EFFECT OF MEDIATING ROUTE CHARACTERISTICS ON THE RELATIONSHIP BETWEEN LOW COST CARRIERS' KEY FACTORS AND AIRLINE PERFORMANCE IN KENYA

BY

MICHAEL OMONDI AOMO

A THESIS SUBMITTED IN FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY IN BUSINESS ADMINISTRATION

DEPARTMENT OF ACCOUNTING AND FINANCE

MASENO UNIVERSITY

DECLARATION

I certify that this thesis is my original work and has not been presented for any degree in any other University. The work reported herein has been carried out by me and all sources of information have been acknowledged by means of references.

Signature _____ Date _____

Michael Omondi Aomo

PhD/BE/00160/2013

SUPERVISORS

This thesis has been submitted for examination with our approval as the University supervisors.

Dr. David Oima, PhD

Department of Accounting and Finance

Maseno University

Signature _____ Date _____

Dr. Moses Oginda, PhD

Department of Management Science

Maseno University

Signature _____ Date _____

ACKNOWLEDGEMENT

I would most sincerely first and foremost wish to thank my supervisors Dr. David Oima and Dr. Moses Oginda for their help and guidance that they provided. They gave many thought-provoking discussions and their very detailed comments and suggestions were essential in the completion of this work. Without their inspiring and encouraging comments, I would not be able to finish this paper. I would like to thank Prof. Lucas Othuon whose input was very vital in validating my model of analysis. I would also like to thank the other members of the Maseno University, School of Business and Economics, such as Dr. Benjamin Ombok, Dr. Fredrick Aila, Dr. Nyongesa, Dr. Odondo, Dr. Robert Mule and Mr. Ben Jack who were very supportive and extremely helpful, very ready to be consulted even through mobile phone conversation. They have been akin to a rock-steady lighthouse, guiding ships on stormy seas. However, it takes a rough sea to make a great captain. Thanks for your support both in knowledge and mentality. In addition I would also like to thank the Director General, Kenya Civil Aviation Authority (KCAA); without his permission to access the aircraft movement data it would have been very difficult to reach this level. Finally, there are also a number of very good friends who were very helpful during this voyage and they include: Vincent and Asher of School of Graduate Studies (SGS), Paddy Leitch Kiptoo, and Mr. Kirui. Mr. Kirui was really helpful in availing the two versions of the statistical software for data analysis.

DEDICATION

I dedicate this work to my lovely wife Rose, my son Cephas Eddy Omondi, my daughter Sophie Whitney Achieng, and to the memory of my son Zephaniah Larry Ogonda who passed on at the tender age of 10 months, for there was never such a lovelier and more attentive angel (may he rest in peace).

ABSTRACT

Studies show that low-cost carriers have gained 15.2% market shares and enplanement has increased by 38% over a period of ten years following their emergence. Whereas flight frequency and load factor are directly influenced by airlines' key factors such as turn-time and fleet capacity, they on the other hand directly influence other airline market parameters. This proposes a mediation possibility. However, the influence of turn-time on carriers' market share, fleet capacity on enplanement, mediating flight frequency and load factor on the relationships, and the effect of low-cost carrier in Kenya were still unknown. There had been a substantial body of research investigating the effect of low-cost carriers on the aviation industry in developed countries but not in Kenya. The purpose of this study, therefore, was to analyze the effect of mediating route characteristics on the relationship between low-cost carriers' key factors and the airline performance for the period 2007 – 2012 in Kenya; which was characterised with steady growth. The specific objectives of the study were to: determine the effect of turn-time on carriers' market share, fleet capacity on enplanement, and the influence of route characteristics as a mediator on the relationship between low-cost carriers' key factors and airline performance. The study was anchored on the theory of enhancement of vessel capacity utilisation; from which a conceptual framework was developed, taking independent variable as low-cost carriers' key factors, dependent variable as airline performance, and mediating variable as route characteristics. Time series correlationsl design was used to capture the changes in the variables over the period. The study was carried out in Kenya. Study population comprised two low-cost carriers whose time series secondary data over 72 months period were analyzed. Sources of secondary data were aircraft log books on which documents review was carried out. Panel unit root tests show all variables are first-order stationary except turn-time and load factor that are zero-order stationary; implying direct association of the variables would yield short-run equillibrium relationships. Panel cointegration tests revealed the series are cointegrated; meaning cointegrating regressions would result in long-run equillibrium relationships. Path regression analyses were used to track the influence of the mediating route characteristics, and findings show the effect of turn-time on carrier's market share (β = -0.94, p= 0.000, R2 =36.4%); implying turn-time significantly predicts carrier's market share, fleet capacity on enplanement (β = 35.41, p = 0.000, R2 = 78.25%); meaning fleet capacity significantly predicts enplanement, mediating flight frequency on turn-time and carrier's market share relation ($\beta_{indirect}$ = -0.94, p= 0.000); implying flight frequency significantly mediates turn-time and carrier's maket share relation, and mediating load factor on fleet capacity-enplanement relation ($\beta_{indirect}$ =5.82, p= 0.001); meaning load factor significantly mediates fleet capacity and enplanement relation. Study concludes turn-time has significant negative effect on carrier's market share, fleet capacity has significant positive effect on enplanement, flight frequency partially and significantly mediates turn-time and carrier's market share relation by 64.14%, and, load factor partially and significantly mediates fleet capacity and enplanement relation by 16.44%. Study recommends: adoption of efficient turn-around models, timely fleet capacity adjustments, increasing flight frequency of flights during holidays and week-ends, stimulating leisure travel demand by lowering fare to enhance load factor. These results may be significant to both government and airlines management in Fleet Size and Mix (FSM) policy formulations and scholars in forming a basis for future research.

TABLE OF CONTENTS

ACRONYMS AND ABBREVIATIONS

ASEAN	-	Australia, South East Asian Region
ASK/M	-	Available Seat Kilometer/Mile
CASK/M	-	Cost per Available Seat Kilometer/Mile
CRMS	-	Carriers' Market Share
ENPL	-	Enplanement
EU	-	European Union
FAA	-	Federal Aviation Administration
FE	-	Fixed Effects
FFV	-	Fly540 Aviation Limited
FLTC	-	Fleet capacity
FMOLS	-	Fully Modified Ordinary Least Squares
FREQ	-	Flight Frequency
FSC	-	Full Service Carriers
GDP	-	Gross Domestic Product
HKJK	-	Jomo Kenyatta International Airport
IATA	-	International Airlines Transport Association
ICAO	-	International Civil Aviation Organization
JFK	-	John F. Kennedy International Airport
JLX	-	Jetlink Aviation Limited
KAA	-	Kenya Airports Authority
KCAA	-	Kenya Civil Aviation Authority
LCC	-	Low Cost Carriers
LDFC	-	Load Factor
NC	-	Network Carriers
OLS	-	Ordinary Least Squares
RASM/K	-	Revenue per Available Seat Kilometer/Mile
RE	-	Random Effect
RPM/K	-	Revenue Passenger Kilometer/Mile
TNTM	-	Turn-time
UK	-	United Kingdom
US	-	United States

OPERATIONAL DEFINITION OF TERMS

Carriers' Market Share: The proportion of the air passengers flown by the low-cost carriers for the particular month of observation.

Enplanement: The total number of passengers ferried by the airlines for the particular month of observation.

Fleet Capacity: the product of the sector wide low-cost carrier fleet number and the seating density of the aircraft operated for the particular month of observation; this gives the total number of seats of an airline.

Flight Frequency: The number of trips or scheduled flights operated by the low-cost carriers for the particular month of observation.

Load Factor: A ratio of unit costs to unit yields. To calculate system-wide load factor, divide Revenue Passenger Miles (RPMs) by Available Seat Miles (ASM); For an individual flight, divide the revenue passengers on board by the aircraft capacity.

Turn-time: the period between the time an aircraft parks at the gate till it can pull out again with a new load of passengers and/or cargo. Before an airplane can make another trip, there are a number of key tasks to be carried out: unloading and loading of passengers and luggage, safety and security checks, catering, cleaning and a variety of administrative tasks.

Available Seat Kilometer/Mile: One seat (empty or filled) flying one mile.

Airline Performance: As a dependent variable, this consists of the carriers' market share and enplanement.

Airline Market Parameters: These are fare, enplanement, market shares etc.

Cost per Available Seat Kilometer/Mile (CASK/M): Unit costs represent how much it costs to fly one seat (empty or filled) one-mile. To calculate unit costs, divide total operating expenses by Total ASM capacity.

Domestic Routes: This includes all routes within the Kenyan region.

Efficient Turn-around Time: The shortest period possible between the time the plane lands and the time she takes off again.

Fleet Size: This refers to the seating density of airplanes a low-cost carrier is operating for the particular month of observation.

Hub-and-spoke System: Air service that starts from one airport to the other, and in which the airline continue to organize for the passengers should a s/he want to connect or continue to another destination.

Low-cost Carriers' Key Factors: This refers to such parameters as the turn-time and fleet capacity.

Legacy Carriers: Also known as Full Service/Network/National carriers owned wholly or partly by the Governments.

Low-cost Carriers: Privately owned airlines that offer scheduled services to passengers at lower fares than the legacy carriers.

Low-cost Carrier Phenomenon: The ability of the low cost carrier to influence the airline market parameters such as fare, enplanement, market shares etc.

Low Fare: This is the average one-way ticket price as charged by an Low-Cost Carrier for the particular month of observation.

Mediator: Route characteristics whose constructs are flight frequency and load factor.

Point-to-Point Service: Air service that starts from one airport to the other without an airline involving itself should a passenger want to connect or continue to another destination.

Revenue Passenger Kilometer/Mile: A paying passenger flying one mile creates an RPM. 100 passengers flying 500 miles generates 50,000 RPMs.

Revenue per Available Seat Kilometer/Mile: Revenue passenger mile (RPM) divide by available seat mile (ASM), or multiply load factor times yield to get the measure of how much revenue we generate per increment of capacity.

Route: An airway link connecting two cities

Route Characteristics: This is the mediating variable, a mechanism through which a low-cost carrier is expected to influence airline performance i.e flight frequency and load factor.

Yield: Average fare per mile; To calculate system yield, divide passenger revenue by total RPMs.

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

CHAPTER ONE
INTRODUCTION

This chapter provides an overview of the background of the study, statement of the problem, objectives of the study, research hypotheses, scope of the study, significance of the study, and the conceptual framework.

1.1 Background of the Study

Route characteristics refer to the airline's flight frequency and load factor on a particular route (Styhre, 2010; Najda, 2003). On the other hand, low-cost carrier (LCC) is a discount airline that is characterized with point-to-point network, pays employees below the industry average wage, offers no frills service, low, simple and unrestricted fares, high frequencies, no interlining, ticketless travel utilizing travel agents and call centers, single-class, high density seating, no seat assignments, and no meals or free alcoholic drinks, single type aircraft with high utilization, secondary or uncongested airports served with short aircraft turns, short sector length, and competitive wages with profit sharing and high productivity (Rosenstein, 2013; Chowdhury, 2007; O'Connell and Williams, 2007).

The current study was anchored on the theory of enhancement of vessel capacity utilisation which refers to the functional process of analysing strategies, identifying and combining measures directed towards both capacity demand and capacity supply to facilitate an increased utilisation with the aim of reducing transport cost per unit. According to Styhre (2010), the processes are repeated with the aim of approaching a desirable level of vessel capacity utilisation and that there is no strict sequence of activities which may well be carried out in parallel. However, Damuri and Anas (2006) and Mirza (2009), Wensveen (2011) and IATA (2015) report that some of those processes influence one another. For example, turn-time influences the number of trips an airplane can make while fleet capacity reductions leads to significant increases in carriers' load factor in the markets. This implies that the nature of the relationships among some of these the variables are rather directional. The study therefore sought to establish the internal connections between the turn-time, flight frequency and market share measures and fleet capacity, load factor and enplanement measures.

Empirically, findings on the effects of the low-cost carrier (LCC) emergence on the aviation industry have shown mixed results. On one hand, research has stressed that the emergence of low cost carriers has had a profound impact in the aviation industry as seen in the works of InterVistas (2014), O'Connell and Williams (2007), Israel (2015), Mertenes and Vowles (2012), Bhaskara (2014), Najda (2003), Manuela (2006), and Campisi, Costa, and Mancuso (2010). On the other hand, in the markets such as Canada, North Atlantic routes and Netherlands, the low-cost carriers have been found not to have any impact (e.g. Lin, 2013; Wu, 2013; Mentzer, 2013).

Market share is the portion or percentage of total sales volume of a market controlled by a particular company or product or a brand (Lambin, 2007). The economic well-being of a business firm can often be summarized in terms of its market share. It is influenced by factors such as price, advertising expenditures, retail availability, product characteristics, quality, speed of service, ease of maintenance, and points of distribution (Govindarajan, 2015; Kotler and Keller , 2012).

Turn-time is the period between the time an aircraft parks at the gate till it can pull out again with a new load of passengers and/or cargo. The significance of turn-around punctuality is not only to reduce delays, but to maintain the linkage and stability of aircraft rotations. Reducing airplane turn-times enhances more efficient airplane utilization (Gok, 2014; Mirza, 2009) by spreading fixed ownership costs over an increased number of trips, reducing costs per seat-mile or per trip. A typical hub-and-spoke system requires longer turn-times to allow for synchronization between the feeder network and trunk routes unlike carriers that operate point-to-point service with simplified fleet structure, fewer airplane types, and, thus, increased airplane utilization (Kunze, Schultz, and Fricke, 2011; Mirza, 2009; Wu and Caves, 2004). More flights mean more paying passengers and, ultimately, more revenue. Benefits of shorter turn-times are significant for shorter average trip distances. In order to optimize airplane utilization, point-to-point carriers operate with significantly faster turn-times at the gate. (Mirza, 2009; Trabelsi *et al.*, 2013; Kunze, Schultz, and Fricke, 2011).

Several studies (Kunze, Schultz, and Fricke, 2011; Trabelsi *et al*, 2013; Vidosavljevic and Tosic, 2010; Norin, 2008; Gok, 2014) have investigated about the models for the turn-around

operations that would minimize delays, and consequently, costs. Bhaskara (2014), Israel (2015) and O'Connell and Williams (2007) employ descriptive statistics in analyzing the rising trend in the low-cost carriers' market share and results indicate that it has resulted in increased enplanement by 38% over 3 months and have gained 15.2% market share as reported by InterVistas (2014) and O'Connell and Williams (2007) respectively.

The low-cost carriers have demonstrated short and quick aircraft turn-arounds, which is an equivalent of speed of service, but without sufficient information on how this has helped them acquire and maintain market share. Studies have only considered the nature of relationship between carriers' market share and fare, and had sought to develop turn-time models that would optimize aircraft utilization by minimizing delays, as well as costs. Thus, the relation between turn-time and carriers' market share was still unknown.

Enplanement is the volume of traffic or the number of passengers ferried by an airline. It is through the transportation of these revenue passengers that an air carrier receives commercial remuneration (Wu, 2015). According to Damuri and Anas (2006) and O'Connell and Williams (2007), the entry of a low-cost carrier into a market has had a market creation effect, where low prices induced more travelers into using air transportation either for the first time and/or instead of other modes, especially those in the short-haul markets. Belobaba, Odoni, and Barnhart (2009) expressed enplanement as a function of departure time, travel time, expected delay, aircraft type, in flight service, price, flight frequency, airport amenities of carrier, frequent flyer plan attractiveness, distance, business travel between two cities, tourism appeal, carrier and flight characteristics.

Fleet capacity refers to the seating density of an airline. The optimal number and size of equipment required depends on the level of travel demand that the carrier will cover (Tolliver-Nigro, 1999; Fu and Ishkhanov, 2004), distance (Pai, 2007), economies of scale in aircraft operation (Boreinstein, 2011), airport characteristics such as runway, and whether hub-spoke or a point-to-point network (Brueckner, 2004). Low-cost carriers generally do not offer business class seating, which takes up a lot of valuable space, and instead offer a dense, single class seating configuration (Rosenstein, 2013; Campisi, Costa & Mancuso, 2010; O'Connell and Williams, 2007). Equipment capacity has a significant impact on the number of equipment required; in

which case the larger the equipment, the higher the average equipment productivity and the smaller the required number of fleet. The optimal number of equipment required depends on the level of travel demand that the carrier will cover (Tolliver-Nigro, 1999).

Empirical evidence (Dresner, 2013; Mertens and Vowles, 2012; InterVistas, 2014; Bhaskara, 2014; Wu, 2013; Lin, 2013) show mixed results on the effect of low-cost carriers on enplanement in the airline market. Mertens and Vowles (2012) used a group of three low-cost carriers and their results show higher figures than InterVistas (2014) and Bhaskara (2014) who assessed the effect of only one low-cost carrier. They all employ descriptive statistics in analyzing their data and have related the changes in enplanement with the low-fare offered by these low-cost carriers. Both Lin (2013) and Wu (2013) use panel data and incorporate the low-cost carrier phenomenon, as one whole variable, in their regression equations without considering the specific key factors. They both find out that low-cost carriers have no effect on enplanement.

Low-cost carriers are characterized by homogenous fleet capacity with dense, single class seating configuration. However, studies have endeavored to find out the impact that the emergence of low-cost carriers would have on enplanement by considering the low-cost carriers' low-fare construct and the findings also show that the effect of low-cost carrier is not uniform across countries. Consequently, there is still no sufficient information on how fleet capacity relates to enplanement.

Flight frequency is the number of trips operated by an airline. It is a central attribute when customers are determining mode choice (Styhre, 2010; Pai, 2007). Higher flight frequency of flights raises the value of the product to the passenger and increased value leads to higher demand and finally higher prices (Boreinstein, 2011). As distance between the two end points increases, aircraft size increases and flight frequency decreases (Pels and Rietveld, 2006). High rates of fleet utilization are a major factor in low-cost carriers' business model. The key for high utilization is to shorten the time between one flight and another (Damuri and Anas, 2006) since turn-times influence the number of trips an airplane can make in a given period of time. It also facilitates a reduction in cost per transported unit thus allows airlines to operate aircraft more

efficiently and for longer utilization periods (Mirza, 2009). A market that has a high concentration of business travelers might be served by smaller aircraft with greater flight frequency, while a market with a high concentration of leisure travelers might be serviced by larger aircraft with lower flight frequency (Pai, 2007).

Several studies (Manuela, 2006; Najda, 2003; Wang *et al*, 2014) have investigated on the flight frequency factor differently. Manuela (2006) considers it as independent variable on fare while Wang *et al*, (2014) investigates it as an independent variable on airline market expansion, and finds a negative correlation between market concentration and flight frequency. Najda (2003) treats it as a moderating variable on fare.

Available information reveal relationships between an airline's key factors such as price, product characteristics, quality, speed of service etc on the realization of and maintenance of market share. This direct relationship is only realizable through several mediating factors such as flight frequency. Since turn-time precedes flight frequency, this study evaluated flight frequency as a mechanism through which turn-time would influence the carriers' market share parameter. Whereas the low-cost carriers have demonstrated high number of flight frequency, there is insufficient information on how this helps them acquire and maintain their market share. The cited studies had investigated flight frequency as either independent or moderating variable with respect to other airline performance parameters such as demand, fare, fleet size and distance between two destinations. No study had considered it as a mediating variable in the relationships between turn-time and carriers' market share.

Load factor is the percentage of seats filled with paying passengers (Campisi, Costa and Mancuso, 2010; O'Connell and Williams, 2007; Borenstein, 2011). High load factors are a major factor in low-cost carriers' business model who base the low-fare on the high occupancy rate of the aircraft (80% load factor) (Damuri and Anas, 2006; Macário, Viegas, and Reis, 2007; Vidovic, Steiner and Babic, 2007). Airlines operating with low load factors have tremendous incentives to reduce fares (Besanko, Dranove, Shanley, and Schaefer 2004). A good load factor assures the necessary utilization and productivity of critical low-cost carrier resources. Low-cost companies' load factors are usually higher than that of the traditional air transport companies,

which means that each low-cost company's aircraft transport more passengers than network carriers (Macário, Viegas, and Reis, 2007; Damuri and Anas, 2006) which enables them reduce costs significantly (Vidovic, Steiner and Babic, 2007). Low load factors reflect delivery of larger-capacity equipment, while capacity reductions leads to significant increases in carriers' load factor in the markets (Wensveen, 2011). It indicates that an airplane is more efficiently utilized when the load factor is high, lowering the operating costs and, as a result, the airfares. A high load factor lowers cost per customer, but also lowers quality and demand (Borenstein, 2011). The per passenger cost of a flight decreases as the load factor rises, which suggests that load factor has a negative coefficient on fare.

Different studies (Rupp, 2007; Tesfay and Solibakke, 2015; IATA, 2015; Jenatabali and Ismail, 2007; Borenstein, 2011; Ramdas and Williams, 2008; Najda, 2003) have investigated load factor differently. IATA (2015) has employed descriptive statistics in analysing the impact of fleet capacity on load factor. Both Tesfay and Solibakke (2015) and Jenatabali and Ismail (2007) have modelled load factor as a function of other independent variables. Rupp (2007) and Ramdas and Williams (2008) investigate it as an independent variable on the on-time performance while Borenstein (2011) investigates as an independent variable on price. Najda (2003) treats as a moderating variable on fare. International Air Transport Association (IATA) (2015) and Jenatabali and Ismail (2007) show mixed results of the effect of fleet capacity on load factor in different countries.

Available information reveal relationships between an airline's key factors such as low-fare, fleet size, and points of distribution etc on enplanement. This direct relationship is only realizable through several mediating factors such as load factor. Since fleet capacity precedes load factor, this study evaluated load factor as a means through which fleet capacity would influence the enplanement parameter. Whereas low-cost carriers' business model is characterised with high load factors, there is insufficient information on how this helps them ferry high number of passengers. The cited studies had investigated load factor as either dependent, independent or moderating variable with respect to other airline performance parameters such as demand, fare,

fleet size and distance between two destinations. No study had considered it as a mediating variable in the relationships between turn-time and carriers' market share.

Despite Kenya signing up to the Yamoussoukro Decision in 1999, which was designed to bring air service liberalisation, the Kenyan aviation market still struggles under the weight of government bureaucracy and high taxation levels on the sector (Business Traveller, 2011). However, amidst these hurdles, there are a number of companies native to the country that are leading the way in successful route and network development. Fly540, the country's first low cost carrier, and Jetlink Aviation, both operate(d) nine destinations in Kenya, and served other points in Uganda, Tanzania, Burundi, South Sudan and Comoros. More recently, Jambojet, a Kenya Airways subsidiary low cost carrier, commenced its operations in April 2014, flying to 4 destinations in Kenya. These airlines are proving that it is possible to follow different but disciplined business models and to deliver both service and financial results to world-class standards. It is about 9 years now, since the introduction of the low-cost carrier business model, yet its impacts on the airline market had not been studied. While there had been a substantial body of research investigating this phenomenon in the US, Canada, Australia, and Europe, there had been little investigation of whether this phenomenon exists in other markets. Mentzer (2013) recommended that there was a need to identify whether there is a low-cost carrier effect in other markets. It is for this reason that the purpose of this study was to analyze the effect of mediating route characteristics on the relationship between low-cost carriers' key factors and the airline performance for the period 2007 – 2012, in Kenya.

1.2 Statement of the Problem

Route characteristics is the airline's flight frequency and load factor on a particular route while low-cost carrier is a discount airline that operates a point-to-point network, pays employees below the industry average wage, and offers no frills service. The reviewed literature had shown that 38% increase in enplanement and 15.2% gain of air passengers' market shares by low-cost carriers over a period of ten years is eminent whenever they emerge in the airline market, and that the effect of low-cost carrier is not uniform across countries. Whereas studies had sought to develop turn-time models that would optimize aircraft utilization by minimizing delays as well as costs, while investigating the impact of low-cost carriers on the airline market, turn-time had

not been considered with respect to carriers' market share. Regarding enplanement, only the low-fare construct had been taken into account but not fleet capacity. In addition, the fact that theories suggest that flight frequency and load factor are influenced by airlines' key factors such as turn-time and fleet capacity, and that they independently have effect on the airline market parameters, it gives a proposition that they are a means through which turn-time and fleet capacity would affect any other variables. However, studies had investigated flight frequency and load factor as either dependent, independent or moderating variable with respect to air fare. No study had considered flight frequency and load factor as mediating variables in the relationship between the low-cost carriers' key factors' and airline performance. Consequently, the influence of turn-time on the carriers' market shares, fleet capacity on enplanement, the mediating role of flight frequency on turn-time and carriers' market share, and the mediating role of load factor on fleet capacity and enplanement were still unknown. While there has been a substantial body of research investigating this phenomenon in the developed countries, there had not been any investigation of whether this phenomenon existed in other aviation market such as Kenya.

1.3 Objective of the Study

The main objective of the study was to analyze the analyze the effect of mediating route characteristics on the relationship between low-cost carriers' key factors and airline performance for the period 2007 – 2012, in Kenya.

The specific objectives of the study were to:

i. Determine the effect of turn-time on the market share of low-cost carriers in Kenya;
ii. Establish the effect of fleet capacity on enplanement by low-cost carriers in Kenya;
iii. Examine the influence of flight frequency as a mediator on the relationship between turn-time and market share of low-cost carriers in Kenya;
iv. Analyze the influence of load factor as a mediator on the relationship between fleet capacity and enplanement by low-cost carriers in Kenya.

1.4 Research Hypotheses

H_0: Turn-time has no effect on the market share of low-cost carriers in Kenya;

H_0: Fleet capacity does not have an impact on enplanement by low-cost carriers in Kenya;

H_0: Flight frequency does not influence the relationship between turn-time and market share of low-cost carriers in Kenya;

H_0: Load factor has no influence the relationship between fleet capacity and enplanement by low-cost carriers in Kenya.

1.5 Scope of the Study

The study was carried out in Kenya. Only the low-cost carriers that were in operation during the period 2007 – 2012 were the subjects of study. The current study analyzed the influence of route characteristics as a mediator on the relationship between low-cost carriers' key factors such as their quick, short turn-times and homogenous dense seating capacity and airline performance such as market share and enplanement.

1.6 Significance of the Study

The study provides useful information regarding fleet size and mix (FSM) related decision making not only to the government but also to the owners and managers of the airlines businesses in Kenya. It enhances the awareness of fleet planning, scheduling and management team about the impact of reducing turn-around activities and enhancing the fleet capacity on a given route. The traveling public will definitely reap benefits in the long run especially when delays are minimized and the inconveniences caused due to inadequate available seats are addressed through more efficient fleet management. The study contributes knowledge towards the global dynamics of low-cost carriers operations as per various market segments. The findings of the study form a basis for further research for other scholars.

1.7 Conceptual Framework

The study was guided by a conceptual framework adapted and modified from the framework for vessel capacity utilization (see Appendix VI), which was relevant for conceptualizing this research. Vessel factor (size), number and type of vessels measures under her "Improvement measures – established capacity" and "definition of sailing schedule" elements respectively, were combined into "fleet capacity". Arrival and departure time measure under "definition of sailing schedule" element, was considered as 'turn-time' for this study. In addition to load factor, flight frequency measure under "route characteristics measure" in the "selection of capacity utilization strategy" element and "departure frequency" measure in the "definition of sailing schedule" element, formed part of the mediating variables for this study. Her intended end results if all these measures are put in place, that is, 'maximum capacity utilization', would be increased carriers' market shares and enplanement in the airline market for this study.

Independent variable is the low-cost carriers' key factors (turn-time, fleet capacity); dependent variable is the airline market (carriers' market share, enplanement) and the mediating variable being route characteristics (flight frequency and load factor). The mediator was expected to explain why or how this relationship occurs. The researcher expected that: the turn-time would have an effect on the carriers' market share; fleet capacity would have an effect on enplanement; flight frequency would mediate the effect of turn-time on carriers' market share; and, load factor would mediate the effect of fleet capacity on enplanement. However, there is also possibility that the fleet capacity may have an effect on the carriers' market share, and the turn-time to have an effect on enplanement. But for purposes of this study, the researcher only investigated the effect of turn-time and fleet capacity on carriers' market share and enplanement respectively.

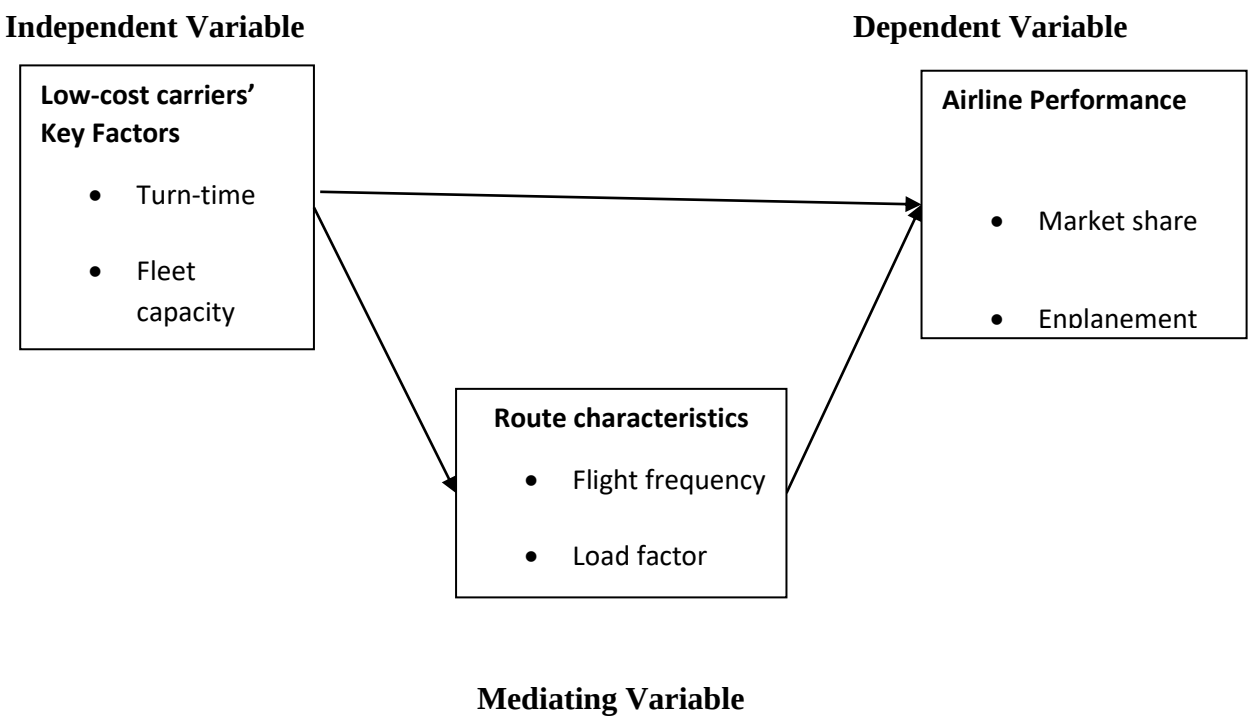


Figure 1.1: Conceptual framework on the effect of mediating route characteristics on the relationship between low-cost carriers' key factors and airline performance.

Source: Adapted from Styhre, 2010

This direct relationship between the low-cost carriers' key factors is only realizable through several mediating route characteristics factors such as flight frequency and load factor. Damuri and Anas (2006) and Mirza (2009) report that turn-times influence the number of trips an airplane can make, while Wensveen (2011) and IATA (2015) also indicate that fleet capacity reductions leads to significant increases in carriers' load factor in the airline markets. Consequently, this study evaluated flight frequency and load factor as mechanisms through which turn-time and fleet capacity would influence the carriers' market share and enplanement parameters respectively. Fairchild and Mackinnon (2010) define a mediator as the third variable that falls in the causal pathway between the predictor variable and the dependent variable. It represents an intervening variable or, stated differently, a mechanism through which an independent variable is able to influence a dependent variable (Baron and Kenny, 1986; Peyrot, 1996). The mediation model offers an explanation for how, or why, two variables are related

where an intervening or mediating variable is hypothesized to be intermediate in the relation between an independent variable and an outcome (Kim, Kaye and Wright, 2001).

CHAPTER TWO
LITERATURE REVIEW

This chapter is sub divided into three sub-section. Each sub-section addresses the following: Review of theory and concepts, empirical studies and summary of literature review.

2.1 Review of Theory and Concepts

2.1.1 Theory of Enhancement of Vessel Capacity Utilisation

The theory of enhancement of vessel capacity utilisation refers to the functional process of analysing strategies, identifying and combining measures directed towards both capacity demand and capacity supply to facilitate an increased utilisation with the aim of reducing transport cost per unit. The framework consists of four elements that are important in attaining a desirable and required level of vessel capacity utilisation. These four elements are: selection of capacity utilisation strategy, definition of sailing schedule, improvement measures for established vessel capacity, and improvement measures for changes in vessel capacity. According to Styhre (2010), the intention is not to cover all aspects of the field, but to offer a toolbox with important contents in order to enhance the vessel's utilisation and reduce the cost per transported unit. The processes, as shown in Appendix VI, are repeated with the aim of approaching a desirable level of vessel capacity utilisation. The iteration normally starts when supply or demand for vessel capacity is changing due to, for example, new trade conditions, competitors entering the market, new customers, or when there is a need for investment in vessel capacity. These measures both directly and indirectly relate to the variables under the current study. Vessels factor (size), number and type of vessels measures under the "Improvement measures – established capacity" and "definition of sailing schedule" elements respectively, were combined into "fleet capacity". Arrival and departure time measure under "definition of sailing schedule" element, was considered as 'turn-time' for this study. In addition to load factor, flight frequency measure under "route characteristics measure" in the "selection of capacity utilisation strategy" element and "departure frequency" measure in the "definition of sailing schedule" element, formed part of the mediating variables for this study.

As much as this theory states that there is no strict sequence of activities (measures) which may well be carried out in parallel, Damuri and Anas (2006) and Mirza (2009) report that turn-times influence the number of trips an airplane can make, while Wensveen (2011) also indicates that fleet capacity reductions leads to significant increases in carriers' load factor in the markets.

These reports imply that turn-time precedes flight frequency and that fleet capacity precedes load factor consequently indicating that there is some sequence among some of these activities. The study was anchored on this theory with a view to establishing the internal connection between the measures. By investigating the influence of the mediating route characteristics (flight frequency and load factor), the researcher believed that internal connections between the following measures would be ascertained: one, turn-time (arrival and departure time measure), flight frequency (route characteristics measure) and market share (increased market share measure); and two, fleet capacity (number and type of vessels), load factor (route characteristics measure) and enplanement (an attribute of increased market share measure).

2.2 The Low Cost Carrier Concepts

According to O'Connell and Williams (2007), the chief difference between low-cost carriers and traditional airlines, or full service carriers (FSCs), fall into three groups: service savings, operational savings and overhead savings. The low-cost model is characterized by specific product and operating features. Product features include: low, simple, and unrestricted fares; high frequencies; point-to-point flights; no interlining; ticketless travel utilizing travel agents and call centers; single-class, high density seating; no seat assignments; and no meals or free alcoholic drinks. Operating features include: single type aircraft with high utilization, secondary or uncongested airports served with short aircraft turns, short sector length, and competitive wages with profit sharing and high productivity (Rosenstein, 2013; Chowdhury, 2007; Campisi, Costa and Mancuso, 2010).

2.2.1 Turn-time

Turn-time is the period between the time an aircraft parks at the gate till it can pull out again with a new load of passengers and/or cargo (Mirza, 2009). There are a number of key tasks to be

carried out during this period: unloading and loading of passengers and luggage, safety and security checks, catering, cleaning and a variety of administrative tasks. The significance of turn-around punctuality is not only to reduce delays, but to maintain the linkage and stability of of aircraft rotations (Wu and Caves, 2004). Turn-time models provide useful information for schedule planning, fleet planning, operations planning, and economic and financial analysis. Reducing airplane turn-times means more efficient airplane utilization, particularly for airlines that emphasize point-to-point routes (Gok, 2014; Mirza, 2009). Improved airplane utilization helps spread fixed ownership costs over an increased number of trips, reducing costs per seat-mile or per trip. More flights mean more paying passengers and, ultimately, more revenue. Benefits of shorter turn-times are significant for shorter average trip distances. In order to optimize airplane utilization, point-to-point carriers operate with significantly faster turn-times at the gate. A typical hub-and-spoke system requires longer turn-times to allow for synchronization between the feeder network and trunk routes (Mirza, 2009; Trabelsi *et al.*, 2013; Kunze, Schultz, and Fricke, 2011; Mirza, 2009; Pai, 2007).

2.2.2 Fleet capacity

The planning of demand-responsive transport services requires addressing two fleet-related decision problems that is, what types of equipment to use and how many to use (Fu, 2003). Fleet size and mix (FSM) is of critical importance for a transport agency because it has an effect on both the costs of delivering the service (capital and operating costs) and the level of service (LOS) that can be provided to the clients in regard to comfort, convenience, and enjoyment (Fu and Ishkhanov, 2004). Equipment capacity has a significant impact on the number of equipment required; in which case the larger the equipment, the higher the average equipment productivity and the smaller the required number of fleet. Larger equipment should be used in high-demand cases (Schofer, *et al*, 2003). The optimal number of equipment required depends on the level of travel demand that the carrier will cover (Tolliver-Nigro, 1999).

The use of a mix of different fleet types, from small to medium and large that have more seats, has an advantage of the cost-effectiveness in dealing with variation in seating requirements as well as spatial and temporal clustering of requests (Fu, 2003). Larger fleet can accommodate, on a single trip, more passengers with different seating needs, which, in turn, can lead to higher

productivity and fewer units required to deliver the service. The use of larger fleets however means higher capital and operating costs, higher emissions, and lower maneuverability. In situations of low demand, smaller fleets are often sufficient to handle the trips without any loss of efficiency (Fu and Ishkhanov, 2004). The use of a particular aircraft type on a route largely depends on the distance (Pai, 2007). As the distance between the two endpoints increases, longer-range (and thus larger) aircraft are needed. An airline may opt to use larger aircraft on a route due to economies of scale in aircraft operation (Babikian *et al*, 2002). With respect to airport characteristics, an increase in runway length results in higher flight frequency and larger plane sizes. Aircraft sizes are larger in a hub-spoke network than in a point-to-point network (Brueckner, 2004). Low cost carriers generally do not offer business class seating, which takes up a lot of valuable space, and instead offer a dense, single class seating configuration as other space consuming items, such as catering galleys and convection ovens, are eliminated.

2.3 Mediating Route Characteristics Concepts

2.3.1 Flight frequency

Flight frequency is a central attribute when customers are determining mode choice (Styhre, 2010; Pai, 2007; Najda, 2003). Higher flight frequency of flights raises the value of the product to the passenger and increased value leads to higher demand and finally higher prices (Manuela, 2006). Passengers travelling on business have a high opportunity cost for travel and value the convenience increased flight frequency provides them. Hence, increased value leads to higher demand and finally higher prices (Boreinstein, 2011). However, according to Manuela (2006) and Macário, Viegas, and Reis (2007), high flight frequency facilitates a reduction in cost per transported unit due to the high fixed costs and allows airlines to operate aircraft more efficiently and for longer utilization periods. Thus, increased efficiency lowers an airline's marginal cost and, consequently, ticket prices.

A market that has a high concentration of passengers with high time costs (business travelers) might be served by smaller aircraft with greater flight frequency, while a market with a high concentration of low time cost passengers (leisure travelers) might be serviced by larger aircraft with lower flight frequency. As distance between the two end points increases, aircraft size

increases and flight frequency decreases (Pels and Rietveld, 2006). High rates of fleet utilization are a major factor in low-cost carriers' business model. With high utilization, a low-cost airline will reduce costs significantly. The key for high utilization is to shorten the time between one flight and another (Damuri and Anas, 2006) since turn-times influence the number of trips an airplane can make in a given period of time (Mirza, 2009). Since turn-time precedes flight frequency, this study evaluated flight frequency as a mechanism through which turn-time would influence the airline market parameters.

2.3.2 Load Factor

Load factor is the percentage of seats filled with passengers or the ratio of unit costs to unit yields (Campisi, Costa and Mancuso, 2010; Najda, 2003; Borenstein, 2011; O'Connell and Williams, 2007). A good load factor assures the necessary utilization and productivity of critical low-cost carrier resources. Low load factors reflect delivery of larger-capacity equipment, while capacity reductions leads to significant increases in carriers' load factor in the markets (Wensveen, 2011). It indicates that an airplane is more efficiently utilized when the load factor is high, lowering the operating costs and, as a result, the airfares. A high load factor lowers cost per customer, but also lowers quality and demand (Borenstein, 2011). The per passenger cost of a flight decreases as the load factor rises, which suggests that load factor has a negative coefficient on fare. Low-cost carriers tend to have higher load factors than their competitors and thus, may result in prices falling on routes (Najda, 2003). High load factors are a major factor in low-cost carriers' business model who base the low-fare on the high occupancy rate of the aircraft (80% load factor) (Damuri and Anas, 2006; Macário, Viegas, and Reis, 2007; Vidovic, Steiner and Babic, 2007; Besanko *et al*, 2004).

2.4 Airline Performance Concepts

2.4.1 Market Share

Market Share is the portion or percentage of total sales volume of a market controlled by a particular company or product or a brand. Out of total purchases of a customer of a product or service, what percentage goes to a company defines its market share (Lambin, 2007). There are various types of market share. Market shares can be value or volume. Value market share is

based on the total share of a company out of total segment sales. Volumes refer to the actual numbers of units that a company sells out of total units sold in the market. The value-volume market share equation is not usually linear: a unit may have high value and low numbers, which means that value market share may be high, but volumes share may be low. In low-cost industries like low-cost carriers, where the products are low value, high volume and there are lots of freebies, comparing value market share is the norm. The economic well-being of a business firm can often be summarized in terms of its market share (Govindarajan, 2015; Kotler and Keller, 2012). A higher market share usually means greater sales, lesser effort to sell more and a strong barrier to entry for other competitors. A higher market share also means that if the market expands, the leader gains more than the others. By the same token, a market leader - as defined by its market share - also has to expand the market, for its own growth. Market share is influenced by factors such as price, advertising expenditures, retail availability, product characteristics, quality, speed of service, ease of maintenance, and points of distribution.

2.4.2 Enplanement

Enplanement is the volume of traffic or the number of passengers ferried by an airline. It is through the transportation of these revenue passengers that an air carrier receives commercial remuneration (Wu, 2015). Belobaba, Odoni, and Barnhart (2009) have expressed enplanement as a function of departure time, travel time, expected delay, aircraft type, in flight service, price, flight frequency, airport amenities of carrier, frequent flyer plan attractiveness, distance, business travel between two cities, tourism appeal, carrier and flight characteristics. According to Damuri and Anas (2006) and O'Connell and Willaims (2007), the entry of a low-cost carrier into a market has had two effects on the overall market. Firstly, a market diversion effect, where air travelers switched from high-fare established route carriers to take advantage of lower fares. Secondly, a market creation effect, where low prices induced more travelers into using air transportation either for the first time and/or instead of other modes, especially those in the short-haul markets (less than 1,500 miles of stage length). Windle and Dresner (1995) and Dresner, Lin, and Windle (1996), stated that there is a paradigm shift in the traditional market place when a low-cost carrier enters; the result is two-fold as there is a decrease in average air fares coupled with an increase in enplanements.

From the reviewed theories, it is evident that fleet capacity determines fleet size required which enhances the flight frequency, demand determines the fleet capacity, higher demand leads to larger fleet capacity, higher preference, higher prices, while higher seating capacity lowers quality, lowers cost, and consequently lower fares. Consecutively, turn-time has been linked to higher flight frequency, higher flight frequency means higher value, higher demand, and higher prices; more flight frequency, more utilization, higher efficiency, less cost, lower prices. While high load factor means more efficient use, lower quality, low demand, and lower prices, with low-cost carrier entry leads to decrease in network carriers' market share and increased enplanement. Also worth noting are the conflicting concepts on the end effect of the flight frequency on ticket prices. However, the following information was still not available in literature: one, the effect turn-time on the carriers' market share, and how much of that effect is explained by flight frequency. Two, the link between low-cost carriers' fleet capacity and enplanement, and to which extent that expected relationship can be attributed to load factor. This study hoped to fill this gap by investigating the influence of the route characteristics constructs (flight frequency and load factor) as a mediator in the expected relationships.

2.5 Empirical Studies

Empirical review advanced findings of other scholars on related areas. The review created comparison that helps to identify gaps. A number of studies gave insight into this topic. A majority of them were conducted by either testing relationships between the variables or the elements of the variables separately, many of them in the developed countries.

2.5.1 The Relationship between Turn-time and Market Share of Low-cost Carriers

In the US, O'Connell and Williams (2007) carried out a study to determine the impact of low-cost carriers' emergence on the full service carriers' market share. They indicate that by the early 1990s, the legacy network carriers included American, Continental, Delta, Eastern, Northwest, United, and USAir, accounted for around 90 percent of the total market share of revenue passenger miles. Between 1998 and 2003, low-cost airlines increased their presence in the 5,000 largest city pair markets raising the number of markets served from 1,594 in 1998 to 2,304 in

2003. Using descriptive statistics on quantitative secondary data, their findings show that the full service carriers' market share had dropped to 74.8 percent.

In the US, Bhaskara (2014) carried out to study to establish the effect of fare offered by Spirit Airlines (a low-cost carrier) on the American Airlines' market share. Using descriptive statistics in his analyses on quantitative secondary data for the period 2010 – 2012, his findings show 4th quarter of 2010, the largest carrier in the market, American Airlines held a 67.4 percent of the market. However, in the first full quarter following Spirit's entry, American Airlines was still the market leader though with a reduced market share of 63.4 percent.

In Europe, Israel (2015) analyzed the airline market to find out the changes in the carriers' market shares following the emergence of low-cost carriers. Using descriptive statistics to analyze the quantitative secondary data for the period between 1980 – 2013, his findings indicate that the market share of low-cost carriers has increased by about 22% between early 1980s to 2013.

In Germany, Kunze, Schultz, and Fricke (2011) used a Monte Carlo Simulation to develop an optimal model for the turn-around operations. The main objective was to achieve a highly automated level in order to react to the delays. The turn-around operations taken into consideration were: de-boarding, catering, cleaning, loading, unloading and boarding. By introducing the sensor technology or checkpoints, the result of this study showed it is possible to achieve a better turn-around within highly automated environment.

In Spain, Trabelsi *et al.* (2013) used a case study of Palma de Mallorca Airport to validate a model for proposed cooperation scheme among airline station managers and ground handling fleet managers. The study considers the problem of managing in a decentralized way airport ground handling, thus, adopt a decentralized management structure, where airline station managers and ground handling fleet managers interact. It was concluded that the cooperation between variety of tactical decision makers would deliver an efficient ground handling multi-fleet management structure.

In Turkey, Gok (2014) used a case study of a Turkish low-cost company that was facing many delays occurring because of subjective scheduling of turn-around operations. The objective was to develop a model which would find an optimal schedule of operations by minimizing the completion time of the last operation. Data was collected from the turn-around operations of Boeing 737-800 aircraft. Models were run for different disembarking/boarding styles and the fastest completion time of turn-around operations was determined. It was concluded that the minimum time of turn-around operations are in domestic-domestic flight type when passenger stair are used for disembarking and air-bridge for boarding.

In Sweden, Norin (2008) developed a detailed conceptual model of the turn-around process and was implemented by a computerized simulation program. The aim was to assess various logistical operations involved in turn-around, and their impact on airport performance. She included a flow of de-icing trucks in her study since limited time span prior to take off, within which de-icing has to be performed, makes it so critical. An optimization approach was developed to plan a schedule for the de-icing trucks. By running the model with the different routings, it was found that scheduling the turn-around activities minimizes delays, hence costs.

In Serbia, Vidosavljevic and Tosic (2010) developed an aircraft turn-around model which included the turn-around operations such as air-bridge positioning/removal, passengers disembarking or boarding, portable water, catering, lavatory service, baggage loading/unloading and fuelling. The objective was to maintain the efficiency of the turn-around operations. According to the two different experiments on the modelling of turn-around, the automatic assignment strategy gave a better result in terms of minimum departure delays when it is compared to the strict gate assignment strategy.

The studies by Gok (2014), Kunze, Schultz, and Fricke (2011), Trabelsi *et al*. (2013), Vidosavljevic and Tosic (2010), Norin (2008) had investigated about the best models for the turn-around operations that would minimize delays, and consequently, costs. Bhaskara (2014), Israel (2015), Sentence (2004) and O'Connell and Williams (2007) employed descriptive statistics in analyzing the rising trend of low-cost carriers' market share. O'Connell and Williams (2007) indicates that low-cost carriers had claimed 15.2% market share from the incumbents' market share within 5 years while Bhaskara (2014) reported that Spirit airlines claimed a market

share of 4% within 3 months from American airlines following her entry. Israel (2015)'s findings indicate that the market share of low-cost carriers has increased world-wide by about 22% over 33 years between early 1980s to 2013. According to Norin (2008), scheduling every operations in the turn-around enhances a better performance and efficiency, while Kunze, Schultz, and Fricke (2011) remark that sensor technology or checkpoints would enhance a better turn-around within highly automated environment. Gok (2014) concluded that the minimum time of turn-around operations are in domestic-domestic flight type when passenger stairs are used for disembarking and air-bridge for boarding. Trabelsi *et al.* (2013) support cooperation between variety of tactical decision makers since it would deliver an efficient ground handling multi-fleet management structure. According to Vidosavljevic and Tosic (2010), the automatic assignment strategy would give a better result in terms of minimum departure delays.

The low-cost carriers have demonstrated short and quick aircraft turn-arounds, which is an equivalent of speed of service, but without sufficient information on how this has helped them acquire and maintain market share. Studies have only considered the nature of relationship between carriers' market share and fare, and had sought to develop turn-time models that would optimize aircraft utilization by minimizing delays, as well as costs. Thus, the relation between turn-time and carriers' market share was still unknown.

2.5.2 The Relationship between Fleet Capacity and Enplanement

In the US, Mertens and Vowles (2012) carried out a study to determine the effects of low-cost carriers in the US domestic routes. They used three low-cost carriers, that is, Jetblue, Frontier and Southwest. Using descriptive statistics in their analyses on quantitative secondary data, their findings show that low-cost carriers' entry into new markets during the study time period (2000 – 2005) had resulted in an increase in the number of passengers by 67.5 percent.

In South Africa, InterVistas (2014) conducted a study to determine the impact that low-cost carriers (kulula) can have on market dynamics along the Johannesburg-Lusaka route. Using descriptive statistics in the analyses of quantitative secondary data, its findings show that three months after Kulula's entry, traffic volumes on the route had increased 38 per cent.

A study by Bhaskara (2014) to find out the effect of ticket prices of Spirit Airlines (a low-cost carrier) on volume of traffic in the US airlines market. Using descriptive statistics in the analyses of quantitative secondary data on a data set from 2010 – 2012, his findings indicate that in the 4th quarter of 2010, the market was measured at 2.789 million passengers but in the first full quarter following Spirit's entry, the market grew by 21.9 percent to 3.399 million passengers.

Dresner (2013) tracked the passenger traffic and prices for 1 year following entry of various low-cost carriers in the US. Using descriptive statistics in the analyses of quantitative secondary data, her findings show that both price decreases and traffic increases were sustained when Southwest (LCC) entered a route that passenger traffic, on average, increased 200% on a route when Southwest entered; 82% for other low-cost carrier entries; and only 17% for entry by the network carriers.

In Netherlands, Lin (2013) carried out a study to analyse the influence of airline deregulation (low-cost carrier entry) on the number of air passengers. Using time series cross-sectional data, Lin constructed a Panel with annual data for the time period 1970-2010 of 20 wealthy countries around the world that all went through different processes of deregulation. He estimated number of passengers as a function of GDP per capita, population and deregulation. The study findings show that 1 percent increase in GDP per capita and population will increase air traffic with 0.21 percent and 0.22 percent respectively. However, deregulation surprisingly had no effect on the number of passengers; with every 1 percent increase in deregulation, air traffic will increase with 0.00 percent.

Wu (2013) conducted a study to evaluate whether the effect of the presence of low-cost airlines on traffic has changed with time. He constructed panel data from both cross-sectional and time series data for the period second quarter of 1997 to the fourth quarter of 2010. The panel data included price, passengers, distance, income, largest market share, vacation and the presence of low-cost airlines. From the multiple panel regressions, the findings revealed that the impact of the presence of low-cost carriers on traffic had diminished – it nolonger existed. The mathematical relation is 1 dollar decrease on price leads to 1.07 more passengers.

Empirical evidence (Dresner, 2013; Mertens and Vowles, 2012: InterVistas, 2014; Bhaskara, 2014; Wu, 2013; Lin, 2013) showed mixed results on the effect of low-cost carriers on enplanement in the airline market. Mertens and Vowles (2012) used a group of three low-cost carriers and their results show higher figures of 67.5 percent than InterVistas (2014) and Bhaskara (2014) that assessed the effect of only one low-cost carrier, finding an increase of 38 per cent and 21.9 percent respectively. Dresner (2013)'s findings show that traffic increased by 200% on a route when Southwest entered, 82% for other low-cost carrier entries, and only 17% for entry by the network carriers. They all employed descriptive statistics in analyzing their data and relate the low-fare to enplanement. Both Lin (2013) and Wu (2013) adopted panel data and they incorporated the low-cost carrier phenomenon, as one whole variable, in their regression equations without considering the specific key factors. They both found out that low-cost carriers have no effect on enplanement.

Low-cost carriers are characterized by homogenous fleet capacity with dense, single class seating configuration. However, studies have endeavored to find out the impact that the emergence of low-cost carriers would have on enplanement by considering the low-cost carriers' low-fare construct and the findings also show that the effect of low-cost carrier is not uniform across countries. Consequently, there is still no sufficient information on how fleet capacity relates to enplanement.

2.5.3 The Influence of Mediating Flight frequency on the Relationship between Turn-time and Market Share of Low-cost Carriers

In China, Wang *et al.* (2014) conducted a study to establish how Chinese airlines have been responding to the ever growing concentrated Chinese airline market. They investigated the flight frequency strategies and aircraft choices for the period 2002 - 2008. Applying time-series correlational design, their empirical investigation suggests that airlines mainly accommodate rapid traffic growth by flying more frequently, although increased aircraft size also contributes to market expansion. They find a negative relationship between market concentration and flight frequency, thereby concluding that Chinese airlines mainly accommodate rapid traffic growth by increasing flight frequency.

In Philippines, Manuela (2006) empirically explored the impact of airline liberalization on fare using a sample of ten routes with varying market characteristics and state of competition for the period 1981–2003. Using multiple regression analysis, he estimated average air fare as a function of number of passengers, departure frequency, cost, income, distance, and the liberalization dummy on the time series data. The study findings indicate that flight frequency variable is highly significant and has a negative impact on airfare per kilometer, since a higher supply leads to a lower price, *ceteris paribus*. Flight frequency is however inelastic in relation to price; with a 10 percent increase in flight frequency, there is a decline of 5.1 percent in the fare levels.

In the US, Najda (2003) carried out a study in order to determine whether or not low-cost carriers significantly impact the pricing of tickets in airline markets. In his study, he conducted an econometric analysis on the second quarter of 2002 dataset. The price equation was estimated as a function of costs, service quality, market demand characteristics, route concentration, route characteristics, hub concentration, low-cost carrier route concentration, and low-cost carrier hub concentration. The study findings from the multiple regression analyses revealed that the effect of the frequency of flights on a route, served by a particular carrier, is positive and significant at the 1 percent level over each fare percentile.

Empirical studies (Manuela, 2006; Najda, 2003; Wang *et al*, 2014) have investigated on the flight frequency variable differently. Manuela (2006) considered it as independent variable on fare while Najda (2003) treated it as a moderating variable on fare. Wang *et al* (2014) investigated it as an independent variable on airline market expansion. Wang *et al* (2014) found a negative relationship between market concentration and flight frequency. Manuela (2006) found out that the flight frequency variable is highly significant and has a negative impact on airfare per kilometer, and is inelastic in relation to price. According to Najda (2003), the effect of the frequency of flights on a route, served by a particular carrier, is positive and significant at the 1 percent level over each fare percentile.

Available information reveal relationships between an airline's key factors such as price, product characteristics, quality, speed of service etc on the realization of and maintenance of market share. This direct relationship is only realizable through several mediating factors such as flight frequency. Since turn-time precedes flight frequency, this study evaluated flight frequency as a

mechanism through which turn-time would influence the carriers' market share parameter. Whereas the low-cost carriers have demonstrated high number of flight frequency, there is insufficient information on how this helps them acquire and maintain their market share. The cited studies had investigated flight frequency as either independent or moderating variable with respect to other airline performance parameters such as demand, fare, fleet size and distance between two destinations. No study had considered it as a mediating variable in the relationships between turn-time and carriers' market share.

2.5.4 The Influence of Mediating Load Factor on the Relationship between Fleet Capacity and Enplanement

IATA (2015) carried out a study to establish the impact of fleet capacity on load factor for the year 2013. Using descriptive statistics in their analyses of quantitative secondary data, findings reveal that in the US, capacity grew at 1.9%, but load factor remained flat at 83.8 per cent. In China, capacity rose 12.2%, but load factor declined 0.6 percentage points to 80.3 per cent. In Japan, capacity expanded by 5.1% and load factor was little changed at 64.3 per cent. In Brazil, capacity reductions by airlines of 3.3% pushed load factor to 76.3 per cent. In India, capacity climbed 3.5% in 2013, and load factor was 74.6%, up 1.7 percentage points. In Russia, there was 9.1% rise in capacity and load factor remained at 74%. In Australia, capacity rose 3.8%, depressing load factor 1.0 percentage point to 76.5 per cent. While in Africa, there was capacity expansion of 5.2% and load factor rose 1.9 percentage points to 69%, the lowest among the regions.

In the US, Rupp (2007) investigated the causes of flight delays from both the airline and passenger perspectives. He uses quantitative secondary data for every domestic flight between January 1995 and December 2004 by mainline carriers. The study findings from the multiple regression analyses' show that economic factors (seating capacity and load factor) and logistical factors (departure time and distance) have significant effects on flight delays.

In Iran, Jenatabali and Ismail (2007) carried out a study to establish the determinants of load factor. They modeled load factor as a function of computerized system, the average length, departures, type of organization, advertising expenses, subsidy, inflation rate, number of seats,

and change in vehicle kilometers. Quantitative secondary data was collected for the period 1997 - 2006. The results from the multiple regression analyses show that number of seats are not significant in explaining the variation in load factors, attributing it to very little variation in the number of seats during this period since the decision of buying aircraft in Iran is limited by the United States' economical and political sanctions.

In the US, Borenstein (2011) carried out a study to establish the determinants of air fare. He estimated air fare on a route as a function of cost, demand and market power indicators by use of multiple regression analyses. Grouping the 19-year estimation period into 4 sub-periods of 4 or 5 years each, he estimated the same equation for each of the sub-periods. He considered dependent variable as the mean fare paid among passenger-trips included in the observation. He found out that 10% decrease in average load factor would explain a price decline of about 15 percent.

Tesfay and Solibakke (2015) conducted a study so as to identify serial and periodic autocorrelation on load factors of the Europe-Mid East and Europe-Far East airline flights with an aim of developing a forecasting model of the load factors. The quantitative secondary data is collected for the period 1991 to 2013. Results show that that the load factors have both periodic and serial correlations for both regional flights. The econometric estimation results also confirm that the load factors of the Europe-Mid East and Europe-Far East flights are both seasonal and differ between flights i.e. the load factor is still far from stable.

In the US, Najda (2003) carried out a study to determine whether or not low cost carriers significantly impact the pricing of tickets in airline markets. In his study, he conducted an econometric analysis on the second quarter 2002 dataset. The price equation was estimated as a function of costs, service quality, market demand characteristics, route concentration, route characteristics, hub concentration, low-cost carrier route concentration, and low-cost carrier hub concentration. The findings from the multiple regression analyses show that the effect of load factor variable is negative and significant at the 1 percent level in the 80th percentile baseline equation. For the median fare, it is negative and significant at the 2 percent level and is not significant for the lowest fares.

Ramdas and Williams (2008) investigated the tradeoff between aircraft capacity utilization and on-time performance by using a 10-year airline industry data set, drawing on queuing theory to disentangle the confounding effects of variability in travel time and capacity exibility along an aircraft's route. They examined how load factor affects on-time performance. Their analyses show that the interaction of utilization and load factor is positive and significant for twelve out of thirteen carriers, meaning increasing load factor leads to greater delays when utilization is high, than when utilization is low.

The cited studies (Rupp, 2007; Tesfay and Solibakke, 2015; IATA, 2015; Jenatabali and Ismail, 2007; Borenstein, 2011; Ramdas and Williams, 2008; Najda, 2003) had investigated load factor variable differently. IATA (2015) employed descriptive statistics in analysing the impact of fleet capacity on load factor. Both Tesfay and Solibakke (2015) and Jenatabali and Ismail (2007) modelled load factor as a function of other independent variables. Rupp (2007) and Ramdas and Williams (2008) investigated it as an independent variable on the on-time performance while Borenstein (2011) investigated as an independent variable on price. Najda (2003) treated it as a moderating variable on fare. IATA (2015) and Jenatabali and Ismail (2007) showed mixed results of the effect of fleet capacity on load factor. According to Rupp (2007), seating capacity and load factor have significant effects on flight delays, while Jenatabali and Ismail (2007) paper concludes that the number of seats are not significant in explaining the variation in load factors. Borestein (2011) reported that a 10% change in average load factor would explain a price decline of about 15 percent. Tesfay and Solibakke (2015) paper results show that the load factors are both seasonal and differ between flights. Ramdas and Williams (2008) show that increasing load factor leads to greater delays when utilization is high, than when utilization is low.

Available information reveal relationships between an airline’s key factors such as low-fare, fleet size, and points of distribution etc on enplanement. This direct relationship is only realizable through several mediating factors such as load factor. Since fleet capacity precedes load factor, this study evaluated load factor as a means through which fleet capacity would influence the enplanement parameter. Whereas low-cost carriers’ business model is characterized with high load factors, there is insufficient information on how this helps them ferry high number of passengers. The cited studies had investigated load factor as either dependent, independent or

moderating variable with respect to other airline performance parameters such as demand, fare, fleet size and distance between two destinations. No study had considered it as a mediating variable in the relationships between turn-time and carriers' market share.

2.6 Summary of Literature Review

Deregulation of the airline industry has prompted the emergence of low-cost carriers thereby changing the business environment in commercial air transport. Due to varying catalytic factors in the growth and development of low-cost carriers, the effect of low-cost carrier is not uniform across countries; there is no low cost carriers' effect in Canada, Netherlands and along trans-Atlantic routes, but the effect is higher in the US than in South Africa, and is lowest in Philippines. Turn-time models provide very useful information for schedule planning, fleet planning, operations planning, and economic and financial analysis since turn-time influences the number of trips an airplane can make. Theories indicate that flight frequency and load factor are influenced by airlines' turn-time and fleet capacity respectively, and that they independently have an effect on the airline performance parameters. The relationship between route characteristics and other airline market parameters have been investigated as either dependent, independent or moderating variables. The influence of turn-time on the carriers' market shares, fleet capacity on enplanement, the mediating role of flight frequency on turn-time and carriers' market share, and the mediating role of load factor on fleet capacity and enplanement had not been investigated. While there has been a substantial body of research investigating this phenomenon in the developed countries, there had been no investigation of whether this phenomenon existed in Kenya, and thus a need to identify whether there is low cost carrier phenomenon in other markets such as Kenya. It is for this reason that the purpose of this study was to analyze the effect of mediating route characteristics on the relationship between the low-cost carriers' key factors and performance for the period 2007 – 2012 in Kenya.

CHAPTER THREE

RESEARCH METHODOLOGY

This chapter is organized under the following sub-headings: research design, study area, target population and sampling techniques, data collection, data analysis and presentation.

3.1 The Research Design

According to Barbara (2006), the research design refers to the overall strategy that the researcher chooses to integrate the different components of the study in a coherent and logical way, thereby, ensuring that the research problem will be effectively addressed. Therefore, in this study, the researcher adapted time series correlational research design that describes patterns of change and help establish the direction and magnitude of causal relationships (Ployhart and Robert, 2010; Kalaian and Rafa, 2008). Measurements are taken on each variable over two or more distinct time periods. This allows the researcher to measure change in variables over time.

3.2 Study Area

The study was carried out in Kenya delineated by the following coordinates: between the latitudes 04˚00´00″N and 04˚42´08.4″S, and longitudes 034˚05´02.9″E and 044˚00´03.8″E.

3.3 Target Population, Sampling Techniques

Ployhart and Robert (2010) define target population as a group of units about which the researcher wants to make judgements. These units can be a group of individuals, customers, companies, products, or just about any subjects in which you are interested. Thus, the target population of this study were 2 low-cost carrier companies, that is, Fly540 and Jetlink Aviation, whose data over a period of 72 months for the year 2007 – 2012 were used in the analysis. This period was characterised with steady growth in the business cycle of the low-cost carriers.

3.4 Data Collection Methods

3.4.1 Sources and Type of Data

Quantitative secondary data for the period 2007 – 2012 were used. Sources of data were airlines statistics from the aircraft log books.

3.4.2 Data Collection Procedure

Research introductory letter was obtained from the School of Graduate Studies of Maseno University, and a letter of permission was also granted by the Director General Kenya Civil Aviation Authority. The researcher reviewed the documents (aircraft log books and registers) and transferred the data to the dummy tables by self.

3.4.3 Instruments for Data Collection

Documents Review (Analysis of Documents) was adopted. In addition, Bart (2011) advises that a researcher should prepare a set of dummy tables (see Appendix II) before beginning the collection process since such tables enable one to think carefully about each piece of information to be collected. It also takes the guesswork out of the analysis phase of the project.

3.5 Data Screening and Cleaning

3.5.1 Analysis for Missing Values

Data were first examined for missing values which are reportedly common in many areas of social research, and can seriously affect results of statistical analysis. According to Allison (2009) missing values reflect situations where valid values for some cases in one or more variables are unavailable for analysis. Consequently, missing values in the current study were evaluated with respect to variables. As shown in Table 3.1, one variable had no missing values. The other five variables had 1 missing value each, representing 0.0069%. A total of 5 values were found unavailable for analysis among the expected 864 values, that is, 144 values for each of the six variables.

Table 3.1: Distribution of Missing Values Per Variable

Variables	Total No. of Values	Missing Values	Percentage of Missing Values per Variable
Carriers' market share (CRMS)	144	01	0.0069
Turn-time (TNTM)	144	01	0.0069
Flight frequency (FREQ)	144	01	0.0069
Enplanement (ENPL)	144	01	0.0069
Fleet Capacity (FLTC)	144	00	0.0000
Load Factor (LDFC)	144	01	0.0069
TOTAL	864	05	0.0347

Source: Researcher, 2016

This figure is by far much fewer than 5% as recommended by Tabachnick and Fidell (2001) for a variable, or an item, to qualify for analysis in the study. Since the missing values were only from one cross-section, they were replaced by the series means of that particular cross section.

3.6 Testing the assumptions of Fixed Effects models

The principal assumptions which justify the use of a fixed-effects model are: 1), Normality assumption, 2) Homogeneity of Variance Assumption, 3) Assumption of Independence. If any of these assumptions is violated, then the forecasts, confidence intervals, and scientific insights yielded by a regression model may be (at best) inefficient or (at worst) biased or misleading (Andrew, 2013; Nau, 2016). These assumptions are: (1) normality of the error distribution, (2) linearity and additivity of the relationship between dependent and independent variables, (3) statistical independence of the errors, and (4) homoscedasticity (constant variance) of the errors.

3.6.1 Test for Normality of the error distribution

Violations of normality create problems for determining whether model coefficients are significantly different from zero and for calculating confidence intervals for forecasts. Since parameter estimation is based on the minimization of squared error, a few extreme observations can exert a disproportionate influence on parameter estimates (Machiwal and Kumar, 2012; Nau, 2016). Calculation of confidence intervals and various significance tests for coefficients are all based on the assumptions of normally distributed errors (Jushan and Serena, 2005; Thode, 2002). If the error distribution is significantly non-normal, confidence intervals may be too wide or too narrow. In this study, the researcher used Jarque-Bera statistical tests for normality. *Jarque-Bera* test-statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution (Startz, 2013); the *Jarque-Bera* statistic tests the null hypothesis of normal distribution, and therefore should not be significant in cases of normal distribution.

Table 3.2: First results of normality test using Jarque-Bera

Date: 04/08/16
Time: 21:31

Sample: 1 72

	CRMS	TNTM	FREQ	ENPL	FLTC	LDFC
Jarque-Bera	14.12586	12.22686	13.17662	2.612934	10.44967	2.315542
Probability	0.000856	0.002213	0.001376	0.270775	0.005381	0.314186
Observations	144	144	144	144	144	144

Source: Research data, 2016

Where:

CRMS = carriers' market share

TNTM = turn-time

FREQ = Flight frequency

ENPL = Enplanement

FLTC = Fleet Capacity

LDFC = Load factor

Results in Table 3.2 show that only ENPL and LDFC series failed to reject the null hypothesis of normal distribution at the 5% significance level. Technically, the normal distribution assumption is not necessary if one is willing to assume the model equation is correct and the only goal is to estimate its coefficients and generate predictions in such a way as to minimize mean squared error (Nau, 2016; Adeloye and Montaseri, 2002). The formulas for estimating coefficients require no more than that, and some references on regression analysis do not list normally distributed errors among the key assumptions. Real data, especially time series data, rarely has errors that are perfectly normally distributed, and it may not be possible to fit your data with a model whose errors do not violate the normality assumption at the 0.05 level of significance (Nau, 2016; Mikusheva, 2016). This was observed even after transforming the data into the natural logs as shown in Table 3.3, the transformed natural logs of TNTM, FREQ and FLTC variables could still not reject the null hypothesis at 5% significance. The researcher then settled on the Nau (2016)'s and Andrew (2013)'s conclusion that it is usually better to focus more on the violations of the other assumptions since normality is a very minor concern.

Table 3.3: Second results of normality test using Jarque-Bera

Date: 04/12/16
Time: 21:35

Sample: 1 72

	LNCRMS	LNTNTM	LNFREQ	ENPL	LNFTLC	LDFC
Jarque-Bera	5.380353	10.87545	26.68088	2.612934	10.44967	2.315542
Probability	0.067869	0.004349	0.000002	0.270775	0.030124	0.314186
Observations	144	144	144	144	144	144

Source: Researcher, 2016

Where:

LNCRMS = natural log of carriers' market share

LNTNTM = natural log of turn-time

LNFREQ = natural log of flight frequency

ENPL = Enplanement

LNFLTC = natural log of fleet capacity

LDFC = Load factor

3.6.2 Other Assumptions

Heterokedasticity, serial correlations and presence of outliers were not necessary for this study. This was due to the fact that Fully Modified Ordinary Least Squares (FMOLS) had been adopted in the panel cointegrating equations as outlined by Phillips and Moon (1999), Pedroni (2000), Kao and Chiang (1997), Phillips and Hansen (1990). This method modifies least squares to account for serial correlation effects and for the endogeneity in the regressors that results from the existence of a cointegrating relationship, as well robustic in dealing with the outliers.

3.7 Other Statistical Tests

3.7.1 Linearity or addivity Tests

Violations of linearity or additivity are extremely serious. If one fits a linear model to data which are nonlinearly or non-additively related, the predictions are likely to be in error. In order to test for linearity, this study adopted Ramsey RESET (Regression Specification Error Test) to detect any incorrect functional form as proposed by Ramsey (1969). The Ramsey RESET tests as shown in the six tables appended in Appendix VIII, indicated no evidence of non-linearity since all the 3 test statistics (t-statistics, F-statistics, and Likelihood ratio) in the second row of the output tables rejected the null hypotheses of non-linearity in the six linear associations of the constructs as proposed from the path regression analyses shown in Figures 3.1a and 3.1b.

3.7.2 Panel Unit Root Test

While dealing with panel data, researcher may have to find out if the data is stationary (Hlouskova and Wagner, 2005). Stationarity of data is when the mean, variance and covariance are time invariant (they do not change over time). This was done by use of panel unit root tests; Y_t is regressed on its lagged value Y_{t-1} and then checked if the estimated slope coefficient is statistically equal to 1. If not, then Y_t is nonstationary. This then requires first differencing of Y_t which is then regressed on Y_{t-1}, if the slope coefficient is 0, then Y_t is nonstationary, and if it negative, then Y_t is stationary (Hansen, 2014; Maddala, 2001; Gujarati, 2004). Any series that is not stationary is said to be non-stationary. PP Fisher Panel unit root testing was performed on the six variables. The null hypothesis being presence of a unit root.

As appended in Appendix VII, the results showed that two series (turn-time and load factor) were stationary at order 0, while the other four variables (fleet capacity, flight frequency, carriers' market share and enplanement) were stationary at order 1. This is implying that the direct associations of the variables would yield short-run equilibrium relationships.

3.7.3 Panel Cointegration Tests

The finding that many macro time-series may contain a unit root has spurred the development of the theory of non-stationary time series analysis (Startz, 2013). Engle and Granger (1987) pointed out that a linear combination of two or more non-stationary series may be stationary. If such a stationary linear combination exists, the non-stationary time series are said to be cointegrated. The stationary linear combination is interpreted as a long-run equilibrium relationship among the variables. Given that most of variables were not stationary at order zero, it was necessary to carry out cointegration tests before deploying the more favorable panel cointegrating regression due to its more accuracy in estimations. The panel cointegration tests were carried out by use of Pedroni Residual Cointegration Tests (PRCT) that evaluate the null against both the homogeneous and the heterogeneous alternatives. This was adopted by the researcher since the Pedroni Residual Cointegration Tests contain 11 t-statistics which will enhance chances of rejecting the null hypothesis of no cointegration at the conventional size of $p<0.05$.

Since the mediation model, as shown in Figures 3.1a and 3.1b would require 6 regression analyses to be carried out, the panel cointegration tests were carried on the following 6 linear combinations. For the first and third objectives, cointegration tests were carried out on: 1), Carriers' market share (CRMS) and turn-time (TNTM); 2), flight frequency (FREQ) and TNTM; and 3), CRMS, FREQ and TNTM. For the second and fouth objectives, cointegration tests were carried out on: 1), Enplanement (ENPL) and fleet capacity (FLTC); 2), Load factor (LDFC) and FLTC; and 3), ENPL, FLTC and LDFC. As appended in Appended IX, Pedroni Residual Cointegration Tests results rejected the null hypothesis of no cointegration at the conventional size of 0.05. This means that cointegrating regressions would result in long-run equillibrium relationships.

3.7.4 Collinearity between Xs and Z (Mediating) Variables

Given that X predicts Z (mediator), multi-collinearity is to be expected in a mediational analysis and it cannot be avoided (Kenny, 2015; Beasley, 2012). In extreme cases, the researcher might not be able to fit the model. However, this problem can be sorted by increasing sample size and/or number of observations (Wu, 2011), or by use of panel data (Gujarati and Porter, 2009; Bruderl, 2005). Collinearity between the regressors in the two mediating equations was measured by Variance Inflation Factors (VIFs). VIFs show how much of the variance of a coefficient estimate of a regressor has been inflated due to collinearity with the other regressors (Startz, 2013). In this study, only the uncentered VIFs were displayed in the Tables 3.26 and 3.27 of results since the original equations did not have a constant, a property of a cross-sectional cointegrating equation. The uncentered VIF is the ratio of the variance of the coefficient estimate from the original equation divided by the variance from a coefficient estimate from an equation with only one regressor (and no constant).

Table 3.4: An Examination of Collinearity between Turn-time and Flight frequency

Variance Inflation Factors

Date: 03/29/16 Time: 22:04

Sample: 1 144

Included observations: 142

Variable	Coefficient Variance	Uncentered VIF
TNTM	0.011750	1.449119
FREQ	5.95E-05	1.449119

Source: Researcher, 2016

Where:

TNTM = turn-time

FREQ = Flight frequency

Table 3.5: Examination of Collinearity between Fleet Capacity anf Load Factor

Variance Inflation Factors

Date: 03/29/16 Time: 22:05

Sample: 1 144

Included observations: 142

Variable	Coefficient Variance	Uncentered VIF
FLTC	8.098672	1.286764
LDFC	2707.747	1.286764

Source: Researcher, 2016

Where:

FLTC = Fleet Capacity

LDFC = Load factor

Results in Table 3.26 and Table 3.27 showed VIFs of 1.449 and 1.287 respectively. A commonly given rule of thumb is that VIFs of 10 or higher may be a reason for concern (Stevens, 2009). This is, however, just a rule of thumb; Allison (2009) says he gets concerned when the VIF is over 2.5. Since VIFs in the tables are less than 1.5, the study concluded that there is no multicollinearity problem between the variables.

3.8 Data Analysis and Presentation

Both descriptive and inferential statistics are utilized. Mean, Standard deviation, median, and percentages have been used to analyze the effect of the low-cost carriers' key factors on the airline performance. Pearson correlation and path regression analyses were also used. It was envisaged that the mediator would either nullify (completely mediate) or reduce (weaken) the causal effect of low-cost carriers' key factors on airline performance. Graphs, charts and tables have also been used for simple, easy and attractive presentation of the collected and analysed data.

3.9 Mediation Regression Model Specification

As shown in Figure 1.1, a mediation model offers an explanation for how, or why, two variables are related where an intervening or mediating variable, M, is hypothesized to be intermediate in the relation between an independent variable, X, and an outcome, Y (Fairchild and Mackinnon, 2010; Kim, Kaye and Wright, 2001). More recent research have supported Baron and Kenny (1986) tests for statistical mediation based on coefficients from two or more of the following equations:

$Y = \beta_1 + cX + \varepsilon_1$ ..... (3.1)

$M = \beta_2 + aX + \varepsilon_2$ ..... (3.2)

$Y = \beta_3 + c'X + bM + \varepsilon_3$ ..... (3.3)

Where:

M is the mediating variable

c is the overall effect of the independent variable X on Y;

c' is the effect of the independent variable X on Y controlling for M;

b is the effect of the mediating variable on Y;

a is the effect of the independent variable X on the mediator;

$\beta_1 - \beta_3$ are the intercepts for each equation; and

$\varepsilon_1 - \varepsilon_3$ are the corresponding residuals in each equation.

After these parameter estimates have been ascertained, Sobel (1982) suggested that indirect effect be calculated by multiplying two regression coefficients from Equations 3.3. and 3.4. A product is formed by multiplying two coefficients together, the partial regression effect for M predicting Y, b_1, and the simple coefficient for X predicting M, a_1:

$\beta_{\textbf{indirect effect}} = b_1 * a_1$ ..... (3.4)

Thus, the proportion of the X-Y relation that is attributable to M will be:

$= (b_1 * a_1)/c$ ..... (3.5)

Sobel Test for the significance of mediation is then determined by use of this formula:

$Z = (ab)/\sqrt{(b^2\, sa^2 + a^2\, sb^2 + sa^2\, sb^2)}$ ..... (3.6)

Where **a** and **b** are the standardized regression coefficients and **sa** and **sb** are their standard errors.

Hoyle and Robinson (2003) cited that prior to using path analytic regression techniques, Pearson correlations among variables in the model are examined. The predictor variable must be significantly associated with the dependent variable and with the mediator; and the mediator must be significantly associated with the dependent variable. The following formula was used to calculate Pearson r correlation (Cohen, Cohen, West, and Aiken, 2003):

$\text{Correlation (r)} = [N\Sigma XY - (\Sigma X)(\Sigma Y)]/\sqrt{([N\Sigma X^2 - (\Sigma X)^2][N\Sigma Y^2 - (\Sigma Y)^2])}$ ..... (3.7)

Where:

r = Pearson r correlation coefficient

N = number of values in each data set

$\sum xy$ = sum of the products of paired scores

$\sum x$ = sum of x scores

$\sum y$ = sum of y scores

$\sum x^2$= sum of squared x scores

$\sum y^2$= sum of squared y scores

In line with the above requirement by Baron and Kenny (1986), the researcher, carried out correlational analysis as below:

Table 3.6: Correlational analysis between Turn-time, Flight frequency and Carriers' Market Share

Covariance Analysis: Ordinary

Date: 04/01/16 Time: 19:20

Sample: 1 72

Included observations: 144

Correlation t-Statistic Probability Observations	CRMS	TNTM	FREQ
CRMS	1.000000		

	144		
TNTM	-0.044578	1.000000	
	-0.531742	-----	
	0.5957	-----	
	144	144	
FREQ	0.817008	-0.266752	1.000000
	16.88403	-3.298231	-----
	0.0000	0.0012	-----
	144	144	144

Source: Researcher, 2016

Table 3.6 indicates that turn-time is negatively correlated with both flight frequency and carrier market share, though the correlation is insignificant with respect to carriers' market share, as shown by the value (r = -0.27, p-value of 0.001) and (r = -0.04, p-value = 0.596). This means that

if turn-time is enhanced, both flight frequency and the carrier market share will reduce, but flight frequency will be more reduced. However, the above table indicates that there is a strong significant positive correlation between flight frequency and carrier market share as shown by the value (r = 0.82, p-value = 0.000). This means that if flight frequency is enhanced, the carrier market share will be enhanced too.

Table 3.7: Correlational Analysis between Fleet Capacity, Load Factor and Enplanement

Covariance Analysis: Ordinary

Date: 04/12/16 Time: 22:50

Sample: 1 72

Included observations: 144

Correlation t-Statistic Probability Observations	ENPL	FLTC	LDFC
ENPL	1.000000		

	144		
FLTC	0.878579	1.000000	
	21.92110	-----	
	0.0000	-----	
	144	144	
LDFC	0.631917	0.474066	1.000000
	9.715891	6.415926	-----
	0.0000	0.0000	-----
	144	144	144

Source: Researcher, 2016

Table 3.7 indicates that fleet capacity has a significant positive correlation with both enplanement and load factor, though the relationship is stronger with respect to enplanement, as shown by the values (r = 0.88, p-value = 0.000) and (r = 0.47, p-value = 0.000) respectively. This means that if fleet capacity increases, both load factor and the enplanement will increase, but enplanement will be more enhanced. However, the above table indicates that there is a strong significant positive correlation between load factor and enplanement as shown by the value r = 0.63, p-value = 000. This means that if load factor is enhanced, enplanement will be enhanced too.

After significant (although this is not always a must condition as stated by MacKinnon, Fairchild, & Fritz, 2007) correlations have been established, three multiple regression analyses are performed. Mediating effects in this study were investigated through path analysis, which is a series of regression equations that track out the direct and indirect path ways between predictor and dependent (or outcome) variables. In the first regression equation 3.2, the significance of the path X to the dependent variable Y is examined. In the second regression equation 3.3, the significance of the path from X to M is examined. Finally, the significance of the path M to Y is examined in the third regression equation 3.4 by using X and M as predictors of Y. In the third equation, simultaneous entry is used. Simultaneous entry allows for controlling the effect of X while the effect of M on Y is examined, and controlling the effect of M while the effect of X on Y is examined. The results are then compared, that is, the relative effect of X on Y (when M is controlled in the third equation) to the effect of X on Y (when M is not controlled in the first equation). If the path X to Y in the third equation is reduced to zero, it provides strong evidence for a single, dominant mediator. If the residual path X to Y is not zero, it indicates that multiple mediating factors may be operating. The degree to which the effect is reduced (the change in the regression coefficient in Equation 3.4 versus the regression coefficient in Equation 3.2) indicates how powerful the mediator is (Baron and Kenny, 1986; Holmbeck, 1997).

Panel data give more informative data, more variability, less collinearity among variables, more degrees of freedom and more efficiency (Gujarati, 2004; Bruderl, 2005). Panel data presents two big advantages over ordinary time series or cross section data. The obvious advantage is that panel data frequently has lots and lots of observations. The not always obvious advantage is that

in certain circumstances panel data allows you to control for unobservables that would otherwise mess up the regression estimation. A key assumption in most applications of least squares regression is that there aren't any omitted variables which are correlated with the included explanatory variables. (Omitted variables cause least squares estimates to be biased). The usual problem is that if you don't observe a variable, you don't have much choice but to omit it from the regression. Panel data allows for the use of fixed effects to make up for the omitted variable.

The general panel data model will consist of three equations as follows:

$Y_{it} = \beta_1 + cX_{it} + u_{1it}$ …… (3.8)

$M_{it} = \beta_2 + aX_{it} + u_{2it}$ …… (3.9)

$Y_{it} = \beta_3 + c'X_{it} + bM_{it} + u_{3it}$ …… (3.10)

Where:

c is the overall effect of the independent variable X on Y respectively;

c' is the effect of the independent variable X on Y controlling for M respectively;

b is the effect of the mediating variable M on Y respectively;

a is the effect of the independent variable X on the mediator M respectively;

$\beta_1 - \beta_3$ is the intercept (cross-section fixed effects) for each equation; and

$u_1 - u_3$ is corresponding residuals (both person-specific and idiosyncratic) in each equation.

i = 1, 2 and is the individual airline dimension (cross-section identifier)

t = 1, 2 .... 72, and is time dimension.

3.9.1 The effect of turn-time on the carriers' market share

To determine the effect of TNTM on CRMS, equation will be:

$Y_{1it} = \beta_1 + c_1X_{1it} + u_{1i}$ …… (3.11)

3.9.2 The effect of the Fleet Capacity on the Enplanement

To establish the effect of FLTC on ENPL, the equation will be:

$Y_{2it} = \beta_2 + c_2X_{2it} + u_{2it}$ ………………………………………..…….......…....... (3.12)

3.9.3 The influence of the mediator variable, flight frequency, on the relationship between the turn-time and carriers' market share

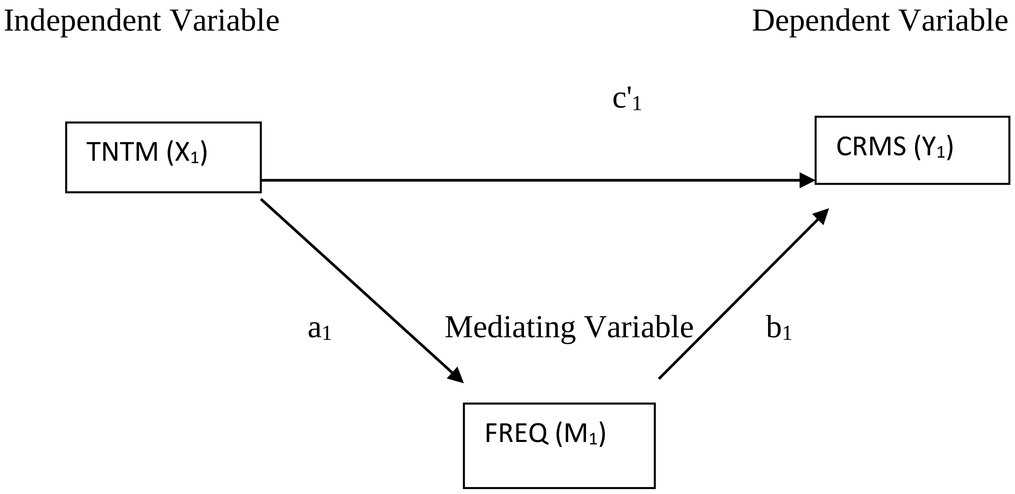


Figure 3.1a: Path Analysis Diagram for the mediated effect of turn-time on carriers' market share

Source: Researcher, 2016

Thus, to examine the influence of the mediating flight frequency on the relationship between turn-time and carriers' market share, the following 3 regression equations will be:

To test if TNTM predicts CRMS →$Y_{1it} = \beta_1 + c_1X_{1it} + u_{1it}$ ……..........…..……. (3.13)

To test if TNTM predicts FREQ→ $M_{1it} = \beta_3 + a_1X_{1it} + u_{3it}$ ……...................…… (3.14)

To test if TNTM still predicts CRMS, when Mediator (FREQ) is in the model → $Y_{1it} = \beta_4 + c'_1X_{1it} + b_1M_{1it} + u_{4it}$ ………………..……….......……………….. (3.15)

3.9.4 The influence of the mediator variable, load factor, on the relationship between fleet capacity and enplanement:

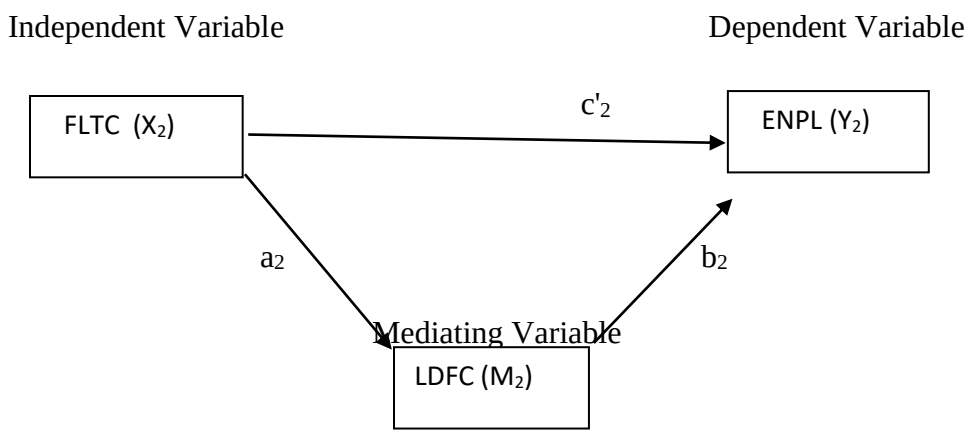


Figure 3.1b: Path Analysis Diagram for the mediated effect of fleet capacity on enplanement

Source: Researcher, 2016

Thus, to examine the influence of the mediating load factor on the relationship between fleet capacity and enplanement, the following 3 regression equations will be:

To test if FLTC predicts ENPL → $Y_{2it} = \beta_2 + c_2X_{2it} + u_{2it}$ …….…..... (3.16)

To test if FLTC predicts LDFC→$M_{2it} = \beta_5 + a_2X_{2it} + u_{5it}$ ……..……..... (3.17)

To test if FLTC still predicts ENPL, when Mediator (LDFC) is in the model →
$Y_{2it} = \beta_6 + c'_2X_{2it} + b_2M_2it + u_{6it}$ …….....…… (3.18)

Where:

CRMS is carriers' market share

TNTM is turn-time

FREQ is flight frequency

ENPL is enplanement

FLTC is fleet capacity

LDFC is load factor

c_1, and c_2, is the overall effect of the independent variable X_1, and X_2 on Y_1 and Y_2 respectively;

c'_1, and c'_2 is the effect of the independent variable X_1, and X_2 on Y_1 and Y_2 controlling for M_1 and M_2, respectively;

b_1, and b_2 is the effect of the mediating variable M_1, and M_2, on Y_1 and Y_2 respectively;

a_1, and a_2 is the effect of the independent variable X_1, and X_2 on the mediator M_1 and M_2 respectively;

$\beta_1 – \beta_6$ is the intercept (cross-section fixed effects) for each equation; and

$u_1 – u_6$ is corresponding residuals (both person-specific and idiosyncratic) in each equation.

According to Wu (2011) and Hoyle and Robinson (2003), the association of M to X, or Y to M, influences the possibility of detecting mediation effects. A high X – M association implies that more variance in M is explained by X, and there is less variance in M to contribute to the prediction of Y. If the M – Y association is slightly stronger than the X – M association, it is easier to detect the mediating effect.

M completely mediates X-Y relation if all the three conditions are met: (1) X predicts Y, that is, $H_{0(1)}$: c = 0 is rejected, (2) X predicts M, that is $H_{0(2)}$: a = 0 is rejected, and (3), X nolonger predicts Y, but M does when both X and M are used to predict Y (Wu, 2011; Hoyle and Robinson, 2003; Fairchild and Mackinnon, 2010), that is, $H_{0(3)}$: b = 0 is rejected and $H_{0(4)}$: $c' = 0$ is not rejected. M partially mediates X-Y relation if all the three conditions are met: (1) X predicts Y, that is, $H_{0(1)}$: c = 0 is rejected, (2) X predicts M , that is, $H_{0(2)}$: a = 0 is rejected, and (3), both X and M predict Y, but X has a smaller regression coefficient when both X and M are used to predict Y than when only X is used, that is, both $H_{0(3)}$: b = 0 and $H_{0(4)}$: $c' = 0$ are rejected. M does not mediate X-Y relation if any of the three conditions are met: (1) X does not predict M, that is $H_{0(2)}$: a = 0 is not rejected (2) M does not predict Y, that is $H_{0(3)}$: b = 0 is not rejected, and (3), the regression coefficient of X remain the same before and after M is used to predict Y, that is $H_{0(4)}$: $c' = 0$ is rejected (Kenny, and Judd, 2014).

CHAPTER FOUR

RESULTS AND DISCUSSIONS

This chapter gives the data descriptive statistics and presents mediation analysis on the hypothesized mediator variable. The results are analyzed based on the objectives of the study which were to determine effect of turn-time on market share, fleet capacity on enplanement, influence of flight frequency as a mediator on the relationship between turn-time and market share, and load factor as a mediator on the relationship between fleet capacity and enplanement in Kenya.

4.1 Descriptive Statistics

Descriptive statistics are used to describe the basic features of the data in a study. They provide simple summaries about the sample and the measures. Together with simple graphics analysis, they form the basis of virtually every quantitative analysis of data (Trochim, 2006). Descriptive statistics do not, however, allow us to make conclusions beyond the data we have analysed or reach conclusions regarding any hypotheses we might have made (Babbie, 2009). They are simply a way to describe our data.

Table 4.1: Summary of the Descriptive Statistics

	CRMS	TNTM	FREQ	ENPL	FLTC	LDFC
Mean	13.25694	32.60417	206.3264	13979.23	295.3542	65.37500
Median	12.00000	29.00000	229.5000	13655.50	284.0000	65.00000
Maximum	31.00000	56.00000	342.0000	30164.00	563.0000	89.00000
Minimum	3.000000	17.00000	54.00000	2471.000	48.00000	39.00000
Std. Dev.	7.483078	11.89360	85.49353	6743.552	179.7084	9.010386
Skewness	0.739046	0.385762	-0.558968	0.279553	0.156009	0.107684
Kurtosis	2.588230	1.798934	2.027209	2.649443	1.717714	3.582701
Jarque-Bera	14.12586	12.22686	13.17662	2.612934	10.44967	2.315542
Probability	0.000856	0.002213	0.001376	0.270775	0.005381	0.314186
Sum	1909.000	4695.000	29711.00	2013009.	42531.00	9414.000
Sum Sq. Dev.	8007.493	20228.44	1045208.	6.50E+09	4618203.	11609.75
Observations	144	144	144	144	144	144

Source: Researcher, 2016

Where:

CRMS is carriers' market share

TNTM is turn-time

FREQ is flight frequency

ENPL is enplanement

FLTC is fleet capacity

LDFC is load factor

The mean of carriers' market share is 13.26% which is about 5% lower than those low-cost carriers in Middle East, which is about 18.5% as reported by O'Connell (2008), while turn-time has a mean of 32.60 minutes, this is almost the same as that reported by Damuri and Anas (2006) for the ASEAN low-cost carriers, but lower than Dresner (2013)'s finding of 46.0 minutes averaged turn-around time for the US low-cost carriers. Flight frequency has a mean of 204.91 scheduled flights over the period. On the other hand, enplanement has a mean of 13868.90 passengers, while fleet capacity has a mean of 295.35 seats. Load factor has a mean of 65.38%, this is consistent with the finding of IATA (2013) which reported a mean of 65.3% for African airlines during the year 2012 but far much lower than Vidovic, Steiner, and Babic (2007)'s finding of 80% in Croatia.

The median is a robust measure of the center of the distribution that is less sensitive to outliers than the mean. The median of carriers' market share is 12%, while turn-time has a median of 29 minutes. Flight frequency has a median of 229.5 number of scheduled flights over the period. On the other hand, enplanement has a median of 13655.5 passengers, while fleet capacity has a median of 284 seats. Load factor has a median of 65 per cent.

Carriers' market share has a maximum value of 31% and a minimum value of 3%. Turn-time maximum value and minimum value are 56 minutes and 17 minutes respectively, while 342 scheduled flights and 54 scheduled flights are the maximum and minimum values respectively for the flight frequency. Enplanement has a maximum value of 30164 passengers and a

minimum value of 2471 passengers, while fleet capacity has a maximum and a minimum value of 563 seats and 48 seats respectively. On the other hand, load factor has a 89% and 39% as its maximum and minimum values.

The standard deviation of carriers' market share is 7.48 seats, while turn-time has a standard deviation of 11.89 minutes. Flight frequency has a standard deviation of 85.49 scheduled flights over the period. On the other hand, enplanement has a standard deviation of 6743.5 passengers, while fleet capacity has a standard deviation of 179.7 seats. Load factor has a standard deviation of 9.01 per cent.

The skewness of a symmetric distribution, such as the normal distribution, is zero. Positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail (Doane and Lori, 2011; Jushan and Serena, 2005). Carriers' market share, turn-time, enplanement, fleet capacity and load factor are positively skewed as indicated by the values 0.74, 0.39, 0.28, 0.16 and 0.11 respectively, this means that the mass of the distribution is concentrated on the right; carriers' market share being the most positively skewed while load factor being the least positively skewed. On the other hand, flight frequency is negatively skewed as shown by the value -0.56, this implies that mass of the distribution is concentrated on the left.

The kurtosis of the normal distribution is 3 (Jushan and Serena, 2005). If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal; if the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal. All variables except load factor are platykurtic as indicated by 2.59 for carrier market share, 1.80, 2.03, 2.65 and 1.72 for turn-time, flight frequency, enplanement and fleet capacity respectively, implying that their standard deviations from the mean are large. Load factor is leptokurtic as indicated by the value 3.58 implying that its standard deviation from the mean is small and fleet capacity has the flattest distribution.

4.2 The Nature of Relationships between the variables

Regarding the path regression analyses developed from Figures 3.1a and 3.1b that were used in this study, this section sought to determine the nature of relationships that existed, as shown by the following six scatter diagrams between: turn-time and carriers' market share, turn-time and flight frequency, flight frequency and carriers' market share, fleet capacity and enplanement, fleet capacity and load factor, load factor and enplanement.

For the first objective, the study sought to determine the effect of turn-time on carriers' market share. Figure 4.1 suggests that turn-time and carriers' market are negatively related. This implies that as turn-time increases, the carriers' market share reduces.

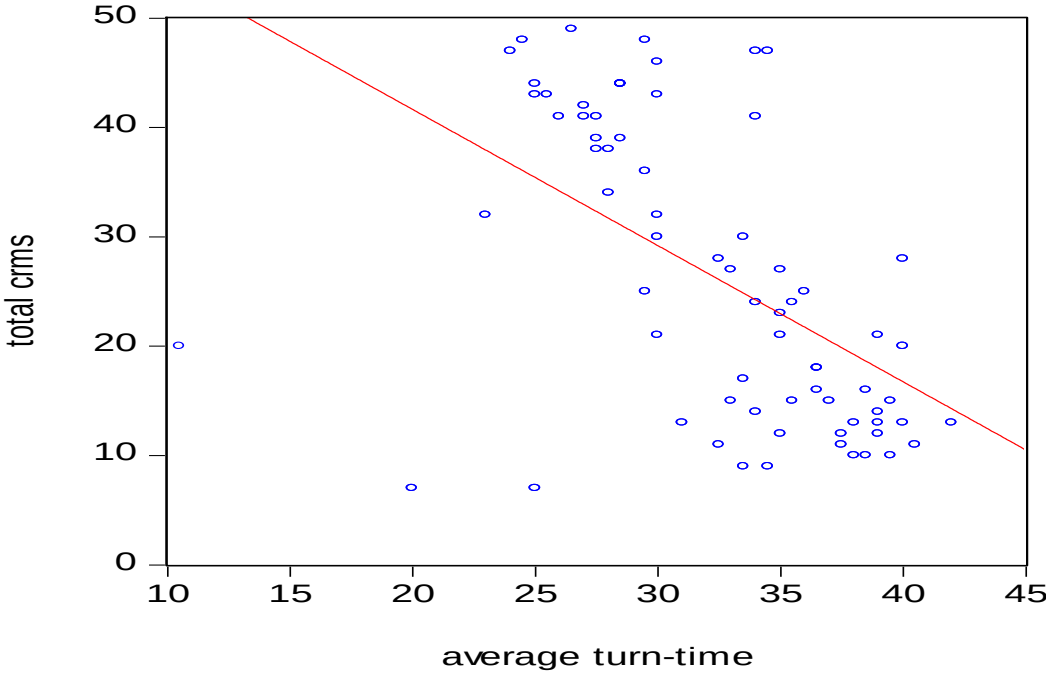


Figure 4.1: Scatter diagram depicting the relationship between turn-time and carriers' market share

Source: Researcher, 2016

For the second objective, the study sought to establish the effect of fleet capacity on enplanement. Figure 4.2 next page suggests that fleet capacity and enplanement are positively related. This implies that as fleet capacity increases, enplanement increases. The plots are not far from the regression fit; this means that fleet capacity does explain much of the variance in enplanement.

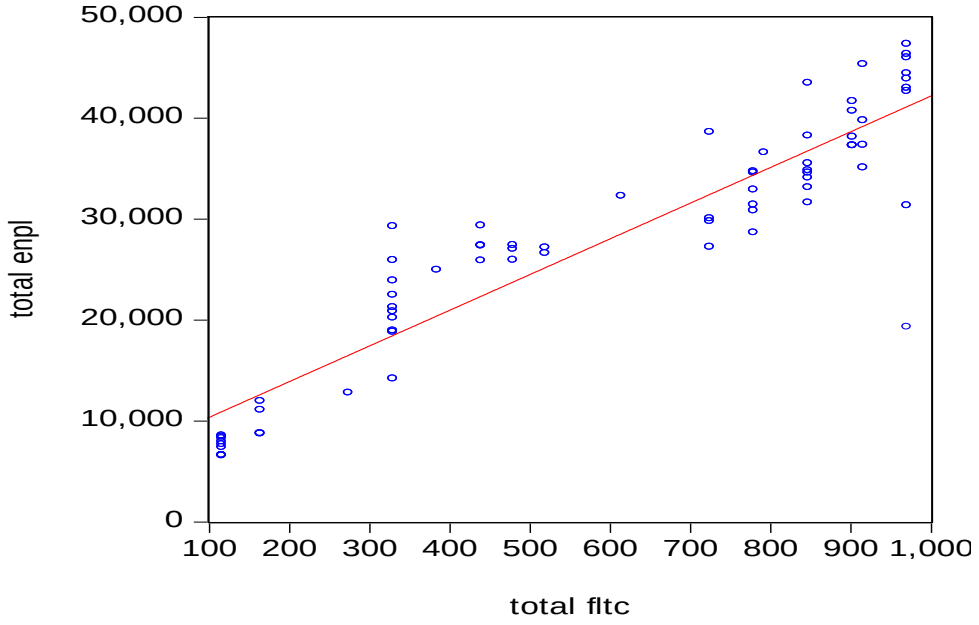


Figure 4.2: Scatter diagram depicting the relationship between fleet capacity and enplanement

Source: Researcher, 2016

For the third objective, the study sought to examine the influence of flight frequency as a mediator on the relationship between low-cost carriers' turn-time and carriers' market share. Figure 4.3a suggests that turn-time and flight frequency are negatively related as indicated by the steep slope. This implies that as turn-time increases, the flight frequency reduces.

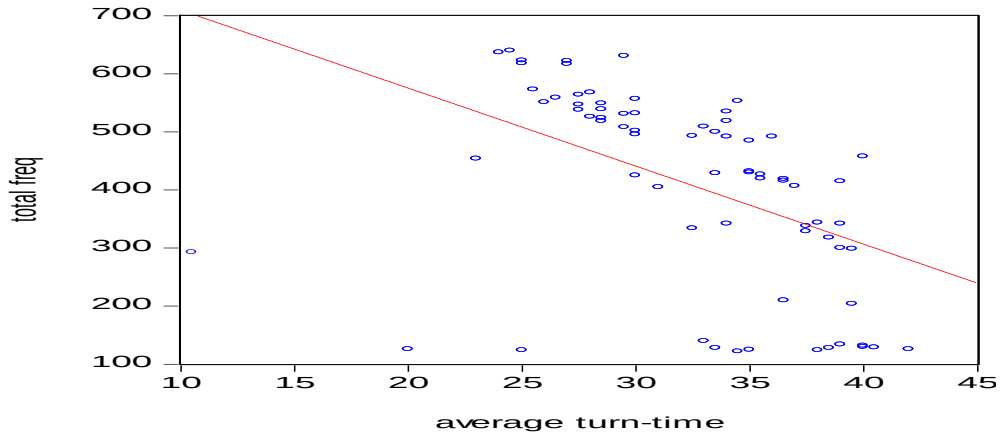


Figure 4.3a: Scatter diagram depicting the relationship between turn-time and flight frequency

Source: Researcher, 2016

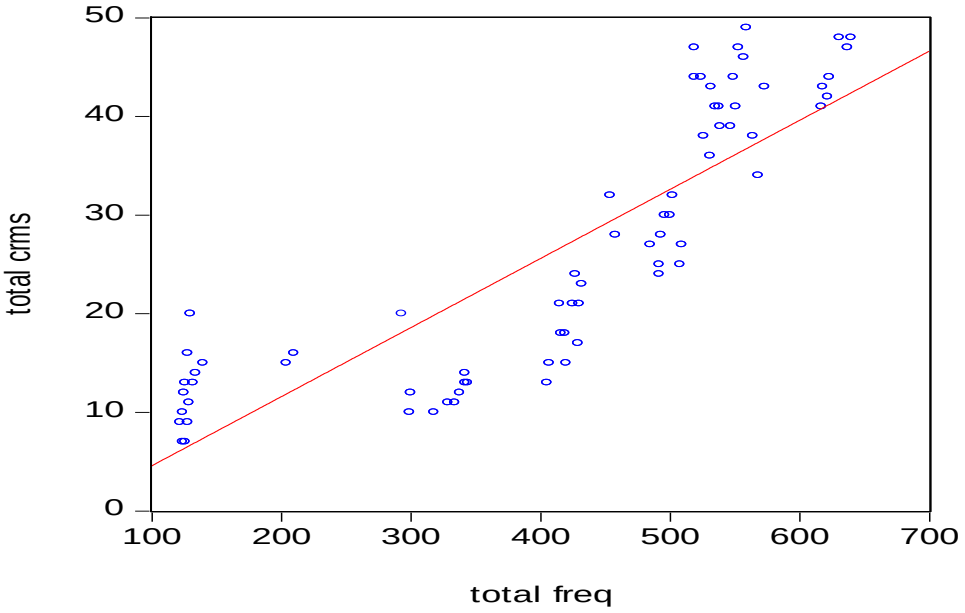


Figure 4.3b: Scatter diagram depicting the relationship between flight frequency and carriers' market share

Source: Researcher, 2016

Figure 4.3b suggests that there is strong positive association between flight frequency and carriers' market share. This implies that as flight frequency increases, carriers' market share increases.

For the fourth objective, the study sought to analyze the influence of load factor as a mediator on the relationship between low-cost carriers' fleet capacity and enplanement. Figure 4.4a suggests that fleet capacity and load factor are positively, though weakly, related as indicated by a relatively flatter slope. This implies that as fleet capacity increases, load factor increases but in small amounts. This is supported by IATA (2015) finding that reported that in Africa, there was fleet capacity expansion of 5.2% and load factor rose 1.9 percentage for the same year 2013.

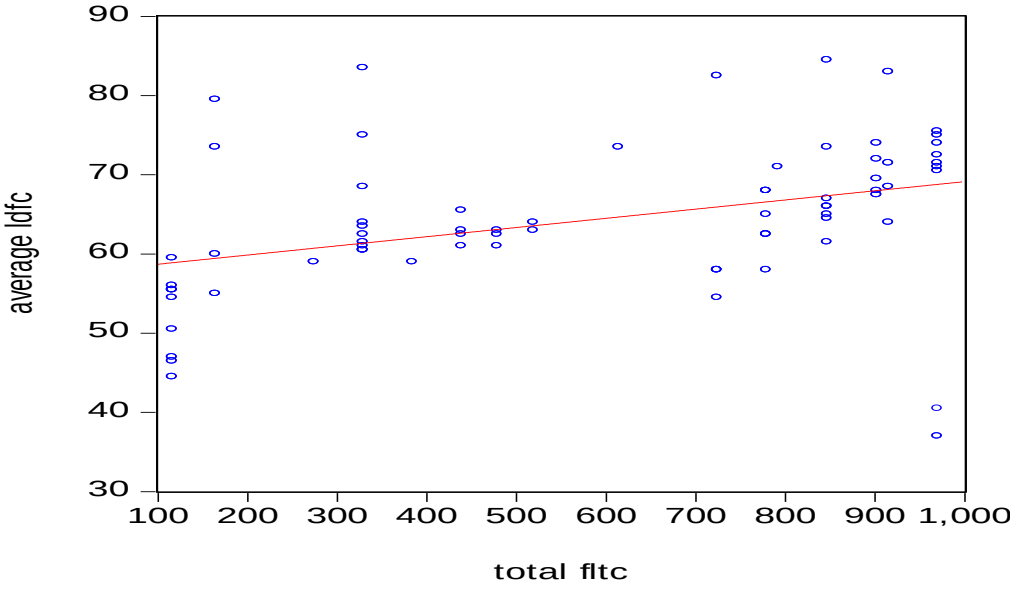


Figure 4.4a: Scatter diagram depicting the relationship between fleet capacity and load factor

Source: Researcher, 2016

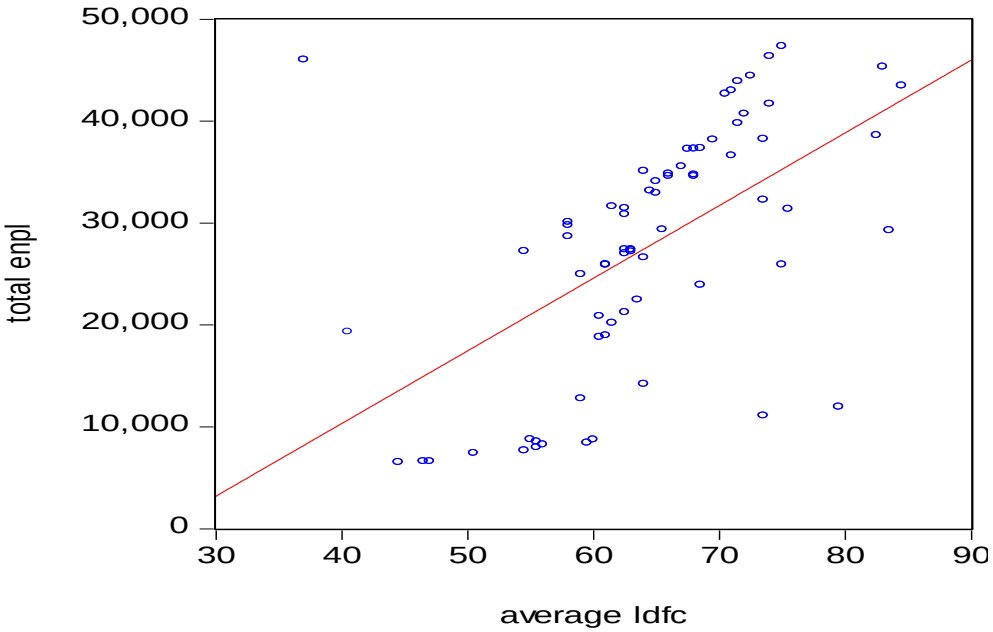


Figure 4.4b: Scatter diagram depicting the relationship between load factor and enplanement

Source: Researcher, 2016

Figure 4.4b suggests that load factor and enplanement are positively related; implying that as load factor increases, enplanement too increases.

4.3 Inferential Analysis

It is well known that many economic time series are difference stationary which produce misleading results, with conventional Wald tests for coefficient significance spuriously showing a significant relationship between unrelated series (Phillips, 1986). Engle and Granger (1987) note that a linear combination of two or more I*(1)* series may be cointegrated, and such linear combination yields a long-run relationship between the variables. Phillips and Moon (1999), Pedroni (2000), Kao and Chiang (1997), Phillips and Hansen (1990) suggested the use of Fully Modified Ordinary Least Square (FMOLS) to provide optimal estimates of cointegrating regressions. The method modifies least squares to account for serial correlation effects and for the endogeneity in the regressors that results from the existence of a cointegrating relationship. Thus, in the following analyses, the reseacher adopted Fully Modified Ordinary Least Square in the panel cointegrating regressions to overcome the problems of heterokedasticity, serial correlations and the outliers which are common with ordinary least squares (OLS).

4.3.1 Effect of Turn-time on the market share of low-cost carriers in Kenya

The first objective examines the effect of turn-time on the market share of low-cost carriers in Kenya. Table 4.2 shows the results of the panel cointegrating regression analysis.

Table 4.2: Regression results of the effect of Turn-time on the carriers' market share

Dependent Variable: CRMS

Method: Panel Fully Modified Least Squares (FMOLS)

Date: 04/01/16 Time: 19:42

Sample (adjusted): 2 72

Periods included: 71

Cross-sections included: 2

Total panel (balanced) observations: 142

Panel method: Pooled estimation

Cointegrating equation deterministics: C

Coefficient covariance computed using default method

Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TNTM	-0.938193	0.135249	-6.936782	0.0000

R-squared	0.363662	Mean dependent var	13.39437
Adjusted R-squared	0.354506	S.D. dependent var	7.444316
S.E. of regression	5.980959	Sum squared resid	4972.290
Long-run variance	90.91638		

Source: Researcher, 2016

The results of the regression analysis in Table 4.2 indicate that turn-time is a significant negative predictor of carriers' market share as indicated by β = -0.9382, against a p-value of 0.0000. This implies that any additional 1 minute of turn-time will result in the reduction of market share by -0.94%. This implies that longer turn-around time results in the loss of market share. The null hypothesis, H_0: that turn-time has no effect on the market share of low-cost carriers in Kenya is rejected. The standard error which is a measure of uncertainty about the true value of the regression (turn-time) coefficient is 0.14%, meaning the coefficient of turn-time could be lower

or higher than -0.94% by 0.14%. The standard error of the regression for this equation is 5.98% meaning that the portion of carriers' market share score that cannot be accounted for by its systematic relationship with values of turn-time is 5.98%. The R^2 statistics measures the overall fit of the regression line, in the sense of measuring how close the points are to the estimated regression line in the scatter plot. The R^2 is 0.364 and the adjusted R^2 is 0.355, the difference in this case being 0.009 which is far much lower than 0.05 as suggested by Field (2009) for the model to be valid, and stable for prediction. Thus, the turn-time construct accounts for 36.4% of the carriers' market share. This is supported by the fact that the standard deviation of the dependent variable is just slightly greater than the standard error of the regression (, that is 7.47 is slightly greater than 5.99). Sample mean of the dependent variable is 13.39% and its standard deviation is 7.44 per cent meaning the values of the carriers' market share lie within this region which is higher or less than 13.39% by 7.44 per cent.

Therefore, the model equation for this relationship is:

crms = C - 0.9382*tntm + (5.98) ..... (4.1)

Where: C represents the individual cross-section fixed effect, and is as follows:

	C
Fly540	32.63
Jetlink	55.84

5.98 being the Standard Error of the regression, that is the discrepancy between the actual values and predicted values of of carriers' market share using the model.

Previous studies (, that is Kunze, Schultz, and Fricke, 2011; Trabelsi *et al*, 2013; Vidosavljevic and Tosic, 2010; Norin, 2008; Gok, 2014) have, however, investigated about the best models for the turn-around operations that would minimize delays, and consequently, costs. Bhaskara (2014), Israel (2015), Sentence (2004) and O'Connell and Williams (2007) reported on the market share that the low-cost carriers have claimed from the incumbents (full service carriers).

O'Connell and Williams (2007) indicates that in the US, the low-cost carriers had claimed 15.2% market share from the incumbents' market share within 5 years from 1998-2003. Bhaskara (2014) reported that Spirit airlines claimed a market share of 4% within 3 months from American airlines following her entry. Israel (2015)'s findings indicate that the market share of low cost carriers has increased world-wide by about 22% over 33 years between early 1980s to 2013. Sentence (2004) reported that LCCs had accumulated around 34 per cent of this market in the UK within 5 years from 1999 – 2004.

Given that low-cost carriers' turn-time construct had not been considered in previous investigations, the relation between turn-time and carriers' market share was still unknown. The current study, which sought to determine the relationship between turn-time and market share of low-cost carriers in Kenya and the results on the first objective indicate that turn-time is a significant negative predictor of market share of the low-cost carriers, that is, one minute longer in the average turn-time will result in a decrease of 0.94% in the low-cost carriers' market share. The results from this study has therefore shown that the economic benefits of implementing efficient turn-around models extend from the immediate reduction of operating costs, as already shown by previous studies, to gain of low-cost carriers' market share in the long run as shown by this study.

4.3.2 Effect of Fleet capacity on Enplanement

The second objective examines the effect of fleet capacity on enplanement by low-cost carriers in Kenya.

Table 4.3: Regression results of the effect of fleet capacity on enplanement

Dependent Variable: ENPL

Method: Panel Fully Modified Least Squares (FMOLS)

Date: 04/12/16 Time: 22:54

Sample (adjusted): 2 72

Periods included: 71

Cross-sections included: 2

Total panel (balanced) observations: 142

Panel method: Pooled estimation

Cointegrating equation deterministics: C

Coefficient covariance computed using default method

Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FLTC	35.41051	2.789528	12.69409	0.0000

R-squared	0.782584	Mean dependent var	14129.99
Adjusted R-squared	0.779456	S.D. dependent var	6668.085
S.E. of regression	3131.474	Sum squared resid	1.36E+09
Long-run variance	26986175		

Source: Researcher, 2016

Therefore, the model equation for this relationship is:

enpl = C + 35.4105*fltc + (3131.47) ..... (4.2)

Where: C represents the individual cross-section fixed effect, and is as follows:

	C
Fly540	4642.18
Jetlink	2703.12

3131.47 being the standard error of the regression, that is the discrepancy between the actual values and predicted values of enplanement using the model.

Results of the regression analysis in Table 4.3 indicate that fleet capacity is a significant positive predictor of enplanement with $\beta = 35.41$, p-value = 0.0000. This implies that any additional 1 seat will result in a monthly increase of 35.41 passengers. The null hypothesis, H_0; that fleet capacity does not have an impact on enplanement by low-cost carriers in Kenya is rejected. The standard error of the fleet capacity effect is 2.79 passengers meaning the coefficient of fleet capacity could be lower or higher than 35.41 passenger by 2.79 passenger. The standard error of the regression for this equation is 3131.47 passengers meaning that the portion of enplanement score that cannot be accounted for by its systematic relationship with values of fleet capacity is 3131.47 passengers. The R^2 is 0.7825 and the adjusted R^2 is 0.7795. The difference in this case is 0.003 which is below the level of 0.05 suggested by Field (2009). This therefore implies that the model is valid, and has stability for prediction. Thus, the regression accounts for 78.25 % of the enplanement. This is supported by the fact that the standard deviation of the dependent variable is by far, actually more than twice, larger than the standard error of the regression (that is, 6668.09 is far much greater than 3131.47). Sample mean of enplanement is 14129.99 passengers, meaning values for enplanement lie within this region which is higher or less than 14129.99 by 6668.09 passengers.

The finding in the current study that fleet capacity was a significant positive predictor of enplanement contradicts the findings by Lin (2013) and Wu (2013). Lin (2013) indicated that low-cost carriers' emergence surprisingly has had no effect on the number of passengers; with every 1 percent increase in deregulation, air traffic would increase with 0.00 percent. Wu (2013) also noted that the impact of the presence of low-cost carriers on traffic had diminished – it no longer existed and that the mathematical relation is 1 dollar decrease on price leads to 1.07 more

passengers. This contradiction could be explained by the fact that Lin (2013)'s study concentrated on deregulation as a whole to be an independent variable while Wu (2013)'s study considered the low-fare construct unlike this study that considered fleet capacity construct. Other researchers (Dresner, 2013; Mertens and Vowles, 2012: InterVistas, 2014; Bhaskara, 2014) employed descriptive statistics in analyzing their data and owed the changes in enplanement to the low-fare construct. Mertens and Vowles (2012) used a group of three low cost carriers and their results show higher figures of 67.5 percent increase in enplanement than InterVistas (2014) and Bhaskara (2014) that assessed the effect of low-fare of only one low-cost carrier, and found an increase of 38 percent and 21.9 percent respectively in enplanement. Dresner (2013)'s findings show that traffic increased by 200% on a route when Southwest, a low-cost airline, entered, and by 82% for other low-cost carrier entries.

Previous studies endeavored to find out the impact that low-cost carriers' low-fare construct would have on enplanement. However, fleet capacity construct had not been considered. Therefore, the impact of low-cost carriers' fleet capacity on enplanement was still unknown. The current study, therefore, sought to investigate the impact of fleet capacity on enplanement by low-cost carriers and the results on the second objective indicate that fleet capacity is a significant positive predictor of enplanement, that is, an increase in seating capacity by 1 seat will result in an increase of 35 more passengers. The results from this study has therefore shown that low-fare construct is not the only determinant of enplanement as shown in the previous studies, but fleet capacity, too, is a significant determinant.

4.3.3 Effect of the flight frequency as a mediator on the Relationship between Turn-time and Market Share of Low-cost Carriers in Kenya

To examine the influence of the mediating flight frequency on the relationship between turn-time and market share of low-cost carriers, the following 3 regression equations were used:

To test if TNTM predicts CRMS $\rightarrow Y_{1it} = \beta_1 + c_1X_{1it} + u_{1it}$ ……..…..…… (4.3)

To test if TNTM predicts FREQ$\rightarrow M_{1it} = \beta_2 + a_1X_{1it} + u_{2it}$ …….....…… (4.4)

To test if TNTM still predicts CRMS, when Mediator (FREQ) is in the model →

$Y_{1it} = \beta_3 + c'_1X_{1it} + b_1M_{1it} + u_{3it}$ ……..…….....……..…….. (4.5)

Where:

c_1, is the overall effect of the independent variable X_1, on Y_1;

c'_1, is the effect of the independent variable X_1, on Y_1 controlling for M_1;

b_1 is the effect of the mediating variable M_1 on Y_1, controlling for X_1;

a_1 is the effect of the independent variable X_1 on the mediator M_1;

$\beta_1 – \beta_3$ is the intercept (cross-section fixed effects) for each equation; and

$u_1 – u_3$ is corresponding residuals (both person-specific and idiosyncratic) in each equation.

STEP 1: Finding out the effect of turn-time on low-cost carriers' market share as denoted by the equation $Y_{1it} = \beta_1 + c_1X_{1it} + u_{1it}$

This step has been dealt with during the analysis of objective I. Refer to Table 4.2 on the results of the analysis of the effect of turn-time on carriers' market share. The model equation was developed as follows:

crms = C - 0.9382*tntm + (5.98) ..... (4.6)

Where: C represents the individual cross-section fixed effect, and is as follows:

	C
Fly540	32.63
Jetlink	55.84

5.98 being the standard error of the regression, that is, the discrepancy between the actual values and predicted values of carriers' market share using the model.

STEP 2: Finding out the effect of turn-time on flight frequency as denoted by the equation $M_{1it} = \beta_2 + a_1X_{1it} + u_{2it}$

Table 4.4: Regression results of the effect of turn-time on flight frequency

Dependent Variable: FREQ

Method: Panel Fully Modified Least Squares (FMOLS)

Date: 04/01/16 Time: 19:49

Sample (adjusted): 2 72

Periods included: 71

Cross-sections included: 2

Total panel (balanced) observations: 142

Panel method: Pooled estimation

Cointegrating equation deterministics: C

Coefficient covariance computed using default method

Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TNTM	-9.936542	1.703997	-5.831313	0.0000

R-squared	0.287001	Mean dependent var	208.3451
Adjusted R-squared	0.276742	S.D. dependent var	84.36354
S.E. of regression	71.74662	Sum squared resid	715513.2
Long-run variance	14431.49		

Source: Researcher, 2016

Results as shown in Table 4.4 indicates that turn-time is a significant negative predictor of flight frequency as shown by β = -9.94 with a p-value of 0.000. This implies that any additional 1

minute in turn-time will result in a monthly flight frequency decrease of 9.94 scheduled flights. The standard error of the turn-time coefficient estimate is 1.70 meaning the coefficient of turn-time for the model could be lower or higher than -9.94 number of scheduled flights by 1.70. The standard error of the regression for this equation is 71.75 scheduled flights meaning that the portion of flight frequency score that cannot be accounted for by its systematic relationship with values of turn-time is 71.75 scheduled flights. The R^2 is 0.2870 and the adjusted R^2 is 0.2767. The shrinkage in this case is 0.0103 which is below the level of 0.05 suggested by Field (2009). This therefore implies that the model is valid, and has stability for prediction. Thus, the regression accounts for 28.7% of the flight frequency. This is supported by the fact that the standard deviation of the dependent variable is slightly larger than the standard error of the regression (that is, 84.36 is slightly greater than 71.75). Sample mean of flight frequency is 208.35 scheduled flights and its standard deviation is 84.36 meaning the values of the flight frequency lie within this region which is higher or less than 208.35 by 84.36 number of scheduled flights.

The study therefore developed the following analytic model for predicting flight frequency:

freq = C -9.9365*tntm + (71.75) ..... (4.7)

Where: C represents the individual cross-section fixed effects, and is as follows:

	C
Fly540	434.43
Jetlink	636.89

71.75 being the standard error of the regression, that is the discrepancy between the actual values and predicted values of flight frequency using the model.

STEP 3: Finding out the effect of flight frequency as a mediator on the relationship between market share of low-cost carriers and turn-time as denoted by the equation $Y_{1it} = \beta_3 + c'_1X_{1it} + b_1M_{1it} + u_{3it}$

Table 4.5: Regression results of the effect of the mediating flight frequency on the relationship between carriers' market share and turn-time.

Dependent Variable: CRMS

Method: Panel Fully Modified Least Squares (FMOLS)

Date: 04/01/16 Time: 19:53

Sample (adjusted): 2 72

Periods included: 71

Cross-sections included: 2

Total panel (balanced) observations: 142

Panel method: Pooled estimation

Cointegrating equation deterministics: C

Coefficient covariance computed using default method

Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TNTM	-0.307877	0.108399	-2.840224	0.0052
FREQ	0.060564	0.007712	7.852773	0.0000

R-squared	0.752959	Mean dependent var	13.39437
Adjusted R-squared	0.747588	S.D. dependent var	7.444316
S.E. of regression	3.740070	Sum squared resid	1930.361
Long-run variance	40.01138		

Source: Researcher, 2016

Table 4.5 indicates that turn-time is a significant negative predictor of carriers' market share with $\beta = -0.3079$ against a p-value of 0.0052. This implies that any additional 1 minute in turn-time, controlling for flight frequency, will result in a monthly carriers' market share decrease of 0.31%. Flight frequency is a significant positive predictor with $\beta = 0.0606$ against a p-value of 0.0000. This means that any additional 1 scheduled flight will result in a monthly increase of

carriers' market share by 0.06%. The standard error of turn-time coefficient estimate is 0.11% meaning the coefficient of turn-time in the equation could be lower or higher by 0.11% while the standard error of flight frequency effect estimate is 0.01 meaning the coefficient of flight frequency could be lower or higher by 0.01%. The standard error of the regression for this equation is 3.74% meaning that the portion of carriers' market share score that cannot be accounted for by its systematic relationship with values of turn-time and flight frequency is 3.74%. The R^2 is 0.7530 and the adjusted R^2 is 0.7476. The difference in this case being 0.0054 which is less than the level of 0.05 suggested by Field (2009). This therefore implies that the model is valid, has stability for prediction. Thus, the regression accounts for 75.30% of the low-cost carriers' market share. This is supported by the fact that the standard deviation of the dependent variable is by far much larger than the standard error of the regression (7.44 is far much larger than, twice the size of, 3.74). This implies that the regression has explained a huge portion of the variance in carriers' market share. Sample mean of carriers' market share is 13.39 per cent flights and its standard deviation being 7.44% means the values of the carriers' market share lie within a region which is higher or less than 13.39% by 7.44 per cent.

Thus, the analytic model for predicting carriers' market share is:

crms = C -0.3079*tntm + 0.0606*freq + (3.74) ..... (4.8)

Where: C represents the individual cross-section fixed effect, and are as follows:

	C
Fly540	5.84
Jetlink	16.14

3.74 being the standard error of the regression, that is, the discrepancy between the actual values and predicted values of carriers' market share using the model.

Thus, the summary of the path regression analyses for the mediating flight frequency will be as follows:

crms = -0.9382*tntm + (5.98) .....(4.9)

freq = -9.9365*tntm + (71.75) .....(4.10)

crms = -0.3079*tntm + 0.0606*freq + (3.74) .....(4.11)

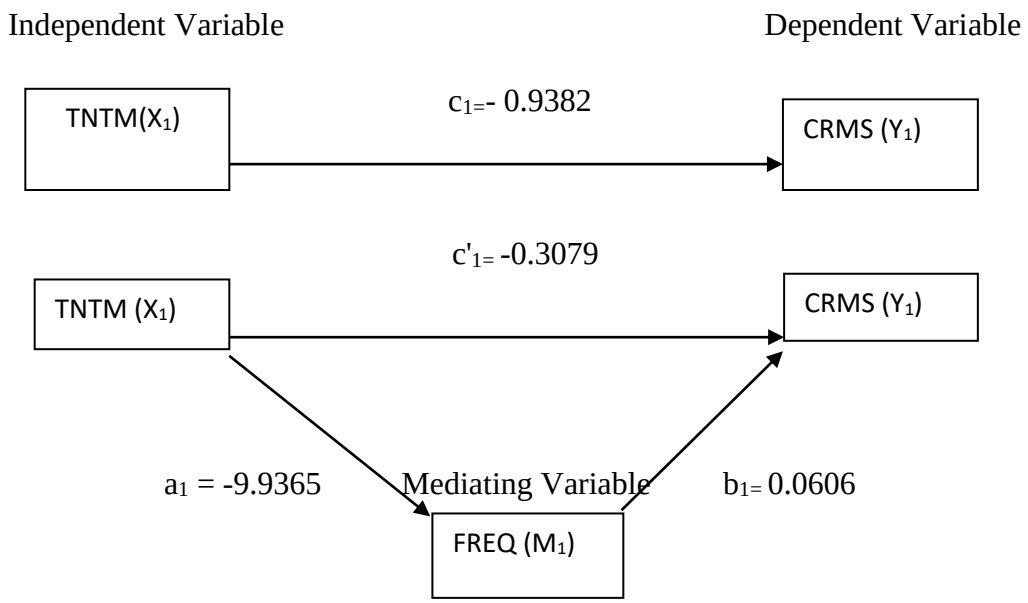


Figure 4.5: Estimated Path Analysis Diagram for the mediated effect of turn-time on carriers' market share

Source: Researcher, 2016

The indirect effect coefficient is then calculated by multiplying two regression coefficients, the partial regression effect for M predicting Y, *b*, and the simple coefficient for X predicting M, *a*, as indicated below:

$\beta_{\textbf{indirect effect}} = b_1 * a_1$ ..... (4.12)

$= 0.0606 * -9.9365$

$= - 0.6018$

Thus, the proportion of the X-Y relation that is attributable to M will be as indicated in the Table 4.6:

Table 4.6: Analysis of the mediating impact of Summary of the results of the influence of flight frequency as mediator on the relationship between turn-time and carriers' market share

	a_1	b_1	Product of a_1b_1	c	Percentage change (a_1b_1 /c)
Turn-time	-9.9365	0.0606	- 0.6019	- 0.9382	64.14%

Source: Researcher, 2016

As summarized in Table 4.6, the effect of turn-time on flight frequency, *a*, is -9.9365; while the coefficient of flight frequency, while controlling for turn-time, is 0.0606. Thus, the product of a_1b_1 is - 0.6018, and the proportion with respect to *c* is 0.6414. This means out of all (100%) effects that turn-time will have on carriers' market share, 64.14% of that effect is attributable to flight frequency.

Significance Test for Mediation

This test determines whether the mediator variable significantly carries the influence of an independent variable to a dependent variable, that is, whether the indirect effect of the independent variable on the dependent variable through the mediator variable is significant (Sobel, 1982; Wu, 2011). The following formula is used:

$$Z = (ab)/\sqrt{(b^2\, sa^2 + a^2\, sb^2 + sa^2\, sb^2)} \quad \text{..... (4.13)}$$

Where **a** and **b** are the standardized regression coefficients and **sa** and **sb** are their standard errors.

The researcher used Statistics Calculator to calculate the Sobel test statistics against a null hypothesis of indirect effect coefficient being zero. This calculator returns the Sobel test statistic, and both one-tailed and two-tailed probability values as shown in the Table 4.7 (http://www.danielsoper.com/ statcalc/calculator.aspx? id=31).

Table 4.7: The Results of the Sobel Test for significance of the mediating flight frequency

A:	-9.9365
B:	0.0606
SE_A:	1.7040
SE_B:	0.0077

(a)

Sobel test statistic:	-4.68208718
One-tailed probability:	0.00000142
Two-tailed probability:	0.00000284

(b)

Source: Researcher, 2016

From Table 4.7, the Sobel test statistics of -4.6821 against a one-tailed p-value of 0.0000 or a two-tailed p-value of 0.0000 implies that the null hypothesis of the indirect effect coefficient being zero is strongly rejected. Thus, the mediating effect of flight frequency is significant.

Conclusion on the Mediating effect of Flight frequency on the Turn-time – Carriers' Market Share Relationship

M (flight frequency) partially and significantly mediates turn-time and low-cost carriers' market share relation by 64.14% since all the 4 conditions have been met: (1), X (turn-time) predicts Y (carriers' market share), that is, $H_{0(1)}$: c = 0 is rejected; (2), X (turn-time) predicts M (flight frequency), that is, $H_{0(2)}$: a = 0 is rejected; (3), both X (turn-time) and M (flight frequency) predict Y (carriers' market share), but X (turn-time) has a smaller regression coefficient when both X (turn-time) and M (flight frequency) are used to predict Y (carriers' market share) than when only X (turn-time) is used, that is, both $H_{0(3)}$: b = 0 and $H_{0(4)}$: $c' = 0$ are rejected; and, (4) the indirect effect coefficient is significant.

Empirical studies (Manuela, 2006; Najda, 2003; Wang *et al*, 2014) have investigated on the flight frequency variable differently. Manuela (2006) considers it as independent variable on fare, Najda (2003) treats it as a moderating variable on fare, and Wang *et al*, (2014) investigated it as an independent variable on airline market expansion. Manuela (2006) found out that the

flight frequency variable is highly significant and has a negative impact on airfare per kilometer, and is inelastic in relation to price. Wang *et al* (2014) find a negative relationship between market concentration and flight frequency. According to Najda (2003), the effect of the flight frequency of flights on a route, served by a particular carrier, is positive and significant at the 1 percent level over each fare percentile.

Since reviewed literature posit flight frequency to be emanating from airlines' turn-time while it also independently influences other airline performance parameters, it therefore suggests that flight frequency would explain why a relationship between turn-time and any other variable occurs. However, previous studies had investigated flight frequency as either independent or moderating variable with respect to other airline performance parameters. No study had considered it as a mediating variable in the relationships between turn-time and carriers' market share, and therefore, its mediation role was still known. The current study, therefore, sought to investigate the influence of flight frequency as a mediator on the relationship between turn-time and market share of low-cost carriers and the results on third objective offers evidence indicating that flight frequency partially and significantly mediates turn-time and carriers' market share relation by 64.14 per cent. The results from this study has therefore shown that flight frequency is an important mechanism through which turn-time influence low-cost carriers' market share.

4.3.4 Effect of Load Factor as a Mediator on the Relationship between Fleet Capacity and Enplanement

To examine the influence of the mediating load factor on the relationship between fleet capacity and enplanement, the following 3 regression equations will be:

To test if FLTC predicts ENPL → $Y_{2it} = \beta_4 + c_2X_{2it} + u_{4it}$ …….....…..… (4.14)

To test if FLTC predicts LDFC→ $M_{2it} = \beta_5 + a_2X_{2it} + u_{5it}$ ….....….....…..... (4.15)

To test if FLTC still predicts ENPL, when Mediator (LDFC) is in the model →
$Y_{2it} = \beta_6 + c'_2X_{2it} + b_2M_{2it} + u_{6it}$ …….....….....…… (4.16)

Where:

c_2 is the overall effect of the independent variable X_2 on Y_2;

c'_2 is the effect of the independent variable X_2 on Y_2 controlling for M_2;

b_2 is the effect of the mediating variable M_2, on Y_2;

a_2 is the effect of the independent variable X_2 on the mediator M_2;

$\beta_4 - \beta_6$ is the intercept (cross-section fixed effects) for each equation; and

$u_4 - u_6$ is corresponding residuals (both person-specific and idiosyncratic) in each equation.

STEP 1: Finding out the effect of fleet capacity on enplanement as denoted by the equation $Y_{2it} = \beta_4 + c_2X_{2it} + u_{4it}$

This step has been dealt with during the analysis of objective II. Refer to Table 4.3 on the results of the analysis of the effect of fleet capacity on carriers' market share. The model equation was developed as follows:

enpl = C + 35.4105*fltc + (3131.47) ..... (4.17)

Where: C represents the individual cross-section fixed effect, and is as follows:

	C
Fly540	4642.18
Jetlink	2703.12

3131.47 being the standard error of the regression, that is, the discrepancy between the actual values and predicted values of enplanement using the model.

STEP 2: Finding out the effect of fleet capacity on load factor as denoted by the equation $M_{2it} = \beta_5 + a_2X_{2it} + u_{5it}$

Table 4.8: Regression Results of the effect of fleet capacity on load factor

Dependent Variable: LDFC

Method: Panel Fully Modified Least Squares (FMOLS)

Date: 04/12/16 Time: 23:01

Sample (adjusted): 2 72

Periods included: 71

Cross-sections included: 2

Total panel (balanced) observations: 142

Panel method: Pooled estimation

Cointegrating equation deterministics: C

Coefficient covariance computed using default method

Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FLTC	0.026781	0.005374	4.983714	0.0000

R-squared	0.227566	Mean dependent var	65.66901
Adjusted R-squared	0.216452	S.D. dependent var	8.697209
S.E. of regression	7.698617	Sum squared resid	8238.349
Long-run variance	100.1477		

Source: Researcher, 2016

Table 4.8 shows that fleet capacity has a significant positive effect on load factor as indicated by $\beta = 0.0268$ against t-statistic of 4.9837. This implies that any additional 1 seat will result in 0.0268 percentage increase in load factor. The standard error of fleet capacity effect estimate is 0.01% meaning the coefficient of fleet capacity could be lower or higher than 0.01%. The standard error of the regression for this equation is 7.68% meaning that the portion of load factor score that cannot be accounted for by its systematic relationship with values of fleet capacity is 7.68%. The R^2 is 0.2276 and the adjusted R^2 is 0.2165, the difference in this case is 0.011 which

is below the level of 0.05 suggested by Field (2009). This therefore implies that the model is valid, has stability for prediction. Thus, the regression accounts for 22.76% of the enplanement. This is supported by the fact that the standard deviation of the dependent variable is slightly larger than the standard error of the regression (8.6972 is slightly larger than 7.6986%). This implies that the regression has explained a small portion of the variance in load factor. Sample mean of the load factor is 65.6690% and its standard deviation being 8.6972% means the values of load factor lie within this region which is higher or less than 865.669% by 8.6972 per cent.

From these results, the model will be:

ldfc = 0.0268*fltc + 7.699 ..... (4.18)

Where: C represents the individual cross-section fixed effect, and is as follows:

	C
Fly540	59.15
Jetlink	56.13

7.699 being the standard error of the regression, that is, the discrepancy between the actual values and predicted values of load factor using the model.

The results imply that, should the low-cost carriers add to its fleet 2 more fifty-seater airplanes, such as a Canadian Royal Jet (CRJ), load factor will improve by 3%. This finding supports that of IATA (2015) though contradicts Jenatabali and Ismail (2007). IATA (2015) reported that in India, fleet capacity climbed 3.5% in 2013, and load factor was 74.6%, up 1.7 percentage points, while in Africa, there was capacity expansion of 5.2% and load factor rose 1.9 percentage points to 69 percent, indicating that an increase in fleet capacity will result in an increase in load factor. However, Jenatabali and Ismail (2007) found out that fleet capacity is an insignificant negative predictor in explaining the variation in load factor, with a negative coefficient of -1.511. This finding reiterates that when more seats are availed (and this is achieved through increasing the number of airplanes), the availability comes with flexibility in fleet scheduling and management. This ensures more reliability that wins the confidence of the travelling public. Increasing the

number of equipment, and consequently the available seats, raises the value of the product to the passenger and increased value leads to higher demand and finally higher load factors. Passengers value the convenience increased capacity provides them. In the end, more bookings are realized which is seen in the form of rising load factor. The finding also implies that unlike in the North America and better part of Europe, Kenya, and to a large extent Africa, still has a segment in her population whose propensity to travel by air can be stimulated through aggressive fare reductions and commercial successes in product designing, promotions, marketing communications, distributions, and service delivery, hence the need to avail more seats.

All the above analyses (Tables 4.3, 4.8) have revealed significant relationships between the variables as required by Baron and Kenny (1986) approach. Thus the mediating effect of flight frequency could now be confidently investigated as shown by the regression equation 4.16.

STEP 3: Finding out the influence load factor as a mediator on the relationship between enplanement and fleet capacity as denoted by the equation $Y_{2it} = \beta_6 + c'_2X_{2it} + b_2M_{2it} + u_{6it}$

Table 4.9: Regression Results of the effect of load factor as a mediator on the relationship between enplanement and fleet capacity

Dependent Variable: ENPL

Method: Panel Fully Modified Least Squares (FMOLS)

Date: 04/12/16 Time: 23:07

Sample (adjusted): 2 72

Periods included: 71

Cross-sections included: 2

Total panel (balanced) observations: 142

Panel method: Pooled estimation

Cointegrating equation deterministics: C

Coefficient covariance computed using default method

Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FLTC	29.48012	2.845817	10.35911	0.0000
LDFC	217.1687	52.03602	4.173430	0.0001

R-squared	0.832678	Mean dependent var	14129.99
Adjusted R-squared	0.829040	S.D. dependent var	6668.085
S.E. of regression	2757.072	Sum squared resid	1.05E+09
Long-run variance	21670020		

Source: Researcher, 2016

Results of the multiple regression analysis (Table 4.9) indicate that both fleet capacity and load factor have significant positive effect on enplanement as indicated by the β = 29.48 against a p-value of 0.0000, and β = 217.17 and a p-value of 0.0001 respectively. This implies that any additional 1 seat will result in 29.48 more passengers. On the other hand, any additional 1% in

load factor will result in an increase of 217.17 passengers. The standard error of fleet capacity effect estimate is 2.85 meaning the coefficient of fleet capacity could be lower or higher than 2.85 number of passengers. The standard error of the regression for this equation is 52.04 passengers meaning that the portion of enplanement that cannot be accounted for by its systematic relationship with values of fleet capacity and load factor is 52.04 passengers. The standard error of the regression is 2757 passengers meaning that the estimated results for enplanement would be a value within a region lower or higher by 2757 passengers. The R^2 is 0.8327 and the adjusted R^2 is 0.8290. The shrinkage in this case is 0.0037 which is below the level of 0.05 suggested by Field (2009). This therefore implies that the model is valid, and has stability for prediction. Thus, the regression accounts for 83.26% of the enplanement. This is supported by the fact that the standard deviation of the dependent variable is by far much larger than the standard error of the regression (6668.08 is far much larger than, more than twice the size of, 2757). This implies that the regression has explained a huge portion of the variance in enplanement. Sample mean of the dependent variable is 14129 and its standard deviation being 6668.08 means the values of enplanement lie within this region which is higher or less than 14129 passengers by 6668.08 passenger.

Thus, the equation model wa developed as follows:

enpl = 29.4801*fltc + 217.1687*ldfc + (2757.07) ..... (4.19)

Where:

C represents the individual cross-section fixed effect, and is as follows:

	C
Fly540	-8128.379
Jetlink	-9413.565

2757.07 being the standard error of the regression, that is, the discrepancy between the actual

values and predicted values of enplanement. Thus, the summary of the path regression analyses for the mediating load factor will be as follows:

enpl = 35.4106*fltc + (3131.47) ..... (4.20)

ldfc = 0.0268*fltc + (7.699) ..... (4.21)

enpl = 29.4801*fltc + 217.1687*ldfc + (2757.07)..... (4.22)

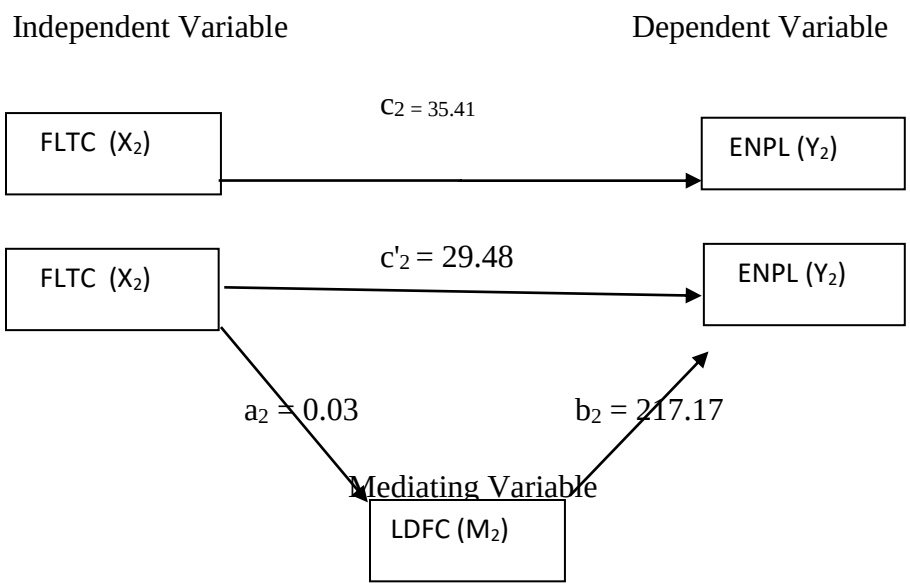


Figure 4.6: Estimated Path Analysis Diagram for the mediated effect of fleet capacity on enplanement

Source: Researcher, 2016

The indirect effect coefficient is then calculated by multiplying two regression coefficients, the partial regression effect for M predicting Y, *b*, and the simple coefficient for X predicting M, *a*, as indicated below:

$\beta_{\textbf{indirect}} = b_2 * a_2$ ..... (4.23)

$= 217.1687 * 0.0268$

$= 5.8201$

The proportion of the X-Y relation that is attributable to M is (ab)/c, and c = 35.4105 as indicated in the Table 4.10 below.

Table 4.10: Summary of the results of the influence of load factor as mediator on the relationship between fleet capacity and enplanement

	a_2	b_2	Product of a_2 b_2	Percentage change (a_2 b_2/c_2)
Regression coefficients	0.0268	217.1687	5.8201	16.44%

Source: Researcher, 2016

As summarized in Table 4.10, the effect of fleet capacity on load factor, a_2, is 0.0268; while the coefficient of load factor, while controlling for fleet capacity, is 217.1687. Thus, the product of a_2b_2 is 5.8201, and the proportion with respect to c_2 is 0.1644. This means that out of all (100%) effects the fleet capacity will have on enplanement, 16.44% of that effect is attributable to load factor.

Significance Test for Mediation

This test determines whether the mediator variable significantly carries the influence of an independent variable to a dependent variable, that is, whether the indirect effect of the independent variable on the dependent variable through the mediator variable is significant (Sobel, 1982; Wu, 2011). The following formula is used:

$Z = (ab)/\sqrt{(b^2\ sa^2 + a^2\ sb^2 + sa^2\ sb^2)}$ ..... (4.24)

Where **a** and **b** are the standardized regression coefficients and **sa** and **sb** are their standard errors.

The researcher used Statistics Calculator to calculate the Sobel test statistics against the null hypothesis of the indirect effect coefficient being zero. This calculator returns the Sobel test statistic, and both one-tailed and two-tailed probability values as shown in the Table 4.11 (http://www.danielsoper.com/ statcalc/calculator.aspx? id=31).

Table 4.11: The Results of the Sobel Test for significance of the mediating load factor

A:	0.0268
B:	217.168
SE_A:	0.00537
SE_B:	52.0360

(a)

Sobel test statistic:	**3.20152605**
One-tailed probability:	**0.00068351**
Two-tailed probability:	**0.00136702**

(b)

Source: Researcher, 2016

The results of Table 4.11 show a Sobel test statistics of 3.2015 against a one-tailed p-value of 0.0007 or a two-tailed p-value of 0.0014 implying that the null hypothesis of the indirect effect coefficient being zero is rejected. Thus, the mediating effect of load factor is significant.

Conclusion on the influence of Load Factor as a mediator on the relationship between fleet capacity and enplanement

M (load factor) partially, and significantly, mediates fleet capacity-enplanement relation by 16.44% since all the 4 conditions have been met: (1), X (fleet capacity) predicts Y (enplanement), that is, $H_{0(1)}$: c = 0 is rejected; (2), X (fleet capacity) predicts M (load factor), that is, $H_{0(2)}$: a = 0 is rejected; (3), both X (fleet capacity) and M (load factor) predict Y (enplanement), but X (fleet capacity) has a smaller regression coefficient when both X (fleet capacity) and M (load factor) are used to predict Y (enplanement) than when only X (fleet capacity) is used, that is, both $H_{0(3)}$: b = 0 and $H_{0(4)}$: c′ = 0 are rejected; and, (4) the indirect effect coefficient is significant.

The findings of this study are different from the findings of Rupp (2007), Tesfay and Solibakke (2015), IATA (2015), Jenatabali and Ismail (2007), Borenstein (2011), Ramdas and Williams (2008) and Najda (2003) since they have investigated load factor variable differently. IATA (2015) has employed descriptive statistics in analysing the impact of fleet capacity on load factor. Both Tesfay and Solibakke (2015) and Jenatabali and Ismail (2007) have modelled load factor as a function of other independent variables. Rupp (2007) and Ramdas and Williams (2008) investigated it as an independent variable on the on-time performance while Borenstein (2011) investigates as an independent variable on price. Najda (2003) treats as a moderating variable on fare. IATA (2015) and Jenatabali and Ismail (2007) show mixed results of the effect of fleet capacity on load factor. According to Rupp (2007), seating capacity and load factor have significant negative effects on flight delays, while Jenatabali and Ismail (2007) paper concludes that the number of seats are not significant in explaining the variation in load factors. Borestein (2011) reports that a 10% change in average load factor would explain a price decline of about 15 percent. Tesfay and Solibakke (2015) paper results show that the load factors are both seasonal and differ between flights. Ramdas and Williams (2008) show that increasing load factor leads to greater delays when airplane utilization is high, than when airplane utilization is low.

Whereas reviewed literature indicate that load factor is influenced by the low-cost carriers' fleet capacity while it is also independently influencing other airline performance parameters, thereby proposing a mediation possibility of load factor in the relationships between fleet capacity and other airline performance parameters, previous works had investigated load factor in the airline market as either a dependent variable, independent variable, or moderating variable on fare. None of the previous studies had considered it as a mediating variable in the relationship between fleet capacity and enplanement. The current study, therefore, sought to investigate the influence of the mediating load factor on the relationship between fleet capacity and enplanement and the results on the fourth objective offers evidence indicating that load factor partially and significantly mediates fleet capacity-enplanement relation by 16.44 per cent. The results from this study has therefore shown that load factor is an important mechanism through which fleet capacity influence enplanement.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

This chapter summarizes the results of the study and reports the conclusions drawn. In addition, practical contributions of the study are discussed together with observed limitations. The chapter concludes by providing potential avenues for future research.

5.1 Summary of Findings

This section provides for the summary of the findings of this study as per the study objectives. The purpose of this study was to analyze the effect of mediating route characteristics on the relationship between low cost carriers' key factors and airline performance for the period 2007 – 2012, in Kenya through a set of objectives realizable by way of diverse analyses.

For the first objective, the study sought to determine the effect of turn-time on market share of low-cost carriers in Kenya. The results of the study revealed a very weak insignificant negative correlation between turn-time and low-cost carriers' market share, and that turn-time is a significant negative predictor of low-cost carriers' market share.

For the second objective, the study sought to establish the effect of fleet capacity on enplanement by low-cost carriers in Kenya. The results of the study revealed that fleet capacity has a very strong significant positive correlation with enplanement and that fleet capacity is a significant positive predictor of enplanement.

For the third objective, the study sought to examine the influence of flight frequency as a mediator on the relationship between low-cost carriers' turn-time and carriers' market share. The results of the study revealed that turn-time is significantly and negatively correlated with flight frequency, there is a very strong significant positive correlation between flight frequency and carrier market share, turn-time is a significant negative predictor of flight frequency, flight frequency is a significant positive predictor of carriers' market share, when both turn-time and flight frequency are included in the equation, turn-time is still a significant negative predictor of carriers' market share though the effect is reduced, and flight frequency is also a significant

positive predictor of carriers' market share. The study has also ascertained that flight frequency partially and significantly mediates turn-time-carriers' market share relation by 64.14 per cent.

For the fourth objective, the study sought to analyze the influence of load factor as a mediator on the relationship between low-cost carriers' fleet capacity and enplanement by low-cost carriers in Kenya. The results of the study revealed that fleet capacity has a strong significant positive correlation with load factor, there is a strong significant positive correlation between load factor and enplanement, fleet capacity is a significant positive predictor of load factor, load factor is a significant positive predictor of enplanement, and when both fleet capacity and load factor are included in the equation, fleet capacity is still significant positive predictor of enplanement though the effect is reduced, and load factor is also a significant positive predictor of enplanement, and load factor partially and significantly mediates fleet capacity-enplanement relation by 16.44 per cent.

This is the first study reporting on the effect of mediating route characteristics on the relationship between low cost carriers' key factors and airline.

5.2 Conclusions

The study set to analyze the effect of mediating route characteristics on the relationship between low-cost carriers' key factors and the airline performance in Kenya through a set of objectives realizable by way of diverse analyses.

For the first objective, the study sought to determine the effect of turn-time on market share of low-cost carriers in Kenya. The results of the study revealed that turn-time is a significant negative predictor of carriers' market share, implying that as the turn-around processes become more complex, the carriers' market share reduces.

For the second objective, the study sought to establish the effect of fleet capacity on enplanement by low-cost carriers in Kenya. The results of the study revealed that fleet capacity is a significant

positive predictor of enplanement, implying that increasing more seats results in more passengers ferried.

For the third objective, the study sought to examine the influence of flight frequency as a mediator on the relationship between low-cost carriers' turn-time and market share of low-cost carriers in Kenya. The results of the study revealed that flight frequency partially and significantly mediates turn-time – carriers' market share relation by 64.14 per cent, implying that the number of trips operated by the low-cost carriers provide a mechanism through which the turn-around time assists low-cost carriers acquire market share.

For the fourth objective, the study sought to analyze the influence of load factor as a mediator on the relationship between low-cost carriers' fleet capacity and enplanement by low-cost carriers in Kenya. The results of the study revealed that load factor partially and significantly mediates fleet capacity-enplanement relation by 16.44 per cent, implying that the load factor is a mechanism through which the low-cost carriers' fleet capacity affect enplanement.

5.3 Recommendations

Optimizing airplane utilization, which includes efficient airplane turn-time at the gates, can help an airline maximize the large capital investment it has made in its airplanes. Efficient airplane utilization requires close coordination among an airline's own fleet planning, schedules planning, passenger reservations, flight operations, ground operations, and airplane maintenance systems, as well as with air traffic controllers and airport authorities. Even a small reduction in the turn-around time at the gate can produce impressive benefits, particularly for short-haul carriers. Based on the first conclusion, airlines, therefore, need to adopt very efficient turn-around models. The key for high utilization is to shorten the time between one flight and another. This requires good operating systems to ensure that all necessary ground handling procedures can be completed during a limited period. One way to simplify ground handling procedures and cut down the time gap is by using one type of aircraft for the airline's whole fleet.

Airline fleet management and planning requires determining the size of service fleet that is most cost-effective. Based on the second conclusion, there is, therefore, a need to identify and adjust

accordingly, from time to time, the optimal fleet capacity for their specific operating conditions and environments without under or over supplying the available seats.

The frequency of service offered by low-cost carriers has an effect on competitors' market share. Unless the low-cost carriers have frequent service, it will be very difficult to continue expanding their business space within the airline market. Based on the third conclusion, low-cost carriers should, thus, try to optimize their fleet utilization by choosing cheaper and less crowded secondary airports, as well as increase their number of scheduled flights during busy seasons like holidays and week-ends.

Since load factor measures the percentage of an airline's output that has been sold to paying passengers, it is a measure of the extent to which supply and demand are balanced at prevailing prices. Based on the fourth conclusion, airlines management therefore needs to work on the two key drivers, that is, pricing and commercial success. This is because fare reductions will generally stimulate demand and commercial success in product design, promotions, marketing communications, distributions, and service delivery will influence load factors.

5.4 Limitations of the Study

One limitation of the study was that information on the network efficiency for airlines in Kenyan Aviation Industry is not available. However, in reality, the network efficiency of airlines at the formative stages is likely to be far much lower compared to the maturity stages. In order to overcome this problem, the study assumed same network efficieny throughout the 72 months period.

The second limitation of the study was that only secondary data were used in the study to assess the effect of low-cost carriers on airline performance as well as the influence of route characteristics as a mediator on that relationships. The original purpose for which the data were maintained by KCAA could have been different from that of the researcher.

5.5 Suggestions for Further Research

Since the network efficiency of airlines at the formative stages are likely to be far much lower compared to the maturity stages, future analysis should consider the use of weighting averages in the analysis. Longitudinal methods such as Generalized Methods of Moments may be used.

Future studies should be designed with a view to interviewing the airlines directors to ascertain the exact airlines management' intentions towards enhancing fleet efficiency in line with shorter turn-around times, and enhanced fleet capacity.

REFERENCES

Adeloye, A. J. and Montaseri, M. (2002). Preliminary streamflow data analyses prior to water resources planning study. *Hydrological Sciences Journal, **47*(5),**679-692.

Allison, P.D. (2009) Multiple Regression: A Primer. Pine Forge Press, Thousand Oaks, CA.

Andrew, G. (2013). *Statistical modelling, causal inference and social science: What are the key assumptions of linear regression?* Accessed at http://andrewgelman. com/2013/08/04/19470/ on 10/04/2016 at 11.00 am.

Babikian, R., Lukacho, S. P., and Waitz, I. A. (2002). The historical fuel efficiency characteristics of regional aircraft from technological, operational, and cost perspectives. *Journal of Air Transport Management, 8,* 389-400.

Babbie, E. R. (2009). *The practice of social research (12th ed.).* Wadsworth. 436 – 440.

Barbara, K. (2006). *What is research design? The context of design. Performance studies methods*. New York University.

Baron, R., and Kenny, D. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations.

Bart, C. (2011). *Exploratory, descriptive and causal research designs.* Retrieved from http://www.slideshare.net/RubayetHassan1/3-types-of-marketing-research-designs-exploratory-descriptive-causal on 05.01.2014 at 10.21pm.

Beasley, M. T. (2012). Power in mediation analysis. *Multiple Linear Regression Viewpoints, 38*(2), 17 – 23.

Belobaba, P., Odoni, A. and Barnhart, C. ((2009). *The global airline industry: library of flight series.* New York: John Wiley & Sons,

Besanko, D., Dranove, D., Shanley, M., and Schaefer, S. (2004). *Economics of strategy.* (3rd ed.). New York: John Wiley and Sons.

Bhaskara, V. (2014). *Has the spirit effect replaced the southwest effect?* Accessed at http://airwaysnews.com/blog/2013/07/20/has-the-spirit-effect-replaced-the-southwest-effect/ on 23.12.2014 at 12.05pm.

Biesanz, J. C., Falk, C. F., & Savalei, V. (2010). Assessing mediational models: Testing and interval estimation for indirect effects. *Multivariate Behavioral Research, 45*(4), 661-701.

Borenstein, S. (2011, November 12). *What happened to airline market power?* Duke University. Retrieved from http://www.pdfdrive.net/what-happened-to-airline-market-power-duke-university-e3115817.html accessed on 11.10.20 14 at 10.00am.

Bruderl, J. (2005, March). *Panel data analysis*. Lecture notes. University of Mannheim. Retrieved from http://www.sowi.uni-mannheim.de/lehrstuehle/ lessm/veranst/ Panelanalyse.pdf on 17/05/2015 at 12.06pm.

Brueckner, J. K. (2004). Network structure and airline scheduling. *Journal of Industrial Economics, 52,* 291-311.

Business Traveller. (2011, January 30). *A frica's low cost carriers – a rare breed.* Retrieved from http://www.businesstravellerafrica.co.za/archive/ 2011/april -2011-2/special-reports/africaa-s-low-cost-carriers-a-a-rare-breed accessed at 28.04.2014 at 09.55 am.

Campisi, D., Costa, R., and Mancuso, P. (2010). The effects of low cost airlines growth in Italy. *Modern Economy, 1*(2), 59-67.

Chowdhury, E. (2007). *Low cost carriers: How are they changing the market dynamics of the U.S. airline industry?* An Honours essay, Department of Economics, Carleton University. Ottawa, Ontario.

Cohen, J., and Cohen, P. (1983). *Applied multiple regression/correlation analysis for the behavioral sciences.* (2nd ed.). Hillsdale, NJ: Erlbaum.

Cohen, J., Cohen, P., West, S., and Aiken, L. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Damuri, Y. R., and Anas, T. (2005, October). *Strategic directions for ASEAN airlines in a globalizing world: The emergence of low cost carriers in South East Asia.* Retrieved from http://aadcp2.org/file/04-008-FinalLCCs.pdf on 03.02.2014 at 10.11am.

Doane, D. P., and Lori, E. S. (2011). Measuring skewness: A forgotten statistic? *Journal of Statistics Education, 19*(2), 1-18.

Dresner, M., Lin, J. C., and Windle, R. (1996). The impact of low-cost carriers on airport and route competition. *Journal of Transport Economics and Policy, 30* (3), 309-328.

Dresner, M. (2013, January 8). *Low-cost carriers*. Tokyo, Japan: University of Maryland.

Engle, R. F., and Granger, C. W. J. (March, 1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica, 55*(2), 251-276.

Fairchild, A., and Mackinnon, D. (2010). *General model for testing mediation and moderation effects.* New York: US National Library of Medicine.

Field, A.P. (2009) Discovering Statistics Using SPSS. 3rd Edition, SAGE, London.

Fu, L. (2003). Analytical model for paratransit capacity and quality-of-service analysis. *In Transportation Research Record: Journal of the Transportation Research Board, No. 1841, TRB, National Research Council.* 81–89. Washington D.C.

Fu, L., and Ishkhanov, G. (2004). *Fleet size and mix optimization for paratransit services*. Ontario: University of Waterloo.

Gok, Y. S. (2014). *Scheduling of aircraft turnaround operations using mathematical modelling: Turkish low-cost airline as a case study.* Master of Science Dissertation, Air Transport Management Department, Coventry University.

Govindarajan, M. (2015) *Marketing management - concepts, cases, challenges and trends.* (2nd ed.). New York: Mc-Graw Hill Companies.

Gujarati, D. N. (2004). *Basic econometrics.* (4th ed.). New York: Mc-Graw Hill Companies.

Gujarati, D. N., and Porter, D. C. (2009). *Basic Econometrics* (5th ed.). Boston: McGraw-Hill Irwin.

Hansen, B. E. (2014). *Econometrics*. (2nd ed.). Department of Economics. University of Wisconsin.

Hlouskova, J., and Wagner, M. (2005, April). *The performance of panel unit root and stationarity tests*. San Domenico, Italy: European University Institute.

Holmbeck, G. (1997). Toward terminological, conceptual, and statistical clarity in the study of mediators and moderators: Examples from the child-clinical and pediatric psychology literatures. *Journal of Consulting and Clinical Psychology, 4,* 599–610.

Hoyle, R. H., and Robinson, J. I. (2003). *Mediated and moderated effects in social psychological research: Measurement, design, and analysis issues.* Thousand Oaks, CA: Sage.

IATA Economics. (2013, January 14). *Airlines financial monitor*. Retrieved from http://www.iata.org/economics on Jan 07, 2014 at 10.33 am.

IATA. (2015). *Passenger demand maintains historic growth rates in 2013.* Geneva, Switzerland: International Air Transport Association (IATA). Retrieved from http://www.iata.org/pressroom/pr/pages/2014-02-06-01.aspx 26/05/2015 at 11.12pm.

InterVistas Consulting Group. (2014, July). *Transforming intra-African air connectivity: The economic benefits of implementing the Yamoussoukro decision.* Geneva: IATA.

Israel, M. (2015). *International low-cost airline market research*. Germany: Tarmac Aviation.

Jenatabali, H., and Ismail, N. (2007). The determination of load factors in the airline industry. *International Review of Business Research Papers, 3*(4), 125-133.

Jushan, B., and Serena, N. (2005, January). Tests for skewness, kurtosis, and normality for time series data. *Journal of Business & Economic Statistics, 23*(1), 49 – 60.

Kalaian, A., and Rafa, M. (2008). Longitudinal studies. In *Encyclopedia of survey research methods*. Paul J. Lavrakas, ed. Thousand Oaks, CA: Sage. 440-441.

Kao, C., and Chiang, M. (1997). *On the estimation and inference of a cointegrated regression in panel data*. Working paper, Department of Economics, Syracuse University.

Kenny, D. A. (2015, December 30). *Mediation.* Accessed at http://davidakenny.net/cm/mediate.htm on April, 03, 2016.

Kenny, D. A., and Judd, C. M. (2014). Power anomalies in testing mediation. *Psychological Science, 25,* 334-339.

Kim, J., Kaye, J., and Wright, L. (2001). Moderating and mediating effects in causal effects. *Issues in Mental Health Nursing, 22,* 63 – 75. Washington DC: Taylor & Francis.

Kotler, P. and Keller, K. (2012) *Marketing management* (14th ed.). New York: Mc-Graw Hill Companies.

Kunze, T., Schultz, K., and Fricke, H. (2011). Aircraft Turnaround management in a highly automated 4D flight operations environment. *International Conference on Application and Theory of Automation in Command and Control Systems (ATACCS)*, Barcelona.

Lambin, J. (2007). *Market-driven management: Supplementary web resource material.* New Jersey: Palgrave Macmillan.

Lin, H. (2013). *The phenomenon of airline deregulation: The influence of airline deregulation on the number of passengers*. Master Thesis, Department of Applied Economics, Erasmus School of Economics, Erasmus University. Rotterdam, Netherlands.

Macário, R., Viegas, J., and Reis, V. (2007). *Impact of low cost operation in the development of airports and local economies.* Accessed at http://www.europarl.europa.eu/activities/expert/eStudies.do?language=EN on 17/01/2014 at 11.45 am.

Machiwal, D. and Kumar, J. K. (2012*). Hydrologic time series analysis: theory and practice - methods for testing normality of hydrologic time series.* Netherland: Springer.

MacKinnon, D.P. (2008). *Introduction to statistical mediation analysis.* Mahwah, NJ: Erlbaum.

MacKinnon, D.P., Fairchild, A.J., and Fritz, M.S. (2007). Mediation analysis. *Annual Review of Psychology, 58*, 593-614.

Maddala, G. S. (2001). *Introduction to econometrics*. (3rd ed.). New York: John Wiley and Sons.

Manuela Jr., W. S. (2006). *The impact of airline liberalization on fare: The case of the Philippines.* University of the Philippines.

Mertenes, D., and Vowles, T. (2012). *Southwest effect – decisions and effects of low cost carriers.* New York: Institute of Behavioral and Applied Management.

Mentzer, M. S. (2013). The elusive low cost carrier effect in the trans-Atlantic airline market.*Journal of Aviation Management and Education, 2* (6), 11 – 19.

Mikusheva, A. (2016). *Economics -time series enalysis.*Massachusetts Institute of Technology. Accessed at http://ocw.mit.edu/courses/economics/14-384-time-series-analysis-fall-2013/ on 10/04/2016 at 10.00 am

Mirza, M. (2009, February 12). *Economic impact of airplane turn-times: Airplane utilization and turn-time models provide useful information for schedule, fleet, and operations planning*. Retrieved from www.boeing.com/commercial/ aeromagazine on 29/05/2015 at 6.43pm.

Najda, C. (2003, May 12). *Low-cost carriers and low fares: Competition and concentration in the US airline industry*. Department of Economics, Stanford University. Stanford.

Nau, R. (2016). *Statistical forecasting: Notes on regression and time series analysis*. Fuqua School of Business, Duke University. Accessed at http://people. duke.edu/~rnau/411home.htm on 11/04/2014 at 9.30 am.

Norin, A. (2008). *Airport logistics: Modeling and optimizing the turn-around process.* Dissertation. Masters Thesis No. 1388, Department of Science and Technology, Linkoping University. Sweden.

O'Connell, F. (2008, October). *The business of low-cost carriers and their impact on the industry*. Cranfield University. Retrieved from http://www.euromedtransport. org/En/image.php? id=905 on 35/03/2014 at 10.20am.

O'Connell, J., and Williams, G. (2007). *The strategic response of full service airlines to the low cost carrier threat and the perception of passengers to each type of carrier.* PhD Thesis, School of Engineering, Cranfield University.

Pai, V. (2007, November 5). *On the factors that affect airline flight frequency and aircraft size.* Irvine Department of Economics, University of California.

Pedroni, P. (2000). Fully modified OLS for heterogeneous cointegrated panels. *Nonstationary Panels, Panel Cointegration and Dynamic Panels. Elsevier Science Inc., 15*, 93–130.

Pels, E., and Rietveld, P. (2006). Airline pricing behaviour in the London–Paris market. *Journal of Air Transport Management, 10* (4), 277-281.

Peyrot, M. (1996). Causal analysis: Theory and application. *Journal of Pediatric Psychology, 21*, 3–24.

Phillips, P. C. B. (1986). Understanding spurious regressions in econometrics. *Journal of Econometrics, 33*,311-340.

Phillips, P., and Hansen, B. (1990). Statistical inference in instrumental variables regression with I(1) processes. *Review of Economic Studies, 57,* 99–125.

Phillips, P., and Moon, H. (1999). Linear regression limit theory for nonstationary panel data. *Econometrica, 67,* 1057–1112.

Ployhart, E., and Robert, V. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of Management, 36,* 94-120.

Ramdas, K., and Williams, J. (2008, June 19). *An empirical investigation into the trade- offs that impact on-time performance in the airline industry*. Retrived from https://www.gsb.stanford.edu/sites/default/files/documents/oit_10_08_ramdas.pdf on 28/04/2014 at 11.10 am.

Ramsey, J.B. (1969). Tests for Specification Errors in Classical Linear Least Squares Regression Analysis. *Journal of the Royal Statistical Society: Series B, 31*(2), 350-371.

Rosenstein, D. E. (2013). The changing low-cost airline model: An analysis of spirit airlines. Department of Aviation, Purdue University: E-pubs. Accessed at http://docs.lib.purdue.edu/atgrads/19 on 19/04/2016 at 4.01pm.

Rupp, N. G. (2007, May 20). Further investigations into the causes of flight delays. Department of Economics, East Carolina University Greenville. Retrieved from http://www.ecu.edu/cs-educ/econ/upload/ecu0707.pdf on 2/05/2015 at 03.43pm.

Schofer, J., Nelson, B., Eash, R., Daskin, M., Yang, Y, Wan, H., ..., and Medgyesy, L. (2003). *TCRP report 98: resource requirements for demand-responsive transportation services,*

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. In S. Leinhardt (ed.), Sociological Methodology 1982 (290-312). Washington DC: American Sociological Association.

Startz, R. (2013). *Eviews Illustrated for Version 8.* Irvine CA, USA: IHS Global Inc.

Stevens, J. P. (2009). *Applied multivariate statistics for the social sciences* (5th ed.). New York, NY: Routledge

Styhre, L. (2010). *Capacity utilisation in short sea shipping.* Goteborg, Sweden: Chalmers Reproservice.

Tabachnick, B. G., and Fidell, L. S. (2001). *Using Multivariate Statistics* (4th ed.). Boston: Allin and Bacon Publishers.

Tesfay, Y., and Solibakke, P. (2015, April 16). Spectral density estimation of European airlines load factors for Europe-Middle East and Europe-Far East flights. *European Transportation Res. Review, 7* (14), 1 -14

Thode, H.C. (2002). *Testing for normality.* New York, USA: Marcel Dekker

Tolliver-Nigro, H. (1999). Choosing a shuttle bus: What should agencies look for when purchasing vehicles for their fleets? *Mass Transit, 37*, 42–48.

Trabelsi, S., Cosenza, C., Cruz, L. and Mora-Camino, F. (2013, July). *An operational approach for ground handling management at airports with imperfect information.* 19th International conference on Industrial Engineering and airports operations. Valladolid, Spain: ICIEOM.

Trochim, W. K. (2006). *Research methods – knowledge base*. Accessed at http://www. socialresearchmethods.net/kb/statdesc.php on 03/03/2016 at 10.10 am

Vidovic, A., Steiner, S., and Babic, R. (2007). *Impact of low cost airlines on the European air transport market.* Retrieved from https://bib.irb.hr/datoteka /260325.ICTS_06_vidovic.pdf on 21.12.2013 at 11.36pm.

Vidosavljevic, A., and Tosic, V. (2010). *Modeling of Turnaround Process Using Petri Nets*. ATRS World Conference.

Wang, K., Gong, Q., Fu, X., and Fan, X. (2014). Frequency and aircraft size dynamics in a concentrated growth market: The case of the Chinese domestic market. *Journal of air transport management, 36*, 50 – 58.

Wensveen, J. G. (2011). *Air transportation: A management perspective.* (7th ed.). Burlington, USA: Ashgate publishers.

Windle, R., and Dresner, M. (1995). The short and long run effects of entry on U.S. domestic air routes. *Transportation Journal, 35* (2), 14-25.

Wu, C., and Caves, R. (2004). Modelling and optimization of the turn-around time at an airport. *Transportation planning and technology, 27* (1), 47 – 66.

Wu, D. (2015), *Enplaned Passengers.* https://dwuconsulting.com/air-traffic/articles /enplaned-passengers

Wu, H. (2011). *How to model mediating and moderating effects*. Workshop Series. Center for Family and Demographic Research: CFDR.

Wu, Y. (2013). *The effect of the entry of low cost airlines on price and passenger traffic.* Master Thesis, Erasmus School of Business, Erasmus University, Rotterdam.

http://www.danielsoper.com/statcalc/calculator.aspx?id=31(forFree StatisticsnCalculators

LIST OF APPENDICES

Appendix I: Letter of Introduction

C/O DEPT OF ACCOUNTING AND FINANCE

SCHOOL OF BUSINESS AND ECONOMICS

MASENO UNIVERSITY

P.O. BOX 333

MASENO

04/08/2015

TO WHOM IT MAY CONCERN

ACADEMIC RESEARCH

I am a student at Maseno University in pursuit of PhD in Business Administration course. As part of the requirements I am carrying out this research entitled, "Mediating Role of Route Characteristics on the Relationship Between Low-Cost Carriers' Key Factors and Airline Performance, Kenya". As one of my key sources of data, your assistance and facilitation will be vital in enhancing the success of his analysis, and consequently the findings to be made thereof. Thus, I need some data regarding: arrival and departure times, the type and size of aircraft operated and number of passengers for the periods 2007 – 2012.

If you have any questions about the survey, you can contact me on 0720 731892 or my supervisors through Maseno University. They are Dr. David Oima and Dr. Moses Oginda.

Thank you and best regards.

Yours faithfully,

Mr. Michael O. Aomo

Appendix II: Dummy Tables for the Secondary Data

1. What is the name of the low-cost carrier? ……...
2. What was your fleet size and composition during the period between 2007 – 2012?

Year	**Quarter**	**Fleet Size (total number of aircraft)**	**Composition of the Fleet (indicate types of planes e.g. 6 CRJs, 1 FK50 or 3 DHC 8 etc**	**Fleet Capacity (product of the Fleet size by seating density)**
2007	Jan			
	Feb			
	Mar			
	Apr			
	May			
	Jun			
	Jul			
	Aug			
	Sep			
	Oct			
	Nov			
	Dec			
2008	Jan			
	Feb			
	Mar			
	Apr			
	May			
	Jun			
	Jul			
	Aug			

	Sep			
	Oct			
	Nov			
	Dec			
2009	Jan			
	Feb			
	Mar			
	Apr			
	May			
	Jun			
	Jul			
	Aug			
	Sep			
	Oct			
	Nov			
	Dec			
2010	Jan			
	Feb			
	Mar			
	Apr			
	May			
	Jun			
	Jul			
	Aug			
	Sep			
	Oct			
	Nov			

	Dec			
2011	Jan			
	Feb			
	Mar			
	Apr			
	May			
	Jun			
	Jul			
	Aug			
	Sep			
	Oct			
	Nov			
	Dec			
2012	Jan			
	Feb			
	Mar			
	Apr			
	May			
	Jun			
	Sep			
	Oct			
	Nov			
	Dec			

3. Indicate in the schedule below the following 5 items: your turn-time, flight frequency, load factor, enplanement and carriers' market share during the period between 2007 – 2012.

Year	Month	Turn-time	Flight frequency	Laod factor	Enplanement	Market share
2007	Jan					
	Feb					
	Mar					
	Apr					
	May					
	Jun					
	Jul					
	Aug					
	Sep					
	Oct					
	Nov					
	Dec					
2008	Jan					
	Feb					
	Mar					
	Apr					
	May					
	Jun					
	Jul					
	Aug					
	Sep					
	Oct					
	Nov					
	Dec					
2009	Jan					
	Feb					

	Mar					
	Apr					
	May					
	Jun					
	Jul					
	Aug					
	Sep					
	Oct					
	Nov					
	Dec					
2010	Jan					
	Feb					
	Mar					
	Apr					
	May					
	Jun					
	Jul					
	Aug					
	Sep					
	Oct					
	Nov					
	Dec					
2011	Jan					
	Feb					
	Mar					
	Apr					
	May					

	Jun					
	Jul					
	Aug					
	Sep					
	Oct					
	Nov					
	Dec					
2012	Jan					
	Feb					
	Mar					
	Apr					
	May					
	Jun					
	Sep					
	Oct					
	Nov					
	Dec					

END OF THE SCHEDULES

THANK YOU

Appendix III: Collected Data sheet 1

4. What is the name of the low-cost carrier? ……**Fly540**……..……...
5. What was your fleet size and composition during the period between 2007 – 2012?

Year	**Quarter**	**Fleet Size (total number of aircraft)**	**Composition of the Fleet (indicate types of planes e.g. 6 CRJs, 1 FK50 or 3 DHC 8 etc**	**Fleet Capacity** **(product of the Fleet size by seating density)**
2007	Jan	1	1 ATR42	(48*1) = 48
	Feb	1	1 ATR42	(48*1) = 48
	Mar	1	1 ATR42	(48*1) = 48
	Apr	1	1 ATR42	(48*1) = 48
	May	1	1 ATR42	(48*1) = 48
	Jun	1	1 ATR42	(48*1) = 48
	Jul	1	1 ATR42	(48*1) = 48
	Aug	1	1 ATR42	(48*1) = 48
	Sep	1	1 ATR42	(48*1) = 48
	Oct	2	2 ATR42	(48*2) = 96
	Nov	2	2 ATR42	(48*2) = 96
	Dec	2	2 ATR42	(48*2) = 96
2008	Jan	2	2 ATR42	(48*2) = 96
	Feb	2	2 ATR42	(48*2) = 96
	Mar	2	2 ATR42	(48*2) = 96
	Apr	2	2 ATR42	(48*2) = 96
	May	2	2 ATR42	(48*2) = 96
	Jun	2	2 ATR42	(48*2) = 96
	Jul	2	2 ATR42	(48*2) = 96
	Aug	2	2 ATR42	(48*2) = 96

	Sep	2	2 ATR42	(48*2) = 96
	Oct	2	2 ATR42	(48*2) = 96
	Nov	2	2 ATR42	(48*2) = 96
	Dec	2	2 ATR42	(48*2) = 96
2009	Jan	2	2 ATR42	(48*2) = 96
	Feb	2	2 ATR42	(48*2) = 96
	Mar	2	2 ATR42	(48*2) = 96
	Apr	2	2 ATR42	(48*2) = 96
	May	2	2 ATR42	(48*2) = 96
	Jun	3	2 ATR42, 1 DHC 8	(48*2) + (40*1) = 136
	Jul	3	2 ATR42, 1 DHC 8	(48*2) + (40*1) = 136
	Aug	3	2 ATR42, 1 DHC 8	(48*2) + (40*1) = 136
	Sep	4	2 ATR42, 2 DHC 8	(48*2) + (40*2) = 176
	Oct	4	2 ATR42, 2 DHC 8	(48*2) + (40*2) = 176
	Nov	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271
	Dec	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271
2010	Jan	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271
	Feb	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271
	Mar	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271
	Apr	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271
	May	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271
	Jun	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271

	Jul	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271
	Aug	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271
	Sep	6	2 ATR42, 3 DHC 8, I CRJ1	(48*2) + (40*3)+(55*1) = 271
	Oct	7	2 ATR42, 3DHC 8, I CRJ1, 1 C208	(48*2) + (40*3)+(55*1) + (13*1) = 284
	Nov	7	2 ATR42, 3DHC 8, I CRJ1, 1 C208	(48*2) + (40*3)+(55*1) + (13*1) = 284
	Dec	7	2 ATR42, 3DHC 8, I CRJ1, 1 C208	(48*2) + (40*3)+(55*1) + (13*1) = 284
2011	Jan	7	2 ATR42, 3DHC 8, I CRJ1, 1 C208	(48*2) + (40*3)+(55*1) + (13*1) = 284
	Feb	7	2 ATR42, 3DHC 8, I CRJ1, 1 C208	(48*2) + (40*3)+(55*1) + (13*1) = 284
	Mar	7	2 ATR42, 3DHC 8, I CRJ1, 1 C208	(48*2) + (40*3)+(55*1) + (13*1) = 284
	Apr	7	2 ATR42, 3DHC 8, I CRJ1, 1 C208	(48*2) + (40*3)+(55*1) + (13*1) = 284
	May	7	2 ATR42, 3DHC 8, I CRJ1, 1 C208	(48*2) + (40*3)+(55*1) + (13*1) = 284
	Jun	7	2 ATR42, 3DHC 8, I CRJ1, 1 C208	(48*2) + (40*3)+(55*1) + (13*1) = 284
	Jul	8	2 ATR42, 3DHC 8, 2CRJ1, 1 C208	(48*2) + (40*3)+(55*2) + (13*1) = 339
	Aug	8	2 ATR42, 3DHC 8, 2CRJ1, 1 C208	(48*2) + (40*3)+(55*2) + (13*1) = 339
	Sep	8	2 ATR42, 3DHC 8, 2CRJ1, 1 C208	(48*2) + (40*3)+(55*2) + (13*1) = 339
	Oct	8	2 ATR42, 3DHC 8, 2CRJ1, 1 C208	(48*2) + (40*3)+(55*2) + (13*1) = 339
	Nov	8	2 ATR42, 3DHC 8, 2CRJ1,	(48*2) + (40*3)+(55*2) + (13*1) =

			1 C208	339
	Dec	9	2 ATR42, 3DHC 8, 2CRJ1, 2 C208	(48*2) + (40*3)+(55*2) + (13*2) = 352
2012	Jan	9	2 ATR42, 3DHC 8, 2CRJ1, 2 C208	(48*2) + (40*3)+(55*2) + (13*2) = 352
	Feb	9	2 ATR42, 3DHC 8, 2CRJ1, 2 C208	(48*2) + (40*3)+(55*2) + (13*2) = 352
	Mar	9	2 ATR42, 3DHC 8, 2CRJ1, 2 C208	(48*2) + (40*3)+(55*2) + (13*2) = 352
	Apr	10	2 ATR42, 3DHC 8, 3CRJ1, 2 C208	(48*2) + (40*3)+(55*3) + (13*2) = 407
	May	10	2 ATR42, 3DHC 8, 3CRJ1, 2 C208	(48*2) + (40*3)+(55*3) + (13*2) = 407
	Jun	10	2 ATR42, 3DHC 8, 3CRJ1, 2 C208	(48*2) + (40*3)+(55*3) + (13*2) = 407
	Sep	10	2 ATR42, 3DHC 8, 3CRJ1, 2 C208	(48*2) + (40*3)+(55*3) + (13*2) = 407
	Oct	10	2 ATR42, 3DHC 8, 3CRJ1, 2 C208	(48*2) + (40*3)+(55*3) + (13*2) = 407
	Nov	10	2 ATR42, 3DHC 8, 3CRJ1, 2 C208	(48*2) + (40*3)+(55*3) + (13*2) = 407
	Dec	10	2 ATR42, 3DHC 8, 3CRJ1, 2 C208	(48*2) + (40*3)+(55*3) + (13*2) = 407

6. Indicate in the schedule below the following 5 items: your turn-time, flight frequency, load factor, enplanement and carriers' market share during the period between 2007 – 2012.

Year	Month	Turn-time	Flight frequency	Load factor	Market share	Enplanement
2007	Jan	21	66	39	3	2471

	Feb	28	68	43	3	2807
	Mar	29	66	43	4	2724
	Apr	22	70	48	4	3225
	May	29	68	57	5	3720
	Jun	25	69	56	5	3709
	Jul	26	72	53	6	3663
	Aug	29	70	54	6	3628
	Sep	29	71	59	6	4021
	Oct	21	72	55	7	3801
	Nov	27	73	69	6	4835
	Dec	27	70	70	8	4704
2008	Jan	26	71	60	7	4089
	Feb	24	90	65	7	5616
	Mar	22	93	69	7	6160
	Apr	28	183	61	6	10716
	May	26	185	60	7	10656
	Jun	27	202	61	6	11829
	Jul	27	214	60	7	12326
	Aug	25	213	63	7	12882
	Sep	26	220	64	9	13516
	Oct	25	222	65	8	13852
	Nov	26	217	71	7	14790
	Dec	25	224	79	8	16988
2009	Jan	24	225	58	7	12528
	Feb	25	223	62	8	13272
	Mar	25	226	63	9	13668
	Apr	23	228	63	8	13789

	May	21	227	68	9	14818
	Jun	24	226	61	9	12499
	Jul	23	229	60	10	12457
	Aug	24	227	61	11	12554
	Sep	24	228	63	10	12640
	Oct	28	225	62	10	12276
	Nov	22	230	72	11	14959
	Dec	29	232	78	12	16346
2010	Jan	24	234	57	11	12048
	Feb	23	230	63	11	13089
	Mar	20	238	60	12	12899
	Apr	22	236	64	12	13643
	May	18	239	62	12	13385
	Jun	19	237	63	12	13487
	Jul	20	236	65	13	13857
	Aug	27	236	70	13	14923
	Sep	21	237	70	14	14986
	Oct	20	238	68	16	13132
	Nov	20	240	70	16	13632
	Dec	30	234	82	17	15569
2011	Jan	19	238	63	15	12166
	Feb	19	246	68	15	13573
	Mar	20	244	65	16	12869
	Apr	18	248	66	16	13281
	May	19	248	65	16	13080
	Jun	18	249	66	15	13335
	Jul	17	254	66	15	14207

	Aug	18	254	66	16	14207
	Sep	22	251	69	17	14677
	Oct	18	259	67	18	14706
	Nov	19	258	69	17	15087
	Dec	20	252	77	16	15178
2012	Jan	18	258	65	13	13117
	Feb	21	251	70	14	13743
	Mar	17	261	71	16	14495
	Apr	17	301	68	16	16660
	May	17	302	68	17	16716
	Jun	18	298	70	17	16980
	Jul	20	292	69	16	16400
	Aug	17	302	72	18	17699
	Sep	19	300	74	19	18070
	Oct	18	298	73	18	17707
	Nov	17	305	75	19	18620
	Dec	21	293	81	20	19318

END OF THE SCHEDULES 1

Appendix IV: Collected data sheet 2

7. What is the name of the low-cost carrier? ……**JetLink**……..……...
8. What was your fleet size and composition during the period between 2007 – 2012?

Year	**Quarter**	**Fleet Size (total number of aircraft)**	**Composition of the Fleet (indicate types of planes e.g. 6 CRJs, 1 FK50 or 3 DHC 8 etc**	**Fleet Capacity (product of the Fleet size by seating density)**
2007	Jan	1	1 FK28	(68*1) = 68
	Feb	1	1 FK28	(68*1) = 68
	Mar	1	1 FK28	(68*1) = 68
	Apr	1	1 FK28	(68*1) = 68
	May	1	1 FK28	(68*1) = 68
	Jun	1	1 FK28	(68*1) = 68
	Jul	1	1 FK28	(68*1) = 68
	Aug	1	1 FK28	(68*1) = 68
	Sep	1	1 FK28	(68*1) = 68
	Oct	1	1 FK28	(68*1) = 68
	Nov	1	1 FK28	(68*1) = 68
	Dec	1	1 FK28	(68*1) = 68
2008	Jan	1	1 FK28	(68*1) = 68
	Feb	3	1 FK28, 2 CRJ1s	(68*1)+(55*2)=178
	Mar	4	1 FK28, 3 CRJ1s	(68*1)+(55*3)=233
	Apr	4	1 FK28, 3 CRJ1s	(68*1)+(55*3)=233
	May	4	1 FK28, 3 CRJ1s	(68*1)+(55*3)=233
	Jun	4	1 FK28, 3 CRJ1s	(68*1)+(55*3)=233
	Jul	4	1 FK28, 3 CRJ1s	(68*1)+(55*3)=233
	Aug	4	1 FK28, 3 CRJ1s	(68*1)+(55*3)=233

	Sep	4	1 FK28, 3 CRJ1s	(68*1)+(55*3)=233
	Oct	4	1 FK28, 3 CRJ1s	(68*1)+(55*3)=233
	Nov	4	1 FK28, 3 CRJ1s	(68*1)+(55*3)=233
	Dec	4	1 FK28, 3 CRJ1s	(68*1)+(55*3)=233
2009	Jan	5	1 FK28, 4 CRJ1s	(68*1)+(55*4)=288
	Feb	6	1 FK28, 5 CRJ1s	(68*1)+(55*5)=343
	Mar	6	1 FK28, 5 CRJ1s	(68*1)+(55*5)=343
	Apr	6	1 FK28, 5 CRJ1s	(68*1)+(55*5)=343
	May	6	1 FK28, 5 CRJ1s	(68*1)+(55*5)=343
	Jun	6	1 FK28, 5 CRJ1s	(68*1)+(55*5)=343
	Jul	6	1 FK28, 5 CRJ1s	(68*1)+(55*5)=343
	Aug	6	1 FK28, 5 CRJ1s	(68*1)+(55*5)=343
	Sep	6	1 FK28, 5 CRJ1s	(68*1)+(55*5)=343
	Oct	6	1 FK28, 5 CRJ1s	(68*1)+(55*5)=343
	Nov	6	1 FK28, 5 CRJ1s	(68*1)+(55*5)=343
	Dec	8	1 FK28, 7 CRJ1s	(68*1)+(55*7)=453
2010	Jan	8	1 FK28, 7 CRJ1s	(68*1)+(55*7)=453
	Feb	8	1 FK28, 7 CRJ1s	(68*1)+(55*7)=453
	Mar	8	1 FK28, 7 CRJ1s	(68*1)+(55*7)=453
	Apr	9	1 FK28, 8 CRJ1s	(68*1)+(55*8)=508
	May	9	1 FK28, 8 CRJ1s	(68*1)+(55*8)=508
	Jun	9	1 FK28, 8 CRJ1s	(68*1)+(55*8)=508
	Jul	9	1 FK28, 8 CRJ1s	(68*1)+(55*8)=508
	Aug	9	1 FK28, 8 CRJ1s	(68*1)+(55*8)=508
	Sep	9	1 FK28, 8 CRJ1s	(68*1)+(55*8)=508
	Oct	9	1 FK28, 8 CRJ1s	(68*1)+(55*8)=508
	Nov	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563

	Dec	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
2011	Jan	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Feb	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Mar	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Apr	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	May	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Jun	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Jul	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Aug	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Sep	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Oct	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Nov	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Dec	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
2012	Jan	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Feb	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Mar	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Apr	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	May	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Jun	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Jul	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Aug	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Sep	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Oct	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Nov	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563
	Dec	10	1 FK28, 9 CRJ1s	(68*1)+(55*9)=563

9. Indicate in the schedule below the following 5 items: your turn-time, flight frequency, load factor, enplanement and carriers' market share during the period between 2007 – 2012.

Year	Month	Turn-time	Flight frequency	Load factor	Market share	Enplanement
2007	Jan	19	60	50	4	4080
	Feb	22	56	50	4	3808
	Mar	40	56	51	5	3884
	Apr	45	58	53	5	4180
	May	47	56	52	5	3960
	Jun	56	60	56	6	4569
	Jul	52	62	58	8	4890
	Aug	55	56	57	7	4341
	Sep	41	54	60	6	4406
	Oct	56	56	65	9	4950
	Nov	53	59	78	7	6258
	Dec	53	60	89	12	7262
2008	Jan	40	69	50	8	4692
	Feb	55	114	53	8	7169
	Mar	51	117	59	9	8041
	Apr	51	116	60	4	8108
	May	52	115	62	5	8306
	Jun	50	116	62	4	8378
	Jul	38	120	61	4	8527
	Aug	50	116	62	4	8378
	Sep	42	122	63	5	8954
	Oct	53	120	72	5	10065

	Nov	49	121	79	5	11136
	Dec	51	120	88	5	12302
2009	Jan	38	180	60	6	12441
	Feb	49	184	60	7	12622
	Mar	48	190	63	9	13685
	Apr	48	192	62	7	13610
	May	46	202	63	8	14550
	Jun	49	193	61	9	13460
	Jul	37	196	65	11	14566
	Aug	47	200	65	13	14863
	Sep	46	202	63	11	14550
	Oct	50	190	66	11	14337
	Nov	48	202	75	12	17321
	Dec	51	226	87	16	22267
2010	Jan	44	258	52	13	15193
	Feb	36	278	53	14	16686
	Mar	46	271	56	15	17186
	Apr	50	256	52	13	15027
	May	47	254	63	16	18064
	Jun	51	248	62	15	17357
	Jul	40	260	65	17	19078
	Aug	40	264	66	17	19669
	Sep	39	265	66	18	19744
	Oct	37	281	74	28	23474
	Nov	37	284	77	28	24623
	Dec	38	285	87	30	27919
2011	Jan	37	288	60	23	19457

	Feb	40	285	61	21	19575
	Mar	40	288	67	27	21727
	Apr	37	290	66	25	21551
	May	49	287	65	25	21005
	Jun	39	290	68	24	22204
	Jul	38	293	70	24	23094
	Aug	34	297	69	25	23075
	Sep	35	298	70	27	23488
	Oct	35	300	77	31	26010
	Nov	41	299	79	29	26597
	Dec	49	301	89	31	30164
2012	Jan	38	310	63	21	21990
	Feb	34	313	67	24	23613
	Mar	34	312	72	27	25294
	Apr	37	316	74	25	26330
	May	33	316	73	26	25974
	Jun	32	325	75	27	27446
	Jul	34	330	74	26	27496
	Aug	31	335	76	29	28667
	Sep	40	331	75	29	27952
	Oct	31	342	77	30	29652
	Nov	29	149	76	13	12750
	Dec	0	0	0	0	0

END OF THE SCHEDULES

THANK YOU

(Source: Field data, 2016)

Appendix V: An Outlook of the Panel Data Table

Airline	Time Period	Year	Month	TNTM	FLTC	FREQ	LDFC	CRMS	ENPL
1	1	2007	Jan	21	48	66	39	3	2471
1	2		Feb	28	48	68	43	3	2807
1	3		Mar	29	48	66	43	4	2724
1	4		Apr	22	48	70	48	4	3225
1	5		May	29	48	68	57	5	3720
1	6		Jun	25	48	69	56	5	3709
1	7		Jul	26	48	72	53	6	3663
1	8		Aug	29	48	70	54	6	3628
1	9		Sep	29	48	71	59	6	4021
1	10		Oct	21	96	72	55	7	3801
1	11		Nov	27	96	73	69	6	4835
1	12		Dec	27	96	70	70	8	4704
1	13	2008	Jan	26	96	71	60	7	4089
1	14		Feb	24	96	90	65	7	5616
1	15		Mar	22	96	93	69	7	6160
1	16		Apr	28	96	183	61	6	10716
1	17		May	26	96	185	60	7	10656
1	18		Jun	27	96	202	61	6	11829
1	19		Jul	27	96	214	60	7	12326
1	20		Aug	25	96	213	63	7	12882
1	21		Sep	26	96	220	64	9	13516
1	22		Oct	25	96	222	65	8	13852
1	23		Nov	26	96	217	71	7	14790
1	24		Dec	25	96	224	79	8	16988
1	25	2009	Jan	24	96	225	58	7	12528
1	26		Feb	25	96	223	62	8	13272
1	27		Mar	25	96	226	63	9	13668

1	28		Apr	23	96	228	63	8	13789
1	29		May	21	96	227	68	9	14818
1	30		Jun	24	136	226	61	9	12499
1	31		Jul	23	136	229	60	10	12457
1	32		Aug	24	136	227	61	11	12554
1	33		Sep	24	176	228	63	10	12640
1	34		Oct	28	176	225	62	10	12276
1	35		Nov	22	271	230	72	11	14959
1	36		Dec	29	271	232	78	12	16346
1	37	2010	Jan	24	271	234	57	11	12048
1	38		Feb	23	271	230	63	11	13089
1	39		Mar	20	271	238	60	12	12899
1	40		Apr	22	271	236	64	12	13643
1	41		May	18	271	239	62	12	13385
1	42		Jun	19	271	237	63	12	13487
1	43		Jul	20	271	236	65	13	13857
1	44		Aug	27	271	236	70	13	14923
1	45		Sep	21	271	237	70	14	14986
1	46		Oct	20	284	238	68	16	13132
1	47		Nov	20	284	240	70	16	13632
1	48		Dec	30	284	234	82	17	15569
1	49	2011	Jan	19	284	238	63	15	12166
1	50		Feb	19	284	246	68	15	13573
1	51		Mar	20	284	244	65	16	12869
1	52		Apr	18	284	248	66	16	13281
1	53		May	19	284	248	65	16	13080
1	54		Jun	18	284	249	66	15	13335

1	55		Jul	17	339	254	66	15	14207
1	56		Aug	18	339	254	66	16	14207
1	57		Sep	22	339	251	69	17	14677
1	58		Oct	18	339	259	67	18	14706
1	59		Nov	19	339	258	69	17	15087
1	60		Dec	20	352	252	77	16	15178
1	61	2012	Jan	18	352	258	65	13	13117
1	62		Feb	21	352	251	70	14	13743
1	63		Mar	17	352	261	71	16	14495
1	64		Apr	17	407	301	68	16	16660
1	65		May	17	407	302	68	17	16716
1	66		Jun	18	407	298	70	17	16980
1	67		Jul	20	407	292	69	16	16400
1	68		Aug	17	407	302	72	18	17699
1	69		Sep	19	407	300	74	19	18070
1	70		Oct	18	407	298	73	18	17707
1	71		Nov	17	407	305	75	19	18620
1	72		Dec	21	407	293	81	20	19318
2	1	2007	Jan	19	68	60	50	4	4080
2	2		Feb	22	68	56	50	4	3808
2	3		Mar	40	68	56	51	5	3884
2	4		Apr	45	68	58	53	5	4180
2	5		May	47	68	56	52	5	3960
2	6		Jun	56	68	60	56	6	4569
2	7		Jul	52	68	62	58	8	4890
2	8		Aug	55	68	56	57	7	4341
2	9		Sep	41	68	54	60	6	4406

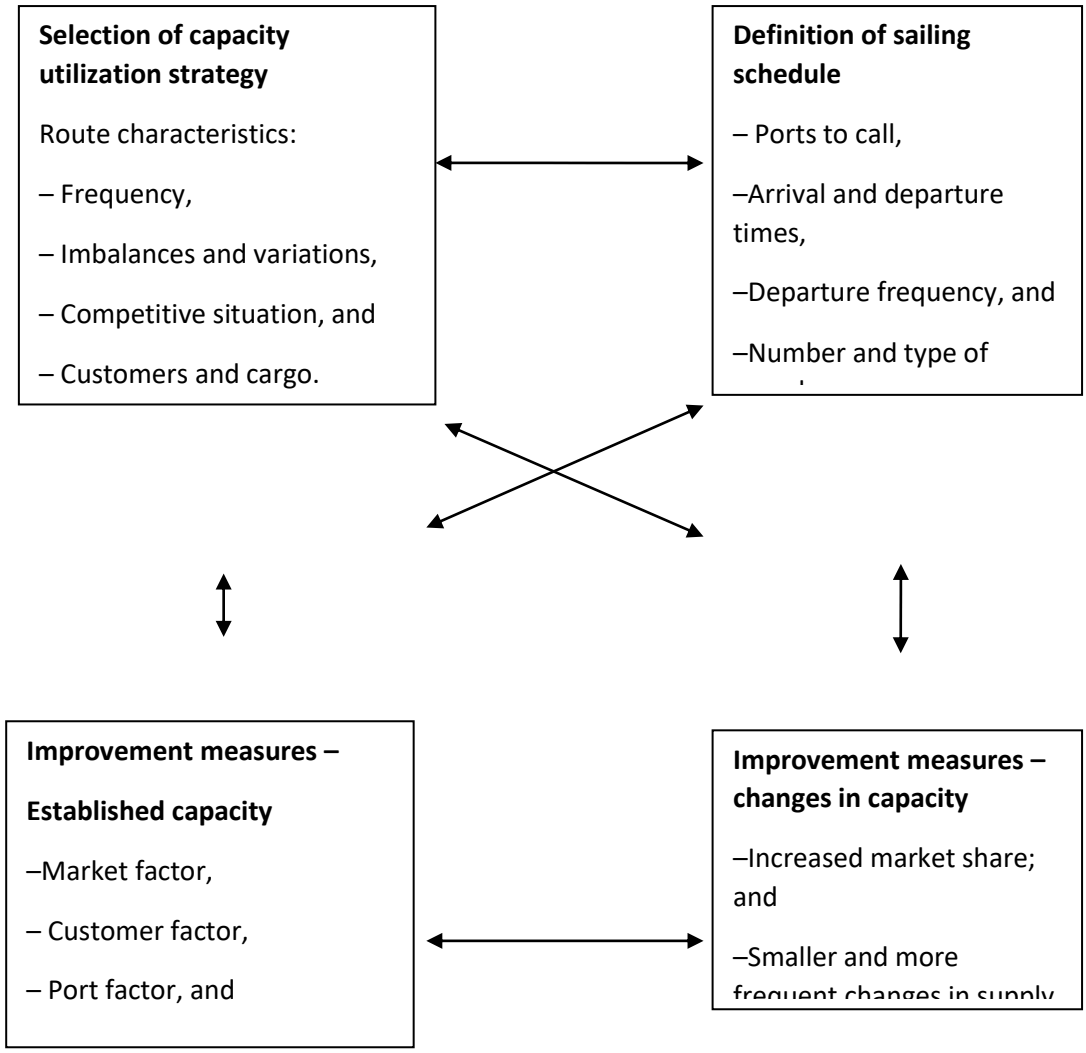
2	10		Oct	56	68	56	65	9	4950
2	11		Nov	53	68	59	78	7	6258
2	12		Dec	53	68	60	89	12	7262
2	13	2008	Jan	40	68	69	50	8	4692
2	14		Feb	55	178	114	53	8	7169
2	15		Mar	51	233	117	59	9	8041
2	16		Apr	51	233	116	60	4	8108
2	17		May	52	233	115	62	5	8306
2	18		Jun	50	233	116	62	4	8378
2	19		Jul	38	233	120	61	4	8527
2	20		Aug	50	233	116	62	4	8378
2	21		Sep	42	233	122	63	5	8954
2	22		Oct	53	233	120	72	5	10065
2	23		Nov	49	233	121	79	5	11136
2	24		Dec	51	233	120	88	5	12302
2	25	2009	Jan	38	288	180	60	6	12441
2	26		Feb	49	343	184	60	7	12622
2	27		Mar	48	343	190	63	9	13685
2	28		Apr	48	343	192	62	7	13610
2	29		May	46	343	202	63	8	14550
2	30		Jun	49	343	193	61	9	13460
2	31		Jul	37	343	196	65	11	14566
2	32		Aug	47	343	200	65	13	14863
2	33		Sep	46	343	202	63	11	14550
2	34		Oct	50	343	190	66	11	14337
2	35		Nov	48	343	202	75	12	17321
2	36		Dec	51	453	226	87	16	22267

2	37	2010	Jan	44	453	258	52	13	15193
2	38		Feb	36	453	278	53	14	16686
2	39		Mar	46	453	271	56	15	17186
2	40		Apr	50	508	256	52	13	15027
2	41		May	47	508	254	63	16	18064
2	42		Jun	51	508	248	62	15	17357
2	43		Jul	40	508	260	65	17	19078
2	44		Aug	40	508	264	66	17	19669
2	45		Sep	39	508	265	66	18	19744
2	46		Oct	37	508	281	74	28	23474
2	47		Nov	37	563	284	77	28	24623
2	48		Dec	38	563	285	87	30	27919
2	49	2011	Jan	37	563	288	60	23	19457
2	50		Feb	40	563	285	61	21	19575
2	51		Mar	40	563	288	67	27	21727
2	52		Apr	37	563	290	66	25	21551
2	53		May	49	563	287	65	25	21005
2	54		Jun	39	563	290	68	24	22204
2	55		Jul	38	563	293	70	24	23094
2	56		Aug	34	563	297	69	25	23075
2	57		Sep	35	563	298	70	27	23488
2	58		Oct	35	563	300	77	31	26010
2	59		Nov	41	563	299	79	29	26597
2	60		Dec	49	563	301	89	31	30164
2	61	2012	Jan	38	563	310	63	21	21990
2	62		Feb	34	563	313	67	24	23613
2	63		Mar	34	563	312	72	27	25294

2	64		Apr	37	563	316	74	25	26330
2	65		May	33	563	316	73	26	25974
2	66		Jun	32	563	325	75	27	27446
2	67		Jul	34	563	330	74	26	27496
2	68		Aug	31	563	335	76	29	28667
2	69		Sep	40	563	331	75	29	27952
2	70		Oct	31	563	342	77	30	29652
2	71		Nov	29	563	149	76	13	12750
2	72		Dec	0	563	0	0	0	0

(Source: Field data, 2016)

Appendix VI: Framework for Enhancement of Vessel Capacity Utilisation



(Source: Styhre, 2010)

Appendix VII: Panel Unit Root Test Results

The following results showed that two series (turn-time (TNTM) and load factor (LDFC)) were stationary at order 0, while the other four variables (fleet capacity (FLTC), flight frequency (FREQ), carriers' market share (CRMS) and enplanement (ENPL)) were stationary at order 1; implying that the direct associations of the variables would yield short-run equilibrium relationships.

Panel Unit Root Test Results for the zero-order CRMS series

Null Hypothesis: Unit root (individual unit root process)

Series: CRMS

Date: 03/28/16 Time: 09:28

Sample: 1 144

Exogenous variables: Individual effects

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 142

Cross-sections included: 2

Method	Statistic	Prob.**
PP - Fisher Chi-square	1.74882	0.7818
PP - Choi Z-stat	0.79740	0.7874

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate Phillips-Perron test results CRMS

Cross Section	Prob.	Bandwidth	Obs
FFV	0.8848	8.0	71
JLX	0.4714	5.0	71

Panel Unit Root Test Results for the first-order CRMS series

Null Hypothesis: Unit root (individual unit root process)

Series: D(CRMS)

Date: 03/28/16 Time: 09:30

Sample: 1 144

Exogenous variables: Individual effects

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 140

Cross-sections included: 2

Method	Statistic	Prob.**
PP - Fisher Chi-square	36.8414	0.0000
PP - Choi Z-stat	-5.25948	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate Phillips-Perron test results D(CRMS)

Cross section	Prob.	Bandwidth	Obs
FFV	0.0001	10.0	70
JLX	0.0001	6.0	70

Panel Unit Root Test Results for the zero-order TNTM series

Null Hypothesis: Unit root (individual unit root process)

Series: TNTM

Date: 03/28/16 Time: 09:31

Sample: 1 144

Exogenous variables: Individual effects

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 142

Cross-sections included: 2

Method	Statistic	Prob.**
PP - Fisher Chi-square	34.3596	0.0000
PP - Choi Z-stat	-5.02884	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate Phillips-Perron test results TNTM

Cross section	Prob.	Bandwidth	Obs
FFV	0.0003	4.0	71
JLX	0.0001	2.0	71

Panel Unit Root Test Results for the zero-order FREQ series

Null Hypothesis: Unit root (individual unit root process)

Series: FREQ

Date: 03/28/16 Time: 09:32

Sample: 1 144

Exogenous variables: Individual effects

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 142

Cross-sections included: 2

Method	Statistic	Prob.**
PP - Fisher Chi-square	2.85680	0.5821
PP - Choi Z-stat	-0.03663	0.4854

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate Phillips-Perron test results FREQ

Cross section	Prob.	Bandwidth	Obs
FFV	0.4989	3.0	71
JLX	0.4805	3.0	71

Panel Unit Root Test Results for the first-order FREQ series

Null Hypothesis: Unit root (individual unit root process)

Series: D(FREQ)

Date: 03/28/16 Time: 09:33

Sample: 1 144

Exogenous variables: Individual effects

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 140

Cross-sections included: 2

Method	Statistic	Prob.**
PP - Fisher Chi-square	49.4345	0.0000
PP - Choi Z-stat	-6.22505	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate Phillips-Perron test results D(FREQ)

Cross section	Prob.	Bandwidth	Obs
FFV	0.0000	4.0	70
JLX	0.0001	1.0	70

Panel Unit Root Test Results for the zero-order ENPL series

Null Hypothesis: Unit root (individual unit root process)

Series: ENPL

Date: 04/12/16 Time: 22:35

Sample: 1 72

Exogenous variables: Individual effects

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 142

Cross-sections included: 2

Method	Statistic	Prob.**
PP - Fisher Chi-square	3.06715	0.5467
PP - Choi Z-stat	-0.11568	0.4540

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate Phillips-Perron test results ENPL

Cross section	Prob.	Bandwidth	Obs
FFV	0.5224	4.0	71
JLX	0.4130	5.0	71

Panel Unit Root Test Results for the first-order ENPL series

Null Hypothesis: Unit root (individual unit root process)

Series: D(ENPL)

Date: 04/12/16 Time: 22:36

Sample: 1 72

Exogenous variables: Individual effects

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 140

Cross-sections included: 2

Method	Statistic	Prob.**
PP - Fisher Chi-square	36.8414	0.0000
PP - Choi Z-stat	-5.25948	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate Phillips-Perron test results D(ENPL)

Cross section	Prob.	Bandwidth	Obs
FFV	0.0001	3.0	70
JLX	0.0001	5.0	70

Panel Unit Root Test Results for the zero-order FLTC series

Null Hypothesis: Unit root (individual unit root process)

Series: FLTC

Date: 03/28/16 Time: 09:35

Sample: 1 144

Exogenous variables: Individual effects

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 142

Cross-sections included: 2

Method	Statistic	Prob.**
PP - Fisher Chi-square	1.17204	0.8827
PP - Choi Z-stat	1.21574	0.8880

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate Phillips-Perron test results FLTC

Cross section	Prob.	Bandwidth	Obs
FFV	0.9290	1.0	71
JLX	0.5991	4.0	71

Panel Unit Root Test Results for the first-order FLTC series

Null Hypothesis: Unit root (individual unit root process)

Series: D(FLTC)

Date: 03/28/16 Time: 09:36

Sample: 1 144

Exogenous variables: Individual effects

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 140

Cross-sections included: 2

Method	Statistic	Prob.**
PP - Fisher Chi-square	57.3674	0.0000
PP - Choi Z-stat	-6.86787	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate Phillips-Perron test results D(FLTC)

Cross section	Prob.	Bandwidth	Obs
FFV	0.0000	1.0	70
JLX	0.0000	6.0	70

Panel Unit Root Test Results for the zero-order LDFC series

Null Hypothesis: Unit root (individual unit root process)

Series: LDFC

Date: 04/12/16 Time: 22:37

Sample: 1 72

Exogenous variables: Individual effects

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 142

Cross-sections included: 2

Method	Statistic	Prob.**
PP - Fisher Chi-square	28.9699	0.0000
PP - Choi Z-stat	-4.48546	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate Phillips-Perron test results LDFC

Cross section	Prob.	Bandwidth	Obs
FFV	0.0024	2.0	71
JLX	0.0002	3.0	71

Appendix VIII: Ramsey RESET Linearity Test Results

The Ramsey Regression Equation Specification Error (RESET) tests as shown in the six tables below, indicated no evidence of non-linearity since all the 3 test statistics (t-statistics, F-statistics, and Likelihood ratio) in the second row of the output tables rejected the null hypotheses of non-linearity in the six linear associations of the constructs as proposed from the path regression analyses shown in Figures 3.1a and 3.1b.

Ramsey RESET Linearity Test Results on the association between CRMS and TNTM

Ramsey RESET Test

Equation: UNTITLED

Specification: CRMS TNTM

Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	8.633589	142	0.0000
F-statistic	74.53885	(1, 142)	0.0000
Likelihood ratio	74.53885	1	0.0000

F-test summary:

	Sum of Sq.	df	Mean Squares
Test Deviance	3912.877	1	3912.877
Restricted Deviance	11367.09	143	79.49015
Unrestricted Deviance	7454.214	142	52.49447
Dispersion SSR	7454.214	142	52.49447

LR test summary:

	Value	df
Restricted Deviance	11367.09	143
Unrestricted Deviance	7454.214	142
Dispersion	52.49447	

Unrestricted Test Equation:

Dependent Variable: CRMS

Ramsey RESET Linearity Test Results on the association between FREQ and TNTM

Ramsey RESET Test

Equation: UNTITLED

Specification: FREQ TNTM

Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	13.52367	142	0.0000
F-statistic	182.8898	(1, 142)	0.0000
Likelihood ratio	182.8898	1	0.0000

F-test summary:

	Sum of Sq.	df	Mean Squares
Test Deviance	1230371.	1	1230371.
Restricted Deviance	2185660.	143	15284.33
Unrestricted Deviance	955289.2	142	6727.389
Dispersion SSR	955289.2	142	6727.389

LR test summary:

	Value	df
Restricted Deviance	2185660.	143
Unrestricted Deviance	955289.2	142
Dispersion	6727.389	

Ramsey RESET Linearity Test Results on the association between CRMS, TNTM and FREQ

Ramsey RESET Test

Equation: UNTITLED

Specification: CRMS TNTM FREQ

Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	11.59173	141	0.0000
F-statistic	134.3681	(1, 141)	0.0000
Likelihood ratio	134.3681	1	0.0000

F-test summary:

	Sum of Sq.	df	Mean Squares
Test Deviance	1313.940	1	1313.940
Restricted Deviance	2692.730	142	18.96289
Unrestricted Deviance	1378.791	141	9.778656
Dispersion SSR	1378.791	141	9.778656

LR test summary:

	Value	df
Restricted Deviance	2692.730	142
Unrestricted Deviance	1378.791	141
Dispersion	9.778656	

Ramsey RESET Linearity Test Results on the association between ENPL and FLTC

Ramsey RESET Test

Equation: UNTITLED

Specification: ENPL FLTC

Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	4.738812	142	0.0000
F-statistic	22.45634	(1, 142)	0.0000
Likelihood ratio	22.45634	1	0.0000

F-test summary:

	Sum of Sq.	df	Mean Squares
Test Deviance	2.98E+08	1	2.98E+08
Restricted Deviance	2.18E+09	143	15243531
Unrestricted Deviance	1.88E+09	142	13254733
Dispersion SSR	1.88E+09	142	13254733

LR test summary:

	Value	df
Restricted Deviance	2.18E+09	143
Unrestricted Deviance	1.88E+09	142
Dispersion	13254733	

Unrestricted Test Equation:

Ramsey RESET Linearity Test Results on the association between LDFC and FLTC

Ramsey RESET Test

Equation: UNTITLED

Specification: LDFC FLTC

Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	14.60024	142	0.0000
F-statistic	213.1670	(1, 142)	0.0000
Likelihood ratio	213.1670	1	0.0000

F-test summary:

	Sum of Sq.	df	Mean Squares
Test Deviance	84516.03	1	84516.03
Restricted Deviance	140815.9	143	984.7267
Unrestricted Deviance	56299.88	142	396.4780
Dispersion SSR	56299.88	142	396.4780

LR test summary:

	Value	df
Restricted Deviance	140815.9	143
Unrestricted Deviance	56299.88	142
Dispersion	396.4780	

Unrestricted Test Equation:

Dependent Variable: LDFC

Ramsey RESET Linearity Test Results on the association between LDFC, FLTC and LDFC

Ramsey RESET Test

Equation: UNTITLED

Specification: ENPL FLTC LDFC

Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	5.146308	141	0.0000
F-statistic	26.48449	(1, 141)	0.0000
Likelihood ratio	26.48449	1	0.0000

F-test summary:

	Sum of Sq.	df	Mean Squares
Test Deviance	1.97E+08	1	1.97E+08
Restricted Deviance	1.25E+09	142	8790517.
Unrestricted Deviance	1.05E+09	141	7452950.
Dispersion SSR	1.05E+09	141	7452950.

LR test summary:

	Value	df
Restricted Deviance	1.25E+09	142
Unrestricted Deviance	1.05E+09	141
Dispersion	7452950.	

Unrestricted Test Equation:

Dependent Variable: ENPL

(Source: Researcher, 2016)

Appendix IX: Panel Cointegration Tests Results

Panel (Pedroni Residual) Cointegration Test Results for the combined CRMS and TNTM series

Pedroni Residual Cointegration Test

Series: CRMS TNTM

Date: 03/28/16 Time: 09:38

Sample: 1 144

Included observations: 144

Cross-sections included: 2

Null Hypothesis: No cointegration

Trend assumption: No deterministic trend

User-specified lag length: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	-0.365461	0.6426	-0.418007	0.6620
Panel rho-Statistic	-3.700828	0.0001	-6.521363	0.0000
Panel PP-Statistic	-3.492341	0.0002	-4.730073	0.0000
Panel ADF-Statistic	-2.419155	0.0078	-2.406358	0.0081

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	-5.176859	0.0000
Group PP-Statistic	-4.829458	0.0000
Group ADF-Statistic	-2.511140	0.0060

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs

FFV	0.393	7.683771	8.022699	3.00	71
JLX	0.717	24.08377	18.07825	2.00	71

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
FFV	0.553	7.190777	1	--	70
JLX	0.741	21.85636	1	--	70

Pedroni Residual Cointegration Tests results indicate that 9 statistics rejected the null hypothesis of no cointegration at the conventional size of 0.05, meaning cointegrating regressions would result in long-run equillibrium relationships.

Panel (Pedroni Residual) Cointegration Test Results for the combined CRMS, TNTM and FREQ series

Pedroni Residual Cointegration Test

Series: CRMS TNTM FREQ

Date: 03/28/16 Time: 09:39

Sample: 1 144

Included observations: 144

Cross-sections included: 2

Null Hypothesis: No cointegration

Trend assumption: No deterministic trend

User-specified lag length: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	0.329997	0.3707	0.174883	0.4306
Panel rho-Statistic	-1.784240	0.0372	-2.273219	0.0115
Panel PP-Statistic	-1.662501	0.0482	-1.970959	0.0244

Panel ADF-Statistic	-0.561352	0.2873	-0.482421	0.3148

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	-1.628294	0.0517
Group PP-Statistic	-1.868812	0.0308
Group ADF-Statistic	-0.142942	0.4432

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
FFV	0.640	3.164612	3.055657	3.00	71
JLX	0.732	7.976562	7.022401	1.00	71

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
FFV	0.753	2.950890	1	--	70
JLX	0.775	7.874358	1	--	70

Pedroni Residual Cointegration Tests results indicate that 5 statistics rejected the null hypothesis of no cointegration at the conventional size of 0.05, meaning cointegrating regressions would result in long-run equillibrium relationships.

Panel (Pedroni Residual) Cointegration Test Results for the combined FREQ and TNTM series

Pedroni Residual Cointegration Test

Series: FREQ TNTM

Date: 03/28/16 Time: 09:40

Sample: 1 144

Included observations: 144

Cross-sections included: 2

Null Hypothesis: No cointegration

Trend assumption: No deterministic trend

User-specified lag length: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	-0.656990	0.7444	-0.647101	0.7412
Panel rho-Statistic	-2.135402	0.0164	-2.523674	0.0058
Panel PP-Statistic	-2.749425	0.0030	-2.852830	0.0022
Panel ADF-Statistic	-1.925440	0.0271	-1.684803	0.0460

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	-1.673344	0.0471
Group PP-Statistic	-2.968294	0.0015
Group ADF-Statistic	-1.658974	0.0486

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
FFV	0.668	1609.828	1311.410	3.00	71
JLX	0.797	1716.095	1087.031	2.00	71

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
FFV	0.791	1360.270	1	--	70
JLX	0.799	1500.349	1	--	70

Pedroni Residual Cointegration Tests results indicate that 9 statistics rejected the null hypothesis of no cointegration at the conventional size of 0.05, meaning cointegrating regressions would result in long-run equilibrium relationships.

Panel (Pedroni Residual) Cointegration Test for the combined ENPL and FLTC series

Pedroni Residual Cointegration Test

Series: ENPL FLTC

Date: 03/28/16 Time: 09:44

Sample: 1 144

Included observations: 144

Cross-sections included: 2

Null Hypothesis: No cointegration

Trend assumption: No deterministic trend

User-specified lag length: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	1.459063	0.0723	1.057476	0.1451
Panel rho-Statistic	-3.740155	0.0001	-2.516896	0.0059
Panel PP-Statistic	-2.632687	0.0042	-2.020145	0.0217
Panel ADF-Statistic	-1.398651	0.0810	-0.974785	0.1648

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	-2.986252	0.0014
Group PP-Statistic	-2.351104	0.0094
Group ADF-Statistic	-1.332034	0.0914

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
FFV	0.884	1671450.	1352548.	3.00	71
JLX	0.495	6777010.	6777010.	0.00	71

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
FFV	0.902	1592308.	1	--	70
JLX	0.486	6872308.	1	--	70

Pedroni Residual Cointegration Tests results indicate that 6 statistics rejected the null hypothesis of no cointegration at the conventional size of 0.05, meaning cointegrating regressions would result in long-run equillibrium relationships.

Panel (Pedroni Residual) Cointegration Test for the combined ENPL, FLTC and LDFC series

Pedroni Residual Cointegration Test

Series: ENPL FLTC LDFC

Date: 04/12/16 Time: 22:43

Sample: 1 72

Included observations: 144

Cross-sections included: 2

Null Hypothesis: No cointegration

Trend assumption: No deterministic trend

User-specified lag length: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	1.013560	0.1554	0.700436	0.2418

Panel rho-Statistic	-2.380408	0.0086	-1.610866	0.0536
Panel PP-Statistic	-2.022835	0.0215	-1.475664	0.0700
Panel ADF-Statistic	-0.235481	0.4069	0.022049	0.5088

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	-2.168442	0.0151
Group PP-Statistic	-1.879939	0.0301
Group ADF-Statistic	-0.283920	0.3882

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
FFV	0.895	1258580.	1572690.	5.00	71
JLX	0.461	4467724.	4419259.	1.00	71

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
FFV	0.896	1268753.	1	--	70
JLX	0.471	4519831.	1	--	70

Pedroni Residual Cointegration Tests results indicate that 4 statistics rejected the null hypothesis of no cointegration at the conventional size of 0.05, meaning cointegrating regressions would result in long-run equillibrium relationships.

Panel Cointegration (Pedroni Residual) Test for the combined LDFC and FLTC series

Pedroni Residual Cointegration Test

Series: LDFC FLTC

Date: 04/12/16 Time: 22:45

Sample: 1 72

Included observations: 144

Cross-sections included: 2

Null Hypothesis: No cointegration

Trend assumption: No deterministic trend

User-specified lag length: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	0.665149	0.2530	0.005479	0.4978
Panel rho-Statistic	-7.921038	0.0000	-7.947623	0.0000
Panel PP-Statistic	-5.302679	0.0000	-5.239487	0.0000
Panel ADF-Statistic	-4.865236	0.0000	-5.038563	0.0000

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	-6.643452	0.0000
Group PP-Statistic	-5.869738	0.0000
Group ADF-Statistic	-4.994443	0.0000

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
FFV	0.439	26.91137	23.28485	3.00	71
JLX	0.421	64.96408	55.87042	4.00	71

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
FFV	0.465	25.82550	1	--	70
JLX	0.334	64.21142	1	--	70

Pedroni Residual Cointegration Tests results indicate that 9 statistics rejected the null hypothesis of no cointegration at the conventional size of 0.05, meaning cointegrating regressions would result in long-run equilibrium relationships.