	0.367	0.396	-0.028
Variance of Y^*:	5.201	5.443	-0.242
Count R^2:	0.903	0.903	0.000
AIC:	7535.207	7504.124	31.083
BIC (df=13/18/-5):	7633.324	7639.978	-6.654
Log-Lik Full Model:	-3754.603	-3734.062	-20.542
Wald (df=12/17/-5):	997.128	901.838	95.290
Prob > LR:	0.000	0.000	0.000
McFadden (adjusted) R^2:	0.155	0.158	-0.003
Cragg-Uhler Nagelkerke) R^2:	0.203	0.208	-0.006
Efron $R^{2:}$	0.107	0.111	-0.004
Variance of Error:	3.290	3.290	0.000
Count (adjusted) R^2:	-0.001	-0.003	0.002
AIC divided by N:	0.538	0.536	0.002
BIC (df=13/18/-5):	7633.324	7639.978	-6.654

Difference of 6.654 in BIC provides strong support for current

E: Trend of Average Fuel Expenditure on Transport, 1991-2017



F: Chi-Squared Test of Independence

Variable	χ2	P-value
Sex	19.953	0.000
Marital Status	30.944	0.000
Location	46.617	0.000
Sector of Employment	145.728	0.000
Status of Employment	38.112	0.000
Time unit of the day	369.256	0.000
Availability of transport	399.770	0.000
Reliability of transport	106.666	0.000